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Do Workers Undervalue COVID-19 Risk? Evidence from Wages and Death Certificate Data
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ABSTRACT

When mortality risks of a job increase, economic theory predicts that wages will rise to compensate workers. COVID-19 became a new source of mortality risk from close contact with other workers and customers. Real wages have risen during the COVID-19 era, but research to date has been sparse on how much of this increase reflects compensating wage differentials for COVID-19 risk on the job. We use 2020- 2021 death certificate data which for the first time includes the decedent's occupation and industry, together with other occupational and industry mortality for previous years from the Census of Fatal Occupational Injuries (CFOI) and wage data from the Current Population Survey (CPS) to examine whether compensating wage differentials for COVID-19 occupational risks are in line with prior estimates of Values of Statistical Life (VSL). First, we find that there are substantial differences in the compensating differentials associated with COVID-19 vs other sources of job-related mortality risk. Full time workers' pay is higher by $24 per week in jobs with a 1 in 1,000 higher risk of COVID-19 mortality, but their pay is $320 higher in jobs with 1 in 1,000 higher risk of non-COVID-19 workplace mortality. The non-COVID-19 mortality wage premiums imply that workers trade off money and mortality risk using a VSL of about $18 million, which is near the upper range of the most cited VSL estimates in the literature. In contrast, the COVID-19 wage premium implies that workers make decisions using a VSL of the range $1.24 - $1.54 million, much lower than standard VSL measures. The results are consistent with workers substantially underestimating or undervaluing the risk of COVID-19 mortality.

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1 Introduction

The COVID-19 pandemic represents the introduction of a new disease and fatality risk into economies worldwide. Because the virus spreads easily when people are in close contact, COVID-19 became a workplace hazard for many types of workers. Labor markets and governments adapted quickly to the new risk, and many workers shifted to remote work modalities to avoid health harm (Barry et al., 2022; Albanesi and Kim, 2021; Cortes and Forsythe, 2023). Some workplaces made investments in new ventilation equipment or adopted social distancing and masking requirements in an effort to mitigate the spread of the disease. However, the costs of effective safety protocols were likely very high and thus incomplete in some jobs. In these cases, people who continued to work exposed themselves to a higher risk of sickness and death. Standard economic theory suggests that this change in risk would generate a compensating response in wages. The basic model of hedonic equilibrium wages implies that workers know and understand the risks associated with different jobs. In these models, workers sort into the job that offers the combination of cash compensation, workplace benefits, and hazards that maximizes their utility. Likewise, firms spend resources on safety investments and make wage offers that minimize costs. Observed wages and risk levels are an equilibrium outcome.

The hedonic wage model is a reasonable starting point for the analysis of labor market responses to the epidemic. However, recent work in behavioral public finance and health economics suggests that people sometimes make systematic errors when evaluating the costs and benefits associated with treatments and conditions that affect their health. As yet, little is known about how the basic hedonic model behaves when workers make perceptual errors related to COVID-19 mortality risk. There are reasons why workers may perceive COVID-19 mortality risks to be more salient and overvalue them, but there are also reasons why perceptions of job insecurity during the COVID-19 era might cause workers to accept less of a wage premium for COVID-19 risks than they might for other fatal occupational risks.

For many years, researchers have relied on the Census of Fatal Occupational Injuries (CFOI) for measuring workplace risk. The CFOI data is comprehensive, incorporating various sources to compile fatality counts. Unfortunately, it is often difficult for researchers to access the data at a level of granularity that facilitates the most rigorous research. For instance, the publicly available version of the CFOI data cannot be disaggregated by occupation and industry, which are important dimensions of job-related risk.[1]

[1]Notably, the restricted version of the CFOI data is designed to allow researchers to use disaggregated

This study makes several contributions. First, we provide initial estimates of wage premiums based on COVID-19 mortality risk, capturing the economic impact of new workplace hazards, and deriving the implied value of a statistical life (VSL).[2] Second, we update the VSL estimates for pre-COVID-19 and post-COVID-19 work-related deaths using the most recent public CFOI data. Third, we introduce a novel source for studying COVID-19 risk and an alternative dataset for examining non-COVID-19 workplace risks. Finally, we offer harmonization tools to navigate the various industry and occupation classification systems commonly used in mortality, workplace fatality, and labor market data.

The first section of the paper explains the data sources and the harmonization tools we use in our work. The second section presents the econometric framework used to estimate wage compensating differentials for both COVID-19 and traditional workplace risks. The third section presents the estimates of compensating wage differentials for COVID-19 risks. The fourth section examines the magnitude of VSL for workplace deaths using the new death certificate data, as well as traditional VSL estimates using the CFOI. Section 5 explores how workers may undervalue COVID-19 risk and contextualizes our findings within the broader literature on VSL. Section 6 concludes.

2 Data

2.1 Death Certificate Data

Typically, job-specific mortality is calculated for deaths from all-causes and not for specific causes of death. This makes it challenging to estimate compensating wage differentials for COVID-19 risks separately from other risks on the job. In this paper, we study workplace mortality risks using the latest data from the CDC Multiple Cause of Death (MCOD) data. The CFOI is the main existing source of data on workplace mortality rates. The public use version of the data consists of workplace fatality rates at the industry level or the occupation level. The data are usually updated and released with a long lag. More detailed data – such as mortality risks within industry by occupation cells – are not publicly available and the

measures of occupation and industry. But these data have been difficult for researchers to obtain (process described at https://www.bls.gov/iif/iif-data-requests.htm but noted as available only depending on available BLS resources) for a variety of reasons, including bureaucratic hurdles and various time delays, and thus are seldom used in research.

[2]To our knowledge, the only other research that has attempted to fill this gap in the literature is a recent paper by Cramer et al. (2024). In that paper, the authors examine "private market compensating differentials for workers facing heightened occupational risks from Covid, as well as any wage increases that might be attributable to state policies". Their findings indicate that "the wage-risk tradeoff and the implied VSL based on market responses were somewhat below the average VSL".

restricted use version of the CFOI data is difficult for researchers to access.

The MCOD data that we use is derived from death certificates – each year of data contains the universe of known deaths in the U.S. Each death record includes a single Underlying Cause of Death (UCD) as well as up to twenty additional causes, which are categorized by four-digit ICD-10 codes. The decedents demographic characteristics are also provided, including state and county of residence, age, gender and race/ethnicity, place of death, and whether the deaths were from income generating activities (Centers for Disease Control and Prevention, 2016). Until recently, the MCOD data did not contain any information on the decedent's occupation or industry. Starting in 2020-2021, the MCOD includes four-digit Census Occupation Code (2010 version) and four-digit Census Industry Code (2012 version). These occupation and industry codes reflect the occupation or industry of the job that the decedent worked *the most* during his/her working life (Steege et al., 2020). The MCOD data are restricted use but the application process is straightforward and the data have been widely used in economic research. However, our paper is the first to exploit the new MCOD data with occupation and industry codes to study workplace risks.

To construct the occupation-by-industry specific variation in COVID-19 mortality rate, we followed four steps. First, we used the underlying cause of death codes to identify COVID-19 deaths in 2020-2021, following methods provided by the CDC and the Armed Forces Health Surveillance Center.[3] To increase the likelihood that the occupation and industry codes referred to the job held at the time of death, we restricted the COVID-19 deaths to individuals who died between ages 18 and 65 years old. Second, we collapsed the individual data to occupation by industry cells, obtaining counts of the number of COVID-19 deaths in each job-type cell. Third, we used the Current Population Survey (CPS) to estimate the number of workers in each job type cell. These employment counts served as the denominator for calculating the COVID-19 fatality risk of each job. Specifically, we estimated the COVID-19 mortality rate per 100,000 workers by dividing the COVID-19 death count by the employment counts and multiplying by 100,000. We derived two measures of the COVID-19 mortality rate: one reflecting the rate in 2020 and another reflecting the average rate for 2020-2021. In our main analysis, we estimate COVID-19 mortality rates at the two-digit occupation-by-industry level. Since these estimates could be noisy for some cells, in robustness checks, we also examine COVID-19 mortality rates at the four-digit occupation and four-digit industry levels.

[3] The list of cause of death codes for COVID-19 includes: J1289 J208 J22 J40 J80 J988 R0955 R05 R0602 R509 U071 U072 B9739 Z03818 Z1158 Z20828 B9789 H669 H6690 H6691 H6692 H6693 J00 J019 J0109 J069 J09 J10 J100 J1000 J1001 J1008 J101 J102 J108 J1081 J1082 J1083 J1089 J11 J110 J1100 J1108 J111 J112 J118 J1181 J1182 J1183 J1189 J129 J18 J181 J189 J209 J40 R05 R509.

2.2 Workplace Fatality Data

2.2.1 MCOD Workplace Fatalities

In addition to COVID-19 workplace mortality rates, we also use the death certificate data to estimate overall workplace fatality rates. To do this, we limited the sample to "workplace deaths", which we classify as deaths that are reported as occurring on a job site or as related to income-generating activities. We collapse the data in occupation by industry cells and divide by CPS employment counts to obtain the workplace fatality rate at the two-digit occupation-by-industry level. We also examine workplace fatality rates at the four-digit occupation and industry levels. We derived two measures of workplace risk: the fatality rate in 2020 and the average fatality rate for 2020-2021.

2.2.2 CFOI Workplace Fatalities

To facilitate comparisons with prior work, we also examine data from the public use CFOI data. The CFOI is designed to capture all work-related fatalities in a given year by reconciling fatalities from different sources, including reports by the Occupational Safety and Health Administration, workers' compensation reports, death certificates, and medical examiner reports (Bureau of Labor Statistics, 2021).[4,5] The published CFOI data on workplace fatalities are aggregated at either six-digit level of details following the Standard Occupation Classification (SOC) or six-digit North American Industry Classification System (NAICS). We obtain the data for 2018-2021 and follow a similar process to calculate the workplace fatality rate after obtaining the fatality count, that is, dividing it by the total number of workers, extrapolated from the Current Population Survey. We arrived at the workplace fatality rate at the four-digit occupation and four-digit industry levels; as noted earlier, the open-source CFOI data do not breakdown at occupation-by-industry level. We calculated the average workplace fatality rates in 2018-2019 and in 2020-2021, the former representing a pre-COVID-19 period and the latter representing post-COVID-19.

[4] While the first two CFOI sources serve both as a first-hand verification and a follow-up examination of work status, for an injury to be classified as work related, the decedent must have been employed at the time of the fatal event and engaged in legal work activity that required him or her to be present at the site of the fatal incident.

[5] It is also worth noting that in 2020-2021, CFOI only included fatal workplace injuries complicated by an illness such as COVID-19 if they were precipitated by an injury.

2.3 Current Population Survey

To study compensating wage differentials, we construct a sample of workers using Current Population Survey (CPS) Monthly Outgoing Rotation Sample data for 2018-2019 and 2021-2022. We obtained individual information on labor market characteristics such as employment status, wages, and hours worked, as well as other demographics, including education, location of residence, race/ethnicity, marital status, and gender. We use the sample to estimate total US number of workers in 2019 by occupation and industry to serve as a denominator for both workplace and COVID-19 mortality rate calculations, using the weights provided in the CPS.

We chose to use four years of CPS data, two before (2018-2019) and two after (2021-2022) the COVID-19 outbreak, to measure within-occupation-by-industry changes in wages, which allows a reasonable amount of time for the post-COVID-19 period to capture any possible changes in workers' compensation. Throughout the analysis, we limited our sample to workers who are between 18 and 65 years old, worked full-time (i.e., more than 34 hours in the last week) and earned more than weekly federal minimum wage applied in 2020. The final data set has 233,770 individual waged workers in 2018-2019 and 196,600 individual waged workers in 2021-2022, respectively.

Then we merged the MCOD COVID-19 mortality rate and workplace fatality rate with the individual CPS worker data at occupation by industry level using the harmonized occupation and industry codes. Likewise, we merge the CFOI workplace fatality rate onto the CPS sample by year and four-digit occupation or year and four-digit industry level.

2.4 Harmonized Occupation and Industry Codes

2.4.1 Two-digit Industry-by-Occupation Census Code

We followed the two-digit occupation-by-industry classification adopted by Gentry and Viscusi (2016) and harmonized the differences between the 2010 and 2018 Census occupation classifications, as well as between 2012 and 2017 Census industry classifications for the CPS individual and MCOD mortality data. The detailed harmonization process is described in the Appendix Figure A7. The method results in 1,077 two-digit occupation-by-industry cells. As the CFOI data are only available either by industry or occupation, we are unable to obtain the workplace fatality and nonfatal incidence rates at the occupation-by-industry level. Instead, we attempted to incorporate these data at the four-digit harmonized occupation or four-digit harmonized industry level, which we explain below.

2.4.2 Four-digit Harmonized Occupation Code

There are three different occupation classification systems from the data sources that we use: SOC 2017, Census 2010 and Census 2018 occupation classifications. We used two methods to harmonize the coding systems. Our first approach is the IPUMS harmonization method which reconciles Census codes across time and space into a harmonized system in 2010. That is, the harmonization creates the lowest common denominator that is fully comparable while retaining all meaningful detail in each CPS sample (IPUMS, 2022). This converts the occupation codes in all CPS years (including in the 1990s) into the harmonized codes in 2010. (See Appendix Figure A8 for navigation details on occupation classifications).

In the second method, we created a harmonization system ourselves, where we only attempted to resolve the differences in the most recent data rather than all years. To guide the process, we use the crosswalk available at `https://www.census.gov/topics/employment/industry-occupation/guidance/code-lists.html`. Details of the harmonization process are described in Appendix Figure A11 and Figure A12.[6] In essence, we harmonized both systems towards the Census 2018 occupation classification and as a result created two crosswalks (i) Census 2010 - Harmonized 2018 and (ii) Census 2018 - Harmonized 2018. More specifically, for codes (single or multiple) that changed from Census 2010 to a single code in Census 2018, we used the 2018 code in Harmonized 2018. If a single 2010 code split into multiple 2018 codes, we assigned the single 2010 code in Harmonized 2018. For multiple-to-multiple code changes, we relied on the highest probability derived from the conversion rate that was given to a match and assigned the resulting code in Harmonized 2018.[7]

The detailed navigation between data sources is described further in Appendix Figure A9. We used the Census 2010 - Harmonized 2018 crosswalk to convert CPS 2018-2019 and CDC MCOD data, and Census 2018 - Harmonized 2018 crosswalk to convert CPS 2021-2022 and workplace fatality data into the same harmonized occupation system. We ended up with 442 harmonized occupations if we employed the IPUMS harmonization system and 476 harmonized occupations if we adopted the O'Neill School harmonization system. Throughout the paper, we show the results for the IPUM harmonized system although the results using the O'Neil School system are similar.[8]

[6]There are similarly three different industry classifications with splits and concatenation of industries but we only described here the harmonization of occupation classification.

[7]Detailed splits, concatenations of occupations and conversion rates for many to many matches are available in Appendix Table 8, Table 9 and Beckhusen (2020).

[8]The empirical results are available upon request.

2.4.3 Four-digit Harmonized Industry Code

We also used the same algorithm to harmonize different industry classifications. There are also three different systems that we harmonized: NAICS 2017, Census 2012 and Census 2017 industry classifications. Similarly to the harmonization of occupations, we used two different harmonization systems, the IPUMS method for all years and the focal years only method. For the latter, we harmonized the codes towards the Census 2017 system. We used the Census 2012 - Harmonized 2017 crosswalk to convert CPS 2018-2019 and CDC MCOD data, and Census 2017 - Harmonized 2017 crosswalk to convert industry codes in CPS individual, workplace fatality and incidence rate data 2021-2022 into the same harmonized industry system. (See Appendix Figure A8 for the navigation details on industry classifications using IPUMS and Appendix Figure A10 for the focal year approach). As a result, we ended up with 220 harmonized four-digit industries if we use the IPUMS system and 263 if we use the focal year approach.

3 Econometric Model

To study the way that workers and firms have responded to changes in workplace mortality risks created by the COVID-19 pandemic, we use a version of the Mincer wage equation that incorporates both the COVID-19 mortality risk and the overall workplace fatality risk (Kniesner and Leeth, 2010). Let w_{ijkt} represent the weekly wage of person i in occupation j and industry k in year t. Let c_{jk} represent the average COVID-19 mortality rate in 2020-2021 in occupation j and industry k and let r_{jk} be the average workplace fatality rate in 2020-2021 in occupation j and industry k. In our main analysis, c_{jk} and r_{jk} are measured using the MCOD data. However, we also calculated the workplace fatality rate in 2018-2021 from the CFOI to facilitate comparisons. Next, D_t^{21} is a dummy variable set to 1 if the observation is drawn from the 2021-2022 CPS sample rather than the 2018-2019 sample. x_{ijkt} is a vector of worker characteristics, including age, gender, education, marital status, race/ethnicity, and time (year and month) and state fixed effects. We pool data from the 2018-2019 and 2021-2022 outgoing rotation groups of the monthly CPS and fit the following OLS regression:

$$ln(w_{ijkt}) = \beta_1 + \beta_2(c_{jk} \times D_t^{21}) + \beta_3(r_{jk} \times D_t^{21}) + \gamma_2 c_{jk} + \gamma_3 r_{jk} + x_{ijkt}\alpha + a_j + b_k + \varepsilon_{ijkt}$$

During the 2018-2019 period, COVID-19 did not exist and was not contributing to a compensating wage differential. However, exposure to COVID-19 risk was not randomly assigned across occupations and it is possible that there was a pre-existing association with wages and the job-types that eventually faced high vs low COVID-19 risk. We use a kind of "difference in difference" logic to adjust for this possible bias. In the regression, γ_3 represents the pre-COVID association between wages and eventual 2020-2021 COVID-19 mortality rate in the job. Once COVID-19 arrives and becomes an actual threat, theory suggests that a compensating differential may emerge that alters the pre-existing association. In the regression, the compensating differential for the new COVID-19 risk is captured by β_2. It measures the proportional increase in wages associated with a marginal increase in level of COVID-19 risk, after adjusting for other characteristics included in the model. If workers value COVID-19 mortality risk then we would expect $\beta_2 > 0$, indicating that wages rose to account for the new risk of COVID-19 exposure. The identification of β_2 comes from the common trend assumption in the difference-in-difference literature. That is, conditional on individual characteristics and fixed effects, the difference in wages between 2018-2019 and 2021-2022 would have stayed the same across occupations and industries in the absence of COVID-19. Workers may also receive a compensating wage differential for non-COVID workplace risks. In the regression, the overall fatality differential is given by γ_3 in the pre-COVID period and by $\beta_3 + \gamma_3$ in the post COVID period.

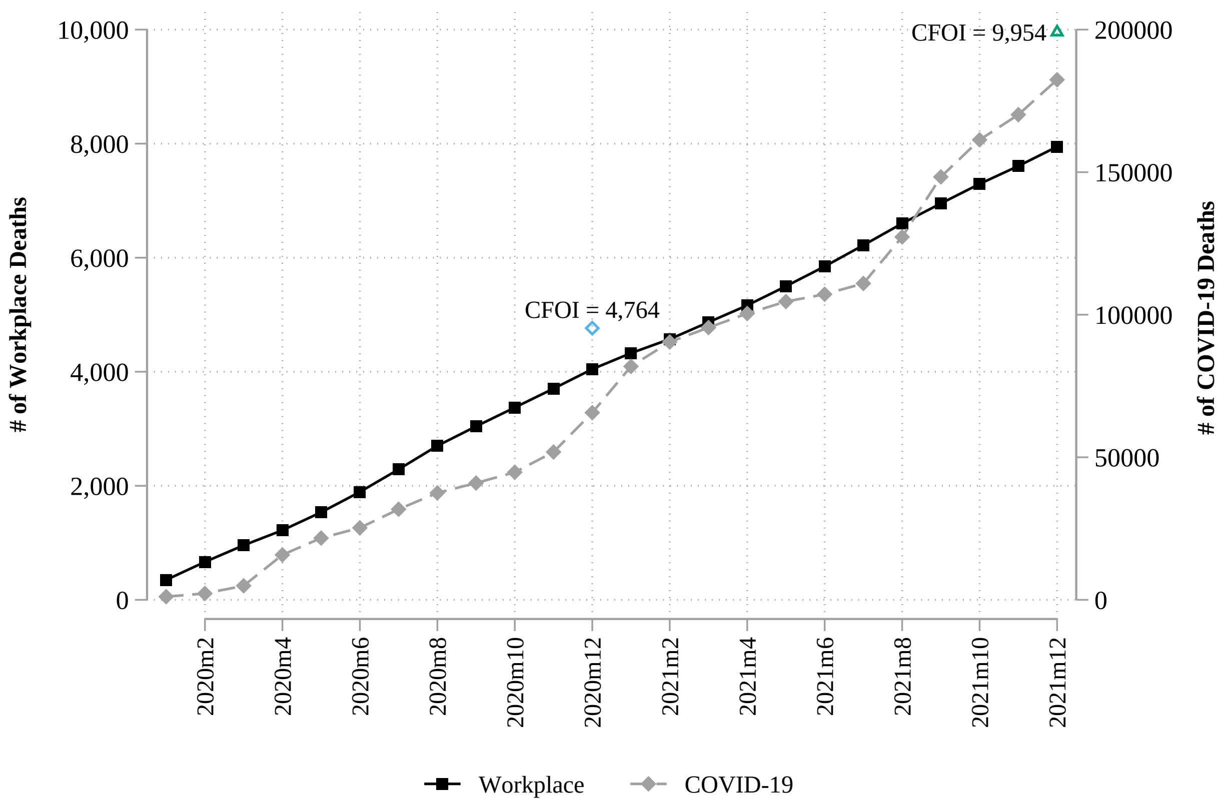
We use the model to estimate the VSL implied by compensating differentials for COVID-19 risk and for workplace fatality risk. Specifically, we let $\bar{w}$ represent the average weekly wage and $\bar{h}$ represent the average weeks worked in the CPS sample. Then the VSL implied by the COVID-19 compensating differential is $VSL_c = \beta_2 \times \bar{w} \times \bar{h} \times 100,000$. The VSL post-COVID implied by the workplace fatality compensating differential is $VSL_r^{post} = (\beta_3 + \gamma 3) \times \bar{w} \times \bar{h} \times 100,000$. The VSL pre-COVID implied by the workplace fatality compensating differential is $VSL_r^{pre} = \gamma_3 \times \bar{w} \times \bar{h} \times 100,000$. In a simple model where people value mortality equally across causes of death, we might expect $VSL_c = VSL_r$. If workers undervalue COVID-19 risk – perhaps due to internalities or incomplete information - then we might expect that $VSL_c < VSL_r^{post}$ and $VSL_c < VSL_r^{pre}$. The ratio of these two VSLs provides one way to measure the degree of undervaluation of mortality risk based on real world data.

4 Results

4.1 COVID and Non-COVID Workplace Risks

Figure 1 shows how COVID-19 and non-COVID workplace fatalities accumulated from 2020 to 2021. By the end of 2021, cumulative COVID-19 mortality at the workplace was approximately 170,000 deaths, which accounts for one-fifth of the total COVID-19 fatalities in the United States.[9] In contrast, work-related fatalities remained relatively steady, reaching a little more than 8000 deaths over the two year period. The workplace fatality numbers quite closely align with the official figures reported by the CFOI, underscoring the credibility of utilizing death certificate data for measuring workplace risks. There are about 120,000 workers in the average occupation-industry cell in our sample. This implies an average COVID-19 mortality rate of 50 deaths per 100,000 workers on average in 2020-2021. The likelihood of workplace fatalities was significantly lower, at 3 deaths in 100,000 workers.

Figure 1: **Fatality at Workplace - COVID-19 Mortality and Work-Related Deaths in 2020-2021**



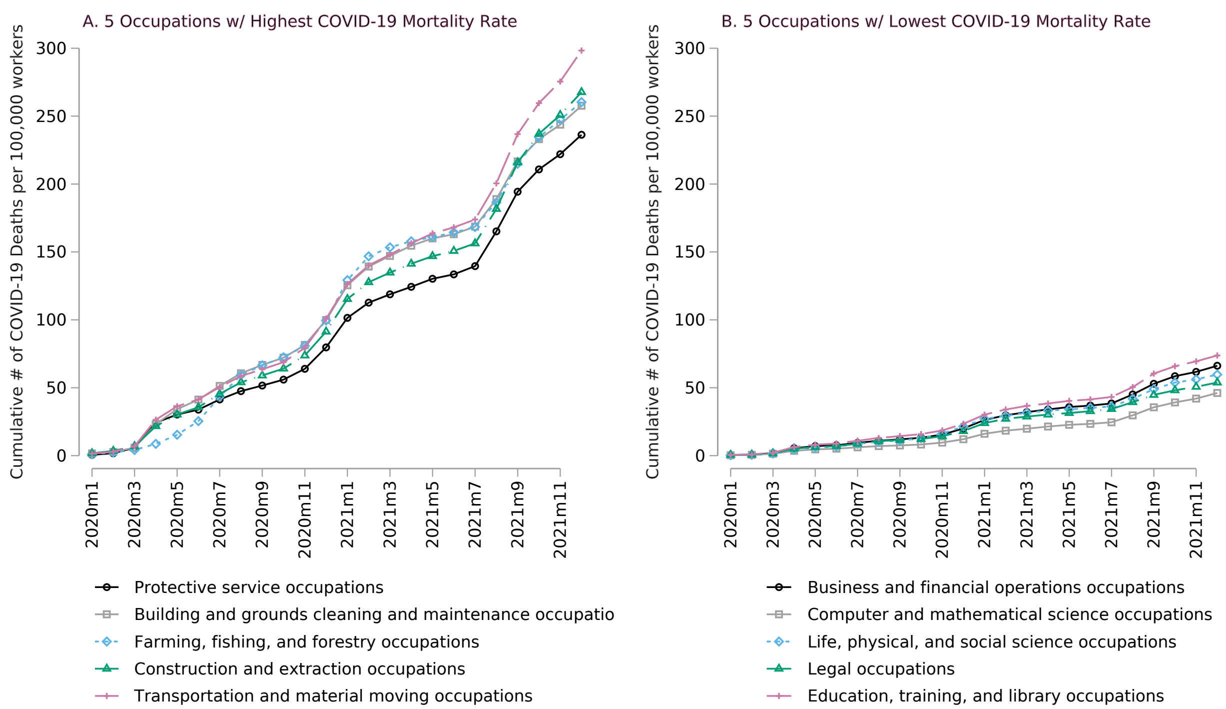
Sources: Multiple Cause of Death for COVID-19 and workplace deaths by occupation and industry in 2020-2021 and Census of Fatal Occupational Injuries in 2020-2021. **Notes:** Figure displays the cumulative COVID-19 deaths and workplace fatalities. Sample includes decedents between 18 and 65 yrs old. COVID-19 death is defined based on ICD-10 for cause of death. Workplace deaths in MCOD data is defined based on income earning activities and place of death. Workplace deaths in CFOI can be downloaded at https://www.bls.gov/iif/fatal-injuries-tables.htm. List of occupations and

[9]The 170,000 death figure is reduced significantly as more restrictions are put on the data (e.g., restrictions on type of income generating activities or at specific worksites). Estimates with the inclusion of these additional restrictions are available upon request.

industries at 2-digit level based on Census classification available at https://www.cdc.gov/nchs/data/dvs/industry-and-occupation-data-mortality-2020.pdf.

Figure 2 shows the most dangerous and safest jobs in terms of probability of COVID-19 death. The low risk occupations are office-based with substantial capacity for working from home, such as business and financial operations, education services, and the sciences. Conversely, the highest COVID-19 risks are faced by people working in transportation, construction, maintenance, and protective services. The COVID-19 risk faced by material moving workers was the highest at 0.3% by the end of 2021. Similar patterns emerge when examining industries (results presented in Figure 3), with transportation and agriculture ranking among the riskiest sectors, while telecommunication and information services, facilitating remote work, emerge as the safest.

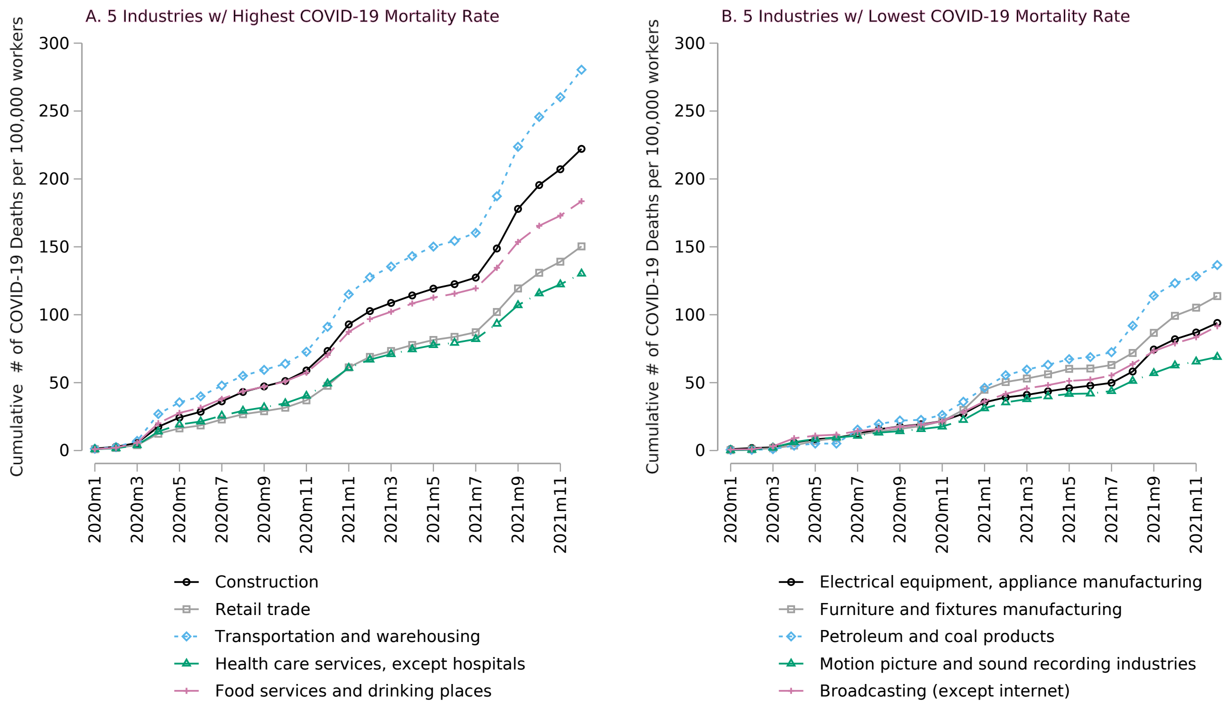
Figure 2: **Rise in COVID-19 Risk Among Occupations**



Sources: CPS Monthly Outgoing Rotation Group sample in 2019 for number of workers and Multiple Cause of Death for COVID-19 deaths by occupation and industry in 2020-2021. **Notes:** Figure displays the cumulative COVID-19 deaths. Sample includes decedents between 18 and 65 yrs old. COVID-19 death is defined based on ICD-10 for cause of death. Workplace death is defined based on activity that generates income and place of injury. COVID-19 mortality rate and workplace fatality rate are COVID-19 and workplace deaths in 2020-2021 per 100,000 workers in 2019, respectively. List of occupations and industries at 2-digit level based on Census classification available at https://www.cdc.gov/nchs/data/

dvs/industry-and-occupation-data-mortality-2020.pdf.

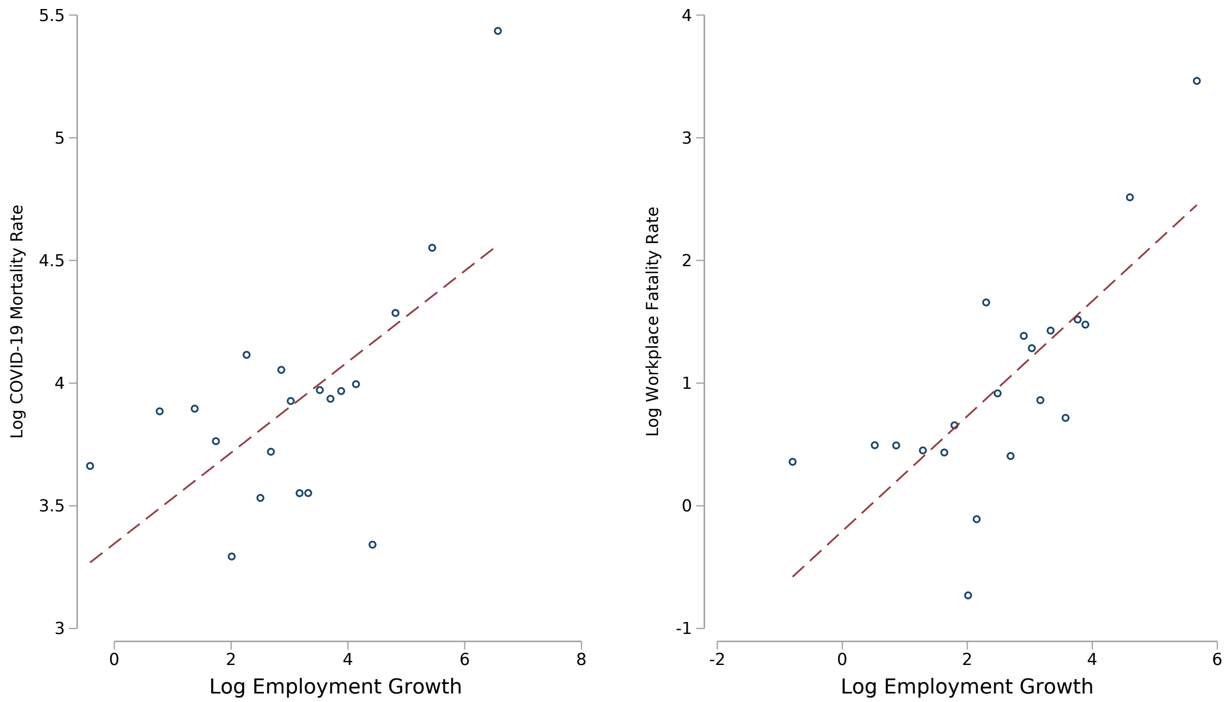
Figure 3: **Rise in COVID-19 Risk Among Industries**



Sources: CPS Monthly Outgoing Rotation Group sample in 2019 for number of workers and Multiple Cause of Death for COVID-19 deaths by occupation and industry in 2020-2021. **Notes:** Figure displays the cumulative COVID-19 deaths and workplace fatalities. Sample includes decedents between 18 and 65 yrs old. COVID-19 death is defined based on ICD-10 for cause of death. Workplace death is defined based on activity that generates income and place of injury. COVID-19 mortality rate and workplace fatality rate are COVID-19 and workplace deaths in 2020-2021 per 100,000 workers in 2019, respectively. List of occupations and industries at 2-digit level based on Census classification available at https://www.cdc.gov/nchs/data/dvs/industry-and-occupation-data-mortality-2020.pdf.

The pandemic also led to substantial changes in employment patterns. Many jobs were destroyed in the early part of the pandemic and there was very rapid employment growth in the middle and later stages of the pandemic. How was employment growth in different job types related to COVID-19 risk and regular workplace risk? Figure 4 presents binned scatter plots, where employment growth between 2019 and 2021 across occupation-by-industry cells is divided into 20 quantiles and plotted against average mortality rates for both COVID-19 and non-COVID-19 causes in 2020-2021. The figure shows that occupation-industries with high employment growth tended to have higher COVID-19 mortality risk and also higher non-COVID mortality risk. This suggests substantial room for the possibility that workers are sorting into jobs partly based on risk preferences.

Figure 4: **Employment Loss and Risks at Workplace**



Sources: CPS Monthly Outgoing Rotation Group sample in 2019 and 2021 for employment and Multiple Cause of Death for COVID-19 and workplace deaths by occupation and industry in 2020-2021. **Notes:** Figure displays a binned scatter plot between employment growth between 2019 and 2021 and COVID-19 mortality and workplace fatality rates. Sample includes 18-65 year old full-time workers who earned above federal minimum wage applied in 2020. COVID-19 death is defined based on ICD-10 for cause of death. Workplace death is defined based on activity that generates income and place of injury. COVID-19 mortality rate and workplace fatality rate are COVID-19 and workplace deaths in 2020-2021 per 100,000 workers in 2019, respectively. List of occupations and industries at 2-digit level based on Census classification available at https://www.cdc.gov/nchs/data/dvs/industry-and-occupation-data-mortality-2020.pdf.

Before turning to the regression results, we present a summary of statistics for the individual variables that we used in our specification in Table 1. The key independent variables of interest are non-COVID-19 and COVID-19 mortality rates calculated based on the worker's occupation and industry. The averages of weekly wages and number of weeks worked are approximately $1,200 and 50 hours respectively. The statistics on non-COVID-19 deaths from CFOI indicates that workplace fatality rate decreases between 2018-2021 by as much as 13.6% and approximately 10% between 2019 and 2020, consistent with 10.7% decrease in workplace fatalities between 2019 and 2020 as published in (Bureau of Labor

Statistics, 2021). This is likely partly the result of the COVID-19 pandemic in 2020, which reduced employment for many people and led many others to work from home and therefore there were fewer fatal accidents in total at work.

When we examine descriptive statistics by race and ethnicity (Table 7) we find that there are many differences in key labor market characteristics. For example, average weekly wages are substantially lower for minoritized populations (977.59 for Hispanic and 1012.29 for Non-Hispanic Black populations) than for non-Hispanic whites (1311.51). Weeks worked per year are approximately the same (50.55 for Hispanic and 50.27 for Non-Hispanic Black populations and 50.85 non-Hispanic whites). The COVID-19 mortality rate in 2020-2021 is substantially worse for minoritized populations (90.9 for Hispanic and 79.57 for Non-Hispanic Black populations) than for non-Hispanic whites (66.79). The overall workplace fatality rate is also much higher for Hispanic (4.53) and non-Hispanic Black (3.06) compared to non-Hispanic white populations (2.68).

4.2 Wage Responses to Workplace Risks

Panel A of Table 2 reports estimated regressions of log wages on COVID risk, workplace risk, and controls.[10] The regressions in the first column adjust for COVID-19 risk but do not control for workplace fatalities and they include occupation and industry fixed effects at the one digit level. The second column adjusts for non-COVID workplace fatality risks as well. The results in the third and fourth column include occupation and industry fixed effects at the two digit level. In all regressions, we clustered the robust standard errors at the occupation-by-industry level for the inferences of coefficient estimates. For the VSLs, we obtained the 95% confidence interval using the delta method of non-linear transformation of the mortality risk coefficients, while keeping the variables of wages and hours worked

[10] A common limitation with many studies in the VSL literature is that they are not able to control for non-fatal injuries in the labor market – often times due to the lack of available injury data at the desired level of granularity. The exclusion of non-fatal injuries can possibly lead to upward bias in the VSL regression coefficients as they are potentially correlated with fatality risk. For example, in dangerous jobs like logging, employers compensate for both higher fatality risk and increased injury risk (e.g., loss of limbs). Thus, the compensating wage differential for fatalities might also reflect compensation for injuries. Similarly, with COVID-19, employers compensate for both higher fatality risk and the possibility of non-fatal illness (e.g., minor illnesses, hospitalizations). Given we do not control non-fatal illnesses in the regression results presented here, it is possible that our estimates may have an upward bias. The magnitude of this possible bias is unclear. As discussed in Carlin et al. (2024), the literature on COVID-19 non-fatal valuations has been limited. The best estimates in the literature suggest non-fatal cases might add another 10%-100% to the total cost of COVID-19 (Kniesner and Sullivan, 2020; Robinson et al., 2022; Viscusi, 2020). While the exact amount is uncertain, the upper end of the range suggests the impact could be significant. As new data becomes available, we urge future studies to improve upon this potential limitation of this study. We thank Elissa Gentry for this insight.

Table 1: **Summary Statistics**

	2018-2019		2020-2021	
	Mean	Std. Dev.	Mean	Std. Dev.
Panel A. Two-digit Census Occupation-by-Industry				
COVID-19 Mortality Rate (per 100,000 workers)	-	-	72.29	65.83
Workplace Fatality Rate (per 100,000 workers)	-	-	3.03	5.32
Panel B. Four-digit IPUMS Occupation				
COVID-19 Fatality Rate (per 100,000 workers)	-	-	71.54	50.77
Workplace Fatality Rate (per 100,000 workers)	-	-	3.03	5.48
CFOI Workplace Fatality Rate (per 100,000 workers)	3.89	8.65	3.36	7.67
Panel C. Workers Labor Market and Demographic Characteristics	2018-2019		2021-2022	
	Mean	Std. Dev.	Mean	Std. Dev.
Weekly Wages ($)	1124.32	684.19	1259.87	717.44
Weeks Worked	50.96	5.22	50.71	5.90
Age	41.16	12.36	41.19	12.38
Female	0.44	0.50	0.45	0.50
Non-Hispanic White	0.61	0.49	0.60	0.49
Non-Hispanic Black	0.13	0.33	0.13	0.34
Hispanic	0.18	0.38	0.19	0.39
High School	0.26	0.44	0.26	0.44
Some College	0.27	0.44	0.25	0.43
College	0.26	0.44	0.27	0.45
College and Above	0.15	0.35	0.16	0.37
Married	0.55	0.50	0.54	0.50
Divorced	0.13	0.34	0.13	0.33
Number of Obs.	233,770	233,770	196,600	196,600

Sources: CPS Monthly Outgoing Rotation Group sample in 2018-2019 and 2021-2022, National Census of Fatal Occupation Injuries for workplace fatalities in 2018-2021, and Multiple Cause of Death 2020-2021. **Notes:** Sample includes 18-65 year old full-time workers who earned above federal minimum wage applied in 2020. COVID-19 death is defined based on ICD-10 for cause of death. Workplace death is defined based on income earning activities and place of death. Reference group for education is Less than High School, race is Other, marital status is Widowed. Harmonized occupation is defined based on IPUMS crosswalk described in https://usa.ipums.org/usa-action/variables/OCC2010#description_section. O'Neill School Harmonized occupation is defined based on Census crosswalk available at https://www.census.gov/topics/employment/industry-occupation/guidance/code-lists.html.

non-stochastic.[11]

The main coefficient of interest is the interaction term between Post 2021 and COVID-19 risk. This is the estimated compensating wage differential for COVID-19. It is positive and statistically significant in all four regressions. This provides supporting evidence that workers were compensated for marginal change in level of COVID-19 risk. Our preferred model is in the fourth column. In that case, the estimated coefficient implies that one additional COVID-19 death per 1,000 workers is associated with a 3 percent increase in weekly wages or approximately $36 in weekly wages. For non-COVID-19 mortality rate, the coefficient of workplace fatality rate of .0038 implies that in the pre-COVID-19 period, one additional workplace fatality per 1,000 workers is associated with 38% increase in average weekly wages. In other words, workers will receive $463 a week in return to one more deaths in 1,000 workers. After the pandemic, the wage premium decreased 12 percentage points which translates to a 26% increase in marginal wages, equivalently $317 per week.

Panel B reports estimates of the implied VSL for both COVID and non-COVID workplace mortality risks. If both risks are perceived as equally bad ways to die – i.e. a death is a death at the workplace – then we would expect the compensating differentials to be equal. On the other hand, since COVID-19 is a new risk, whereas the other sources of workplace risk (such as pollution and lung cancer, or mining accident risks) have been priced into wages for years, workers, firms as well as the government might have experienced "mistakes" in internalizing COVID-19 risk. This could cause undervaluation or overvaluation of VSL for COVID-19 risk. The implied VSL estimates from our regressions suggest that the people do not value the two risks equally and that the compensation for COVID risk is much smaller than the compensation for non-COVID risk. Non-COVID-19 mortality wage premiums imply that workers trade off money and mortality risk using a VSL of about $23 million. In contrast, the COVID-19 wage premium implies that workers make decisions using a VSL of $1.56 million. The ratio of VSL for COVID-19 risk to that of workplace risk is just above 6.6%.

As mentioned earlier, we also used the average mortality rate for 2020-2021 to estimate the VSL due to COVID-19 for the entire period. The inclusion of this variable is supported by the significant increase in mortality rates in 2021 (as shown in the previous analysis), along with COVID-related developments such as vaccines, the highly contagious Omicron variant, and increased public understanding of virus transmission. However, while we expect the results to be robust and significant for the entire period, we do not have a strong prior regarding significant changes in coefficients for two reasons. First, our data set spans only

[11]See Viscusi and Gentry (2015) for an alternative method of calculating the inferences of VSL which accounts for both mortality risk and wages as two random variables.

Table 2: **Regression Estimates: Compensating Differentials for COVID-19 and Workplace Deaths in 2020**

Panel A. Regression Estimates (Dependent Variable: Log of Weekly Wages)				
Post2021 X COVID-19 Mortality Rate in 2020	0.0002***	0.0003***	0.0002***	0.0003***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Workplace Fatality Rate in 2020	-	0.0036**	-	0.0038***
	-	(0.0015)	-	(0.0010)
COVID-19 Mortality Rate in 2020	-0.0006***	-0.0008***	-0.0005***	-0.0006***
	(0.0001)	(0.0002)	(0.0001)	(0.0001)
Post2021 X Workplace Fatality Rate in 2020	-	-0.0014*	-	-0.0012*
	-	(0.0007)	-	(0.0006)
Panel B. Implied VSL Estimates				
COVID-19 VSL (Mil.)	1.30	1.83	1.08	1.56
	[0.38 , 2.21]	[0.72 , 2.94]	[0.34 , 1.81]	[0.64 , 2.47]
Other Fatality VSL (pre-COVID) (Mil.)	-	22.40	-	23.60
	-	[3.67 , 41.13]	-	[11.94 , 35.26]
COVID-19/Other VSL Ratio (%)	-	8.17	-	6.60
Panel C. Estimation Sample Averages				
Average Wages($)	1220.57			
Average # of Weeks Worked (Weeks)	50.78			
COVID-19 Mortality Rate in 2020	48.59			
Workplace Fatality Rate in 2020	2.92			
1 digit Occupation + Industry Fixed Effects	Yes	Yes	No	No
2 digit Occupation + Industry Fixed Effects	No	No	Yes	Yes
Year & Month Fixed Effects	Yes	Yes	No	No
State Fixed Effects	Yes	Yes	No	No
Individual Controls	Yes	Yes	Yes	Yes
Number of Observations	311,835	311,835	311,835	311,835

Sources: CPS Monthly Outgoing Rotation Group sample in 2018-2019 and 2021-2022, and Multiple Cause of Death for COVID-19 deaths and workplace deaths in 2020-2021. **Notes:** Sample includes 18-65 year old full-time workers who earned above federal minimum wage applied in 2020. Post 2021 is equal 1 if in 2021-2022 and 0 if 2018-2019. COVID-19 death is defined based on ICD-10 for cause of death. Workplace death is defined based on income earning activities and place of death. List of occupations and industries at 2 digit and 1 digit based on Census classification available at `https://www.cdc.gov/nchs/data/dvs/industry-and-occupation-data-mortality-2020.pdf`. Controls include individual age, age squared, sex, education, marital status, race and ethnicity. Implied VSL estimate $= \frac{\partial w}{\partial r} \times \bar{w} \times \bar{h}_w \times 100{,}000$. All regressions are weighed by outgoing rotation group sampling weights. 95% confidence intervals in brackets. Standard errors clustered at two-digit industry-by-occupation level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

two years, making our identification based primarily on the within variation in mortality risk across occupations and industry cells. If the changes in 2021 are nonsystematic, they will likely have a minimal impact on our estimates. Second, the impacts of COVID-related developments could simply offset each other in terms of worker perceptions of COVID-19 risks in 2021 compared to 2020.

Table 3 confirms the earlier results when the probabilities of workplace risks are calculated over the entire post-COVID-19 period. On one hand, the coefficients for wage compensating differentials for COVID-19 are somewhat smaller. One more COVID-19 deaths in 1,000 workers is associated with a \$24 increase in weekly wages, resulting in a VSL of \$1.24 million. On the other hand, the wage premiums for non-COVID-19 workplace risk are somewhat larger for both pre-and-post COVID-19 periods leading to higher implied VLS estimates of approximately \$27 million.

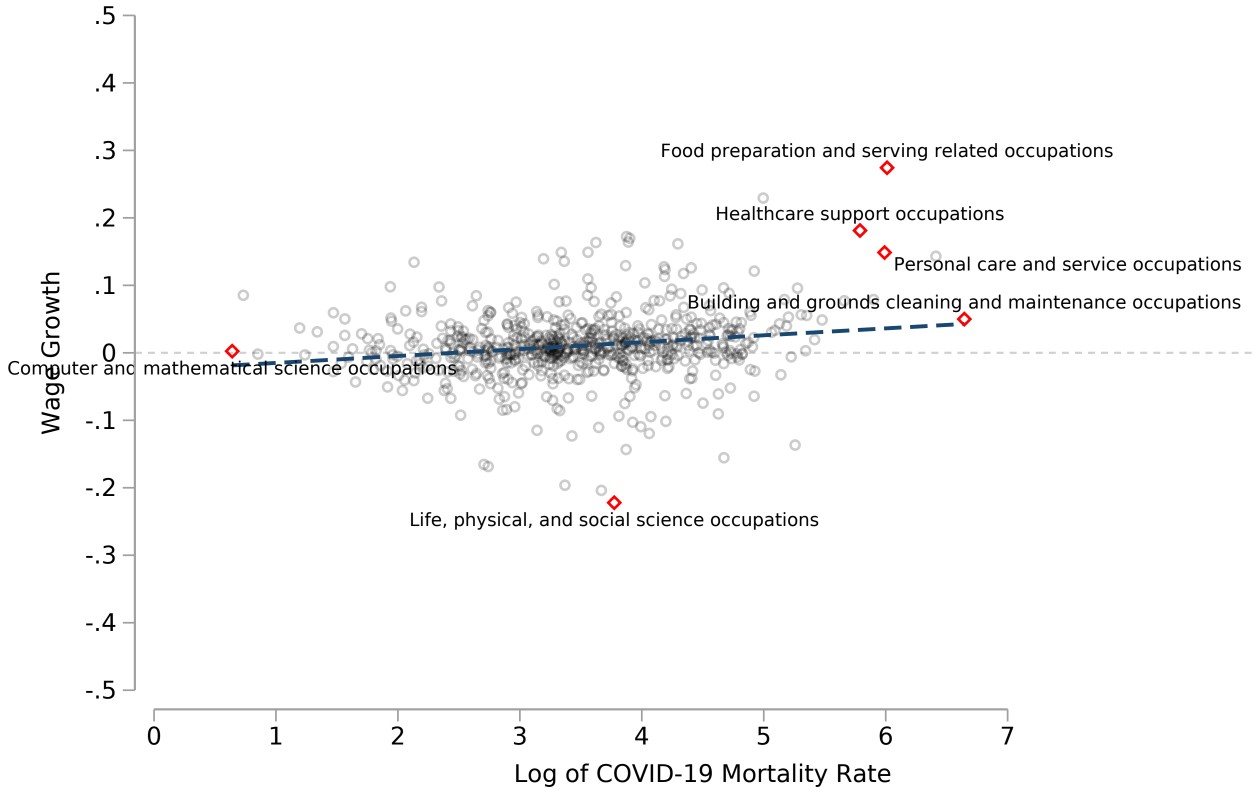
The positive wage compensating differentials captured in our regressions suggest the existence of a wage-risk trade-off for COVID-19. To explore which occupations and industries are more responsive to the wage-risk trade-off, Figure 5 plots the relationship between the log of COVID-19 mortality rate and wage growth from 2018-2019 to 2021-2022 across different occupation-by-industry cells.

Table 3: **Regression Estimates: Compensating Differentials for COVID-19 and Workplace Deaths in 2020-2021**

Panel A. Regression Estimates (Dependent Variable: Log of Weekly Wages)				
Post2021 X COVID-19 Mortality Rate in 2020-2021	0.0001***	0.0002***	0.0001***	0.0002***
	(0.0001)	(0.0001)	(0.0000)	(0.0001)
Workplace Fatality Rate in 2020-2021	-	0.0044**	-	0.0044***
	-	(0.0019)	-	(0.0012)
COVID-19 Mortality Rate in 2020-2021	-0.0004***	-0.0005***	-0.0003***	-0.0005***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Post2021 X Workplace Fatality Rate in 2020-2021	-	-0.0017**	-	-0.0015**
	-	(0.0007)	-	(0.0006)
Panel B. Implied VSL Estimates				
COVID-19 VSL (Mil.)	0.90	1.45	0.75	1.24
	[0.26 , 1.54]	[0.54 , 2.35]	[0.24 , 1.27]	[0.51 , 1.98]
Other Fatality VSL (pre-COVID) (Mil.)	-	27.16	-	27.34
	-	[4.58 , 49.75]	-	[13.17 , 41.52]
COVID-19/Other VSL Ratio (%)	-	5.32	-	4.55
Panel C. Estimation Sample Averages				
Average Wages ($)		1220.57		
Average # of Weeks Worked (Weeks)		50.78		
COVID-19 Mortality Rate in 2020-2021		72.43		
Workplace Fatality Rate in 2020-2021		3.02		
1 digit Occupation + Industry Fixed Effects	Yes	Yes	No	No
2 digit Occupation + Industry Fixed Effects	No	No	Yes	Yes
Year & Month Fixed Effects	Yes	Yes	No	No
State Fixed Effects	Yes	Yes	No	No
Individual Controls	Yes	Yes	Yes	Yes
Number of Observations	311,835	311,835	311,835	311,835

Sources: CPS Monthly Outgoing Rotation Group sample in 2018-2019 and 2021-2022, and Multiple Cause of Death for COVID-19 deaths and workplace deaths in 2020-2021. **Notes:** Sample includes 18-65 year old full-time workers who earned above federal minimum wage applied in 2020. Post 2021 is equal 1 if in 2021-2022 and 0 if 2018-2019. COVID-19 death is defined based on ICD-10 for cause of death. Workplace death is defined based on income earning activities and place of death. List of occupations and industries at 2 digit and 1 digit based on Census classification available at https://www.cdc.gov/nchs/data/dvs/industry-and-occupation-data-mortality-2020.pdf. Controls include individual age, age squared, sex, education, marital status, race and ethnicity. Implied VSL estimate $= \frac{\partial w}{\partial r} \times \bar{w} \times \bar{h}_w \times 100{,}000$. All regressions are weighed by outgoing rotation group sampling weights. 95% confidence intervals in brackets. Standard errors clustered at two-digit industry-by-occupation level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 5: **Jobs with Levels of Wage Compensating Differentials for COVID-19 risk**



Sources: CPS Monthly Outgoing Rotation Group sample in 2018-2019 and 2021-2022 for weekly wages, and Multiple Cause of Death for COVID-19 deaths and workplace deaths by occupation and industry in 2020. **Notes:** Figure displays the relationship between weekly wage growth between 2018-2022 and log of COVID-19 mortality rate in 2020. Sample includes 18-65 year old full-time workers who earned above federal minimum wage applied in 2020. COVID-19 death is defined based on ICD-10 for cause of death. Workplace death is defined based on income earning activities and place of death. COVID-19 mortality rate and workplace fatality rate are per 100,000 workers. List of occupations and industries at 2-digit level based on Census classification available at https://www.cdc.gov/nchs/data/dvs/industry-and-occupation-data-mortality-2020.pdf. Controls include individual age, age squared, sex, education, marital status, race and ethnicity.

The figure shows that occupations that faced higher levels of COVID-19 risk also experienced significant wage growth. For instance, jobs with high COVID risk – such as food preparation and serving, healthcare, personal care workers, and building and maintenance – saw substantial wage increases. On the other hand, low-risk occupations, such as those in computer and mathematical sciences, showed almost no change in wage growth. This suggests that the labor market responded to the new health risks of certain jobs by adjusting equilibrium wages. It also suggests that some of the wage growth experienced in some low paying jobs may reflect a deterioration in job quality rather than a real increase in earnings.

4.3 CFOI Workplace Fatalities

In the literature on VSL and workplace risk, researchers typically rely on the CFOI data for workplace fatality counts. To understand how our analysis might be affected by MCOD vs CFOI data, we replicated our main analysis using more aggregate data to facilitate a head to head comparisons on the MCOD vs CFOI data. Table 1 indicates that the mean workplace fatality rates are similar between the two data sources. Figure A6 compares the distribution of workplace fatality risk in the MCOD data vs the CFOI data. The horizontal axis measures the share of occupations and the vertical axis measures the workplace fatality rate. The black line shows the CFOI data and the grey line shows the MCOD data. The two curves are very similar at most points in the distribution. However, the CFOI data indicates a slightly larger share of occupations with moderate fatality risks and the MCOD data indicates a somewhat higher share of occupations with very high fatality risks.

Building on these descriptive statistics, we proceeded to estimate the Mincerian wage equation using each of the two measures as an independent variable to directly compare wage compensating differentials and the implied VSL estimates. We excluded individual worker data prior to 2020 and fit wage regressions for the years 2021-2022. The independent variable is the average workplace fatality rate for 2020-2021. The results, presented in Table 4, indicate that the compensating wage differentials and VSL estimates derived from the two data sources are both statistically significant and positive. The compensating differential based for one additional death per 1,000 workers is approximately 29% based on CFOI and approximately 38% based on MCOD data. The implied VSL is \$18.39 million using CFOI and \$24.28 million based on MCOD data. The confidence intervals on the two estimates overlap and both are near the upper bound of traditional estimates.

Table 5 reports estimated regression coefficients from models that include MCOD measures of COVID risk and CFOI measures of other workplace fatality risk using data for the entire period. The wage premiums for COVID-19 are consistent with the main result, which is around 0.2% of weekly wage or equivalently \$24. The VSL for workplace risk is \$25.66 and \$19.65 million in pre- and post-COVID-19 periods, respectively. When we control for occupation and industry fixed effects at four-digit level, the VSLs for pre-COVID are \$5.76 and \$2.88 million respectively.

Table 4: **Compensating Differentials for Workplace Fatalities by Harmonized 4-digit Occupation Code - MCO vs. CFOI Data**

Panel A. Regression Estimates (Dependent Variable: Log of Weekly Wages)	**MCOD**	**CFOI**
Workplace Fatality Rate for 2020-2021	0.0038**	0.0029**
	(0.0016)	(0.0012)
Panel B. Implied VSL Estimates		
Other Fatality VSL (post-COVID) (Mil.)	24.28	18.39
	[3.85 , 44.72]	[3.95 , 32.83]
Panel C. Estimation Sample Averages		
Average Wages ($)	1259.87	
Average # of Weeks Worked (Weeks)	50.71	
Workplace Fatality Rate for 2020-2021	3.00	3.33
4-digit Harmonized Occupation Fixed Effects	Yes	Yes
Year & Month Fixed Effects	Yes	Yes
State Fixed Effects	Yes	Yes
Individual Controls	Yes	Yes
Number of Observations	196,600	196,600

Sources: CPS Monthly Outgoing Rotation Group sample in 2021-2022, Multiple Cause of Death in 2020-2021 for COVID-19 deaths and Census of Fatal Occupational Injuries in 2020-2021 for workplace deaths. **Notes:** Sample includes 18-65 year old full-time workers who earned above federal minimum wage applied in 2020. Post 2021 is equal 1 if in 2021-2022 and 0 if 2018-2019. COVID-19 death is defined based on ICD-10 for cause of death. Workplace death is defined based on income earning activities and place of death. 4-digit Harmonized occupation is defined based on IPUMS crosswalk described in https://usa.ipums.org/usa-action/variables/OCC2010#description_section. Controls include individual age, age squared, sex, education, marital status, race and ethnicity. Implied VSL estimate = $\frac{\partial w}{\partial \pi} \times \bar{w} \times \bar{h}_w \times 100,000$. All regressions are weighed by outgoing rotation group sampling weights. 95% confidence intervals in brackets. Standard errors clustered at 4-digit occupation level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4.4 Do People Undervalue COVID-19 Risk?

The non-COVID-19 mortality wage premium implies that workers trade off money and mortality risk using a VSL of about $18 million, according to our most conservative estimate using the CFOI data. In contrast, the COVID-19 wage premium implies that workers make decisions using a VSL in the range of $1.24-$1.56 million. How do these values compare to other estimates in the VSL literature? That depends on a number of factors such as whether these values are compared to the population average VSL, VSL estimates after adjusting by demographics, or type of death.

A variety of methods have been used to previously calculate the VSL in society. These include stated and revealed preference studies from different types of market settings – health and safety products, labor markets, etc. The most common approach, which we follow, evaluates the tradeoff between wages and workplace fatality rates. Most estimates in the literature find the average population-wide VSL ranges between $6 million and $17 million (US$2021) (Aldy and Viscusi, 2008; Hammitt, 2020; Kniesner et al., 2010, 2012; Kniesner and Viscusi, 2019; Kniesner et al., 2022, 2024; Robinson and Hammitt, 2016; Rohlfs et al., 2015; Viscusi, 1993, 2004, 2010, 2018b,a, 2020, 2021; Viscusi and Aldy, 2003) with the most precise estimates coalescing around an $11 million VSL. This value is close to those currently being utilized by U.S. government agencies. For example, the Department of Transportation uses an $11.9 million VSL, the Environmental Protection Agency uses an $11.0 million VSL, and the Department of Health and Human Services uses an $11.6 million VSL (US$2021) (Environmental Protection Agency, 2010; US Department of Health and Human Services, 2016; US Department of Transportation, 2016).[12]

While the literature has generally found estimates coalescing around an $11 million VSL, differences start to emerge when adjustments are made by demographics. For example, African Americans or Mexican immigrant VSL estimates are typically lower than their White counterparts (Viscusi, 2010). Likewise, lower income groups tend to have lower VSL estimates when compared to higher income groups. Income elasticities range from 0.6 to 1.4, meaning a 10% decrease in income generally corresponds with a 6%-14% decrease in the VSL (US Department of Transportation, 2016; Doucouliagos et al., 2014; Hammitt and Robinson, 2011; US Department of Health and Human Services, 2016; Lindhjem et al., 2011; Kniesner et al., 2010; Masterman and Viscusi, 2018; Viscusi and Aldy, 2003; Viscusi and Masterman, 2017; Viscusi, 2018b).

[12] The vast majority of the VSL estimates used by these agencies come from CFOI revealed preference labor market studies. This is not surprising since many prominent VSL researchers regard the CFOI based studies as the gold standard in the profession (Viscusi, 2018b).

Table 5: **Compensating Differentials for COVID-19 Deaths (MCOD)and for Workplace Fatalities (CFOI) by Harmonized 4-digit Occupation Code**

Panel A. Regression Estimates (Dependent Variable: Log of Weekly Wages)				
Post2021 X COVID-19 Mortality Rate	0.0001***	0.0002***	0.0002***	0.0002***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Workplace Fatality Rate for 2020-2021	-	0.0042***	-	0.0010*
	-	(0.0010)	-	(0.0005)
COVID-19 Mortality Rate for 2020-2021	-0.0008***	-0.0009***	-	-
	(0.0002)	(0.0001)	-	-
Post2021 X Workplace Fatality Rate in 2020-2021	-	-0.0006	-	-0.0007**
	-	(0.0005)	-	(0.0003)
Panel B. Implied VSL Estimates				
COVID-19 VSL (Mil.)	0.90	1.28	0.96	1.34
	[0.45 , 1.35]	[0.69 , 1.86]	[0.51 , 1.41]	[0.79 , 1.88]
Other Fatality VSL (pre-COVID) (Mil.)	-	25.66	-	5.76
	-	[14.37 , 36.95]	-	[-0.67 , 12.20]
COVID-19/Other VSL Ratio (%)	-	4.97	-	23.18
Panel C. Estimation Sample Averages				
Average Wages ($)	1191.81			
Average Number of Weeks Worked (Weeks)	50.83			
COVID-19 Mortality Rate (per 100,000 workers)	72.45			
CFOI Workplace Fatality Rate (per 100,000 workers)	3.58			
2-digit Occupation Fixed Effects	Yes	Yes	No	No
4-digit Harmonized Occupation Fixed Effects	No	No	Yes	Yes
Year & Month Fixed Effects	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes
Individual Controls	Yes	Yes	Yes	Yes
Number of Observations	430,370	430,370	430,370	430,370

Sources: CPS Monthly Outgoing Rotation Group sample in 2018-2019 and 2021-2022, Multiple Cause of Death in 2020-2021 for COVID-19 deaths and Census of Fatal Occupational Injuries in 2018-2021 for workplace deaths. **Notes:** Sample includes 18-65 year old full-time workers who earned above federal minimum wage applied in 2020. Post2021 is equal 1 if in 2021-2022 and 0 if 2018-2019. COVID-19 death is defined based on ICD-10 for cause of death. Workplace death is defined based on income earning activities and place of death. 4-digit Harmonized occupation is defined based on IPUMS crosswalk described in https://usa.ipums.org/usa-action/variables/OCC2010#description_section. Controls include individual age, age squared, sex, education, marital status, race and ethnicity. Implied VSL estimate $= \frac{\partial w}{\partial r} \times \bar{w} \times \bar{h}_w \times 100,000$. All regressions are weighed by outgoing rotation group sampling weights. 95% confidence intervals in brackets. Standard errors clustered at 4-digit occupation level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Most of the estimates in the literature are based off of small incremental changes in fatality risk. Researchers then take these changes and estimate how much individuals are willing to pay to reduce their risk of death. A standard example will show that on average people are typically willing to pay about $110 for every one per 100,000 reduction in fatality risk (equating to an $11 million VSL).

However, it is less clear how people value larger changes in risk exposure. Are people willing to pay $1,100 for a one in 10,000 fatality risk reduction? What about paying $1.1 million for a one in 10 reduction in fatality risk? At some point budget constraints start to play a larger role in the calculations and people simply can't afford the risk reduction being offered. The literature has found that the calculations typically don't get distorted until the risk factors reach a threshold of one per 1,000 (Alolayan et al., 2017; Eeckhoudt and Hammitt, 2001, 2004; Hammitt, 2020; Kaplow, 2005; Robinson et al., 2022). Once the risk factor passes this threshold, then people may use a lower VSL due to budget constraints.

Interestingly, some of the most deadly professions analyzed have shown lower VSL estimates in comparison to those found in the general population. Lavetti (2020) examined commercial fishing deckhands in the Alaskan Bering Sea to estimate compensating wage differentials and the VSL. He found high fatality rates (close to the one per 1,000 threshold) for deckhands with an estimated VSL coalescing around $6.6 million after controlling for unobserved worker, firm and match heterogeneity, and removing the effects of endogenous job assignment. A separate paper by Schnier et al. (2009) examined a broader sample of Alaskan commercial fisherman. They found fatality rates of about 142 per 100,000 with corresponding VSL estimates ranging from $4.6 million to $5.5 million per statistical life. In another example, Goucher and Horrace (2012) examined fatality rates in one of the most deadly professions on earth – Himalayan Mountain guides in Nepal and India. They found fatality rates of about 450 per 100,000 and corresponding VSL estimates in the $4.5 million to $6.0 million range.

One of the most hotly debated topics in the literature is whether and how age might play a factor in VSL estimates. The two most common techniques used to estimate the VSL by age are the constant value of a statistical life year (VSLY) approach and the inverted-U method (Robinson et al., 2021). The constant VSLY approach first takes the central VSL estimate (around $11 million) and divides it by the discounted life expectancy at the average age in society providing a constant VSLY. Researchers then multiply this constant VSLY by the discounted life expectancy for the specific age group being studied. The mechanics of this methodology are straightforward, the constant VSLY approach increases the VSL for younger populations and lowers it for the elderly. Notably, the constant VSLY approach is only theoretical in nature and not rooted in the empirical literature. This is an important limitation since empirical VSL estimates are typically more accepted by the economics profession.

In contrast, the inverse-U approach has its foundation based upon empirical estimates in the literature. The inverse-U approach typically takes the same labor market data used to estimate the standard average VSL and splits the data by using age brackets. This way, researchers can see if different age groups, *ceteris paribus*, are willing to pay different amounts of money for the same reduction in fatality risk which then provides different VSL estimates by age. What does this pattern look like? Just like its name states, it follows an inverted-U shaped pattern. The lowest value of the U-shaped pattern starts at the age of 18 (with a VSL of \$5.7 million), increases until it hits its peak at age 46 (\$13.5 million), and then declines until retirement age (\$8.8 million US\$2021) (Aldy and Viscusi, 2008).

In Table 7, we present estimates of compensating wage differentials by race and ethnicity. We find that the coefficient on the key interaction term in the wage regression shows a larger positive and statistically significant number for Black non-Hispanic populations, compared to that for non-Hispanics whites, but the estimate for Hispanics is smallest in magnitude (and not statistically significantly different from zero). The implied VSL numbers for COVID risks are thus larger for non-Hispanic Black than non-Hispanic white populations. The VSL for other workplace fatality risks are more closer for non-Hispanic whites and non-Hispanic Blacks (33.62 vs 36.97). A closer examination of racial and ethnic disparities in COVID era VSL is warranted (for example, to understand whether the wage-risk functional forms may differ, given that initial wage distributions are different) but deserve more attention than we are able to devote within the scope of this paper.

In addition to changes in demographic-based VSL estimates, different values have been found when comparing types of deaths. Dreadful deaths in particular have been shown to have higher VSL estimates in comparison to more "normal" deaths. For example, Liu et al. (2005) found VSL premiums to avoid SARS deaths in Taiwan in the early 2000s. In another example, researchers found the VSL premium for avoiding terrorism deaths may be as high as twice that of normal deaths in society (Robinson et al., 2010). Even cases of influenza have been shown to have a VSL premium due to the dread factor (Gyrd-Hansen et al., 2008). One of the most documented VSL premiums has been associated with cancer. Viscusi et al. (2014) found the cancer VSL premium is 21% higher than the normal VSL. Clearly dread can be a major factor in calculating the VSL for certain disease types.

How do the estimates in Table 2, Table 3 and Table 5 relate to these types of adjustments or standard VSL values? It appears that the non-COVID-19 VSL (\$18 million as the lowest estimate) could be categorized as being located near the upper range of the standard VSL estimates in the literature which generally are shown to be between \$6 million and \$17 million. In contrast, the COVID-19 VSL of \$1.24-\$1.54 million that we find appears to be an outlier when compared to other estimates in the literature. As a comparison, Viscusi (2018a) analyzed over 1,000 VSL estimates from 68 studies and calculated distributions of the estimates by quantile. For CFOI USA based studies, the lowest VSL estimates presented were a \$5.4 million point estimate at the 10th percentile and \$3.3 million at the 5th percentile. It is unclear how far down the \$1.24 million value that we find would rank, but it would likely be somewhere in the low single digits. In short, it is an outlier that rarely is seen in the literature.

Potential reasons for the significantly lower VSL for COVID-19 could be multifaceted. First, if both risks were perceived as equally fatal – a death is a death, whether it occurs at the workplace or due to COVID-19 – one would expect similar compensating differentials. However, since COVID-19 is a novel risk, various sectors, including workers, firms, and the government, might have faced 'errors' in internalizing this risk. For example, workers might not optimally account for their risk preferences due to incomplete information. Additionally, firms, thanks to the flexibility of remote work options, might not experience a significant increase in the marginal cost of equipment to mitigate COVID-19 spread. Furthermore, although the US labor market is more adaptable to COVID-19 than many European markets (García-Cabo et al., 2023), the inherent rigidity might still hinder a swift adjustment in wages to accommodate this new risk. All of these reasons provide rational explanations about why individuals might undervalue COVID-19 risks so significantly relative to other workplace risks as indicated by the empirical results.

5 Conclusion

Our paper is the first to use the new MCOD data to study the way workplace mortality risks affect labor market outcomes. We examine the labor market response to a new risk that has not been studied before–COVID-19 risks on the job–and we ask whether workers value this new risk differently from other occupational mortality risks.

We find that there are substantial differences in the compensating differentials associated with COVID-19 vs other sources of job-related mortality risk. Full time workers' pay is higher by \$24 per week in jobs with a 1 in 1,000 higher risk of COVID-19 mortality, but their pay is \$320 higher in jobs with a 1 in 1,000 higher risk of non-COVID-19 workplace mortality. The non-COVID-19 mortality wage premiums imply that workers trade off money and mortality risk using a VSL of about \$18 million, which is near the upper range of the most cited VSL estimates in the literature. In contrast, the COVID-19 wage premium implies that workers make decisions using a VSL of the range $1.24 - $1.54 million. The results are consistent with workers substantially underestimating or undervaluing the risk of COVID-19 mortality.

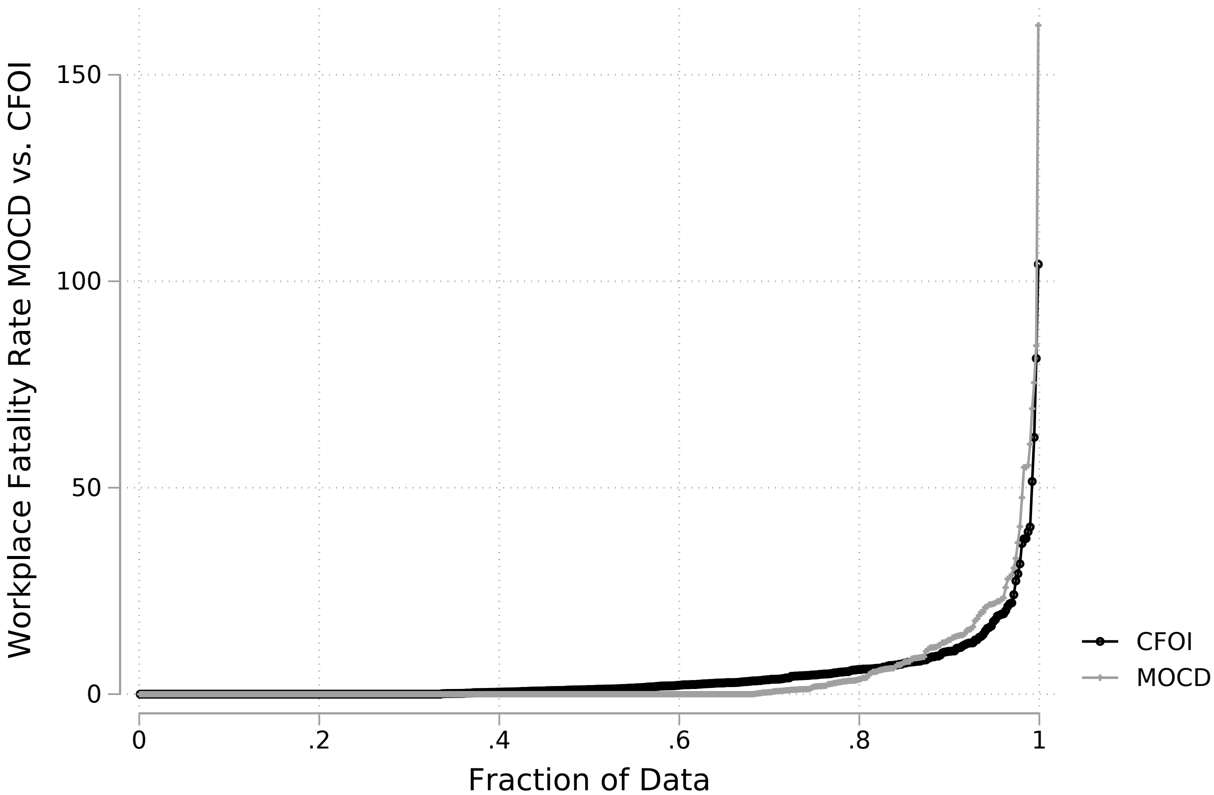
There are several limitations that should be held in mind. One is that occupational mortality concepts are measured using data where the death could have occurred not at work and not due to work conditions. For example, even if lung cancer deaths occur to mine workers after they have stopped working in the mines, that cancer is still a workplace fatality risk. Similarly, some deaths might occur at work (such as genetically determined cardiovascular risks) but not be linked to workplace conditions. In the MCOD data, mortality reflects the job most associated with an individual. If individuals are older than 65, the chance that they did not hold that job in 2020 is higher, so that their COVID mortality is less linked to that job. We limit the MCOD data to those aged under 65 to reduce this measurement error, and assume that all systematically higher rates of deaths in certain jobs are plausibly due to the nature of the work rather than for spurious reasons. We should view the mortality differentials between jobs to reflect what exists even after firms and workers have reduced workforce mortality risks through other means. However, we assume that workers are able to assess these risks that remain, which is an assumption that is easily violated. Similarly, we stratify our estimates by race and ethnicity as an initial attempt to explore disparities in implied COVID VSL, but we acknowledge that a full investigation to uncover the mechanisms responsible for observed differences would require much further analysis.

In our work, the role of controlling for compositional change is important. This is because a change in wages due to a compositional change may be wrongly attributed to COVID-19 risk differentials. This is important because there were high rates of job separations during COVID-19. These changes might not be orthogonal to workplace risks. It is possible that those for whom COVID-19 risks are the most costly (e.g., family member who is immunocompromised) may be the first to leave those jobs; this is no different from other scenarios of compensating wage differentials: in equilibrium, individuals have sorted across jobs such that they are in their best fit job, and it is from this vantage point that we judge whether riskier jobs have higher pay.

This study fills an important gap in the literature by providing updated estimates of the COVID-19 mortality risk-based wage premiums arising from new workplace risks, and the implied value of statistical life. In addition, we introduce a new and practical alternative dataset for researchers to use in future workplace mortality studies. While the findings presented here are somewhat preliminary due to the short time-period analyzed, we view them as a major first step for how to precisely measure COVID-19 fatality risks and their associated compensating wage differentials on the job. As new data continue to be released each year, these estimates should become more precise and useful for policy studies going forward. That said, the estimates presented in this paper are timely, new to the literature and relevant for understanding the new workplace fatality risks in the broad-based U.S. economy.

Appendix

Figure A6: Distribution of Workplace Fatality Rate: MCOD vs CFOI



Sources: Census of Fatal Occupational Injuries and Multiple Cause of Death 2020 and 2021 for workplace deaths by 4-digit occupation and CPS Monthly Outgoing Rotation Group sample in 2019 for number of workers. **Notes:** Sample includes 18-65 year old full-time workers who earned above federal minimum wage applied in 2020. **Notes:** Figure displays the quantile plot of workplace deaths from two different data sources. Each dot represents a 4-digit harmonized occupation. Workplace deaths in MCOD data is defined based on income earning activities and place of death. Workplace deaths in CFOI can be downloaded at https://www.bls.gov/iif/fatal-injuries-tables.htm. Harmonized occupation is defined based on IPUMS crosswalk described in https://usa.ipums.org/usa-action/variables/OCC2010#description_section.

Appendix B. Harmonization and Navigation Across Occupation and Industry Classification Systems

Figures A7-A10 describe the navigations between different occupation and industry classification systems. Figures A11 and A12 details different types of matches for occupation harmonization.[13] Tables B1 and B2 list the occupations that split and concatenate between Census classifications in 2010 and 2018.

[13] We adopted the similar algorithm for harmonization of industry codes. Details are available upon request

Table 6: **Robustness Check: Compensating Differentials using MCOD COVID-19 Deaths and Workplace Fatalities by Harmonized 4-digit Occupation Code**

Panel A. Regression Estimates (Dependent Variable: Log of Weekly Wages)				
Post2021 X COVID-19 Mortality Rate	0.0001***	0.0002***	0.0002***	0.0003***
	(0.0000)	(0.0001)	(0.0000)	(0.0001)
Workplace Fatality Rate for 2020-2021	-	0.0080***	-	-
	-	(0.0016)	-	-
COVID-19 Mortality Rate for 2020-2021	-0.0008***	-0.0011***	-	-
	(0.0002)	(0.0002)	-	-
Post2021 X Workplace Fatality Rate in 2020-2021	-	-0.0012***	-	-0.0016***
	-	(0.0005)	-	(0.0004)
Panel B. Implied VSL Estimates				
COVID-19 VSL (Mil.)	0.90	1.32	0.96	1.62
	[0.45 , 1.35]	[0.69 , 1.95]	[0.51 , 1.41]	[1.00 , 2.24]
Other Fatality VSL (pre-COVID) (Mil.)	-	48.32	-	-
	-	[29.53 , 67.10]	-	-
COVID-19/Other VSL Ratio (%)	-	2.74	-	.
Panel C. Estimation Sample Averages				
Average Wages ($)	1191.81			
Average # of Weeks Worked (Weeks)	50.83			
COVID-19 Mortality Rate for 2020-2021	72.45			
Workplace Fatality Rate for 2020-2021	3.02			
2-digit Occupation Fixed Effects	Yes	Yes	No	No
4-digit Harmonized Occupation Fixed Effects	No	No	Yes	Yes
Year & Month Fixed Effects	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes
Individual Controls	Yes	Yes	Yes	Yes
Number of Observations	430,370	430,370	430,370	430,370

Sources: CPS Monthly Outgoing Rotation Group sample in 2018-2019 and 2021-2022, and Multiple Cause of Death for COVID-19 deaths and workplace deaths in 2020-2021. **Notes:** Sample includes 18-65 year old full-time workers who earned above federal minimum wage applied in 2020. Post 2021 is equal 1 if in 2021-2022 and 0 if 2018-2019. COVID-19 death is defined based on ICD-10 for cause of death. Workplace death is defined based on income earning activities and place of death. 4-digit Harmonized occupation is defined based on IPUMS crosswalk described in https://usa.ipums.org/usa-action/variables/OCC2010#description_section. Controls include individual age, age squared, sex, education, marital status, race and ethnicity. Implied VSL estimate $= \frac{\partial w}{\partial r} \times \bar{w} \times \bar{h}_w \times 100,000$. All regressions are weighed by outgoing rotation group sampling weights. 95% confidence intervals in brackets. Standard errors clustered at **4-digit occupation level** in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: **Compensating Differentials by Race using MCOD COVID-19 Deaths and Workplace Fatalities by 2-digit Occupation-by-Industry Code**

	(1) Non-Hispanic White	(2) Non-Hispanic Black	(3) Hispanic	(4) Others
Panel A. Regression Estimates (Dependent Variable: Log of Weekly Wages)				
Post2021 X COVID-19 Mortality Rate in 2020-2021	0.0002***	0.0004**	-0.0000	0.0002
	(0.0001)	(0.0002)	(0.0001)	(0.0001)
Workplace Fatality Rate in 2020-2021	0.0050***	0.0073***	0.0036***	0.0009
	(0.0012)	(0.0014)	(0.0011)	(0.0019)
COVID-19 Mortality Rate in 2020-2021	-0.0005***	-0.0005***	-0.0003***	-0.0007***
	(0.0001)	(0.0002)	(0.0001)	(0.0002)
Post2021 X Workplace Fatality Rate in 2020-2021	-0.0016**	-0.0033**	-0.0004	0.0027*
	(0.0007)	(0.0013)	(0.0010)	(0.0016)
Panel B. Implied VSL Estimates				
COVID-19 VSL (Mil.)	1.13	2.03	-0.24	1.43
	[0.33 , 1.92]	[0.37 , 3.68]	[-1.18 , 0.70]	[-0.53 , 3.39]
Other Fatality VSL (pre-COVID) (Mil.)	33.62	36.97	18.02	6.18
	[17.31 , 49.93]	[22.57 , 51.37]	[7.71 , 28.32]	[-21.33 , 33.68]
COVID-19/Other VSL Ratio (%)	3.36	5.48	-1.32	23.18
Panel C. Estimation Sample Averages				
Average Wages ($)	1311.51	1012.29	977.59	1422.01
Average # of Weeks Worked (Weeks)	50.85	50.27	50.55	51.03
COVID-19 Mortality Rate in 2020-2021	66.79	79.57	90.90	61.45
Workplace Fatality Rate in 2020-2021	2.68	3.06	4.53	2.07
2-digit Occupation + Industry Fixed Effects	Yes	Yes	Yes	Yes
Year & Month Fixed Effects	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes
Individual Controls	Yes	Yes	Yes	Yes
Number of Observations	206,771	32,207	46,749	26,108

Sources: CPS Monthly Outgoing Rotation Group sample in 2018-2019 and 2021-2022, and Multiple Cause of Death for COVID-19 deaths and workplace deaths in 2020-2021. **Notes:** Sample includes 18-65 year old full-time workers who earned above federal minimum wage applied in 2020. Post 2021 is equal 1 if in 2021-2022 and 0 if 2018-2019. COVID-19 death is defined based on ICD-10 for cause of death. Workplace death is defined based on income earning activities and place of death. Controls include individual age, age squared, sex, education, marital status, race and ethnicity. Implied VSL estimate = $\frac{\partial w}{\partial r} \times \bar{w} \times \bar{h}_w \times 100{,}000$. All regressions are weighed by outgoing rotation group sampling weights. 95% confidence intervals in brackets. Standard errors clustered at 2-digit occupation level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure A7: **Navigation Across Two-digit Occupation and Industry Classification Systems**

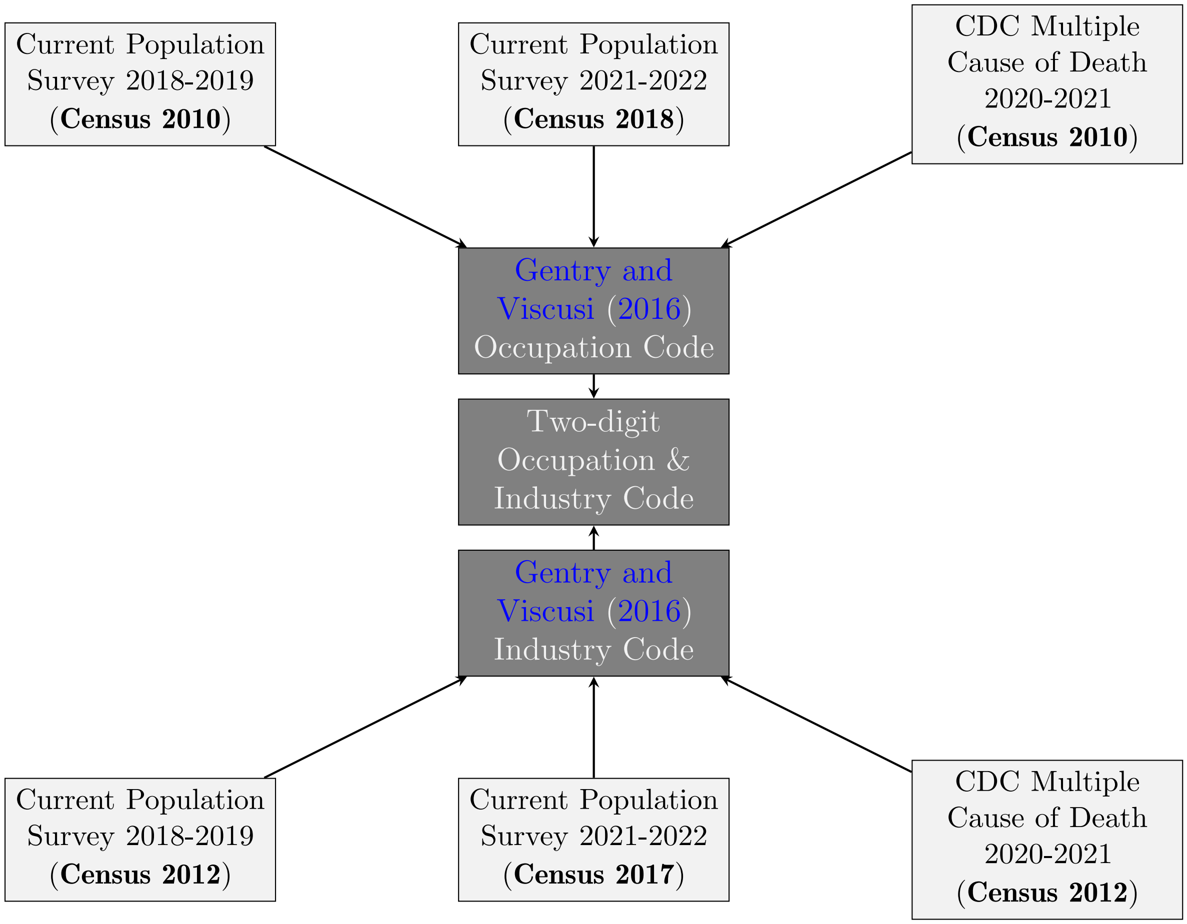


Figure A8: **Navigation Across Four-digit Occupation and Industry Classification Systems Using IPUMS**

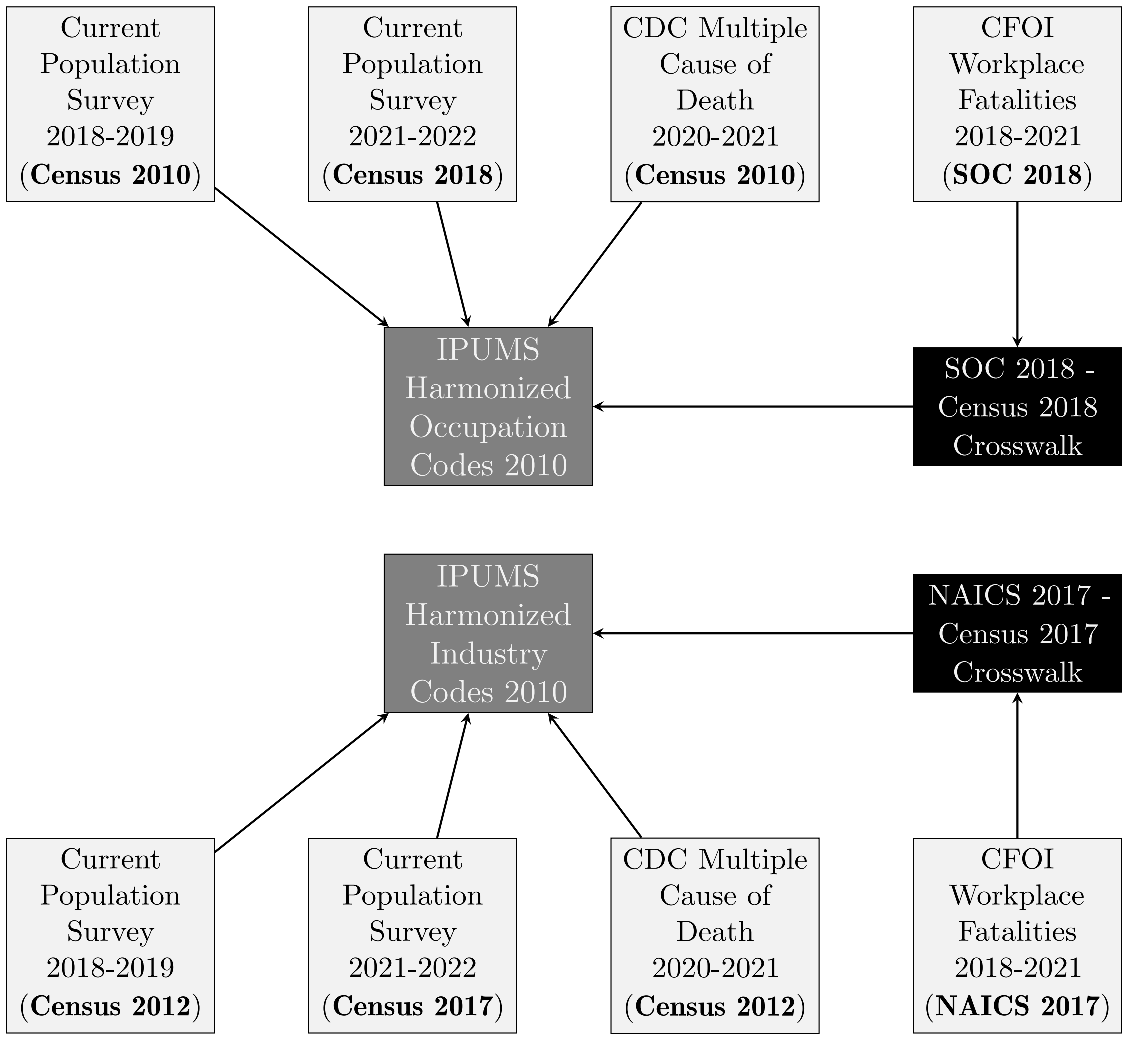


Figure A9: **Navigation Across Four-digit Occupation Classifications using O'Neill's Harmonization System**

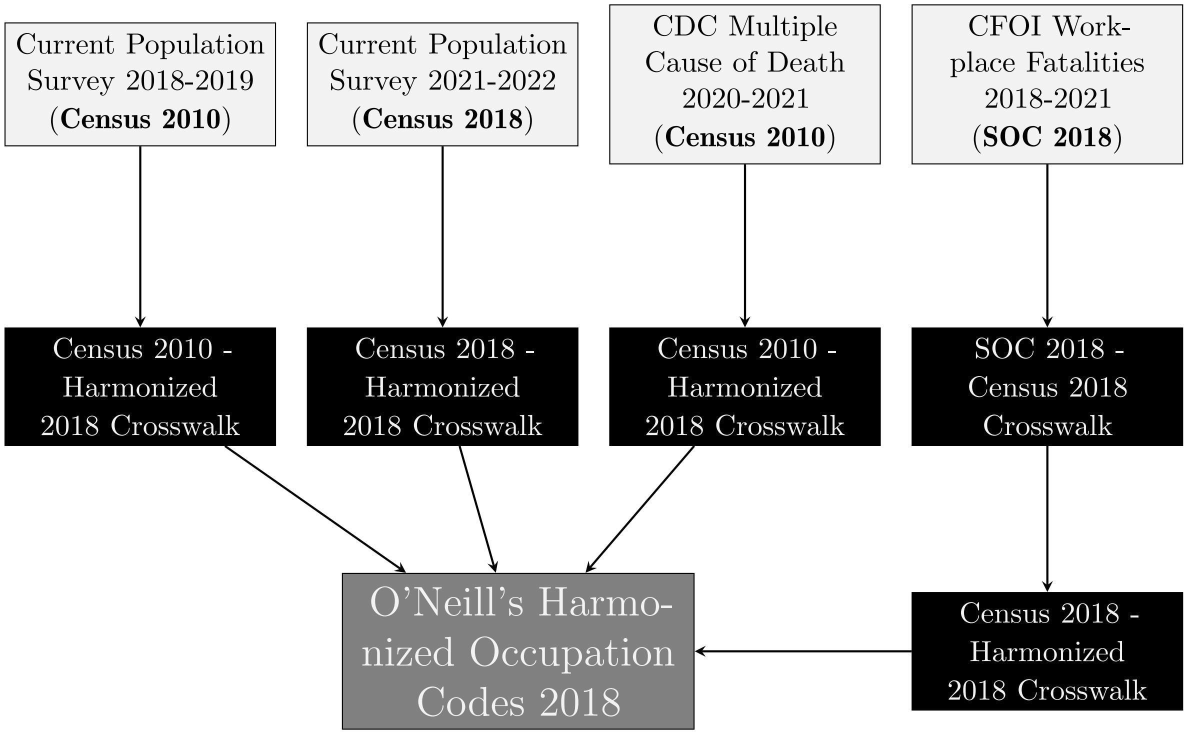


Figure A10: **Navigation Across Four-digit Industry Classifications using O'Neill's Harmonization System**

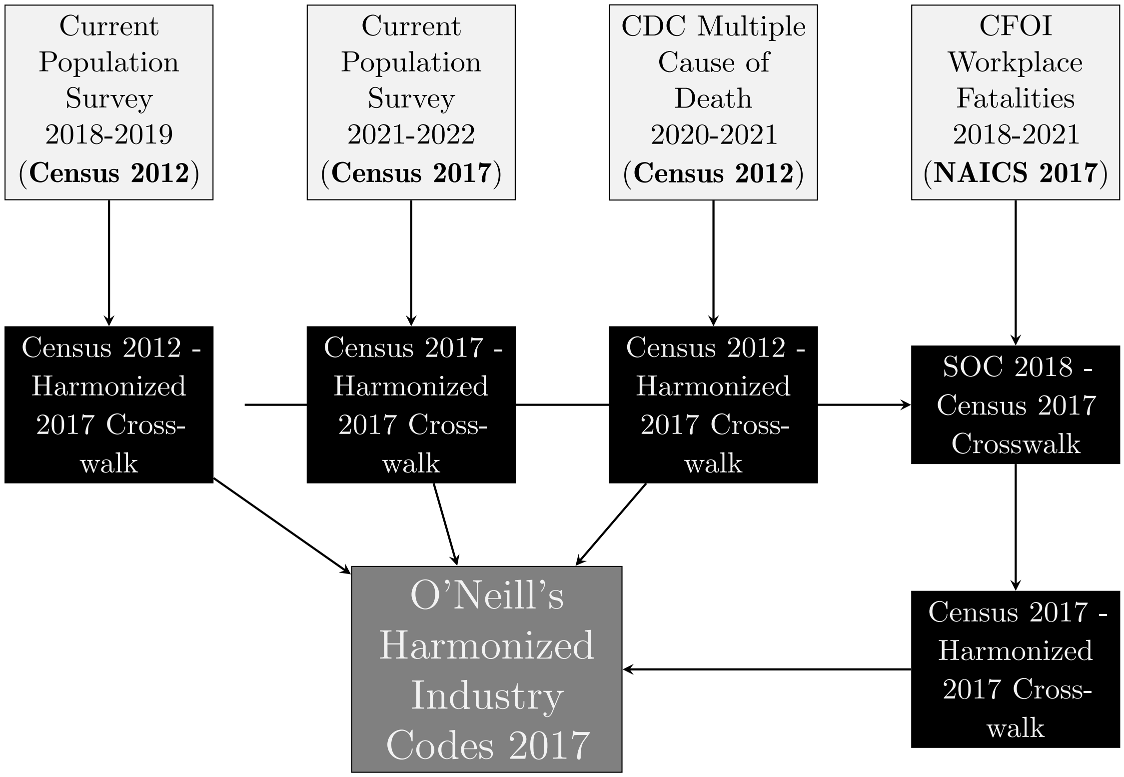
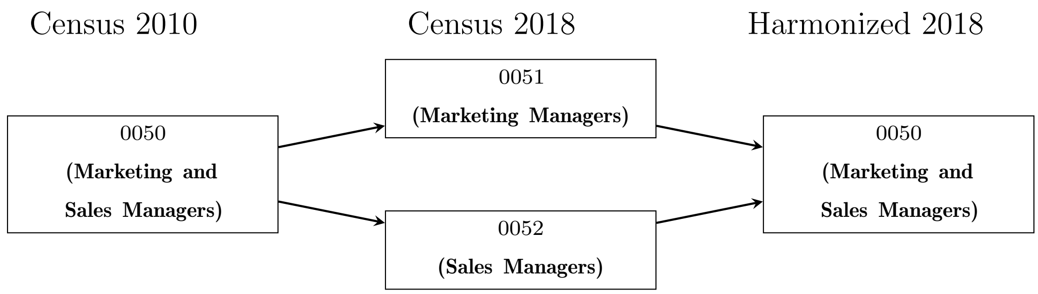


Figure A11: **Harmonization of Occupation Codes in 2010 and 2018**

1. One to many matches



2. Many to one matches

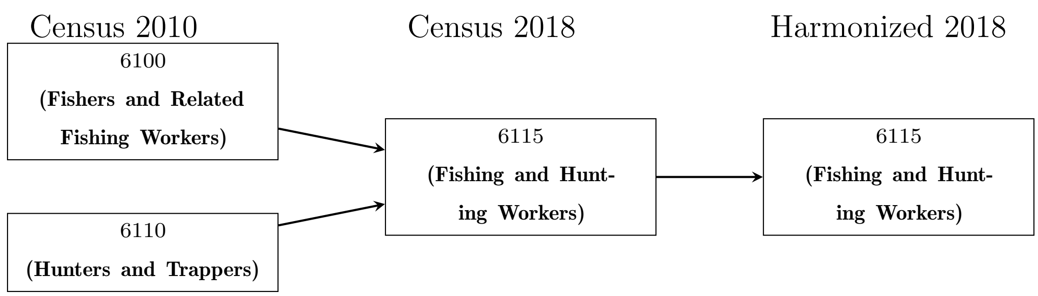
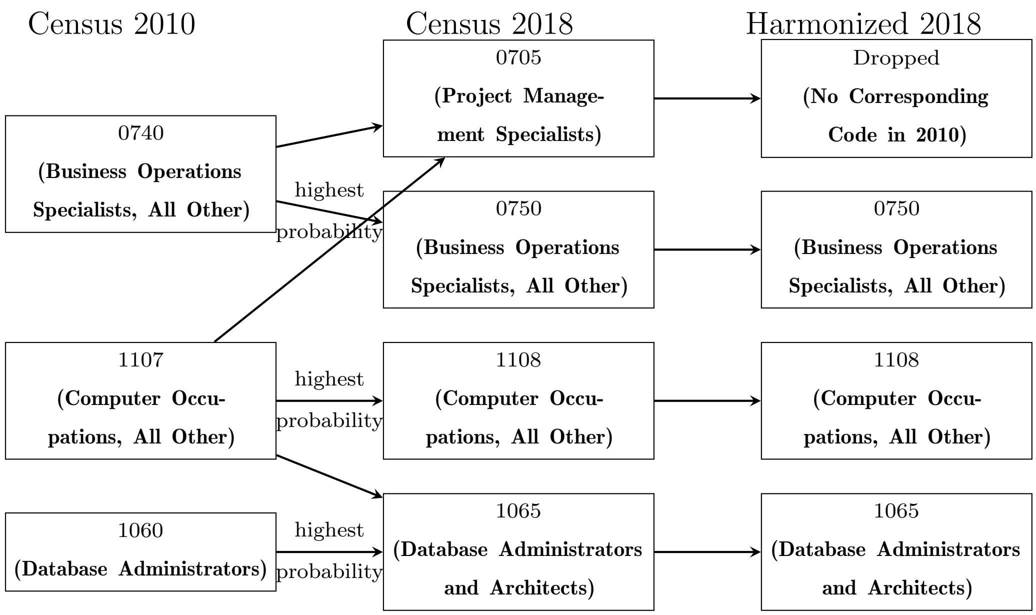


Figure A12: **Harmonization of Occupation Codes in 2010 and 2018 (cont.)**

3. Many to many matches



4. One to one matches with changes

Census 2010		Census 2018		Harmonized 2018
2540 **(Teacher Assistants)**	→	2545 **(Teacher Assistants)**	→	2545 **(Teacher Assistants)**

5. One to one matches with no changes

Census 2010		Census 2018		Harmonized 2018
3050 **(Pharmacists)**	→	3050 **(Pharmacists)**	→	3050 **(Pharmacists)**

Table 8: **List of Occupations that Splits between 2010 and 2018**

2010	2010 Title	2018	2018 Title
0050	Marketing and Sales Managers	0051	Marketing Managers
		0052	Sales Managers
0100	Administrative Services Managers	0101	Administrative Services Managers
		0102	Facilities Managers
1020	Software Developers, Applications and Systems Software	1021	Software Developers
		1022	Software Quality Assurance Analysts and Testers
1030	Web Developers	1031	Web Developers
		1032	Web and Digital Interface Designers
1300	Architects, Except Naval	1305	Architects, Except Landscape and Naval
		1306	Landscape Architects
1540	Drafters	1541	Architectural and Civil Drafters
		1545	Other Drafters
1550	Engineering Technicians, Except Drafters	1551	Electrical and Electronic Engineering Technologists and Technicians
		1555	Other Engineering Technologists and Technicians, Except Drafters
1740	Environmental Scientists and Geoscientists	1745	Environmental Scientists and Specialists, Including Health
		1750	Geoscientists and Hydrologists, Except Geographers

1820	Psychologists	1821	Clinical and Counseling Psychologists
		1822	School Psychologists
		1825	Other Psychologists
2000	Counselors	2001	Substance Abuse and Behavioral Disorder Counselors
		2002	Educational, Guidance, and Career Counselors and Advisors
		2003	Marriage and Family Therapists
		2004	Mental Health Counselors
		2005	Rehabilitation Counselors
		2006	Counselors, All Other
2010	Social Workers	2011	Child, Family, and School Social Workers
		2012	Healthcare Social Workers
		2013	Mental Health and Substance Abuse Social Workers
		2014	Social Workers, All Other
2160	Miscellaneous Legal Support Workers	2170	Title Examiners, Abstractors, and Searchers
		2180	Legal Support Workers, All Other

		2862	Court Reporters and Simultaneous Captioners
2340	Other Teachers and Instructors	2350	Tutors
		2360	Other Teachers and Instructors
2630	Designers	2631	Commercial and Industrial Designers
		2632	Fashion Designers
		2633	Floral Designers
		2634	Graphic Designers
		2635	Interior Designers
		2636	Merchandise Displayers and Window Trimmers
		2640	Other Designers
2720	Athletes, Coaches, Umpires, and Related Workers	2721	Athletes and Sports Competitors
		2722	Coaches and Scouts
		2723	Umpires, Referees, and Other Sports Officials
2750	Musicians, Singers, and Related Workers	2751	Music Directors and Composers
		2752	Musicians and Singers
2860	Miscellaneous Media and Communication Workers	2861	Interpreters and Translators
		2865	Media and Communication Workers, All Other
3060	Physicians and Surgeons	3065	Emergency Medicine Physicians
		3070	Radiologists
		3090	Other Physicians

		3100	Surgeons
3260	Health Diagnosing and Treating Practitioners, All Other	3270	Healthcare Diagnosing or Treating Practitioners, All Other
		3261	Acupuncturists
3320	Diagnostic Related Technologists and Technicians	3321	Cardiovascular Technologists and Technicians
		3322	Diagnostic Medical Sonographers
		3323	Radiologic Technologists and Technicians
		3324	Magnetic Resonance Imaging Technologists
		3330	Nuclear Medicine Technologists and Medical Dosimetrists
3400	Emergency Medical Technicians and Paramedics	3401	Emergency Medical Technicians
		3402	Paramedics
		3421	Pharmacy Technicians
3420	Health Practitioner Support Technologists and Technicians	3422	Psychiatric Technicians
		3423	Surgical Technologists
		3424	Veterinary Technologists and Technicians
		3430	Dietetic Technicians and Ophthalmic Medical Technicians
		3545	Miscellaneous Health Technologists and Technicians

3540	Other Healthcare Practitioners and Technical Occupations	1980	Occupational Health and Safety Specialists and Technicians
		3550	Other Healthcare Practitioners and Technical Occupations
3600	Nursing, Psychiatric, and Home Health Aides	3601	Home Health Aides
		3603	Nursing Assistants
		3605	Orderlies and Psychiatric Aides
3730	First-Line Supervisors, All Other	3725	First-Line Supervisors of Security Workers
		3735	First-Line Supervisors of Protective Service Workers, All Other
3800	Bailiffs, Correctional Officers, and Jailers	3801	Bailiffs
		3802	Correctional Officers and Jailers
3955	Lifeguards, Recreational, Other Protective Service Workers	3946	School Bus Monitors
		3960	Other Protective Service Workers
4250	Grounds Maintenance Workers	4251	Landscaping and Groundskeeping Workers
		4252	Tree Trimmers and Pruners
		4255	Other Grounds Maintenance Workers
4520	Miscellaneous Personal Appearance Workers	4521	Manicurists and Pedicurists
		4522	Skincare Specialists
		4525	Other Personal Appearance Workers

4620	Recreation and Fitness Workers	4621	Exercise Trainers and Group Fitness Instructors
		4622	Recreation Workers
5520	Dispatchers	5521	Public Safety Telecommunicators
		5522	Dispatchers, Except Police, Fire, and Ambulance
5700	Secretaries and Administrative Assistants	5710	Executive Secretaries and Executive Administrative Assistants
		5720	Legal Secretaries and Administrative Assistants
		5730	Medical Secretaries and Administrative Assistants
		5740	Secretaries and Administrative Assistants, Except Legal, Medical, and Executive
6440	Pipelayers, Plumbers, Pipefitters, and Steamfitters	6441	Pipelayers
		6442	Plumbers, Pipefitters, and Steamfitters
6840	Mining Machine Operators	6850	Underground Mining Machine Operators
		6950	Other Extraction Workers
9120	Bus Drivers	9121	Bus Drivers, School
		9122	Bus Drivers, Transit and Intercity
		9141	Shuttle Drivers and Chauffeurs

9140	Taxi Drivers and Chauffeurs	9141	Shuttle Drivers and Chauffeurs
		9142	Taxi Drivers

Table 9: **List of Occupations that Concatenate between 2010 and 2018**

2010	2010 Title	2018	2018 Title
3850	Police and Sheriff's Patrol Officers	**3870**	Police Officers
3860	Transit and Railroad Police		
4050	Combined Food Preparation and Serving Workers, Including Fast Food	**4055**	Fast Food and Counter Workers
4060	Counter Attendants, Cafeteria, Food Concession, and Coffee Shop		
4410	Motion Picture Projectionists	**4435**	Other Entertainment Attendants and Related Workers
4430	Miscellaneous Entertainment Attendants and Related Workers		
6100	Fishers and Related Fishing Workers	**6115**	Fishing and Hunting Workers
6110	Hunters and Trappers		
6300	Paving, Surfacing, and Tamping Equipment Operators	**6305**	Construction Equipment Operators
6310	Pile-Driver Operators		
6320	Operating Engineers and Other Construction Equipment Operators		
6420	Painters, Construction and Maintenance	**6410**	Painters and Paperhangers
6430	Paperhangers		
6930	Helpers–Extraction Workers	**6950**	Other Extraction Workers
6940	Other Extraction Workers		

7600	Signal and Track Switch Repairers	**7640**	Other Installation, Maintenance, and Repair Workers
7630	Other Installation, Maintenance, and Repair Workers		
7920	Extruding and Drawing Machine Setters, Operators, and Tenders, Metal and Plastic	**7925**	Forming Machine Setters, Operators, and Tenders
7930	Forging Machine Setters, Operators, and Tenders, Metal and Plastic		
7940	Rolling Machine Setters, Operators, and Tenders, Metal and Plastic		
7960	Drilling and Boring Machine Tool Setters, Operators, and Tenders, Metal and Plastic	**8025**	Other Machine Tool Setters, Operators, and Tenders
8010	Lathe and Turning Machine Tool Setters, Operators, and Tenders, Metal and Plastic		
8020	Milling and Planing Machine Setters, Operators, and Tenders, Metal and Plastic		
8120	Multiple Machine Tool Setters, Operators, and Tenders, Metal and Plastic	**8225**	Other Metal Workers and Plastic Workers
8150	Heat Treating Equipment Setters, Operators, and Tenders, Metal and Plastic		

8160	Layout Workers, Metal and Plastic		
8200	Plating and Coating Machine Setters, Operators, and Tenders, Metal and Plastic		
8210	Tool Grinders, Filers, and Sharpeners		
8220	Metal Workers and Plastic Workers, All Other		
8360	Textile Bleaching and Dyeing Machine Operators and Tenders	**8365**	Textile Machine Setters, Operators, and Tenders
8400	Textile Cutting Machine Setters, Operators, and Tenders		
8410	Textile Knitting and Weaving Machine Setters, Operators, and Tenders		
8420	Textile Winding, Twisting, and Drawing Out Machine Setters, Operators, and Tenders		
8430	Extruding and Forming Machine Setters, Operators, and Tenders, Synthetic and Glass Fibers	**8465**	Other Textile, Apparel, and Furnishings Workers
8440	Fabric and Apparel Patternmakers		
8460	Textile, Apparel, and Furnishings Workers, All Other		
8520	Model Makers and Patternmakers, Wood	**8555**	Other Woodworkers

8550	Woodworkers, All Other		
8860	Cleaning, Washing, and Metal Pickling Equipment Operators and Tenders	**8865**	Other Production Equipment Operators and Tenders
8900	Cooling and Freezing Equipment Operators and Tenders		
8840	Semiconductor Processors	**8990**	Other Production Workers
8965	Production Workers, All Other		
9230	Railroad Brake, Signal, and Switch Operators	**9265**	Other Rail Transportation Workers
9260	Subway, Streetcar, and Other Rail Transportation Workers		
9340	Bridge and Lock Tenders	**9430**	Other Transportation Workers
9420	Other Transportation Workers		
9500	Conveyor Operators and Tenders	**9570**	Conveyor, Dredge, and Hoist and Winch Operators
9520	Dredge, Excavating, and Loading Machine Operators		
9560	Hoist and Winch Operators		
9740	Tank Car, Truck, and Ship Loaders	**9760**	Other Material Moving Workers
9750	Material Moving Workers, All Other		

Declarations

Confict of interest: No financial or other conflicts to declare.

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