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Job loss and psychological distress during the COVID-19 pandemic: Longitudinal Analysis from residents in nine predominantly African American low-income neighborhoods

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Abstract

While psychological distress is a common sequelae of job loss, how that relationship continued during the COVID-19 pandemic is unclear, for example, given higher health risk to working due to disease exposure. This paper examines changes in psychological distress depending on job loss among a cohort of randomly selected residents living in nine predominantly African American low-income neighborhoods in Pittsburgh PA across four waves between 2013 and 2020. Between 2013 and 2016, we found an increase in psychological distress after job loss in line with the literature. In contrast, between 2018 and 2020 we found change in psychological distress did not differ by employment loss. However, residents who had financial concerns and lost their jobs had the largest increases in psychological distress, while residents who did not have serious financial concerns—potentially due to public assistance—but experienced job loss had no increase in distress, a better outcome even than those that retained their jobs. Using partial identification, we find job loss during the pandemic decreased psychological distress for those without serious financial concerns. This has important policy implications for how high-risk persons within low-income communities are identified and supported, as well as what type of public assistance may help.

KEYWORDS
COVID-19, employment, job loss, psychological distress

JEL CLASSIFICATION
I18, I30, J18, J20, J68

1 | INTRODUCTION

The COVID-19 pandemic has had severe impacts on population health in the United States. Public health policies aimed at limiting the spread of the virus and preventing the healthcare system from becoming overwhelmed had significant effects on employment, particularly during the early months of the pandemic (Gupta et al., 2020). Between March and May 2020 (the first three months of stay-at-home orders in many states), the United States saw record-level increases in unemployment claims, with tens of millions of new claims filed (U.S. Department of Labor, 2020). Prior research has established that involuntary job separation is associated with decreases in health and well-being, including increased risk of depression and distress, and reduced life-satisfaction (Gebel & Voßemer, 2014). Although COVID-19 has posed a significant potential threat to health and well-being overall, job loss during the early pandemic may have had more mixed impacts on health. For example, particularly among those whose jobs were in a frontline or "higher-risk" position, being separated from the job may have introduced relief by reducing exposure to the virus. More robust financial assistance programs during the pandemic, such as federal stimulus payments, may further have mitigated the impact of job loss on psychological health operating through financial strain.

Still, lower socioeconomic status populations and certain racial/ethnic minorities, including African Americans, have been particularly vulnerable to these negative sequela as they may have been more likely to lose their jobs (Cowan, 2020; Mongey et al., 2020; Wozniak, 2020). Lower income individuals in particular have reported having more constrained financial resources during loss of employment (Pew Research Center, 2020). Gaffney et al. (2020) showed individuals receiving unemployment benefits during the pandemic were more likely to report running out of food and to report having lower self-reported health than those working. In response, legislation was passed to assist workers in the United States, including the CARES Act, Paycheck Protection Plan, and state-level loosening of unemployment claims requirements. Many workers who lost their jobs during the pandemic were eligible to receive benefits greater in size than their lost wages (Ganong et al., 2020). However, despite the federal and state-level policies in response to the COVID-19 employment shocks, many people continue to suffer from severe economic distress (Beland et al., 2020).

In this paper, we use a longitudinal panel of low-income, predominantly African American older adults to evaluate how changes in employment during the early months of the pandemic associate with changes in moderate to serious psychological distress. We contrast this relationship using the same longitudinal panel data collected in 2013 and 2016. The panel was initially developed using randomly-sampled households enrolled by door-to-door recruitment in 2011 from a selection of predominantly African-American neighborhoods in Pittsburgh, Pennsylvania. In this paper, we use the surveys that had questions surrounding psychological distress, administered in 2013, 2016, 2018, and during the early weeks of the pandemic in late March to late May of 2020.

Our paper has several important findings that can inform public policy as we move through the pandemic and in future public health crises. We find an overall increase in the rates of moderate to serious psychological distress from 2018 (19.2%) to the early months of the pandemic in 2020 (30.4%). That overall increase in psychological distress in our sample population is large, and similar to the magnitude of the increase in psychological distress we estimate for those who transitioned from employment to unemployment between 2013 and 2016. Our 2016 estimates for the relationship between job loss and psychological distress reflect prior research. We find that levels and changes in psychological distress in the early months of the pandemic 2020 were similar between employment groups—including those who lost their jobs—in contrast to our own sample in 2013–2016 and to the literature on job loss. Although those who lost their jobs had similar rates of psychological distress during the pandemic as those who did not lose their jobs, financial distress moderated this relationship. Participants who lost their jobs and had financial concerns demonstrated the largest changes in psychological distress, at over a 25% increase from 2018 to 2020, while those who lost their jobs and did not have financial concerns had lower distress rates than those that kept their jobs, at around a 5% decrease. This finding may be pandemic-specific given there are health risks to working in-person, and those who do not have financial concerns and can work from home are insulated from changes in psychological distress associated with either their job loss or exposure to the virus from work. In addition, there is potential that a higher proportion of those who lost their job during the early period of the pandemic (late March to May 2020) viewed the displacement as temporary and/or felt less stigmatized by COVID-related job loss as compared to job loss occurring in other (non-pandemic) years.

Finally, we use partial identification to put bounds on the causal impact of job loss. Partial identification allows for the estimation of the range of potential causal effects under relatively weak assumptions. Weaker assumptions in the model widens the bounds yielding higher levels of statistical uncertainty, but with more defensible underlying assumptions (Tamer, 2010). For 2013–2016, we estimate a confidence interval around the causal impact of −29.1–16.0% points. Thus, we cannot identify a causal impact of job loss on psychological distress. This stands in contrast to our estimate between 2018 and the early months of the pandemic, where we find an overall increase in psychological distress across adults regardless of employment category, but observe a negative causal impact from job loss, that is, that job loss led to lower psychological distress. This is particularly true for those without strong financial concerns, the only group whose confidence interval around the partial identification causal estimate interval is entirely negative. The partial identification places the causal point estimate between a 6.8 and 47.4% point reduction in the probability of psychological distress from job loss during the pandemic for those without financial concerns. During at least the early stages of the COVID-19 pandemic for this low-income population, providing income security, and not necessarily job security, was perceived as critical to minimizing psychological distress, especially given the feared health risks of working for many individuals. Policies that try to sustain employment through the pandemic may not alone remove increases in psychological distress, given financial security is a critical moderator in the relationship between job loss and psychological distress during the pandemic.

1.1 | Literature review

A large body of prior work has established that economic recessions, job loss, and even the uncertainty about potential job loss, may lead to poorer mental health. Margerison-Zilko et al. (2016) and Cooper (2011) provide reviews of the literature of the impact of the Great Recession and prior recessions, respectively, and find negative impacts on mental health. The results tend to be stronger for self-reported well-being (Gebel & Voßemer, 2014; Michaud et al., 2016). Job loss has been found to lead to large decreases in self-reported health, especially for those whose job loss is related to health reasons and depressive symptoms (Burgard et al., 2007), as well as increased expenditure on antidepressants (Kuhn et al., 2009). Psychological distress is higher for those who lost their job or were unemployed, compared to being employed (Libby et al., 2010).

On the other hand, some research has found that for the average worker (as opposed to the individuals who lost their jobs), general health may actually improve in a recession (Ruhm, 2000, 2003). Hypothesized and investigated reasons include a decrease in the opportunity cost of time leading to individuals engaging in healthier activities such as more exercise, more sleep, and attending to routine doctors visits. Further, health improvements from job loss may be observed if there are hazardous working conditions and physical exertion from employment (Dee, 2001; Ruhm, 2000, 2003). Sullivan and Von Wachter (2009) found that job loss increased the risk of mortality, and have discussed the differences between the average worker during a recession, as would be calculated from Ruhm's (2000, 2003) approaches using state-level economic conditions, and the marginal worker who loses their job. Still, other research has found the opposite. During the Great Recession, there was an overall increase in mental illness; with the greatest increase for African Americans (Lo & Cheng, 2014).

Julià et al. (2017) provide an excellent review of the literature on the effect of job precariousness on health, finding across several studies that health worsens with higher job insecurity. Perceived job security has strong negative impacts on self-reported mental health (Bardasi & Francesconi, 2004; Cottini & Ghinetti, 2018; Kachi et al., 2018; Watson & Osberg, 2018). Low-income populations' experience with job loss is particularly concerning. Workers with a priori worse health tend to experience larger decreases in physical and mental health from job loss (Schiele & Schmitz, 2016). One third of the decline in health after job loss has explained by financial strain, and in analyses which looked at this, income did not mediate this effect (Huijts et al., 2015). Adams-Prassl et al. (2020) found during the early pandemic months in 2020 that lockdown measures worsened mental health. Breslau, Finucane, et al. (2021) demonstrated that there was a significant worsening of psychological distress during the COVID-19 pandemic at the national-level, across socio-economic groups. McGinty et al., 2020 also found increases in serious psychological distress between 2018 and April 2020, which was higher for those with household income below $35,000. Holingue et al. (2020) found statistically significant higher levels of distress for those with incomes below $40,000.

There is an emerging literature on the effect of COVID-19 on employment and psychological distress outcomes. Gupta et al. (2020) found that stay-at-home restrictions were related to significant increases in unemployment, with the largest effects for non-essential industries. Beland et al. (2020) showed an overall increase in unemployment and fewer hours worked. The effect was larger in states that implemented stay-at-home orders. Mongey et al. (2020) found workers employed in jobs that have more personal-proximity and lower work-from-home are more likely to be impacted by social distancing measures. These individuals are disproportionately less educated and lower income. Cowan (2020) found an increase in the likelihood of becoming unemployed during the pandemic but a decline in the labor-force participation, an increase in absenteeism, and a decrease in hours worked, with more vulnerable populations having worse changes than non-vulnerable populations. Breslau, Roth, et al. (2021) found that job loss during the COVID-19 pandemic was significantly related to higher serious psychological distress. Further, around one third of the impact of prior psychological distress on subsequent distress could be attributed to the relationship between prior psychological distress and loss of job or disruption in health care. Finally, Couch et al. (2020) found that unemployment among African Americans increased less than expected when compared to previous recessions. However, African Americans were still found to be at increased risk of job loss (Couch et al., 2020).

Together, the literature suggests that job loss during the pandemic for vulnerable populations may lead to heightened psychological distress rates. Our paper adds to this literature by providing the first estimates of the impact of COVID-19 on changes in psychological distress through changes in employment among a low-income African American sample, and comparing those changes within-sample to the impacts on psychological distress from job loss pre-pandemic. Given the recent research outlined above on the labor market effects of COVID-19 it is likely that our cohort has experienced larger impacts of the pandemic than the general population in the United States given they are located in a low-income neighborhood. Furthermore, although our data was collected prior to the killing of George Floyd on May 25, 2020 and subsequent Black Lives Matter protests, the movement and raised awareness of racism and inequities particularly for African Americans brought light to the unequal impacts of COVID-19 that we observed. This paper is, to our knowledge, the first to use individual-level longitudinal data evaluating the impact of COVID-19 on employment outcomes and psychological distress among low-income African American workers. Thus, our analysis hopes to add critical information to this research gap and derive important policy considerations.

2 | CONTEXT

2.1 | Setting

This paper evaluates a cohort of predominantly African American households (around 95% of our sample) that were originally randomly sampled in 2011 from low-income predominantly African-American neighborhoods in Pittsburgh, PA as part of the PHRESH (Pittsburgh Hill/Homewood Research on Neighborhood Change and Health) study (Dubowitz et al., 2015). The original study was designed to examine the impact of a new full-service supermarket that opened in one of the neighborhoods and therefore, in initial recruitment of households the primary food shopper was interviewed (Dubowitz et al., 2019). In the original sample enrolled in 2011, there were 1372 households. Of these, 1321 were able to be recontacted in 2013 (and 1190 were deemed eligible to participate) to form the basis of the cohort we refer to in this paper (i.e., years where data collected included employment, psychological, and financial distress) (Dubowitz et al., 2015). Loss to follow-up occurred for multiple reasons – including death, inability to re-contact, and moving outside of the study areas. The households were interviewed in 2013, and again in 2014, 2016, 2018, and 2020.

On March 13, 2020, the Mayor of Pittsburgh declared a State of Emergency which allowed for official cancellation and limiting of large gatherings, and events which required City permits. On March 15, 2020, the county called for all non-essential businesses to close voluntarily and most schools, including Pittsburgh Public Schools, were closed for in-person instruction. The Pennsylvania governor issued a stay-at-home order for the county on March 23, 2020, which is when our survey began. Pittsburgh had experienced relatively low exposure to COVID-19 during the sample frame; as of May 25, 2020, Allegheny County had a total of 1805 confirmed cases and 160 deaths, for a rate of 1.48 cases per 1000 people. At the time, this rate ranked 9th lowest out of the 42 counties in the United States with a population of at least one million people.[1] Thus, the effects we see in this early data are expected to be primarily driven by the mitigation policies and decreased labor demand rather than the direct health impacts of the virus.[2]

2.2 | Conceptual framework

There are several mechanisms through which job loss could be associated with psychological distress during the COVID-19 pandemic among a low-income population. First, workers may interpret the loss of the job as a signal of their having lower productivity and value in the workforce, which may increase distress. Associated with this, they may feel anxiety or shame in telling other people about their job loss (Creed & Muller, 2006). Even with the unemployment benefit system in the United States, job loss is typically related to short and potentially long term decreases in income, which also may increase psychological distress (Huijts et al., 2015). For those whose health insurance is tied to their employment, job loss may also disrupt health coverage and usage, which again is likely to increase distress (Breslau, Roth, et al., 2021). Each of these pathways are not unique to the pandemic.

However, there are also potential mechanisms through which job loss may contribute to *lower* psychological distress—some of which may be stronger during the pandemic. Job loss may relax the opportunity cost of time, allowing individuals to engage in physically and mentally healthy activities at a higher rate than when they were employed (Ruhm, 2000). Further, if work is associated with hazardous health conditions or mentally taxing endeavors, then cessation of work may improve health. This may be particularly true during the pandemic for in-person employees, as they face heightened risk of infection of COVID-19. Concerns about heightened risk of exposure and infection while on the job may increase psychological distress, which would be stronger during the pandemic. Thus, job loss may reduce anxiety surrounding job-related exposure to infection.

Additionally, job loss during the pandemic may be perceived as temporary and attributed to external factors (i.e., the pandemic), rather than shortcomings of the individual. As such, pandemic-related job loss may carry less stigma than job loss at other times, and subsequently have lesser negative impact on psychological distress. There were also temporary public policies put in place to mitigate the economic fallout from the pandemic, including federal stimulus payments and extended benefits from the unemployment insurance program. These policies could potentially limit the negative impacts of job loss. Thus, the net effects of job loss during the pandemic on psychological distress are ambiguous given the different hypothesized mechanisms operating in different directions.

3 | METHODS

3.1 | Key measures

3.1.1 | Psychological distress

Psychological distress is based on the common Kessler Psychological Distress Scale K6 (Kessler et al., 2002). Respondents are asked six questions constructed to determine their level of psychological distress (see Appendix Table A1 for the questions used for this scale). They respond using a Likert scale which is scored from 0 (none of the time) to 4 (all of the time), after which the scores are summed across the six questions to form the K6 score, with a minimum score of 0 and a maximum of 24. To facilitate interpretation, we follow the common classification of moderate to serious psychological distress (which for the purposes of this paper we refer to as "psychological distress") as K6 greater than or equal to 8 based on Kessler et al. (2003), although we repeat the main results using the underlying continuous scale and report the regression results in Appendix Table A1.

3.1.2 | Employment Status

The questions surrounding employment were different depending on the survey wave. In 2013 and 2016, respondents were asked if they were working full time, part time, were unemployed, or were out of the labor force. In 2018, they were simply asked if they were employed or not working. In 2020, they were asked if they were working immediately before the start of the pandemic, and if so, if they were still working the same or more hours; if they were working fewer hours; or if they were no longer working.

The different employment categorizations across waves can be seen in Table 1, which reports the counts of individuals in each employment group. Our analysis does not pool across all four waves given changes in the employment questions mentioned above. Instead, we examine changes between 2013 and 2016 as well as 2018–2020. For the 2018 to 2020 survey waves, although we examine changes in psychological distress between 2018 and 2020, we examine changes in employment that occurred between right before the time of the survey, between late March and May 2020, based upon responses in the 2020 survey. We focus on this time period, during the earliest weeks of the pandemic, because the primary intent of this paper is to examine psychological distress arising from employment changes during the pandemic, captured in the 2020 survey questions. We do a sensitivity test to compare these main results to any job loss that occurred between the 2018 and 2020 surveys.

Another reason for separating out the two timeframes is that we can observe whether there were decreased work hours in the 2020 survey (self-reported), while the earlier waves only collected data on the more coarsely-measured transition between full-time to part-time. Additionally, decreased work hours may represent a planned and voluntary scaling down of work time

TABLE 1 Number of sample respondents in each employment group

Timeframe 1: 2013–2016		2016 Full time work	Part time work	Unemployed	Out of labor force
2013	Full time work	a) 123	b) 22	c) 5	d) 19
	Part time work	e) 19	f) 49	g) 9	h) 24
	Unemployed	i) 9	j) 12	k) 9	l) 13
	Out of Labor force	m) 5	n) 18	o) 10	p) 354

Timeframe 2: 2018–2020		2020 Employed 2020 pre-pandemic and during pandemic without reduced hours	Hours decreased during COVID	Lost job during COVID	Not employed 2020 pre-COVID
2018	Employed	q) 99	r) 35	s) 56	t) 31
	Not employed	u) 21	v) 6	w) 18	x) 330

related to partial retirement, which may be optimal for the worker and unassociated with psychological distress. A movement to partial retirement may be more likely in the 3 -year gap than the gap between the start of the pandemic and two to 3 months later. Third, while in the earlier waves we observed the difference between individuals being out of the labor force and those unemployed, we did not collect information on labor force status for those not working in the 2018 or 2020 survey. Therefore, we could not distinguish these categories.

From the employment questions in the various survey waves, we create four employment groups per wave, defined in Table 2. These are: (1) Employed both time periods without reduction in hours; (2) Employed both time periods but with reduced hours; (3) Lost job; and (4) Not working at the outset. While for convenience we categorize the employment changes into similar groups between the two timeframes (2013–2016 and 2018–2020), the definitions are not exactly the same, as noted above and as defined in Table 2. However, the earlier waves nonetheless offer an interesting within-sample comparison regarding the impact of employment changes on psychological distress.

3.1.3 | Financial Concerns

A key variable in our analysis is whether the respondent had financial concerns during the 2020 survey. This is based off the question "What would you say is your biggest financial concern now?" Options include food, rent/mortgage, medical bills or medicine, utilities or not having any financial concerns. Appendix Table A1 reports the full wording of the question and the response options. We classify a person as having financial concerns if they report anything but 5: "I do not have any financial concerns."

3.2 | Sample descriptives

Table 3 presents the summary statistics from our analytic sample. There are between 600 and 700 individuals in our sample in each timeframe. Our sample is predominantly low income, with the average annual household income per adult under $20,000. The sample is older, with an average age around 60 years old (standard deviation of 15). In 2020, nearly half of the sample had no post-secondary education, and 15% held a college degree. The sample is predominantly female, partially due to the primary shopper design of the sample. Only 16% of the sample were married. Most respondents lived in the Hill District of Pittsburgh (which is the omitted reference group in the analysis).

For each individual who reported that they were working before the pandemic, we asked an open-ended question regarding their occupation during the 2020 COVID survey. We categorized their open-ended responses into whether the pre-pandemic job was health-related or not, given specific challenges related to healthcare workers during the pandemic. 17 percent of our sample

TABLE 2 Definitions of employment groups

Waves	Definition	Location in Table 1	N (%)
1. Employed both time periods without reduction in hours			
2013–2016	Employed 2013 and 2016 without reduced hours	Cells a, e, f	191 (27.3%)
2018–2020	Employed 2020 pre-pandemic and during pandemic without reduced hours	Cells q, u	120 (20.1%)
2. Employed both time periods but reduced hours			
2013–2016	Full time employed 2013 to part time 2016	Cell b	22 (3.1%)
2018–2020	Employed 2020 pre-pandemic and during pandemic with reduced hours	Cells r, v	41 (6.9%)
3. Lost job			
2013–2016	Employed 2013 but not 2016	Cells c, g	14 (2.0%)
2018–2020	Employed 2020 pre-pandemic but not during pandemic	Cells s, w	74 (12.4%)
4. Not working at the outset			
2013–2016	Not employed 2013 or out of labor force 2016	Cells d, h, i-p	473 (67.6%)
2018–2020	Not employed 2020 pre-pandemic	Cells *t*, x	361 (60.6%)

Note: Employment groups for the 2018–2020 timeframe are based on their responses in the 2020 survey which reports on employment both pre-pandemic 2020 and early pandemic (late March through May 2020).

TABLE 3 Sample statistics

	2016 (*N* = 700)		2020 (*N* = 596)	
	Mean	Std. Dev.	Mean	Std. Dev.
Prior psychological distress	0.200	0.400	0.192	0.394
Psychological distress	0.190	0.393	0.304	0.460
Change in psychological distress from prior survey	−0.010	0.423	0.110	0.513
Baseline income ($1000)	13.845	14.047	15.277	14.826
Age	58.681	15.201	61.824	13.876
Age between 50 and 65	0.410	0.492	0.381	0.486
Age older than 65	0.339	0.474	0.440	0.497
Some college	0.319	0.466	0.393	0.489
College graduate	0.140	0.347	0.148	0.355
Male	0.206	0.405	0.161	0.368
Married	0.166	0.372	0.164	0.371
Lived in homewood	0.257	0.437	0.292	0.455
Didn't live in hill or homewood	0.099	0.298	0.079	0.270
No children at home	0.773	0.419	0.810	0.392
Homeowner	0.277	0.448	0.332	0.471
Health job[a]			0.067	0.250
Has financial concerns			0.607	0.489

[a]Health job is manually coded based on open responses of job type. Psychological distress is an indicator for having a K-6 score of 8 or higher, which is considered moderate to serious psychological distress. Baseline income ($1000) is income per adult in household in baseline year (2013 or 2018) in thousands of dollars. Table A4 presents the means for each of the four waves for the covariates, while Tables A5 and A6 presents the outcome for the subgroups.

that were working before the pandemic were in a health-related job. We do not classify workers into essential job categories, given the wide range of definitions. Additionally, we find 60.7% of the sample had a financial concern.

Table 3 also reports the outcome, the proportion of respondents classified as having psychological distress. In the 2013–2016 timespan, the rates of psychological distress were similar in both survey waves, at around 20% of the sample. The rate was similar in 2018 as well; however, during the pandemic survey in 2020, that value increased to over 30%. Our sample's average psychological distress scores in both 2018 and 2020 are above (worse than) the average score for the United States in every year reported by Keyes et al. (2014), that is, between 1997 and 2011, which included the Great Recession.

3.3 | Sample attrition

Given the groupings of waves, we discuss sample attrition in terms of the change within each grouping. There were 1043 respondents in 2013 who answered the employment and psychological distress questions. Of these, 700 responded again in the 2016 survey with responses to the employment and psychological distress questions, for a retention rate of 67.1%. Appendix Table A2 provides the demographics of the 700 respondents in both waves compared to the 343 survey participants who responded in 2013 but not 2016. Retained respondents were statistically different along several demographics.

There were 812 respondents in the 2018 survey who answered the psychological distress and employment questions. Of these, 569 responded in the 2020 wave, for a retention rate of 70.1%. Appendix Table A3 provides the demographics of the two groups. There are again statistically significant differences between the retained and non-retained survey participants. As a result of the attrition and statistical differences, for both survey groupings, we generate attrition weights by estimating a logistic regression of survey retention on the demographic variables. From the estimated model we predict the probability of retention given the demographic variables, and generate the attrition weights as the inverse of the predicted probability of retention. We use these attrition weights in all regression analysis in the paper (Holliday et al., 2020). Primary causes of attrition include an aging population (i.e., deaths) as well as a highly vulnerable, high-risk population.

3.4 | Modeling

3.4.1 | Linear regression methodology

We examine how, holding constant individual characteristics, differences in employment changes are related to levels of or changes in psychological distress. To estimate these relationships, we use linear regression models (Equations 1 and 2). Equation (1) estimates the level of psychological distress, while Equation (2) estimates the change in psychological distress from the prior to the current period.

$$Y_{it} = \alpha^L + \beta^L Y_{it-1} + X_{it}\gamma^L + \sum_{k=2,3,4} \delta_k^L Emp.Group\,k_{it} + \varepsilon_{it}^L \tag{1}$$

$$Y_{it} - Y_{it-1} = \alpha^D + X_{it-1}\gamma^D + \sum_{k=2,3,4} \delta_k^D Emp.Group\,k_{it} + \varepsilon_{it}^D \tag{2}$$

Y_{it} is our binary measure of moderate to serious psychological distress. The parameters of interest are δ_k^L and δ_k^D for $k = 2, 3, 4$, which measure the difference in psychological distress for those who were employed both periods but decreased work hours (δ_2^L), those who lost their employment (δ_3^L), and those who were not working at the outset (δ_4^L), each compared to the reference category, those who were still working with the same or more work hours. X_{it} controls for the demographics and characteristics of the sample, as defined in Table 3. In Equation (1), we additionally control for the prior level of psychological distress as an important predictor of current psychological distress.

In these regressions, δ_k^L and δ_k^D do not necessarily capture the causal impact of job loss or hours decrease on psychological distress. There may be reverse causality, selection bias, and omitted variable bias. Measuring the outcome as a change score (Equation 2) and controlling for the prior level of distress (Equation 1) alleviate some of these issues, but not all. While the causal estimates are of interest and will be bounded in the partial identification analysis described below, the relationships captured by these regressions are critical to understand, and may be more relevant in identifying the most at-risk groups. That is, there is value in knowing which groups of workers we predict would have the highest level of psychological distress even without knowing whether loss of employment *causes* changes in psychological distress. Knowing if those that have lost their job are experiencing high levels of psychological distress and whether they have increased since the start of the pandemic helps identify at-risk populations.

Throughout all analysis, we estimate the standard errors using heteroskedasticity-robust (Huber-Eiker-White) standard errors, which does not assume homoskedasticity but does assume independence of the error terms across observations.

3.4.2 | Moderating role of financial concern methodology

We next expand upon the model in Section 3.3.1 by examining whether the relationship between job loss and psychological distress is moderated by the financial concern of the individual. While the study population is low-income, there may be variability in the degree to which they have concerns about their ability to pay for housing, health care, food, or utilities, perhaps due to public assistance programs and saving. Given the relatively small sample size for employment groups 2 and 3 (see Table 1), for this interaction analysis we combine lost job with decreased hours to form a new employment group, "lost employment or reduced work hours during the pandemic," which we refer to as employment group $2 \cup 3$. We then interacted employment group with the financial concerns variable, yielding Equations (3) and (4).

$$\begin{aligned} Y_{it} = \theta^L + \rho^L Y_{it-1} + X_{it}\lambda^L + \tau^L finan.\,concerns_i \\ + \sum_{k=2\cup 3,4} \left(\psi_k^L Emp.Group\,k_{it} + \phi_k^L Emp.Group\,k_{it} \times finan.concerns_i\right) + \eta_{it}^L \end{aligned} \tag{3}$$

$$\begin{aligned} Y_{it} - Y_{it-1} = \theta^D + X_{it}\lambda^D + \tau^D finan.\,concerns_i \\ + \sum_{k=2\cup 3,4} \left(\psi_k^D Emp.Group\,k_{it} + \phi_k^D Emp.Group\,k_{it} \times finan.concerns_i\right) + \eta_{it}^D \end{aligned} \tag{4}$$

3.4.3 | Partial identification methodology

We use partial identification methodology to estimate the place bounds on the causal impact, using the methodology developed and used in Manski (1995), Manski (1997), and Manski and Pepper (2000), Kreider and Pepper (2007), and Kreider et al. (2012). Given sample size concerns, we again use the combined employment group $2 \cup 3$ and consider this the "treatment" group, that is, $D = 1$ for this group. The treatment effect we are targeting is the change in probability of psychological distress from loss of employment, that is, $\Pr(Y(1) = 1|D = 1) - \Pr\text{-}(Y(0) = 1|D = 1)$. The second term is not observed, and we use the partial identification methods to put bounds around this difference. Note that in doing so, we drop individuals in employment group 4 (those not employed at the outset) in order to have the counterfactual outcome be still working without loss of employment ($D = 0$).

Using these groups, we implement partial identification strategies. This allows us to construct ranges in which the causal estimate lies depending on different assumptions. Manski's (1995, 1997) ranges hinge on combinations of different assumptions. We employ combinations of the monotone treatment selection (MTS) assumption and the monotone instrumental variable (MIV) assumption. The partial identification modeling and estimation is as follows. Let $Y(t)$ be the outcome of psychological distress if the person was assigned employment-loss status t ($t = 1$ for having experienced employment loss, and $t = 0$ for having kept their job with the same or more work hours). Let D represent the observed employment loss status of each individual.

MTS assumes for $t = 0{,}1$ that

$$\Pr(Y(t) = 1|D = 0) \leq \Pr(Y(t) = 1|D = 1) \tag{5}$$

This assumption is about the selection process and the resulting bias that arises on estimates. Intuitively, the assumption is that individuals who experienced loss of employment, on average, have higher probabilities of psychological distress than individuals who did not experience loss of employment, *regardless of the loss of* employment. For example, individuals experiencing more psychological distress in the baseline period may be more likely to quit or lose their jobs than those not experiencing distress. Although they may also experience additional psychological distress from job loss (Breslau, Finucane, et al., 2021), their propensity to have psychological distress may increase the probability of distress again in the following period. The MTS assumption is aligned with such a set-up, as those who lost their jobs would have counterfactually still had higher levels of distress than those who did not lose their jobs, if neither group had lost their jobs. We only observe $Y(t)$ for the actual job loss status, that is, $\Pr(Y(0) = 1|D = 0)$ and $\Pr(Y(1) = 1|D = 1)$. The two inequalities ($t = 0{,}1$) from Equation (5) help bound this counterfactual.

MIV assumes that there exists a variable such that, for each combination of (t,d)

$$\text{For all } z_1 \leq z_2,\ \Pr\left(Y(t) = 1|D = d, Z = z_1\right) \leq \Pr(Y(t) = 1|D = d, Z = z_2) \tag{6}$$

For the MIV, we use the negative of the baseline income level (2018 for 2020 and 2013 for 2016) as the monotone instrumental variable Z. The MIV assumption for the level of psychological distress then means that, for any individual in a given employment loss assignment (t) and actual job loss occurrence (d), the probability of having psychological distress is weakly greater if they had lower prior income. This is considerably weaker than the linear IV model assumption of mean independence, where in this case we would be assuming that baseline income is not associated at all with psychological distress. MIV allows for baseline income to be related outside of the endogenous treatment variable, but requires a weakly monotonic relationship. The MIV assumption can also help tighten the partial identification bounds of the causal impact of employment loss on psychological distress.

As Manski and Pepper (2000) show, these assumptions lead to direct estimates of the partially-identified bounds of the causal effect of treatment. We use the tebounds package in Stata version 17.0 to estimate these bounds (McCarthy et al., 2015). Confidence intervals are bootstrapped in the tebounds package with 100 bootstraps and adjusted for finite sample bias (Kreider & Pepper, 2007).

4 | RESULTS

Prior to examining the relationships between employment and psychological distress, we first examine the characteristics of the sample associated with being in each employment group, reported in Appendix Tables A7 and A8. We find that baseline income, as measured in thousands of dollars, is an important indicator for change in employment status. Among this already low-income population, the coefficient in Table A8 for 2020 of 0.005 implies that in this sample, for each $2000 higher adjusted income in 2018, the person had a 1% point higher likelihood of being in the employment group of retaining their job without reduced hours during the pandemic. A one-standard deviation increase in the baseline income (around $17,000) is associated with over 8% points higher likelihood of retaining employment. Prior income had similar effects in 2016. Some college attainment is also associated with higher likelihood of retaining employment. This finding is consistent with Adams-Prassl et al. (2020), who found women and those without college degrees were most likely to have lost their jobs during the pandemic.

4.1 | Linear regression results

Table 4 reports the regressions of psychological distress and change in psychological distress on employment status and controls. Transitioning from being employed in 2013 to being unemployed in 2016 is related to a large increase in psychological distress (0.236% points), consistent with the literature of the impacts of job loss prior to the pandemic. That difference is statistically different from the reference group, those employed 2013 and 2016 without reduced hours. There is also a marginally significant increase in the change in psychological distress from 2013 to 2016 for those employed in 2013 but not in 2016 compared to those employed in both waves without reduction in hours. During the early months of the pandemic, there was no statistically significant difference between the employment groups in psychological distress and the point estimates were much smaller. However, as shown previously in Table 3, there was a large *overall* increase in psychological distress between 2018 and 2020.

We use the regressions to estimate the covariate-adjusted predicted outcome for the change in psychological distress between waves in both time groups testing out what the overall sample predicted outcome would be if everyone had been in each given employment group. To do so, we estimate the predicted outcomes for the entire sample as if they were in each employment group for each prediction. Doing so allows us to adjust for observed differences in the sample of those within each employment group and have a covariate-adjusted comparison. Figure 1 presents these predictions, along with 95% confidence interval bars. The comparison between the two timeframes is striking. For the change in psychological distress from 2013 to 2016, none of the groups had a change that is statistically different from zero, although the group of those who lost their jobs have the only positive coefficient and a much larger magnitude coefficient compared to the other employment groups. The increase in probability of psychological distress from losing a job in 2016 is about equal to that of those who did not lose their job during the pandemic. During the pandemic, there was a statistically significant increase in psychological distress for those who lost their jobs and for those who did not lose their jobs and had no decrease in hours worked. The prediction for those still working but with decreased hours was smaller and not statistically significant. As a result, for the 2018–2020 timeframe there is no large increase in psychological distress for those who lost their jobs. This stands in contrast to the 2013–2016 timeframe results and the findings in the literature for prior periods.

Several of the other coefficients in Table 4 are of interest. Unsurprisingly, the psychological distress K-6 score from the prior wave is a highly significant predictor of current psychological distress. We find no gender differences in psychological distress. This stands in contrast to Adams-Prassl et al. (2020), who found that decreases in mental health from lock-down measures during the pandemic were entirely driven by decreases among women. Those with higher education have lower levels of psychological distress during the 2013–2016 timeframe. We did not find the same effect during the pandemic. Older workers tend to have lower levels of psychological distress and change in distress in both timeframes.

As a comparison to Table 4, we repeat the model for the 2018–2020 timeframe but further divide the employment groups to separate those not employed immediately before the pandemic into two additional groups: (1) those not employed in both 2018 and immediately before the pandemic, and (2) those employed in 2018 but not immediately before the pandemic. The results are presented in Appendix Table A9. The marginally significant finding in Table 4 for change in psychological distress being lower for those not employed before the start of the pandemic is separated out into the two coefficients. First, there is a significant negative effect for those employed in 2018 but not before the start of the pandemic. Second, there is an insignificant effect for those not working in 2018 or 2020.

Table A10 in the Appendix repeats the regressions, but uses the underlying 0 to 24 K-6 score instead of the binary categorization of psychological distress. Overall, the findings were similar when using the continuous distress score.

4.2 | The moderating role of financial concerns

We next examine how the results are moderated by financial situation during the pandemic. We do not have a parallel question in 2016, and so we limit this analysis to 2020. Given the small sample and the intention to stratify by financial concern, we combine those with reduced hours with those who lost their job in a single category. Table 5 reports the results (Table A11 in

TABLE 4 Regression results for psychological distress

Variables	Psychological distress 2016	Psychological distress 2020	Change in psychological distress 2013–2016	Change in psychological distress 2018–2020
Full time employed 2013 to part time 2016	−0.0358		−0.00671	
	(0.0450)		(0.0569)	
Employed 2013 but not 2016	0.236**		0.176*	
	(0.107)		(0.104)	
Not employed 2013 or out of labor force 2016	0.0676**		0.0154	
	(0.0338)		(0.0401)	
Employed 2020 pre-pandemic and during pandemic with reduced hours		0.00798		−0.0662
		(0.0804)		(0.0825)
Employed 2020 pre-pandemic but not during pandemic		0.0747		0.0365
		(0.0648)		(0.0787)
Not employed 2020 pre-pandemic		−0.00513		−0.107*
		(0.0519)		(0.0578)
Psychological distress in prior wave	0.0329***	0.0319***		
	(0.00369)	(0.00464)		
Prior wave's income ($1000)	−0.000636	−0.00181	0.00110	−5.93e–05
	(0.000779)	(0.00140)	(0.00104)	(0.00185)
Some college	−0.0627*	−0.0746*	−0.0210	0.0108
	(0.0324)	(0.0431)	(0.0408)	(0.0514)
College graduate	−0.0976**	−0.0990*	−0.0465	−0.0446
	(0.0397)	(0.0583)	(0.0462)	(0.0692)
Male	0.0101	0.00452	0.0450	0.0786
	(0.0352)	(0.0516)	(0.0445)	(0.0627)
Married	0.00687	−0.0864*	0.0312	−0.124**
	(0.0376)	(0.0460)	(0.0446)	(0.0572)
Age: 50–65	−0.0300	−0.181***	0.0129	−0.149*
	(0.0392)	(0.0659)	(0.0451)	(0.0837)
Age: Older than 65	−0.100**	−0.215***	0.0104	−0.0757
	(0.0438)	(0.0732)	(0.0499)	(0.0891)
Homeowner	−0.0213	0.0347	−0.0179	0.0148
	(0.0331)	(0.0426)	(0.0404)	(0.0525)
No children at home	−0.0270	0.0444	−0.0583	−0.0219
	(0.0366)	(0.0694)	(0.0430)	(0.0828)
Lives in homewood	0.0208	0.0359	−0.0580	−0.0196
	(0.0339)	(0.0419)	(0.0434)	(0.0500)
Doesn't live in hill or homewood	−0.0837*	−0.0619	−0.0979**	−0.0419
	(0.0428)	(0.0729)	(0.0456)	(0.0984)
Constant	0.114**	0.356***	0.0226	0.296***
	(0.0476)	(0.0692)	(0.0571)	(0.0729)
Observations	700	569	700	569

TABLE 4 (Continued)

Variables	Psychological distress 2016	Psychological distress 2020	Change in psychological distress 2013–2016	Change in psychological distress 2018–2020
R-squared	0.239	0.169	0.015	0.036
Outcome mean	0.196	0.312	−0.0138	0.114

Note: Baseline income ($1000) is income per adult in household in baseline year (2013 or 2018) in thousands of dollars. Reference education group is high school or less. Reference age is 18–64. Reference neighborhood is Hill District. Robust standard errors in parentheses.

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

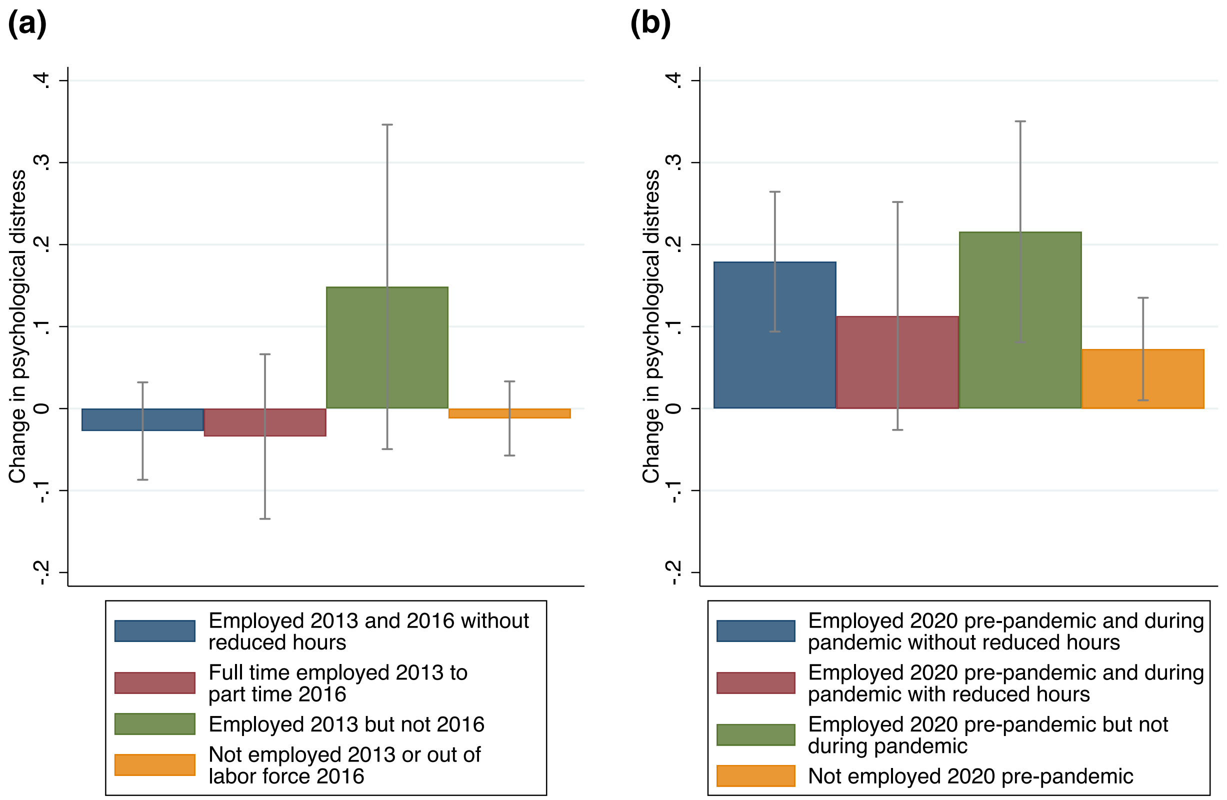

FIGURE 1 Predicted change in psychological distress by employment status. (a) 2013–2016 (b) 2018–2020. Based on predictions from the regressions in Table 4 [Colour figure can be viewed at wileyonlinelibrary.com]

the appendix contains the full results of the regression for all variables). For both the level of psychological distress during the pandemic and the change from 2018 to 2020, among those with no financial concerns, those who lost their job or had decreased hours had significantly lower psychological distress than those who kept their jobs without reduced hours (a 16.8 or 20.6% point decrease for the two outcomes, respectively). In contrast, that same difference among those with financial concerns is positive and not statistically different from zero (e.g., for 2020 psychological distress, $-0.168 + 0.257 = 0.089$). The difference between those contrasts captured by the interaction between financial concerns and lost or decreased employment is highly significant. We repeat the analysis of Table 5 for the underlying K-6 score, presented in the Appendix in Table A12, and the results are similar.

These results may reflect perceptions of the nature of the pandemic for residents of low-income neighborhoods, where employment may be anticipated to entail an increased risk of exposure to the virus and may thus increase psychological distress. Therefore, if the person is financially secure, not working during the pandemic may actually benefit psychological well-being.

Figure 2 presents the covariate-adjusted predicted probability of psychological distress (panel a) and change in probability of psychological distress (panel b), based on the regressions in Table 5. As in Figure 1, these are calculated as predictions for the entire sample, testing how the predictd outcome changes depending on each counterfactual employment group and financial concern status. Here, we can more directly see the underlying findings in these figures—the highest levels of distress are for those that lost their jobs or had reduced hours, *and* had financial concerns, with a probability of distress around 40% and an

TABLE 5 Regression results by financial concerns

	2020	Change from 2018 to 2020
Lost employment or reduced work hours during pandemic	−0.168**	−0.206**
	(0.0703)	(0.0888)
Not employed 2020 pre-pandemic	−0.101	−0.208**
	(0.0685)	(0.0830)
Financial concerns	0.0789	0.0827
	(0.0799)	(0.0830)
Lost employment or reduced work hours during pandemic X financial concerns	0.257**	0.240*
	(0.106)	(0.124)
Not employed 2020 pre-pandemic X financial concerns	0.116	0.118
	(0.0925)	(0.102)

Note: $N = 590$. The regressions additionally include 2018 income, some college, college graduate, gender, age 50—65, age over 65, homeowner, no children at home, living in Homewood, and living in a different neighborhood from Homewood and Hill. Appendix Table A11 presents full regression results. Robust standard errors in parentheses.

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

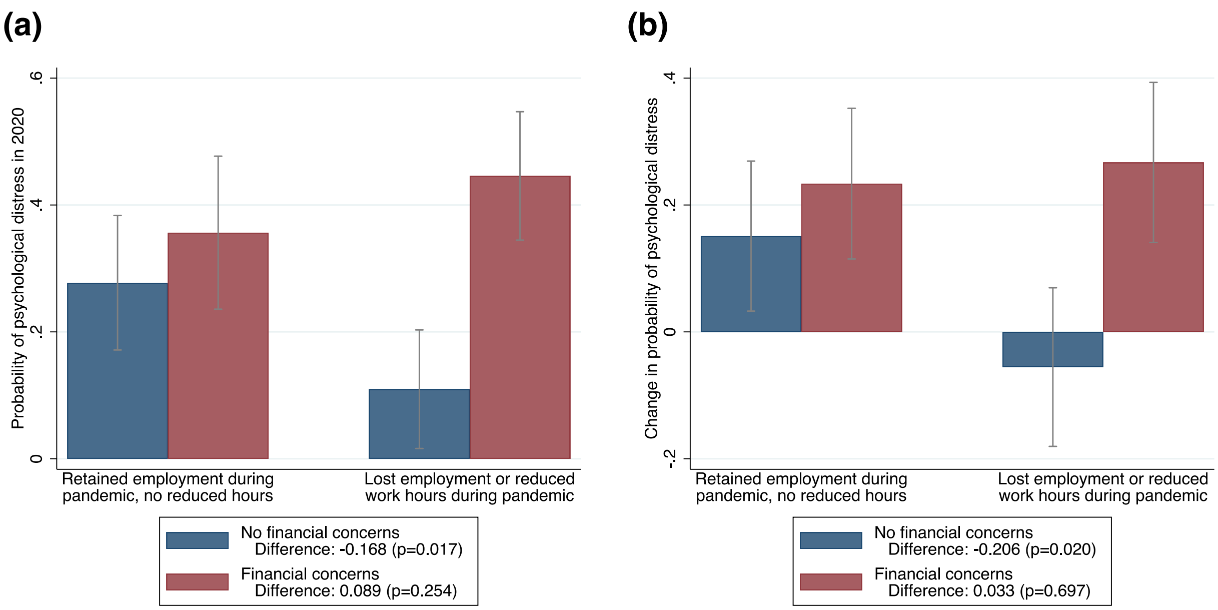

FIGURE 2 Predicted outcomes by financial concern and job loss (a) Probability of psychological distress (b) Change in probability of psychological distress. Predictions based on regression results from table 5. Whiskers denote 95% confidence interval. Difference refers to the difference between those who lost employment or reduced hours during the pandemic versus those who retained employment during the pandemic and had no reduction in work hours. The parameter for No financial concerns difference is given by the coefficient on "Lost employment or reduced work hours during pandemic" in Table 5, while the parameter for Financial concerns Difference is given by the sum of the coefficients on "Lost employment or reduced work hours during pandemic" and "Lost employment or reduced work hours during pandemic X financial concerns" in Table 5 [Colour figure can be viewed at wileyonlinelibrary.com]

increase of over 20% points. The lowest values are for those who also lost their job or had reduced hours, but did not have financial concerns, at around 10% probability and no change in the probability of psychological distress. Meanwhile, the predicted probabilities for those who kept their job are in between the two probabilities for those who lost their job, with no statistically significant difference for those who had financial concerns versus those that did not.

4.3 | Partial identification results

Finally, we use partial identification methodology to identify the potential range of the causal impact of job loss on psychological distress, shown in Table 6. As a reminder, in the MTS we assume that people who lose their job will on average have higher levels of psychological distress than people do not lose their job, *if they had had the same employment outcome*. The MIV assumption is that, conditional on actual employment status, within a given job loss assignment, lower baseline income is weakly monotonically related to higher levels of psychological distress. Starting with the 2016 wave, we can see that under the MIV and MTS assumption, the range of causal parameters is wide and crosses zero, such that we cannot with confidence make claims in our data that losing a job causes an increase or a decrease in psychological distress.

For the 2018–2020 timeframe, the MIV and MTS assumption interval now only contained in the negative range, although the confidence interval does cross zero. Thus, there is some evidence that during the pandemic, the causal impact of a stop in working was to decrease the probability of psychological distress.

We next separate the sample into those reporting having financial concerns and those that do not. For the MIV and MTS assumption, the bounds and confidence interval on the bounds are strictly negative for those with no financial concerns. Thus, we can with reasonable confidence conclude that the causal impact of loss of employment during the pandemic for those without financial concerns among this low-income population was a decrease in the probability of psychological distress, with the confidence interval on the bounds spanning a decrease of 6.8–47.4% points. In fact, the MIV assumption is unnecessary for this finding for those who lost employment with no financial concerns, as the MTS assumption alone yields a strictly negative confidence interval. Examining those with financial concerns, the bounds span zero in every case. Note that the point estimates from the linear model are consistent with these results, although the partial identification results tend to be larger in magnitude than the linear regression results. For example, for the second column of Table 6, the confidence interval on the MIV and MTS assumption of employment loss is −0.519 to 0.164. In Table 4, we find estimates of 0.00798 for those with reduced hours and 0.0747 for those who lost their job, falling within the higher end of the partial identification confidence interval. For those with no financial concerns, Table 5 shows a −0.168 difference or those who had decreased employment versus those who did not, in contrast to the MIV and MTS confidence interval here of −0.474 to −0.068. Again, the point estimate from the linear model lies within the confidence interval but near the top of the range.

5 | DISCUSSION

In this study, we examine the relationship between job loss and psychological distress during the early weeks of the COVID-19 pandemic among a low-income, predominantly African American population in Pittsburgh, PA. We contrast these results among the same population a few years prior to the pandemic. Our analyses of the population found that moving to unemployment was associated with higher levels of psychological distress, mirroring the literature. However, our analysis of the same

TABLE 6 Partial identification bounds on causal impact of job loss

	2016	2020	2020, no financial concerns	2020, financial concerns
Exogenous selection model				
Bounds	[0.058, 0.058]	[0.086, 0.086]	[−0.150, −0.150]	[0.101, 0.101]
CI	[−0.070, 0.204]	[−0.039, 0.199]	[−0.275, −0.014]	[−0.002, 0.287]
No monotonicity assumptions (worst case selection)				
Bounds	[−0.242, 0.758]	[−0.455, 0.545]	[−0.422, 0.578]	[−0.468, 0.532]
CI	[−0.291, 0.811]	[−0.536, 0.607]	[−0.530, 0.663]	[−0.532, 0.619]
MTS assumption				
Bounds	[−0.242, 0.058]	[−0.455, 0.086]	[−0.422, −0.150]	[−0.468, 0.101]
CI	[−0.291, 0.204]	[−0.536, 0.199]	[−0.530, −0.014]	[−0.532, 0.287]
MIV and MTS assumption				
Bounds	[−0.242, 0.046]	[−0.455, 0.006]	[−0.406, −0.158]	[−0.468, −0.051]
CI	[−0.291, 0.160]	[−0.519, 0.164]	[−0.474, −0.068]	[−0.527, 0.277]

Abbreviations: CI, confidence interval; MIV, monotone instrumental variable; MTS, monotone treatment selection.

sample during the early months of the pandemic demonstrated that on average, increases in psychological distress were approximately equivalent among those who lost jobs and those who retained jobs. The change in level of psychological distress was similar to that observed among those that moved from working to not working between 2013 and 2016. However, that average increase in psychological distress masked a critical heterogeneity based on the experience of financial strain. Those reporting financial concerns who lost their jobs had the highest levels of psychological distress, while those that did not have financial concerns but also lost their jobs have the lowest levels (not statistically significant).

Finally, using partial identification, we show that during the pandemic there is evidence that job loss caused a decrease in the probability of psychological distress among our sample, a pattern not observed in the 2013–2016 data. In particular, we find relatively strong evidence that job loss caused smaller increases in psychological distress among those that have no financial concerns compared to other workers who kept their jobs and also had no financial concerns, with the confidence interval for the causal impact of job loss ranging between 6.8 and 47.4% lower probability of psychological distress. This may be due to the perceived dangers of in-person work during the pandemic as well as a perception of job loss during the pandemic being more temporary and less stigmatized than in other periods. These findings have relevance to how public policy is shaped both to support individuals experiencing psychological distress and the method by which financial and employment aid are delivered by the government.

5.1 | Limitations

In our regression analysis, we are unable to account for omitted variable bias connecting the likelihood of losing employment and changes in psychological distress. Examining *changes* in psychological distress helps control for such factors, but does not eliminate omitted variables that may affect both changes in psychological distress and changes in employment, such as changes in health status of loved ones (COVID-19 or otherwise) or a divorce. Additionally, we do not account for reverse causality outside of the partial identification—individuals who have an increase in psychological distress may be more likely to lose their employment due to their psychological distress. However, the primary purpose of this paper is to understand the ongoing pandemic among a particularly vulnerable population, and thus the causal impacts underlying those dynamics are not as important to understanding what people are experiencing and which groups are at highest risk. Additionally, we implement partial identification to put bounds around the causal impact.

Another limitation is the relatively small sample and thus weak power, with under 600 participants in the 2020 timeframe. Additionally, financial distress was analyzed as a categorical variable. Having a more continuous measure of financial distress would allow for higher power in separating out the moderating impact under investigation and fewer false positives of true financial distress. Also, we only examined one potential mechanism (financial distress), but it is possible that there are other mechanisms, and future research could investigate these. Additionally, focusing on one geographic area limits the external validity of our findings.

Our study also is limited by examining neighborhoods within one specific metropolitan area that may not necessarily be generalizable to other predominantly African American, low-income urban neighborhoods. Also, the sample size is relatively limited. Additionally, we had attrition rates between waves of around 30%. Nonetheless, we control using attrition weights to correct for non-random attrition from the sample.

Despite these limitations, this study has several notable strengths. The panel nature of our data allows us to track within-person changes in the probability of psychological distress. From a policy standpoint, quantifying levels of psychological distress can inform policymakers as to which groups are under the most distress and in most need of further resources. This facilitates a more targeted policy response in providing additional assistance for newly distressed persons. Additionally, from a statistical standpoint, our empirical strategy controls for time-invariant characteristics that are likely correlated with both the well-being outcomes and employment status. One advantage of our study being limited to one metropolitan area is that we do not need to measure and account for differences in the level of the pandemic and for differences in policy across geographies that may be difficult to measure. Geographic or place-based policy differences may impact both employment and psychological distress without including additional identifying variation for how we should consider people in different employment scenarios being affected.

Next, because our sample consists of primarily African American residents from low-income neighborhoods that are likely to already be high risk both for negative employment shocks and high psychological distress, they are also of heightened concern for public policy. In 2018, our sample's average psychological distress scores in both 2018 and 2020 were above the average score for the United States in every year between 1997 and 2011 (Keyes et al., 2014).

5.2 | Conclusion

Our results are part of a constellation of new results in the research community that help policy makers understand the impact of the pandemic among low-income workers. These findings are critical for understanding psychological distress among a sample of low-income workers living in predominantly African American neighborhoods during the pandemic, as well as potential ways to address these outcomes. Given the additional stress of working, at least during times of heightened virus exposure in the workplace, we find that losing a job may actually decrease psychological distress if the individuals are financially secure. Thus, a major concern of meeting these particular mental health needs of this population is connected to income, and less to short-term employment solutions. Our study suggests that public policy aiming to mitigate the detrimental impacts on psychological distress due to COVID-19 or policies in response to the pandemic should include a focus on those that have low income, and in particular, those that are both financially vulnerable and have lost their jobs. Policies that protect employment will not be as effective during the pandemic in mitigating increases in psychological distress as policies that provide direct financial support, and not require work. This is in contrast to the effect of job loss while not in a pandemic, both according to our findings here and to prior research. These findings may be specific to the early pandemic, both given the uncertainty around exposure risk by working in person and uncertainty about whether job loss would be temporary (lasting a few weeks or month) or more long-term or permanent. Further research could follow-up longer term to examine the extent to which the findings in this paper persist over a longer time period.

The low-income African American neighborhoods in Pittsburgh where our cohort lives is not dissimilar from communities in other metropolitan areas in the United States, and there may be lessons applicable to these other communities. Policymakers should work in, for, and with these neighborhoods to increase financial assistance the number of case workers for mental health clinics, and potentially to relax regulations surrounding who qualifies for financial and health benefits. Based on our results, these targeted policies will improve the psychological wellbeing of local residents. It is unclear when this population will recover from the pandemic, both in terms of employment and in terms of psychological distress. Both the financial and mental recovery may not happen at the same time (Huijts et al., 2015). However, smart policy can best position these communities to have a more effective and meaningful recovery.

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CONFLICT OF INTEREST

We have no conflicts of interest related to our submission of "Job Loss and Psychological Distress During the COVID-19 Pandemic: Longitudinal Analysis from Residents in Nine Predominantly African American Low-Income Neighborhoods".

DATA AVAILABILITY STATEMENT

Research data are not shared.

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ENDNOTES

[1] Authors' calculations using COVID-19 Dashboard by the Center for Systems Science and Engineering at Johns Hopkins University (2020).

[2] During the survey time period, COVID-19 infection rates were very low in Pittsburgh. A question around COVID-19 diagnosis was introduced about three-quarters of the way through data collection; of the one quarter of the sample asked, only two respondents reported having COVID-19.

Given our high level of missing data on that question and the low rate of infection at this time, we do not include a control for this in later regression analysis.

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