



Race/Ethnicity and Employment Insecurity: Impacts of COVID-19 on the US Labor Force and Beyond

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Abstract

Using the Household Pulse Survey and American Community Survey, this study examines employment insecurity experienced across different racial/ethnic groups of the U.S. labor force under the pandemic disruptions. It highlights significant employment security disparities based on race, ethnicity, and income during the pandemic. However, there are no significant gender and racial disparities within the lowest income group when controlling for other conditions. In contrast, gender and racial disparities in EI are much more pronounced among mid-to-high income groups. Non-White individuals were disproportionately affected by job loss due to health and COVID-related employment issues, unlike Whites who faced unemployment more due to other factors. This pattern was more evident among lower-income groups. The trends shifted in later stages, with high-income Black and Hispanic workers becoming more likely to be unemployed due to non-health and non-employment reasons. Middle-income workers across all races were least likely to stop working for reasons other than COVID-related health or employment issues. In addition, regardless race or ethnicity, women more likely to be unemployed due to health reasons and less so due to employment issues compared to men, and the gender disparities increased with higher household incomes. We propose that the apparent immediate effects of the pandemic are actually indicative of deeper, systemic issues within the U.S. labor market, specifically the occupational segregation tied to race/ethnicity, gender, and class. Recovery efforts must take a holistic approach and integrate economic development policies, workforce development strategies, and social policies targeting poverty alleviation, health disparities, and people of color.

Keywords Employment insecurity · Race/ethnicity · Gender · Occupational segregation · Working poor · Pandemic

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Introduction

The COVID-19 pandemic has dealt a swift and profound blow to labor markets worldwide. Its immediate impact, particularly acute in the initial phase, was marked by an exceptional attribute: it stemmed directly from an unparalleled imposition of lockdowns that curtailed economic activities (Lea, 2020). Despite this distinct trigger, the ensuing recession bore similarities to past economic contractions, such as the Great Recession of 2007–2009 (Kalleberg & Von Wachter, 2017), in terms of its uneven toll. Empirical research on a global scale has revealed the asymmetrical burden of the downturn, with the less educated, women, immigrants, people of color, and sexual minorities bearing a disproportionate share of its adverse effects (Cortes & Forsythe, 2022; Martell & Roncolato, 2023). While considerable scholarly attention has been devoted to the pandemic's initial phase, there remains a significant gap in understanding the persistent and evolving disparities, particularly those along racial and ethnic lines. Moreover, discussions on the causative factors of these disparities are notably scarce. To create effective intervention strategies, it is imperative to analyze the longitudinal trends, understand how various racial, ethnic, and socioeconomic groups have adapted to the changing labor market dynamics as the pandemic has unfolded, and to thoroughly investigate the root causes of these persistent inequalities.

This study utilizes data from the National Household Pulse Survey (HPS), covering April 2020 to October 2021, to investigate employment insecurity within the U.S. labor force amidst the pandemic. It specifically addresses the following questions: Who were affected by job loss? How did patterns of job loss vary among different racial and ethnic groups? What were the contributing factors to these variations over time?

The study reveals pronounced disparities in employment security among racial/ethnic and gender groups, which are complicated when intersected with income disparities. Notably, the working poor, irrespective of race or ethnicity, faced a substantially higher likelihood of unemployment compared to other income brackets. Additionally, significant racial and gender disparities in employment insecurity were observed among mid-to-high income groups. The study establishes significant correlations between unemployment, racial/ethnic and gender occupational segregation, and low-wage jobs. It suggests that deep-rooted occupational segregation across and within racial and gender groups underpins these disparities and will continue to influence the recovery process and future labor market positioning of these groups.

This study makes several contributions. Very few studies have examined the effects of COVID-19 on employment insecurity across racial/ethnic groups beyond the early stages of the pandemic. While existing studies provide an important snapshot of labor market distortions after the first pandemic wave, the gradual economic revival that came later may have changed the picture and may have different implications. This paper provides comprehensive evidence of employment insecurity through a comparative and longitudinal perspective. Furthermore, our results not only corroborate the heightened disadvantages faced by lower-income workers and racial minorities, but also demonstrate the dynamic interaction between race/ethnicity, gender, and income over time. Crucially, this study links scholarship on socioeconomic vulnerability during crises to the persistent issues of occupational segregation by race/eth-

nicity, gender, and class. It expands our understanding of how systemic racial and gender disparities shape employment insecurity and compound the challenges for marginalized groups during periods of upheaval (Gemelas & Davison, 2022; Peacock et al., 2014).

The COVID crisis has not only intensified poverty and inequality but has also substantially reshaped the organization of work (Fana et al., 2020; Kramer & Kramer, 2020). Presently, technologies like ChatGPT and broader AI innovations raise concerns about potential job displacement and exacerbating income and wealth disparities in the US (Kochhar, 2023). The evidence presented in this study underscores the necessity of addressing longstanding labor market segregation. It advocates for comprehensive strategies to transform the socioeconomic conditions of the working poor and racial/ethnic minorities, and ensure their equal participation in and benefits from technological changes. An integrated policy approach that combines economic growth and labor development with social initiatives aimed at reducing poverty, eliminating health disparities, and providing equitable opportunities for all racial groups is imperative for a just recovery.

Literature Review: Labor Market Segregation and Uneven Impacts of COVID-19

According to the resilience literature, disastrous events disproportionately impact individuals who are already socially and economically disadvantaged (Peacock et al., 2014). Marginalized groups experience higher levels of poverty and often live in areas that are more prone to disasters, with less employment, poorer housing, and less protection from aid-providing institutions (Bergstrand et al., 2015). As a result, disasters lay bare inequalities – e.g., in resources, information, and the ability to act – and magnify existing difficult situations and relationships. For instance, research has found that damage done by disasters is more severe for Hispanics and African Americans than for whites, and that these two groups, as well as female-headed households, struggle with the process of obtaining financial assistance from the government to help with the housing recovery process (Van Zandt et al., 2012). Certain racial/ethnic minorities are reluctant to evacuate, which in part is due to limited transportation and lack of alternative shelter (Benevolenza & DeRigne, 2019). Furthermore, these groups may face limited access to financial assistance; and some undocumented ethnic/racial individuals avoid seeking assistance for fear of legal issues (Rufat et al., 2015).

While these studies have provided valuable insights, they are mainly based on experiences of previous natural disasters and housing issues, and the economic impacts of a public health crisis like COVID-19 have seldom been examined in resilience literature. For the 2001 recession, DiPasquale (et al., 2021) demonstrated that income inequality is highly intersected with race and ethnicity, and the poor are particularly vulnerable to economic recessions. Likewise, during the 2007–2009 Great Recession, economic turmoil was widespread in the U.S., but racial and ethnic minorities suffered disproportionately. Unemployment soared, and home foreclosures were more common among African American and Latino homeowners (Pfeffer

et al., 2013). Minority groups, including less-educated individuals and men, faced greater job losses (Hout et al., 2011). Even as Latino immigrants secured employment post-recession, their declining wages highlighted their labor market precariousness (Kochhar et al., 2010). The enduring impact on communities of color from this period remains a critical area for investigation.

During the COVID-19, people of color, women, the less educated, and those with non-standard contracts (e.g., temporary workers), and those who had already suffered from secondary labor market pay and working conditions, experienced the hardest impact of the pandemic crisis, with their jobs becoming even more precarious and vulnerable (Fana et al., 2020). Han and Hart (2021) demonstrate that labor markets in recent decades have become increasingly volatile and more workers have experienced economic insecurity by working in sectors with precarious conditions, low material rewards and few benefits, and disempowerment in the workplace. They argue that COVID-19 has simply laid bare such economic insecurity. In the U.S., focusing on frontline occupational status between January 1 and June 30, 2020, Gemelas and Davison (2022) demonstrate that previously employed workers in marginalized populations were more likely to suffer job loss during the economic decline attributable to COVID-19. Black or African American workers were much more likely to have lost or left lower-risk and potentially more secure non-frontline positions relative to White workers in the first half of 2020.

Gender differences in employment affected by COVID-19 are also noted by studies based on experiences from different countries (Cortes & Forsythe, 2022; Fana et al., 2020). Based on the U.S. the Current Population Survey from the second quarter in 2019 to the second quarter in 2020, Han (2021) finds that pandemic's impact varied across sectors, with women in service industries facing the greatest economic harm. Intersectionality of race, gender, and education further contributes to disparities across sectors. Tverdostup (2023) argues that parenthood is a major driver for women experiencing significant declines in employment and work hours, particularly in industries affected by the pandemic. Although telework and education mitigated the expansion of the gender wage gap, women with young children still suffered more than men.

The crisis has highlighted the persistent differences across race/ethnicity and gender in wages and employment opportunities (Akee et al., 2019; Del Río & Alonso-Villar, 2015; Grusky, 2019). Segmentation theorists argue that, rather than a single labor market, we have multiple markets as a result of social structures and institutional mediation (Reich et al., 1973; Schrover et al., 2007). The simplest case is a dual market in which labor is bifurcated into primary and secondary sectors. Primary industries are those with greater power to amass surpluses and therefore greater leeway in providing labor with opportunities to return, while the secondary sector comprises low-wage, unstable jobs with limited mobility (Averitt, 1968). Lacking the same opportunities for stable career employment as White men, ethnic minorities (and new immigrants) tend to emerge as the replacement group and are overrepresented in the secondary labor market (Ellis & Wright, 1999; Wang, 2010). Consistently, using a national dataset from 2006 to 2016 in the U.S., Kim and Golden (2022) find that part-time underemployment is concentrated among workers who are non-

White, lower income, and employed in certain service occupations that face greater risks of financial insecurity.

Similar to racial minorities, women are overrepresented in certain occupations, commonly referred to as “feminized” occupations, such as clerical, retail, cleaning, catering, and caring roles. These jobs are often part-time, low-paid, and offer limited career prospects. The devaluation of women’s work and the lack of bargaining power contribute to the lower wages associated with female-dominated occupations (Cohen & Huffman, 2003). Additionally, this segregation exposes women to greater vulnerability during economic downturns, leading to higher rates of underemployment (Kim & Golden, 2022). Kameråde and Richardson (2018) argue that gender segregation is the key factor that shapes the propensity of job losses during a recession and that gender segregation exposed women to higher risks of underemployment than men during and after the recession of 2008.

Taking all these factors together, we would expect that the long-term segregation and segmentation of labor markets by race/ethnicity and gender consigned many households of color to low-wage jobs in the most vulnerable sectors under economic disruptions. As such, pandemic-induced labor market distortions have had significantly different impacts across racial groups, with people of color being more negatively impacted. However, very few studies have examined the loss of employment across race/ethnicity and over time, and even fewer have directly examined the reasons for employment loss during this period. The unique, near real-time HPS data thus provides an important opportunity to address these issues.

Data and Methodology

Data

Our main data source, the HPS, is an experimental data product of the U.S. Census Bureau aimed at providing timely data about how the COVID-19 pandemic has impacted households across the country from a socioeconomic perspective. It asks questions about how the household’s housing, education, employment, food security, and health have been affected by the ongoing crisis, and has provided near-real-time weekly data since April 2020. The Census Bureau’s Master Address File (MAF) is used as the source of sampled housing units (HUs) for the HPS. A systematic sample of all eligible HUs is drawn for each of 66 independent sample areas comprising the top 15 MSAs and 50 States plus the District of Columbia. The sample size within each of the sampling areas was adjusted for an anticipated response rate of 9%. The two-stage sample design entails special treatment at the phase of statistical analyses, as analyzing a cluster sample as if it were a simple random sample will usually underestimate the standard errors (Lumley, 2011). In addition, we utilize the HPS’s person weights to adjust for differential selection probabilities for each household/person and non-response bias. Following the sampling design of the HPS, our analyses allow for generalization to the entire U.S. labor force.

Five phases of the HPS, from April 23, 2020 to October 2021, are used to highlight the potential racial/ethnic differences in employment insecurity during the COVID-

19 pandemic.¹ Phase 1 comprises 12 weeks of data collection and covers the period from April 23, 2020 to July 21, 2020. Since Phase 2, August 19, 2020, ended on October 26, 2020, data collection and dissemination have been on a bi-weekly basis, but the HPS continues to call them “weeks” to maintain continuity. Phase 3 began on October 28, 2020, ended on March 29, 2021, and collected 10 weeks of data. Phase 3.1 began on April 14, 2021, ended on July 5, 2021, and collected six weeks of data. Phase 3.2 ran from July 21, 2021 to October 11, 2021, and collected six weeks of data. Table 1 presents the dependent variables, key independent variables, and control variables used in the analyses.

It is important to recognize that there is significant variation within each racial and ethnic group in terms of religion, culture, ancestral origin, and physical appearance (Hamilton & Form, 2003). Nevertheless, these racial and ethnic categories remain significant for understanding labor market segregation or concentration, as demonstrated in numerous previous studies (Wang & Pandit, 2007). Starting in 2000, the race question in the US Census underwent substantial changes to allow respondents to report as many races as they deemed necessary to describe themselves. Additionally, each respondent is asked to identify their Hispanic/Spanish/Latino origin and classify it according to their country of origin whenever possible. Origin, as defined by the Census Bureau, encompasses ancestry, lineage, heritage, nationality group, or country of birth. Therefore, people of Hispanic origin may belong to any race. Following the definitions provided by the Census Bureau, in this study, a respondent is categorized as Non-Hispanic White alone, Non-Hispanic Black alone, Non-Hispanic Asian alone, Hispanic or Latino of any race, or all other groups with two or more races (referred as “White”, “Black”, “Asian”, “Hispanic”, and “Others” thereafter).

Since the HPS does not provide information on occupations, we used the Integrated Public Use Microdata Series (IPUMS USA) (Ruggles et al., 2022), which provides microdata at the individual and household level for the American Community Survey (ACS) 2021 as a supplement, to detail the occupations of workers unemployed during the pandemic. The ACS 2021 provides a one-in-a-hundred national random sample of the U.S. population, asking a similar question to the HPS - “Last week, did this person work for pay at a job (or business)?” Although the survey’s sample is different from that of the HPS, the ACS 2021 provided us with the most reliable estimation of the U.S. labor force status during the pandemic. We confined our analyses to the employed labor force of national ACS2021 in order to find out their employment sectors.

Measurement of Employment Insecurity (EI)

We used a variable drawn from the HPS to measure employment insecurity, a variable related to the question “In the last 7 days, did you do ANY work for either pay or profit?” The respondent is asked to select from two options “Yes” and “No.” In our model, we coded it as a binary variable (EI), with 1 representing employment insecurity (did not do ANY work for either pay or profit) and 0 representing employ-

¹ Phase 3.2 data from July 21, 2021 to October 11, 2021 was the most recent data available to us when we started this research project.

Table 1 Descriptions and summary statistics of dependent and independent variables

Variable	Description	Proportion/ Average	Relationship with EI	
			Proportion/Average (EI = 1)	EI Gap
Dependent variable				
EI	Employment insecurity indicator: Did not do ANY work for either pay or profit in the last 7 days. The universe excludes those that have retired or did not want to be employed.	0.303 (0.0062)		
Key independent variables				
Race/Ethnicity (ref. = White)				
White	Non-Hispanic White alone.	0.620 (0.027)	0.266 (0.0047)	26,301***
Black	Non-Hispanic Black alone.	0.113 (0.011)	0.386 (0.0064)	
Hispanic	Respondent of Hispanic, Latino, or Spanish origin, maybe of any race.	0.173 (0.023)	0.381 (0.01)	
Asian	Non-Hispanic Asian alone.	0.054 (0.008)	0.271 (0.008)	
Others	Non-Hispanic, any other race alone, or race in combination.	0.040 (0.0029)	0.360 (0.006)	
Household income (ref. = Low)				
Low	Total household income (before taxes) less than \$25,000: in 2019 (Weeks 1–35); in 2020 (Weeks 34–39).	0.152 (0.0047)	0.598 (0.0061)	198,691***
Below Median	Total household income (before taxes) between \$25,000 and \$74,999: in 2019 (Weeks 1–35); in 2020 (Weeks 34–39).	0.407 (0.0073)	0.337 (0.0078)	
Median	Total household income (before taxes) between \$75,000 and \$199,999: in 2019 (Weeks 1–35); in 2020 (Weeks 34–39).	0.361 (0.0061)	0.182 (0.0057)	
High	Total household income (before taxes) \$200,000 and above: in 2019 (Weeks 1–35); in 2020 (Weeks 34–39).	0.080 (0.0064)	0.119 (0.0039)	
Sex at birth (ref. = Male)				
Male	Male respondent at birth.	0.489 (0.0021)	0.266 (0.0067)	12,332***
Female	Female respondent at birth.	0.511 (0.0021)	0.339 (0.0058)	
Control variables				
Age	Age of the respondent.	44.919 (0.132)	45.58 (0.172) Difference in mean = 0.953	9.2515***
Marital Status (ref. = Never Married)				

Table 1 (continued)

Variable	Description	Proportion/ Average	Relationship with EI	
			Proportion/Average (EI=1)	EI Gap
Never Married	Never Married.	0.279 (0.0056)	0.338 (0.007)	24,903***
Married	Currently married.	0.554 (0.0045)	0.259 (0.0057)	
Divorced/ separated/ widowed	Divorced/separated/widowed.	0.167 (0.003)	0.391 (0.0062)	
Household size				
Size	Total number of people in the household.	3.455 (0.031)	3.636 (0.037)	16.129***
Children	Percentage of individuals under 18 years old in the household.	17.191 (0.212)	18.08 (0.253)	9.6925***
			Difference in mean=0.26	
			Difference in mean=1.276	
Tenure (ref. = Own Free)				
Own Free	Owned free and clear.	0.176 (0.0056)	0.310 (0.0056)	41,346***
Own Mortgage	Owned with a mortgage or loan.	0.480 (0.0097)	0.242 (0.0051)	
Rent	Rented.	0.326 (0.0127)	0.377 (0.0065)	
Rent Free	Occupied without payment of rent.	0.017 (0.0006)	0.539 (0.008)	
Education (ref. = Bachelor)				
Bachelor	Bachelor's degree (for example BA, BS, AB) or graduate degree (for example master's, professional, doctorate).	0.34 (0.01)	0.174 (0.0052)	92,150***
Some College	Some college, but degree not received or is in progress, or associate's degree (for example AA, AS).	0.309 (0.0061)	0.32 (0.0066)	
High School	High school graduate or equivalent (for example GED), some high school, or less than high school.	0.351 (0.007)	0.414 (0.0078)	
Week	Which week of the survey (1–39).			

Note In the last two columns, a statistical test accounting for survey design was performed to assess the difference in the distribution of EI status for the corresponding covariate. A two-sample t-test was conducted if the covariate is a continuous variable (e.g., Age). In contrast, a Pearson's X-squared test (Rao & Scott adjustment) was conducted if the covariate is a categorical variable (e.g., Gender). * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

ment security. We were able to exclude the population not at risk of employment insecurity by looking at the response to an additional question addressed to those who selected “No” to an additional question: “What is your main reason for not working for pay or profit?”. This question asked respondents to select one from 12 possible main reasons. Two of these possible reasons – “retired” and “did not want to be employed” – accounted for 37.7% and 4.7% of the total responses respectively.

These individuals were not considered members of the labor force and were excluded from our analyses.

Methodology

We adopted survey-weighted generalized linear models to examine disparities in employment insecurity by race/ethnicity, income group, and sex at birth (Lumley & Scott, 2017). Since our response variable was binary, with 1 indicating employment insecurity and 0 indicating employment security during the pandemic, a logit link function is adopted to link the linear predictors and the mean of EI probabilities. Our logistic regression model is formalized in Eq. (1):

$$g(E(Y_i)) = \alpha + \beta_R \text{Race}_i + \beta_S \text{Sex}_i + \beta_I \text{Income}_i + \beta_{RSI} \text{Race}_i \times \text{Sex}_i \times \text{Income}_i + \beta_1 X_{i1} + \beta_2 X_{i2} + \dots + \beta_k X_{ik} \quad (1)$$

$$g(\pi_i) = \log\left(\frac{\pi_i}{1 - \pi_i}\right)$$

where $E(Y_i)$ is the expected value of Y_i , the indicator of employment insecurity for person i , π_i is the probability of experiencing employment insecurity for person i , $g(\pi_i)$ is the logit link function of π_i , and also the log function of the odds of experiencing employment insecurity, and Race_i , Sex_i , and Income_i are the key variables of interest, namely, race/ethnicity, sex at birth (used interchangeably with gender), and income group for i . We also included the three-way interactions between race/ethnicity, sex/gender, and income group to capture potential interaction effects among the three variables.

Our models further incorporated several control variables, X_{i1}, \dots, X_{ik} , encompassing various housing, demographic, and socioeconomic factors that could potentially confound the relationships between race/ethnicity, sex/gender, income group, and employment insecurity. These variables include age (and its squared term), marital status, and educational attainment of the respondent, as well as the structure of the household, such as housing tenure, size of the household, and percentage of individuals under 18 years old within the household. Table 1 provides summary statistics including the mean and standard deviation of these variables. We further assessed the relationship between each of these variables and our key outcome variable, EI. A two-sample t-test was conducted if the covariate is a continuous variable (e.g., Age), while a Pearson's X-squared test (Rao & Scott adjustment) was conducted if the covariate is a categorical variable (e.g., marital status). These statistics cover the U.S. population who were in the labor force during the study period. The survey week was incorporated into the model as a continuous variable to take account of temporal heterogeneity.

The dataset was divided into two distinct periods: Stage 1 (Weeks 1–33) and Stage 2 (Weeks 34–39). This division was necessitated by the fact that our key variable, "Income," corresponded to different years for these stages, stemming from changes in the HPS survey question by the Census Bureau since Week 34. In Stage 1, we

utilized household income data from 2019—before the pandemic—while in Stage 2, household income for 2020 was used to capture the economic impact of the pandemic. Recognizing that the financial conditions before and during the pandemic might have distinct influences on employment insecurity, it was imperative to assess these stages separately. Accordingly, we executed two logistic regression models, one for each stage. While endogeneity is not a central issue in this study, we wish to clarify that our analysis does not assert a causal relationship between Economic Insecurity (EI) and the variables of race/ethnicity, sex/gender, and income.

We adopted survey-based estimators for the GLMs, which accounted for the survey design and thus provided valid estimates for coefficients and standard errors. Following best practices for interpreting nonlinear interaction effects in the literature (Mize, 2019; Mustillo et al., 2018), we present the interaction effects as predicted probabilities in this study². Specifically, the quantity of interest is the marginal effect (ME), defined as the difference between two predicted probabilities, with only the variable of interest (e.g., race/ethnicity) changing and the other variables being held constant. Our focus is the average marginal effects (AMEs), estimated by calculating an ME for every observation in the sample and then averaging these effects. For instance, the AME of gender for low-income Whites is the average difference between the predicted probability of EI for low-income White women and that for low-income White men for all observations, which is essentially the first difference between predicted probabilities and would be interpreted as the gender gap for low-income Whites. Further, we adopted the Wald test for interaction effects, which tests the equality of an AME to the AME of the reference group (Mize, 2019). For instance, the gender gap for high-income Whites is compared with the gender gap for low-income Whites (reference group) using the Wald test. If the null hypothesis is rejected, we conclude the effect of gender is significantly different between high- and low-income Whites. The interaction effects of gender are thus correspondent to the second difference in predicted probabilities. We examined all three sides (i.e., race/ethnicity, gender, and income) to the interaction effects following the recommended best practice by Mize (2019). In practice, the R package “survey” was used for model estimation, and the R package “marginaleffects” was adopted for calculating AMEs and conducting Wald tests (Lumley, 2004; Arel-Bundock et al., *Forthcoming*).

Then, we analyzed the ACS 2021 (IPUMS USA) to discover occupational concentration by race/ethnicity for the entire labor force and the unemployed. After aggregating occupations at the two-digit level, we calculated the odds ratio for each occupation to determine the degree of concentration. The odds ratio (OR) for a focal racial/ethnic group working in occupation j is denoted as shown in Eq. (2):

$$OR = \frac{E_j / E_{J-j}}{O_j / O_{J-j}} \quad (2)$$

² We acknowledge that the Editor’s comments have encouraged us to adopt the most recent best practices in this field.

The numerator is the ratio of the number of racial/ethnic workers (group E) in occupation j to the number of group E 's workers in all other occupations ($J - j$); and the denominator represents the same ratio for all other workers (O_j / O_{J-j}). Following common practice in ethnic labor market segmentation literature (Wang & Pandit, 2007), an occupation with an $OR \geq 1.2$ is regarded as an ethnic niche occupation that has a concentration of a particular ethnic group (i.e., White, Black, Hispanic, Asian, and Other in this study).

Findings

General Patterns of EI Across Groups and over Time

Racial and Ethnic Differences

Our analyses showed that an average of 30.4% of the U.S. labor force experienced recent employment loss during the study period of April 23, 2020 - October 11, 2021. However, significant differences existed among racial/ethnic, sex, and income groups. Blacks, Hispanics, and Others groups had suffered the most – as many as 38.6%, 38.1%, and 36% of these groups respectively had suffered from EI, in contrast to a much smaller percentage of Whites (26.6%) and Asians (27.1%). Differences in EI across these five racial/ethnic groups are statistically significant at the 1% level as indicated by the result from the Pearson's X-squared test shown in Table 1.

Average weekly trends of EI for the racial/ethnic groups show many short-term fluctuations. They generally followed a decreasing trend after short-term fluctuations were smoothed out using the exponential moving average technique as shown in Fig. 1(a). From April 23 to July 21, 2020, the national average rate decreased slightly from 37.2 to 36.3% while greater decreases were observed for Whites (from 34.4 to 32.5%) and Asians (from 35.6 to 34.6%). In contrast, the other three groups experienced a slight increase. For the subsequent period, we observed a sharp decline around mid-August 2020 across all groups – only around 29.6% of Americans experienced EI, an 18% decline within a month.

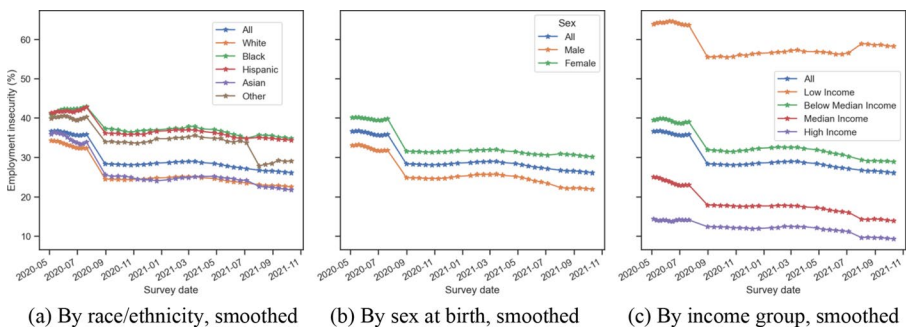


Fig. 1 Average trends of EI amid the COVID-19 pandemic

For about five months, the EI rate stabilized, until it started to climb around January 2021, before stopping around March 2021. After this, the employment insecurity situation kept improving for all racial/ethnic groups until early July 2021, when once again circumstances diverged. On average, EI worsened in late July 2021 but abated through the rest of the period till mid-October 2021. By the end of the study period, 29.3% of Americans had suffered from EI. The situation evolved in a similar manner for Blacks, Hispanics, and Whites, though the levels were very different. Black and Hispanic groups ended up with 38.1% and 38.5% respectively suffering from EI, while the figure for Whites was 24.8%. In contrast, Asians and Others experienced a sharp decrease in late July 2021, and the levels for the two groups stabilized for the rest of the study period, ending up at 25.4% and 32.8% respectively (Fig. 1a).

Differences between Men and Women

We also observed a sharp contrast in EI between women and men (Fig. 1b). While an average of 26.7% of men experienced EI, the average for women was 33.9%. Their difference is statistically significant at the 1% level as indicated by the result from the Pearson's X-squared test shown in Table 1. Temporally, EI for men and women took similar paths during the study period; but despite ups and downs for both, women consistently suffered more. In addition, over time, the gender gap widened – from 7.6% in April 2020 to 8.4% in October 2021.

Differences by Income Group

We considered four income groups: households earning less than \$25,000 annually were classified as “Low Income”; those earning between \$25,000 and \$74,999 were put into the category “Below Median”; those earning between \$75,000 and \$199,999 were “Median”; and those with an annual income above \$200,000 and were “High Income”. As discussed earlier, the household income was the 2019 level for the earlier phases of the HPS; and starting from Phase 3.2 (Weeks 34–39, July 21 to October 11, 2021), the income level referred to was that for 2020.

Figure 1c illustrates a significant disparity in EI across income groups. Throughout the study period, only 12% of “High Income” households experienced EI, compared to a staggering 59.8% of “Low Income” households—nearly five times as many. “Below Median” income households also faced substantial challenges, with one-third experiencing EI. Conversely, households earning above the “Median” income had a lower incidence, at 18.2%. Notably, while the trend of EI declined for the three higher-income groups in 2021, it increased for low-income households. This indicates that lower-income households disproportionately suffer from EI and have the least resilience and ability to recover.

Regression Results for Employment Insecurity

As shown in Table 2, we estimated two logistic regression models: Model (1) for the subsample of Stage 1 (Weeks 1–33) and Model (2) for Stage 2 (Weeks 34–39), each of which incorporated key variables of interest, including race/ethnicity, sex/gender,

Table 2 Marginal effects of income and differences in effects of income across gender and ethnicity on EI (Stage 1, $N=1,713,549$)

			White	Black	Hispanic	Asian	Other	
Men	Below	Below	-0.266***	-0.24***	-0.194***	-0.142***	-0.224***	
		Median	(0.010)	(0.015)	(0.015)	(0.024)	(0.022)	
		Median-Low Gap (AME)						
			Interaction	0.026	0.072***	0.124***	0.042*	
			Effect	(0.015)	(0.016)	(0.028)	(0.02)	
	Median	Median-Low	-0.385***	-0.39***	-0.308***	-0.295***	-0.352***	
		Gap (AME)	(0.01)	(0.015)	(0.02)	(0.025)	(0.023)	
		Interaction						
			Effect	-0.005	0.077***	0.09**	0.033	
		Effect	(0.015)	(0.021)	(0.029)	(0.02)		
High	High -Low	-0.44***	-0.463***	-0.37***	-0.373***	-0.405***		
	Gap (AMEs)	(0.009)	(0.025)	(0.015)	(0.028)	(0.032)		
	Interaction							
		Effect	-0.02	0.071***	0.068*	0.035		
		Effect	(0.025)	(0.017)	(0.03)	(0.032)		
Women	Below	Below	-0.214***	-0.238***	-0.152***	-0.194***	-0.221***	
		Median	(0.006)	(0.009)	(0.016)	(0.025)	(0.014)	
		Median-Low						
			Interaction	0.052***	0.028*	0.114***	0.072**	0.045**
			Effect	(0.010)	(0.012)	(0.020)	(0.072)	(0.015)
	Median	Median-Low	-0.301***	-0.345***	-0.241***	-0.268***	-0.32***	
		Gap (AME)	(0.007)	(0.011)	(0.020)	(0.016)	(0.014)	
		Interaction						
			Effect	0.084***	0.04**	0.143***	0.116***	0.065***
		Effect	(0.009)	(0.015)	(0.023)	(0.018)	(0.017)	
High	High -Low	-0.319***	-0.370***	-0.291***	-0.352***	-0.378***		
	Gap (AME)	(0.008)	(0.027)	(0.032)	(0.025)	(0.020)		
	Interaction							
		Effect	0.121***	0.07**	0.15***	0.088***	0.062**	
		Effect	(0.008)	(0.026)	(0.033)	(0.026)	(0.023)	

Note (1) The reference of the second difference is the AME of income (e.g., Below Median-Low gap=Below Median – Low, Median-Low Gap=Median - Low) for White men. (2) * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. Standard errors are in the parentheses below the estimates

income class, and their three-way interaction terms, together with the control variables. AMEs for each key variable were further estimated and compared using Wald tests to investigate the interaction effects.

We visualized the predicted probabilities based on key variables using group-specific observations in Fig. 2. The effect of gender does not appear to be constant across racial/ethnic and income groups. For instance, at Stage 1, the effect of gender is larger for higher-income groups than for lower-income groups. We also observed nuances of gender effects for different racial/ethnic groups. For instance, within the median income class, the gender effect increased for all groups except Blacks. Similarly, race/ethnicity and income effects do not seem to be constant across subgroups. We will present AMEs (first differences in predicted probabilities) and interaction effects (second differences in predicted probabilities) for further discussion.

Effects of Income

As measured by AMEs in Table 2, higher income was significantly associated with lower EI at both stages within each racial/ethnic and gender group. At Stage 1,

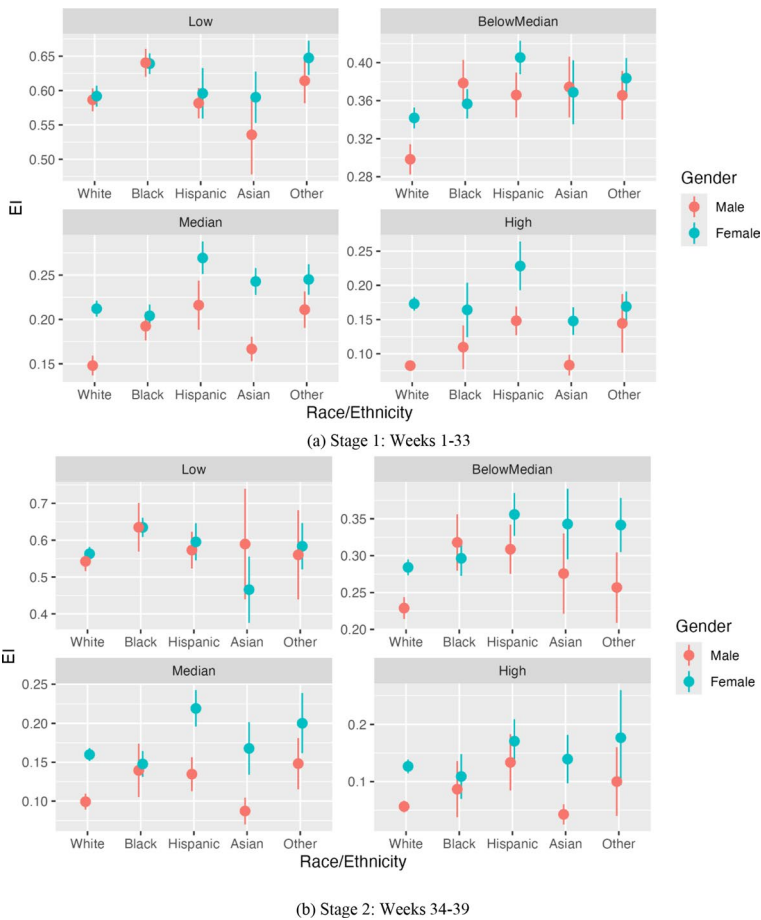


Fig. 2 Predicted probabilities of EI by race/ethnicity, gender, and income

below-median-income White men (\$25,000 ~ \$74,999) had a significantly lower probability of experiencing EI than low-income White women ($D=-0.266; p<0.001$), while the median-low gap increased to 0.385 ($D=-0.385; p<0.001$) and the high-low gap further increased to 0.44 ($D=-0.44; p<0.001$). The negative association between incomes and EI was similarly present for each of the other racial/ethnic and gender subgroups and persisted to Stage 2, as shown in Table 3. However, by Stage 2, while the income gap has narrowed for several female minorities (i.e., Asian and Other women), it had widened for White and minority men. Notably, the gap in EI between the below median and low-income groups diminished for Asian women.

The income effect was not constant across racial/ethnic and gender subgroups and the income gap in EI was always the largest for White males. At Stage 1, while income class had a similarly large effect for White and Black men, its effect was significantly smaller for Hispanic and Asian men. For instance, median-income Hispanic men had a lower probability of experiencing EI than their low-income counterparts ($D=-0.308; p<0.001$). This gap was significantly smaller than the median-low

Table 3 Marginal effects of income and differences in effects of income across gender and ethnicity on EI (Stage 2, $N=224,544$)

			White	Black	Hispanic	Asian	Other	
Mean	Below Median	Below	-0.292***	-0.299***	-0.241***	-0.281***	-	
		Median-Low Gap (AME)	(0.015)	(0.043)	(0.028)	(0.072)	0.259*** (0.066)	
		Interaction Effect		-0.007 (0.048)	0.052 (0.032)	0.011 (0.076)	0.033 (0.067)	
	Median	Median-Low Gap (AME)	-0.401***	-0.445***	-0.389***	-0.430***	-	
		Interaction Effect	(0.014)	(0.038)	(0.030)	(0.085)	0.339*** (0.065)	
		High -Low Gap (AME)	-0.439***	-0.487***	-0.395***	-0.472***	-	
	High	High -Low Gap (AME)	(0.016)	(0.055)	(0.039)	(0.085)	0.409*** (0.077)	
		Interaction Effect		-0.044 (0.041)	0.013 (0.033)	-0.029 (0.089)	0.062 (0.064)	
		Interaction Effect		-0.048 (0.059)	0.044 (0.043)	-0.034 (0.089)	0.030 (0.077)	
	Women	Below Median	Below	-0.242***	-0.296***	-0.203***	-0.091	-
			Median-Low Gap (AME)	(0.010)	(0.020)	(0.027)	(0.058)	0.209*** (0.035)
			Interaction Effect	0.050**	-0.004	0.090**	0.201***	0.083* (0.038)
Median		Median-Low Gap (AME)	-0.336***	-0.409***	-0.295***	-0.225***	-	
		Interaction Effect	(0.013)	(0.022)	(0.032)	(0.055)	0.306*** (0.040)	
		High -Low Gap (AME)	-0.354***	-0.434***	-0.362***	-0.247***	-	
High		High -Low Gap (AME)	(0.013)	(0.035)	(0.034)	(0.040)	0.346*** (0.055)	
		Interaction Effect	0.085***	0.004	0.077*	0.191***	0.092 (0.057)	
		Interaction Effect	(0.016)	(0.036)	(0.037)	(0.038)		

Note (1) The reference of the second difference is the AME of income (e.g., Below Median-Low gap=Below Median - Low, Median-Low Gap=Median - Low) for White men. (2) * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. Standard errors are in the parentheses below the estimates

gap for White men (DD=0.077; $p < 0.001$). Similarly, the high-low income gap for Hispanic men was significantly smaller than the high-low gap for White men (DD=0.071; $p < 0.001$). Meanwhile, income had a larger effect on White men than women of any racial/ethnic group. For instance, high-income White women had a lower probability of experiencing EI than their low-income counterparts (D=-0.319; $p < 0.001$), but the gap was significantly smaller than that observed for White men (DD=0.121; $p < 0.001$). By Stage 2, the smaller income effects observed for Hispanic and Asian men diminished, while the smaller income effects observed for women persisted except for Black women, for whom income has a similar effect to men.

Effects of Sex/Gender

At Stage 1, low-income women and men had a similar probability of experiencing EI for each racial/ethnic group, while in contrast, women were significantly more likely

to experience EI for most mid-to-high racial/ethnic subgroups (Supplementary File 1). One prominent example is high-income Whites: the probability of White women experiencing EI was much higher than that for White men ($D=0.098$; $p<0.001$). A similar pattern was observed for Stage 2 except that the gender gap closed for all Black income subgroups (Supplementary File 2).

The gender effect, with females being more likely to experience EI, varied with income and race/ethnicity. For both Stages, it was significantly larger for higher-income-, White, Hispanic, and Asian subgroups, but less so for Black and Other groups. At Stage 1, median-income Asian women were more likely than men to experience EI ($D=0.083$; $p<0.001$). The gap was significantly larger than the gender gap for low-income Whites ($DD=0.086$; $p<0.001$).

Effects of Race/Ethnicity

Compared with Whites, minority groups generally had a higher probability of experiencing EI regardless of the income class, with this effect being more pronounced for men than for women (Supplementary Files 3, 4). For instance, the below-median-income Black men had a higher probability of experiencing EI than their White counterparts ($D=0.063$; $p<0.001$). In contrast, we did not observe significantly different probabilities when it came to below-median-income Black and White women ($D=0.004$; $p>0.05$). Another major exception is the low-income male Hispanic-White Gap ($D=-0.031$; $p<0.05$). Contrary to all the other AMEs, low-income Hispanic men had a lower probability of experiencing EI than low-income White men, though, by Stage 2, the gap had closed ($D=-0.013$; $p>0.05$). At Stage 2, many of the racial/ethnic gaps diminished. For instance, the large gap observed between median-income Hispanic and White men at Stage 1 ($D=0.055$; $p<0.001$) had closed by Stage 2 ($D=0.022$; $p>0.05$).

The racial/ethnic effect was far from constant across income and gender subgroups. Focusing on the Black-White gap at Stage 1, the estimated AME was 0.03 for low-income men, while the gap was the largest for below-median-income men ($D=0.063$, $p<0.001$; $DD=0.033$, $p<0.05$) and did not exist for high-income men ($D=0.022$, $p>0.05$; $DD=-0.008$, $p>0.05$). In contrast, the Black-White gap for low-income women was not significantly different from that for low-income men ($D=0.023$, $p<0.001$; $DD=-0.006$, $p>0.05$). However, race had a smaller effect on mid-to-higher income women, and in fact, we did not observe a significant Black-White gap for below-median-, median-, and high-income women. The story was much different for the Hispanic-White gap. As introduced before, low-income Hispanic men were the only subgroup that had a lower probability of experiencing EI than their White counterparts. For below-median- to high-income- men and below-median- to median-income women, the Hispanic-White gap was reversed – it was always significant and positive, indicating that Hispanics were more likely to experience EI than Whites at the same income level. By Stage 2, the racial/ethnic effect had been less heterogeneous across income and gender groups.

Overall, different from most existing studies on racial and gender disparities, our findings reveal a more complex picture. When accounting for all other variables, the effect of sex generally increased with income, and minority racial/ethnic groups

had a significantly higher probability of EI than their White counterparts except for low-income Hispanic men. Moreover, income played a significant role in reshaping racial and gender disparities. While no significant gap was observed between White and non-White individuals or between men and women within each racial group among low-income groups, gender and racial disparities in EI became much more pronounced among mid-to-high-income groups.

Reasons for Not Working in the Past Seven Days

The HPS asked about the main reasons for not working in the past seven days. The respondent was asked to select only one of twelve main reasons. Two of them were for those not in the labor force and, therefore, were eliminated from our sample. We classified the remaining 10 reasons for not working into three general categories: Health, Employment, and “Other” reasons. Health was comprised of three reasons related to COVID-incurred illness, lack of support, or concerns: sick or caring for someone who was sick with coronavirus symptoms (4.7%); caring for children not in school or daycare (10.7%); and concern about getting or spreading the coronavirus (1.4%). Employment comprised three reasons related to COVID-incurred unemployment: laid off or furloughed due to the pandemic (25.4%); employer closed temporarily due to the pandemic (9.8%); and employer gone out of business due to the pandemic (2.8%). “Other” reasons collapsed four choices: caring for an elderly person (2.9%); sick (not coronavirus related) or disabled (11.3%); without transportation to work (0.5%); and “Other” reasons (30.5%). Overall, COVID-incurred health reasons covered 16.8% of the unemployed; COVID-incurred employment problems covered 38%; and 45.2% of the unemployed were affected by problems not directly pandemic related.

We coded each of the three overall categories of reasons for EI as a binary variable and ran a logistic regression using a design similar to the earlier one (Eq. (1)). Then, we examined how reasons for not working varied across race/ethnicity, sex/gender, and income groups. Similar additional control variables were included. The predicted probabilities of EI for each of the three reasons by race/ethnicity, sex/gender, and income were visualized in Fig. 3.

In general, compared to Whites, non-Whites were more likely to lose employment due to COVID-incurred health and employment reasons, but less likely for “Other” reasons. For example, at Stage 1, among low-income men, Hispanics had a higher probability of experiencing EI due to COVID-related health issues than Whites ($D=0.066$, $p<0.001$); and low-income Asian men had a much higher probability of experiencing EI due to COVID-incurred employment issues than low-income White men ($D=0.163$, $p<0.001$). In contrast, Whites were more likely to experience EI due to “Other” reasons. For those with household income below \$25,000, the probability of experiencing EI due to “Other” reasons decreased by 0.105 ($D=-0.105$, $p<0.001$), 0.121 ($D=-0.121$, $p<0.001$), 0.168 ($D=-0.168$, $p<0.001$), and 0.056 ($D=-0.056$, $p<0.001$) for Black, Hispanic, Asian, and Other men, respectively, compared to White men.

Moreover, the racial disparities observed among low-income men may not necessarily extend to higher-income groups. Illustrated in Fig. 3(1a), during Stage 1,

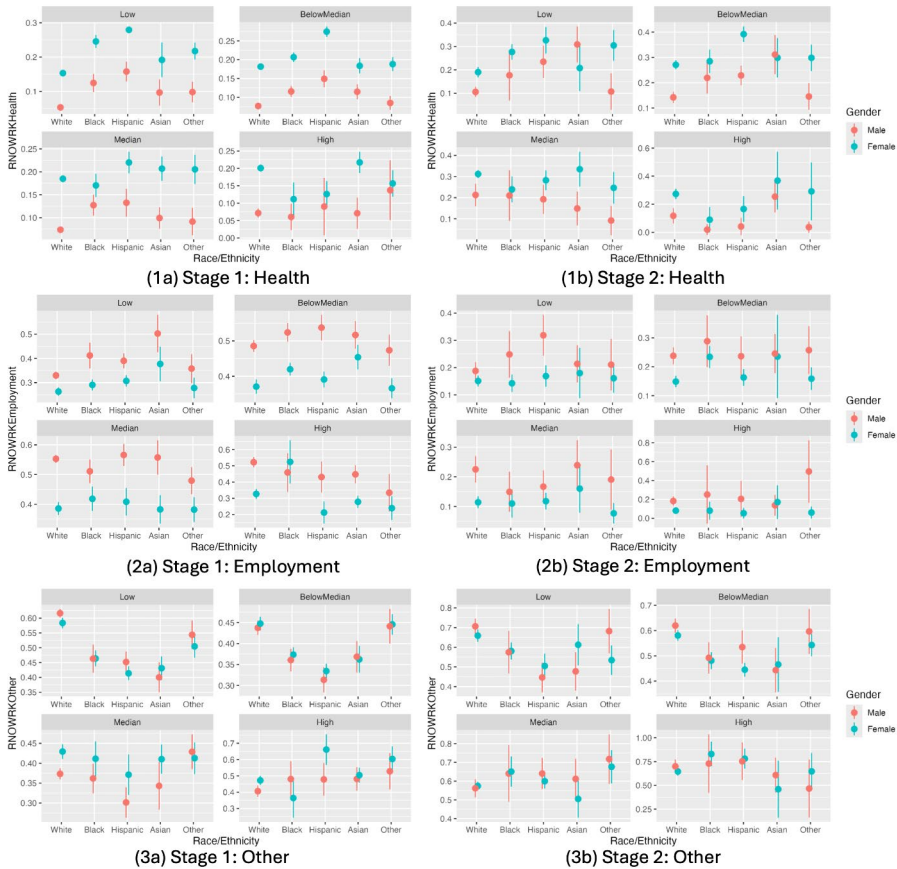


Fig. 3 Predicted probabilities of EI for different reasons by race/ethnicity, gender, and income

within the high-income bracket, White women were more prone to unemployment due to health concerns compared to Black women, in contrast to the trend observed among low-income men or women. Specifically, high-income Black women had a lower probability of EI than high-income White women ($D=-0.069, p<0.05$). Similarly, high-income Asian ($D=-0.007, p<0.001$) and Other ($D=-0.157, p<0.001$) men were less likely to experience EI due to COVID-incurred employment reasons than high-income White men, which also applied to the Hispanic-White gap for high-income women ($D=-0.096, p<0.01$).

Income has a different effect for Whites and non-Whites. At Stage 1, below-median-income White men were more likely to experience EI than their low-income White groups ($D=0.017, p<0.001$) while the income effect was absent for other White subgroups. In contrast, selected lower-income Black, Hispanic, and Other subgroups were considerably more likely to experience health-related challenges compared to their higher-income counterparts. For instance, low-income Black men had an increased probability of EI than high-income Black men ($D=-0.08, p<0.001$) while the income effect was as large when it came to women ($D=-0.094, p<0.001$).

Similarly, the median-low income gap was -0.034 ($p < 0.001$) for Hispanic men and -0.052 ($p < 0.001$) for Hispanic women. These patterns observed at Stage 1 generally persisted at Stage 2. A notable change was that more White groups ended up being more likely to experience EI than their low-income counterparts due to health reasons, including median-income White men ($D=0.067$, $p < 0.05$) and median- ($D=0.048$, $p < 0.001$) and below-median-income ($D=0.054$, $p < 0.001$) White women.

Low-income workers were less prone to experience unemployment due to COVID-incurred employment reasons compared to their higher-income counterparts. At Stage 1, the disparity between higher-income and low-income workers was significant for Whites, Blacks, and Hispanics regardless of gender, but less pronounced for Asian groups. However, by Stage 2, the magnitude of difference across all groups had fallen and the income effect was even reversed for some groups. For instance, high-income White women had a lower probability of EI than their low-income counterparts ($D=-0.068$, $p < 0.001$), and the same applied to the median-low gap for Hispanic men ($D=-0.146$, $p < 0.001$).

In general, low-income groups were more likely to experience employment loss due to “Other” reasons compared to higher-income groups. Interestingly, across all racial/ethnic groups, the middle-income class was the least likely to encounter employment interruption for “Other” reasons, suggesting a relatively inelastic response from this group, who ceased working only due to COVID-incurred health or employment issues. However, by Stage 2, the probability of not working due to reasons other than health or employment increased for all racial/ethnic and income groups (Fig. 3(3b)).

Furthermore, notable gender differences were observed in our analysis. Women, compared to men, faced a higher risk of unemployment due to health concerns but were less likely to experience unemployment for COVID-incurred employment reasons. For instance, during Stage 1, low-income White women had a higher probability of experiencing EI than low-income White men due to COVID-incurred health reasons ($D=0.073$, $p < 0.001$), whereas low-income White women were less likely to experience EI than low-income White men due to COVID-incurred employment reasons ($D=-0.056$, $p < 0.001$). The gender disparity in COVID-incurred health reasons remained consistent across income groups for Whites.

In contrast, as household income increased, the gender gap in EI for COVID-incurred employment reasons widened. In other words, White women were considerably less likely to lose employment for COVID-incurred employment reasons compared to their male counterparts as their household income grew. Similar gender disparities in EI were observed across other racial/ethnic groups, albeit with varying magnitude. For example, below-median-income Hispanic women had a higher probability of experiencing EI than their male counterparts due to COVID-incurred health reasons ($D=0.098$, $p < 0.001$), whereas no significant gender difference was found in health reasons for high-income Hispanics ($D=0.033$, $p > 0.05$).

Overall, our study reveals that non-Whites were more likely to experience unemployment due to pandemic-related health and employment issues compared to Whites, who were primarily affected by “Other” reasons. This relationship varied by income, with low-income groups facing higher unemployment due to health reasons compared to higher-income groups. Gender differences were also pronounced,

with women more likely to be unemployed due to health reasons and less so due to employment issues compared to men, and these disparities increased with higher household incomes. Our categorization of ‘Health’ reasons includes various factors that are directly related to COVID-incurred illness, lack of support, or concerns, as well as indirect factors like caring for sick individuals or children without access to school or daycare, and anxiety about contracting or spreading the virus. These findings align with Tverdostup (2023), suggesting that gender disparities in unemployment may arise from job distortions between men and women. Moreover, these disparities may perpetuate traditional gender norms in the division of household labor, rendering female employment more vulnerable and posing a threat to long-term employment recovery.

What do the Interaction Effects Mean?

The HPS data shows that the pandemic had a disproportionate impact across sectors, hitting some much harder than others. Essential sectors that mandate physical presence, including accommodation and food services, arts, entertainment, and recreation, and educational services, were among the hardest hit. These sectors, which encompass roles like grocery, convenience, and drug store employees, public transit workers, truckers, warehouse and postal staff, healthcare providers, and childcare and social service workers, were crucial in maintaining societal functions during the pandemic, and remained open as mandated by federal or state governments.

However, it is these very sectors that tend to be characterized by lower wages. As shown by the national data aggregated from the ACS for 2021 (Supplementary File 5), the income disparities within the labor market are pronounced, with management, business, science, and technology roles standing as some of the highest-paid positions, in stark contrast to the lower wages typical of personal services, agriculture, and transportation. Thus, it is the working poor who were more frequently employed in the essential service industry, where the necessity of face-to-face interaction increased the health risks associated with COVID-19. This dynamic has exacerbated the health divide between affluent and low-income populations. This could explain why earlier we saw significant disparities between high and low-income workers when the different reasons were investigated.

Compounding this issue is the concentration of people of color within these low-paid, pandemic-vulnerable sectors. They account for one third of the workforce in wholesale, retail trade, and accommodation and food services (Kang & Wang, 2022). Figure 4 depicts the distribution of the national labor force, segmented by occupation (X-axis) and income (Y-axis: legend on the right), across various racial/ethnic groups (Y-axis: legend on the left). A darker shade indicates a higher income bracket. This illustration reveals the income disparities across different occupations and highlights the variations in income within a single occupation among diverse racial/ethnic groups.

In the short term, this employment in essential sectors provided some protection against job loss for people of color and the working poor, since these industries largely continued to operate during the pandemic. Nevertheless, this employment also entailed a heightened exposure to COVID-19, increasing the risk of illness and,

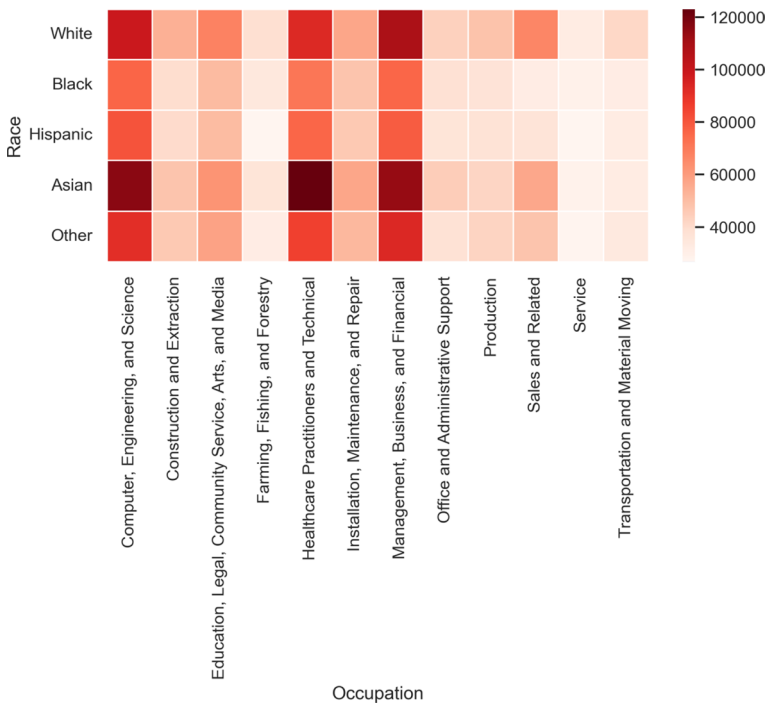


Fig. 4 Average income for each occupation and each race/ethnicity

potentially, employment insecurity (EI) in the long run. This explains why COVID-19-incurred unemployment was less likely for the working poor and people of color; however, as pandemic progressed, health reasons became increasingly important for job loss.

To illustrate the compounding effects of occupational concentrations by race and ethnicity, income, and EI, we first calculated the odds ratios for various occupations across race/ethnicity. An occupation with an odds ratio above 1.2 was classified as an ethnic niche (Wang & Pandit, 2007), where a higher ratio indicates a stronger degree of concentration within that ethnic group. According to Fig. 5 (Layer 1 – occupation concentration by race), White workers predominantly occupied niches in (1) management, business, and financial occupations, (2) education, legal and community services, arts, and media, (3) healthcare services, and (4) installation services. Black workers' niches were primarily in (1) transportation, and material movement, (2) personal services, and (3) office and administrative support. For Hispanic workers, niches were observed in (1) farming, fishing, and forestry, (2) personal services, and (3) construction and extraction. Asian workers showed significant representation in (1) computer, engineering, and science occupations, and (2) healthcare and technical services. The "Others" category did not exhibit pronounced concentrations in any particular niche.

Next, we assessed concentration patterns of unemployment by occupation and race/ethnicity (Layer 2 - unemployment concentration; see Supplementary File 6). We found a Pearson's correlation coefficient between the racial concentration in



Fig. 5 Occupation segregation measured by odds ratio

occupations (Layer 1) and the corresponding unemployment concentration (Layer 2) to be at 0.91 (p-value<0.000). This data implies a strong association between the occupational concentration by race and the subsequent unemployment trends within those occupations.

We further combined data layers for income (Layer 3), unemployment rates (Layer 2), and race/ethnicity (Layer 1) to create Fig. 6. Each grid within this figure represents an employment sector categorized by race and income, with the accompanying number indicating the unemployment rate for that particular sector. The color coding within each illustrates the income level, the darker, the higher. This multidimensional representation reveals that unemployment rates soar within lower-paid sectors—depicted on the right side of the graph—and these sectors see a disproportionate representation of Black and Hispanic workers (as established in Fig. 5).

Upon synthesizing the three investigative layers—namely, the concentration of unemployment, racial/ethnic occupational segregation, and the prevalence of low-wage sectors with high unemployment rates—a stark revelation emerges: communities of color, notably Black and Hispanic individuals, are overrepresented in sectors that not only offer lower wages but also exhibit higher susceptibility to pandemic-related disruptions. Moreover, these racial/ethnic minority groups have also endured elevated rates of infection and greater vulnerability to COVID-incurred health

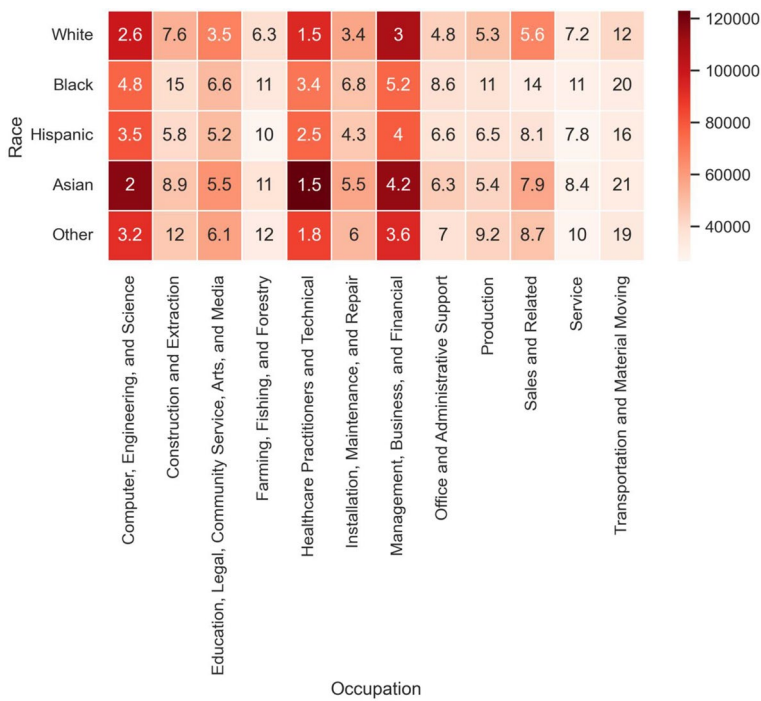


Fig. 6 Unemployment rate (%) by race, income, and occupation

impacts, as suggested by existing health disparity research (Fana et al., 2020; Yu et al., 2021).

In essence, the interaction terms of race and income crystallize the correlations between these layers. The correlations indicate that the immediate effects of the pandemic on the labor market, as captured by “EI within the last week,” are inextricably linked to deep-seated labor market segregation marked by race/ethnicity and socioeconomic status. Those segments of the workforce most adversely affected by the pandemic were also the ones facing the most severe employment challenges during lockdowns, due to their overrepresentation in sectors that were either shuttered or fundamentally altered, characterized by high joblessness, precarious employment conditions, inequality, and a significant presence of low-income workers. Thus, the pandemic has not only intensified existing economic disparities but has also highlighted and potentially solidified longstanding labor market inequities.

Conclusion

The labor market has long been plagued by persistent racial and gender disparities, which are further exacerbated by catastrophic events. This is not a novel phenomenon, as existing studies have underscored the vulnerability of people of color and women during the COVID-19 pandemic (Fana et al., 2020; Giannakis & Brugge-man, 2017; Han & Hart, 2021). Building upon this established knowledge, our study

contends that racial and gender disparities in employment insecurity are significantly influenced by income levels. Specifically, lower-income groups have been disproportionately affected due to their overrepresentation in lower-paid, essential service roles, which bore the brunt of economic disruptions. Across all racial/ethnic groups, the “working poor” faced a considerably higher risk of unemployment compared to higher-income groups, with Blacks experiencing the highest rates. However, when controlling for other conditions, there are no significant gender and racial disparities within the lowest income group. In contrast, gender and racial disparities in EI are much more pronounced among mid-to-high income groups. This is concerning as few studies have emphasized the substantial challenges confronting the middle-class workforce (Frank, 2013; Sullivan et al., 2020).

Non-Whites exhibited higher rates of EI than Whites due to COVID-incurred health and employment disruptions but were less impacted by “Other” reasons. As the pandemic progressed to Stage 2, EI attributed to health reasons increased across all groups, particularly among Asians, while employment-related EI declined. Remarkably, income disparities among Whites were minimal concerning health-related EI, yet stark contrasts emerged for low-income Blacks and Hispanics, who faced higher health-related EI than their wealthier coethnic counterparts. Moreover, low-income workers across all racial/ethnic groups were more vulnerable to unemployment due to health rather than employment reasons, with the middle-income bracket being the least affected by “Other” reasons. Additionally, the analysis revealed that women generally experienced higher unemployment rates than men due to health reasons, and this gender gap widened among higher-income brackets across racial/ethnic groups. These findings indicate that higher-income women face unique challenges or make different choices during economic downturns compared to their male counterparts.

We propose that the apparent immediate effects of the pandemic are actually indicative of deeper, systemic issues within the U.S. labor market, particularly occupational segregation tied to race/ethnicity, gender, and socioeconomic status (Averitt, 1968; Gemelas & Davison, 2022). Women and people of color, often situated at the lower end of the labor market hierarchy, found their sectors particularly susceptible to pandemic disruptions. These groups were already disproportionately burdened by COVID-19 incurred health and economic threats, alongside longstanding constraints in childcare, housing, and transportation that historically affect the working poor and people of color (Yu et al., 2021). The situation was exacerbated by social distancing, strict restrictions, and lockdowns that left the working poor and the minority middle-income workers with few options—compelled to work in sectors ill-suited for remote work and prone to shutdowns, with inadequate means to combat the pandemic. The interactive relations between race/ethnicity, gender, class, and employment insecurity indicate that the negative repercussions on the labor market for those most susceptible to COVID-19’s fallout will persist beyond the health crisis.

Given these considerations, recovery strategies must tackle both immediate needs and the deep-rooted challenges associated with occupational segregation. The stark spotlight cast by the pandemic on longstanding labor market disparities, alongside the amplifying effects of movements like “Black Lives Matter,” has underscored the urgent need to confront racial inequities. Additionally, the pandemic has exposed racial disparities in COVID-19’s toll, highlighted violence against Asians, and

revealed the politicization of health crises (Devakumar et al., 2020; Hawkins, 2020; Yearby & Mohapatra, 2020).

Addressing these systemic issues requires sustained action to dismantle historical exclusionary practices, combat stereotypes, and discrimination against people of color in the workplace. Efforts must focus on technological investment, education, and networking opportunities for the economically disenfranchised to ensure equal participation and economic growth. Long-term legislative measures are essential to reduce the vulnerability of the marginalized workforces and their dependents, alongside comprehensive reforms in resource management. Moreover, sector-specific policies are also needed to uplift traditionally low-skilled, marginalized industries (Cortes & Forsythe, 2022; Fana et al., 2020). To be effective, policies aimed at economic growth, workforce development, and social reform should be integrated, with a concerted focus on poverty reduction, health inequality mitigation, and the support of communities of color.

The study also has several limitations. Primarily, the HPS data does not distinguish between voluntary and involuntary job separations, a critical distinction as economic relief measures might prompt some individuals to opt out of returning to work—a decision fundamentally different from being forced out of employment. Pearson's chi-squared tests (Supplementary File 7) indicate a higher incidence of EI among workers or households receiving government support, such as unemployment insurance, stimulus payments, or rental assistance. Future research should evaluate the labor force's response to various policy interventions, investigating how they impact labor force participation and employment status. This would help design more effective assistance programs on employment decisions during the recovery phase.

Furthermore, our analysis offers a nationwide snapshot of these dynamics during the peak impact of the pandemic. However, it does not establish causality between race/ethnicity, income, unemployment, and occupational segregation; rather, it identifies correlations among these variables when controlling for other factors. Consistent with research preceding the pandemic, our results suggest that labor force crises like those driven by COVID-19 are rooted in enduring vulnerabilities that particularly affect socioeconomically disadvantaged groups, including people of color and the working poor. For a deeper understanding of causality, subsequent research would benefit from longitudinal data analysis.

Supplementary Information The online version contains supplementary material available at <https://doi.org/10.1007/s11113-024-09911-5>.

Data Availability The HPS data are publicly available at <https://www.census.gov/data/experimental-data-products/household-pulse-survey.html>. The ACS data are publicly available at <https://usa.ipums.org/usa/>. Replication code using these data, in R format, will be available upon request with the authors.

Declarations

Conflict of Interest The authors declare no conflicts of interest.

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