Income Loss and Financial Distress during COVID-19: The Protective Role of Liquid Assets

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ABSTRACT

Nearly a quarter of U.S. households have experienced job or income losses related to the COVID-19 pandemic. Liquid assets mitigate financial distress in the face of financial shocks such as job loss, yet this relationship in the midst of the COVID-19 pandemic is unknown. Using a nationally representative sample of U.S. households (N = 4,383) who completed a survey in the early days of the pandemic, we examined pre-pandemic liquid assets as a moderator of the relationship between job and income loss and difficulty meeting financial obligations and use of high-cost financial resources. Estimates from propensity score-weighted linear probability models indicated that greater liquid assets lessened the probability of experiencing all eight measures of financial distress and most measures of distress among households experiencing job or income losses. Policy efforts to help households build emergency savings can help households better prepare for future pandemics while also supporting public health responses.

INTRODUCTION

The COVID-19 pandemic introduced a public health and economic crisis unlike we have ever seen in the U.S. Stay at home, social distancing, and other public health measures to slow the spread of the coronavirus greatly disrupted daily routines, including work, educational, and economic activities. The result is a macro economic crisis comprised of simultaneous demand, supply, and financial shocks. Consumers are traveling less and purchasing fewer goods and services that bring them into close contact with others, global supply chains are disrupted, and financial service systems are facing liquidity strains (Brinca, Duarte, & e Castro, 2020; Triggs & Kharas, 2020).

The tripartite macroeconomic shock of COVID-19 is greatly affecting U.S. households. The unemployment rate more than tripled in just two months—from 3.8% in February to 14.4% in April 2020, eclipsing the highest rate during the Great Recession (Kochhar, 2020a). In an April 2020 survey, almost a quarter of respondents said they or someone in their households experienced a job or income loss due to COVID-19. These losses were much higher than average among Hispanic, low-income, and young adults (Despard, Grinstein-Weiss, Chun, & Roll, 2020). Roughly half of the jobs lost in the early weeks of the pandemic have been regained. However, the rate of job recovery has been lower among Hispanic men, black workers, those with less than a college education, and mothers with school-age children (Long, Van Dam, Fowers, & Shapiro, 2020).

Despite passage of the $2.2 trillion Coronavirus Aid, Relief, and Economic Security (CARES) Act - which included stimulus payments and additional unemployment benefits, and a partial economic recovery, U.S. households continue to struggle financially. Since the beginning of major efforts to slow the spread of the coronavirus in March 2020, a quarter of households have had trouble paying their bills, a third have dipped into assets – including retirement savings to pay bills, and 17% have received food assistance in their communities (Parker, Minkin, & Bennett, 2020). Unsurprisingly, households that have experienced a job or income loss during COVID-19 were two to three times more likely to experience a range of material hardships, even after controlling for income and demographic characteristics (Despard, Grinstein-Weiss, et al., 2020). Over half (57%) of U.S. households surveyed in July 2020 who said they experienced an employment disruption since March 2020 and were not receiving unemployment benefits said they were "just getting by" or "finding it difficult to get by". This proportion dropped only to 46% among those received unemployment benefits (Board of Governors of the Federal Reserve System, 2020).

The degree to which households can weather a major economic storm such as COVID-19 may depend on their financial standing entering the crisis, particularly their liquid assets such as emergency savings. Yet many households are liquidity constrained; nearly half lack emergency savings equal to three or more months of ordinary expenses (FINRA [Financial Industry Regulatory Authority] Investor Education Foundation, 2019). Almost a third of households would not use cash to pay for an unexpected $400 expense (Board of Governors of the Federal Reserve System, 2020) and nearly half could not come up with funds to cover a $2,000 expense within 30 days (Lusardi, Schneider, & Tufano, 2011).

Liquidity is an important aspect of financial health. The ability to access $2,000 in an emergency is a strong predictor of subjective financial well-being, controlling for other factors such as income (Sun, Kondratjeva, Roll, Despard, & Grinstein-Weiss, 2018). Liquid assets have a buffering effect with respect to material hardship (Gjertson, 2016; Sabat & Gallagher, 2019), including amidst financial shocks such as a job loss (Despard, Guo, et al., 2018; McKernan, Ratcliffe, & Vinopal, 2009). The buffering effect of liquid assets is important given the commonality of typical financial shocks; nearly 60% of households experienced a shock such as a drop in income, major car repair, and trip to the hospital in 2014 (The Pew Charitable Trusts, 2017).

Of course, there is nothing usual about the macroeconomic effects of the COVID-19 pandemic as a shock affecting nearly all U.S. households. Spells of unemployment are prolonged, returns to work are uneven as re-opening plans change, and various forms of public assistance are intermittent and in some cases, difficult to access.

Amidst the uncertainty of COVID-19, it is important to understand households' financial resilience. Using a nationally representative sample of 5,038 households who completed a survey between April 29 and May 20 concerning the economic impacts of COVID-19, we examined how liquid assets mitigate financial distress amidst job and income losses. Findings from our study can guide public policies to help financially gird households against major events like COVID-19 and ensure that economically vulnerable households do not face a disproportionate level of risk for material hardship.

Public policies that enable households to financially withstand a global event like COVID-19 have important public health implications. Individuals able to remain stably housed and who do not feel financially compelled to engage in high-risk employment or other income generating activities are more likely to comply with important stay at home and social distancing guidelines. Liquid assets are an important aspect of household financial resilience to enable such responses.

The seasonally-adjusted unemployment rate in the U.S. peaked at 14.7% in April 2020, just weeks after stay at home and social distancing measures were enacted in response to the coronavirus outbreak, eclipsing the Great Recession's peak of 10.0% in October 2009. The unemployment rate in 2020 has since dropped in every month since April to a current level of 7.9% in September (Bureau of Labor Statistics, 2020a). The number of employed workers dropped by 20.5 million from February to May 2020 – a 13% decline compared to a 5% decline during the Great Recession (Kochhar, 2020b).

Unemployment and reduced work hours have not been experienced equally. The loss in employed workers was four percentage points greater among women compared to men, and greater among female and male Black, Asian, and Hispanic workers compared to White workers. By age, the loss in employed workers was 25% among those 16 to 24 years old – 12 to 16 percentage points higher than all other age groups. By education, the loss in employed workers was 17% among those with a high school diploma compared to 6% of those with a college degree or higher (Kochhar, 2020b).

The drop in employed workers across different demographic categories may in part reflect voluntary work separations. Examining job and income loss at the household level offers a more complete picture of the economic effects of COVID-19. An August 2020 Pew Research Center survey of 13,200 U.S. adults found that 42% of respondents said they or someone in their household had lost a job or taken a pay cut because of COVID-19. This rate was highest for Hispanic (53%), followed by black (43%) and white (38%) respondents; by age, this rate was highest among those 18 to 29 years old. Lower-income respondents were also more likely to experience a job loss or pay cut than middle or upper income respondents (Parker et al., 2020).

Disparities in employment and income losses are related to industries hard hit by COVID-19 due to social distancing guidelines including leisure and hospitality, education, health services, and retail. These industries employ greater proportions of women, people of color, younger people, and people with less education (Kochhar, 2020a). Telework also helps explain these disparities. A quarter to a third of workers have worked from home at different periods during COVID-19. Those who work from home are more likely to have higher educational attainment and be employed in white collar industries. Teleworkers are also more likely to be Asian or White than Black or Hispanic, and to be 25 years or older (Bureau of Labor Statistics, 2020b).

Roughly half of the jobs lost during these early stages have been recovered, yet the initial job losses and subsequent recoveries have not been experienced equally. For example, white women have regained 61% of the jobs they lost while black women have regained only 34% (Long et al., 2020).

HOUSEHOLD LIQUIDITY AND FINANCIAL DISTRESS

A household's liquid assets – amounts held in checking and savings accounts, cash, and pre-paid debit cards – are resources to be drawn upon if and when income is insufficient to cover household expenses like rent, car payments, and food and to cover large and irregular expenses (e.g., repair or replace a major household appliance). Liquid assets can help households avoid financial distress, such as over-drafting bank accounts and falling behind on credit card payments. Entering the COVID-19 pandemic, households' liquid assets could be used to help meet basic needs following a job loss or drop in work hours, particularly for households waiting for or ineligible to receive unemployment assistance.

Having liquid assets lessens the risk for material hardship (Despard, Guo, et al., 2018; Gjertson, 2016; McKernan et al., 2009; Sabat & Gallagher, 2019) – difficulties meeting basic needs (Beverly 2001) such as paying rent and utility bills. Among a sample of 1,760 households living in economically disadvantaged neighborhoods, Gjertson (2016) found that those who said they or their spouse or partner save for emergencies were less likely to experience any one of five types of hardship within the past 12 months. However, this study did not measure the amount of liquid assets.

Liquid assets are especially important to forestall financial distress and material hardship in the wake of financial shocks. Analyzing data from the 1996 and 2001 panels of the Survey of Income and Program Participation (SIPP), McKernan et al. (2009) compared households with and without enough liquid assets to cover three months of consumption at the federal poverty level. Those with this level of liquid assets were less likely to experience material hardship following a financial shock such as a job loss or departure of a parent from the household. This decreased likelihood was greater among households in the bottom two-third of the income distribution. Despard et al. (Despard, Guo, et al., 2018) found that among a sample of low-income tax filers, the direct effect of financial shocks on material hardship was 90.5% of the total effect, while the indirect effect of liquid assets, measured as a continuous variable, was 9.5%. That is, a small proportion of the effect of shocks on hardship was mitigated by liquid assets. A follow-up study found that this indirect effect – as moderated by race – was nearly two and three times less among Hispanic and Black households, respectively, compared to White households (Despard, Grinstein-Weiss, Guo, Taylor, & Russell, 2018).

A common rule of thumb is for households to have at least three months' worth of living expenses in liquid assets – a standard that only slightly more than half of U.S. households can attain (FINRA Investor Education Foundation, 2019). Yet lesser amounts of liquid assets may be sufficient for coping with shocks. Sabat and Gallagher (2019) found that liquid assets of $2,467 with a 95% confidence interval of $1,814 to $3,011 predicted the steepest decline in the risk of experiencing a material hardship. This amount is a little more than a month of living expenses at the federal poverty level for a family of four—much less than the three months' standard used by McKernan et al. (2009) to predict hardship.

Use of Credit-Based Alternative Financial Services

A sign of financial distress in households may be turning to credit-based alternative financial services (CAFS) offered by non-bank businesses such as payday, auto title, and pawnshop loans. These products are designed to meet consumers' short-term credit needs (Carter, 2015)—particularly households that have exhausted their liquid assets and have little choice but to turn to CAFS to avoid an eviction, utility cut-off, or hunger.

CAFS use may reflect financial distress rather than a desire to meet just a short-term need. Over two-thirds of borrowers use payday loans to pay for ordinary household expenses such as for housing and food; only 16% use these loans to deal with an expense shock such as a car repair (Horowitz, Bourke, & Roche, 2012). Access to payday lending is associated with increased probability of experiencing food insecurity (Chang, 2019) while CAFS use itself is associated with food insecurity (Bartfeld & Collins, 2017).

CAFS use may also exacerbate financial distress. Annualized interest rates on these loans exceed 300% (Bertrand & Morse, 2011; Consumer Financial Protection Bureau, 2013; Edmiston, 2011) while only 36% of initial loans are repaid, ending a loan sequence. More than 80% of payday loans are renewed within two weeks (Consumer Financial Protection Bureau, 2014), suggesting that borrowers become trapped in high-interest cycles of debt to cope with cash flow problems (Consumer Financial Protection Bureau, 2013). On average, borrowers take out eight loans in a year and pay $520 in interest (Horowitz et al., 2012).

Liquid assets appear to be negatively associated with CAFS. For example, Despard et al. (2017) found that an increase in $500 in liquid assets was associated with lesser odds of using CAFS among lower-income tax filers. Brobeck (2008) found that low- and moderate-income (LMI) households with less than $500 in emergency savings were more likely to use CAFS than LMI households with $500 or more in savings.

The evidence reviewed above indicates that liquid assets may help buffer the adverse effects of events like job and income loss with respect to financial distress, including use of high-cost credit. Yet whether liquid assets mitigate the effects of shocks on hardship may depend on the type and magnitude of the shocks. Prior research measures ordinary shocks like the need for a car repair whereas shocks related to and experienced during a global pandemic such as COVID-19 may be different.

Also, the relationship between liquid assets and material hardship may be bi-directional (Gjertson, 2016); when income routinely falls short, a household cannot build liquid assets. For example, Despard et al. (2020) found that households' ability to cover usual expenses explains a substantial proportion of variance in the likelihood of having emergency savings. Thus, it is important to measure liquid assets at the start of a period during which material hardship is observed. Furthermore, evidence concerning how varying levels of liquid assets are associated with financial distress – including in the wake of financial shocks - is limited and not yet determined with respect to the effects of the COVID-19 pandemic. For households affected by COVID-19 job and income losses, liquid assets may lessen the likelihood of financial distress.

CONCEPTUAL FRAMEWORK & STUDY PURPOSE

The precautionary savings motive holds that individuals insure against future income uncertainty by building assets (Leland, 1978) and change consumption to meet liquidity targets to help smooth consumption in anticipation of future changes in income (Carroll, 1997; Deaton, 1991). Accumulating assets thus may provide households with readily available resources to drawn down to smooth consumption when income proves insufficient.

Liquid assets – cash, checking and savings account balances, and prepaid debit cards - can help households respond to ordinary financial shocks, such as a car repair or an emergency room visit. In helping households cope with these shocks, liquid assets can help households avoid financial distress, such as falling behind on credit card payments, over-drafting bank accounts, and/or turning to high-cost credit such as payday loans. Yet the degree to which households are financially prepared to cope with a job and/or income loss due to a major, unexpected, and global event like the COVID-19 pandemic is unknown. Accordingly, our research questions are:

RQ1: Are COVID-19 related job and/or income losses associated with a greater likelihood of experiencing financial distress?

RQ2: Are higher levels of liquid assets associated with lesser likelihood of financial distress?

RQ3: Does the relationship between levels of liquid assets and the likelihood of financial distress vary based on COVID-19 related job and/or income loss?

Our study fills a gap in knowledge by examining how households are faring economically during a global pandemic whereas prior research examined ordinary and idiosyncratic events, such as a car breaking down. Furthermore, we assess the link between shocks and financial distress measuring liquid assets at the beginning of a period during which hardship might have been experienced to eschew the bi-directional nature of assets and hardship. These features of our study help determine the degree to which liquid assets help households cope with the economic fallout of COVID-19.

Findings from our study can help inform public policies designed to help households deal with the economic fallout of unforeseen macroeconomic shocks. Households need financial supports in the immediate aftermath of these events, yet policies aimed at helping households build liquid assets to insure against these events may prove even more effective.

METHODS

Sample and Data

Data for this study come from the Socio-Economic Impacts of COVID-19 Survey, which was fielded by researchers at Washington University in St. Louis from April 27, 2020, to May 12, 2020, using Qualtrics online panels. The panel used in this study was developed using quota sampling techniques to ensure that the sample approximated United States demographic characteristics in terms of age, gender, race/ethnicity, and income.[1]

The survey response rate was 10.8%, with 16,200 adults entering the survey. Of these respondents, 8,564 were excluded because they failed to meet quota requirements to ensure national representativeness on the established sampling criteria, 1,541 were excluded because they failed quality checks embedded in the survey, and 51 were excluded due to not meeting the minimum age criteria of 18 years. After these exclusions, 6,044 respondents remained in the sample, and 5,038 completed the survey. Additional checks on the characteristics of this sample revealed that it also approximated the U.S. population in terms of state of residence, in addition

[1] Research has demonstrated that online, non-probability samples using Qualtrics panels generate samples that closely approximate those of the General Social Survey, which is considered the gold standard in survey administration (Zack, Kennedy, & Long, 2019).

to the quotas specified above. Finally, we excluded respondents who did not provide a response to the questions used in this analysis, resulting in a final analytical sample of 4,757.

Measures

Dependent Variables

The dependent variables in this analysis fall into two broad categories of financial distress. The first category captures the extent to which households may be falling behind on their financial obligations and expenses during the COVID-19 pandemic, which we operationalize in terms of households skipping essential bills, carrying credit card debt from month-to-month (versus paying down their entire credit card bill each month), falling behind on their credit card debt, and overdrafting from a bank account. To measure skipping essential bills, we asked respondents "Was there a time in the past 3 months when you or someone in your household skipped paying a bill or paid a bill late due to not having enough money?" (Yes=1, No=0). To measure carrying card debt, we asked "In the past 3 months, have you or anyone in your household carried an unpaid balance month-to-month on one or more credit cards?" (Yes=1, No=0). To measure falling behind on credit card debt, we asked "Are you or anyone in your household behind on payments or in collections for one or more credit cards?" (Yes=1, No=0).[2] Finally, to measure account overdrafts, we asked respondents "In the last 3 months, how many times have you or someone in your household over-drafted your bank account or wrote a check for more than what was in your account?" For this question, respondents could state that they over-drafted their bank account "Never," "1 time," "2 times," or "3 or more times," but for the purposes of this analysis

[2] Analyses using the two credit card-related dependent variables are restricted to households who report owning a credit card (n=4,276).

we collapse this variable into a binary variable coded as 1 if respondents had ever over-drafted their account in the prior 3 months, and 0 otherwise.

The second category of financial distress variables captures the usage of high-cost financial resources during the pandemic. We include four types of high-cost financial resources: Auto title loans, payday loans, the use of pawn shops, and selling blood plasma. Auto title loans, payday loans, and pawn shops are all considered to be credit-based alternative financial services, while selling blood plasma may be considered an indicator that a household cannot make ends meet out of their regular income streams, and have to turn to alternatives like blood plasma sales to supplement income shortfalls.[3] For each of these resources, we asked how many times in the last 3 months the respondent or someone in their household had used these resources (Never, 1 time, 2 times, or 3 or more times). Respondents who indicated they had ever used a given resource in the past 3 months were coded as 1, and were coded as 0 otherwise.

The timeframe referenced by each of the above variables gives us confidence that we are measuring events that happened during the COVID-19 pandemic. As noted above, the survey was administered between April 27, 2020, and May 12, 2020, meaning that the 3-month timeframe in the above questions captured the period immediately before the pandemic through the large unemployment spike in April and May. However, to ensure that we were actually measuring events directly related to the pandemic, we asked a series of follow-up questions to

[3] There exists very little academic research on the usage of blood plasma sales and their potential consequences for the health and well-being of those that sell blood plasma. Per the Plasma Protein Therapeutics Association, an industry trade group, there were more than 53 million plasma "donations," or sales, in 2019 (Plasma Protein Therapeutics Association, 2019). Donors can receive $30 to $50 for each donation, and can donate up to twice a week (Shaefer & Ochoa, 2018). The long-term health effects of frequent donations remain unclear, however, there are indications that high-frequency use may have short-term health effects such as fainting, migraines, and reductions in protein and other biomarkers (Dodt, Strozyk, & Lind, 2019; Laub, Baurin, Timmerman, Branckaert, & Strengers, 2010). Given these risks, we consider blood plasma sales to be a high-cost financial resource.

respondents ascertaining whether or not a given event was a result of the pandemic. For example, if a respondent indicated that their household had skipped an essential bill in the past 3 months, we asked if they skipped that bill "due to financial issues caused by the COVID-19 pandemic." Similarly, if a respondent indicated that they used any of the high-cost financial resources we study, we asked if they used that resource to "help with financial issues caused by the COVID-19 pandemic." We include the results of our estimates using these COVID-19-specific outcomes as a robustness check to our main analysis.

Treatment Variable

The COVID-19 pandemic and the associated job and income losses can be reasonably considered an exogenous shock on households' finances. Prior to late February, there was extremely low awareness of COVID-19 in the United States,[4] and the job losses that came in April and May were both large and acute—between February and April the unemployment rate increased by a factor of more than 4 (Bureau of Labor Statistics, 2020a). As such, it is unlikely that households or businesses changed their behavior substantially in the months prior to the pandemic, minimizing concerns around the endogeneity of our outcomes with regard to this large economic shock.

The treatment variable in this study captures whether or not a household lost a job or lost income as a result of the COVID-19 pandemic. To construct the job or income loss variable, we asked respondents "Have you lost a job or lost income as a result of the COVID-19 pandemic?" and, if they were married or living with a partner, "Has your spouse or partner lost a job or lost income as a result of the COVID-19 pandemic?" If respondents answered affirmatively to either of these

[4] This is confirmed by examining Google Trends data for online searches of the term "Coronavirus" over the past year. Searches were functionally nonexistent through 2019, and only began rising significantly in late February. For details, see: https://trends.google.com/trends/explore?date=2019-12-01%202020-10-27&geo=US&q=coronavirus

questions, they were coded as experiencing a COVID-19-related job or income loss at the household level (=1); if they responded negatively to both questions, they were not coded as experiencing a COVID-19-related job loss at the household level.

Independent Variable

The key independent variable in this analysis, other than the treatment variable, measures the amount of liquid assets held by a household prior to the pandemic. To construct our liquid asset variable, we first asked respondents whether they owned a checking account, a savings account, or held any cash. If respondents reported that they had any of these liquidity sources, we then asked respondents to report how much they held in these sources at the time of the survey, and 3 months prior (before the pandemic). If respondents reported that they did not have a given liquidity source, they were coded as having $0 in that source. Our measure of respondents' total liquid assets prior to the pandemic is thus the sum of the values of each of these liquidity sources. Following the construction of the total liquid assets measure, we then divide pre-pandemic liquid assets into quartiles. The 1st quartile ranges from $0 to $2,000 in pre-pandemic liquid assets, the 2nd quartile ranges from $2,001 to $8,225, the 3rd quartile ranges from $8,250 to $28,600, and the 4th quartile includes anyone with more than $28,600 in liquid assets.[5]

Control Variables

The control variables in our model were selected based on their expected correlation with selection into experiencing a COVID-19-related job or income loss, or their expected correlation with the dependent variables of interest. The array of control variables used in this study include

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[5] Both liquid asset and income variables in this study are top-coded at the 99th percentile. One other thing to note about the liquid asset measure is that there are a disproportionate number of observations in the first quartile (n=1,730). This is due to the fact that the quartiles were calculated conditional on ownership of at least $1 in liquid assets. Respondents who reported that they had $0 in liquid assets were then included in the bottom quartile.

the respondents' employment status prior to the pandemic, the employment status of their spouse/partner prior to the pandemic, whether they were married or living with a partner, age, gender, race/ethnicity, number of children in the household, health insurance status prior to the pandemic, current school enrollment, educational attainment, housing status (e.g., own, rent, or neither), access to a vehicle, credit card ownership, self-reported physical health prior to the pandemic, household income in 2019, and bank account ownership.

Analytical Approach

The primary challenge in estimating the impact of COVID-19-related job or income loss on household outcomes is that employment losses during the pandemic did not occur at random. For example, workers who were lower-income, considered non-essential, who could not work from home, or who lived in areas with strict lockdowns were more exposed to the risks of lost employment or income than those outside of those categories. These inherent differences may also explain variations in the outcomes we examine—if economically vulnerable workers were both more likely to experience COVID-19-related job/income losses and more likely to skip bills, fall behind on debt payments, or use alternative financial services, our estimates of the relationship between job/income loss and these outcomes would be biased. To correct for this potential endogeneity, we use propensity score analysis techniques to balance the group who experienced a COVID-19-related job/income loss with those who did not on observed covariates.

Our study relies on a counterfactual framework in which "treated" (those who experienced a COVID-19-related job/income loss) and "comparison" (those who did not experience a COVID-19-related job/income loss) have both observable and unobservable outcomes (Guo & Fraser, 2014). In this framework, we can use inverse probability of treatment weights to balance our sample (Austin, 2011) and calculate the average treatment effect (ATE) of COVID-19-related job/income loss on our outcomes of interest. The ATE weights for the treated observations in our sample are calculated as $w_i = \frac{1}{p(x_i)}$, while the ATE weights for cases in the comparison group are calculated as $w_i = \frac{1}{1-p(x_i)}$.

A typical approach to calculating propensity scores uses logistic regression to estimate the propensity of experiencing a given treatment, conditional on observed covariates. However, model misspecification errors may bias treatment effect estimates in analyses with binary outcomes (Drake, 1993; Freedman & Berk, 2008). To address this potential issue, we use generalized boosted regression modeling (GBM), a nonparametric approach to estimating propensity scores that has been demonstrated to reduce the likelihood of model misspecification errors (McCaffrey, Ridgeway, & Morral, 2004). The GBM approach uses automated modeling algorithms and machine learning techniques to identify the propensity score weights that minimize the overall mean effect size differences between a large array of covariates. To estimate propensity scores using GBM, we used the TWANG—Toolkit for Weighting and Analysis of Non-equivalent Groups—package (Ridgeway, Morral, Griffin, & Burgette, 2014) in STATA. To specify our propensity score model, we estimate the propensity of experiencing a COVID-19-related job/income loss conditional on the full array of independent and control variables discussed above. Using GBM, we re-estimated this model over 10,000 iterations (or "trees") to find the optimal propensity score weights that minimize the standard differences between households that experienced a COVID-19-related job/income loss and those that did not on observable characteristics.

Following the estimation of propensity score weights, we estimate the relationship between our outcomes of interest, COVID-19-related job/income loss, and liquid assets, by employing two sets of propensity score-weighted linear probability models. The first set of models estimates the marginal effects of both COVID-19-related job/income loss and liquid assets on our outcomes of interest. This set of models is of the following general form:

$$y_i = \beta_0 + \beta_1 COVID\_Shock_i + \beta_2 Liq\_Quartile_i + \delta_i \pi + \varepsilon_i \quad (1)$$

where *y* is one of eight measured financial distress outcomes for household *i*, *COVID_Shock* is an indicator capturing whether or not a household experienced a COVID-19-related job/income loss, and *Liq_Quartile* is a categorical variable measuring which of the four pre-pandemic liquid asset quartiles a household occupied. δ_i is a vector of the control variables discussed above, and ε_i is an error term. We employ both propensity score weights as well as covariate controls in our outcome models in order to minimize the mean square error of our estimated treatment effects; an approach known as “doubly robust” estimation (Bang & Robins, 2005; Huppler-Hullsiek & Louis, 2002). That is, the covariates we used in our estimation of the propensity scores are also controlled for in our outcome models.

The second set of models estimates the degree to which liquid assets can moderate the impact of COVID-19-related job/income loss, as follows:

$$y_i = \beta_0 + \beta_1 COVID\_Shock_i + \beta_2 Liq\_Quartile_i + \beta_3 (COVID\_Shock_i * Liq\_Quartile_i) + \delta_i \pi + \varepsilon_i \quad (2)$$

where the coefficient β_3 estimates the marginal effect of experiencing a COVID-19-related job/income loss and inhabiting a given liquid asset quartile relative to the reference group, which in this case is households in the lowest liquid asset quartile who did not experience a job/income loss. All other variables in this Equation 2 are identical to those of Equation 1.

RESULTS

Sample Characteristics

Table 1 presents the descriptive statistics of the sample prior to propensity score weighting. The sample well approximates the U.S. population in terms of gender, income, race/ethnicity, and age. However, the sample is highly educated as 57% have at least a Bachelor's Degree. Prior to the pandemic, two-thirds of respondents reported being employed either full-time or part-time, with the vast majority of these engaged in traditional wage and salary employment rather than self-employment. The mean amount of liquid assets held by the sample was around $27,000 while the median was only $5,500, indicating that this variable is very right-skewed.

Table 1 also reports the characteristics of those who reported a job or income loss due to COVID-19 with those who did not, and includes both the standardized differences between these groups and the results of significance tests comparing them. Using the common balance threshold of a 0.2 standardized difference, we see that the sample is reasonably well-balanced across many indicators even prior to propensity score weighting, although we simultaneously observe many statistically significant differences based on the experience of a COVID-19-related job or income loss. However, there are some notable differences between the groups. Older households, non-students, childless households, and households where the respondent or their spouse/partner was retired or unable to work due to a disability were less likely to report a COVID-19-related job or income loss. By contrast, full-time students or households where the respondent or their spouse/partner were self-employed or employed part-time were more likely to report a job or income loss.

Table 1. Descriptive Statistics, by COVID-19 Job/Income Loss (Unweighted)

Characteristic	Sample	COVID-19 Job/Income Loss	No COVID-19 Job/Income Loss	Standardized Differences	p-value
Total	100.00	28.67	71.33		
Age, Mean (SD)	46.9 (16.8)	42.6 (16.3)	48.6 (16.7)	-0.36	0.000
Gender, Female (%)	49.99	44.65	52.14	0.15	0.000
Race, White (%)	61.78	63.64	61.04	0.05	0.006
Race, Black (%)	12.28	9.82	13.26	-0.11	0.006
Race, Hispanic (%)	5.40	4.77	5.66	0.05	0.006
Race, Asian (%)	17.51	18.99	16.92	-0.04	0.006
Race, Other (%)	3.03	2.79	3.12	-0.02	0.006
Children, 0 (%)	74.27	68.04	76.78	-0.20	0.000
Children, 1 (%)	12.80	16.28	11.41	0.15	0.000
Children, 2 (%)	9.48	11.51	8.66	0.10	0.000
Children, 3+ (%)	3.45	4.18	3.15	0.06	0.000
Student, Full-Time (%)	15.01	20.97	12.61	0.23	0.000
Student, Part-Time (%)	5.47	7.84	4.51	0.15	0.000
Student, No (%)	79.52	71.19	82.88	-0.29	0.000
Ed, Less than HS (%)	0.97	1.03	0.94	0.01	0.000
Ed, HS Degree (%)	27.87	29.91	27.06	0.06	0.000
Ed, Two-Year Degree (%)	13.35	13.49	13.29	0.01	0.000
Ed, Bachelor's Degree (%)	36.20	38.20	35.40	0.06	0.000
Ed, Graduate Degree (%)	21.61	17.38	23.31	-0.14	0.000
Housing, Own w/ Mortgage (%)	40.05	40.40	39.91	0.01	0.000
Housing, Own In Full (%)	26.84	21.11	29.15	-0.18	0.000
Housing, Rent (%)	28.19	32.26	26.55	0.13	0.000
Housing, Neither Own/Rent (%)	4.92	6.23	4.39	0.09	0.000
Health, Excellent/Very Good (%)	52.11	53.81	51.43	0.05	0.189
Health, Good (%)	34.64	34.16	34.84	-0.05	0.189
Health, Poor (%)	13.24	12.02	13.73	-0.01	0.189
Health Insurance, Yes (%)	94.35	92.30	95.17	-0.12	0.000
Vehicle, Yes (%)	88.50	87.68	88.83	-0.04	0.262
HH Income in 2019, Mean (SD)	86999.0 (70435.6)	88300.2 (69404.5)	83762.1 (72862.7)	-0.06	0.049
HH Income in 2019, Median	70000.0	65000.0	74000.0		
Liq. Assets pre-COVID, Mean (SD)	27472.9 (59361.5)	21899.0 (51383.2)	29713.7 (62147.8)	0.14	0.000
Liq. Assets pre-COVID, Median	5500.0	4532.5	6000.0		
Bank Account, Yes (%)	96.99	96.77	97.08	-0.02	0.574
Credit Cards, 0 (%)	9.71	10.34	9.46	0.03	0.791
Credit Cards, 1 (%)	17.49	17.01	17.68	-0.02	0.791
Credit Cards, 2 (%)	22.81	22.87	22.78	0.00	0.791
Credit Cards, 3+ (%)	49.99	49.78	50.07	-0.01	0.791
Emp., Self-Emp. Full-Time (%)	7.27	11.66	5.51	0.24	0.000
Emp., Self-Emp. Part-Time (%)	3.47	6.96	2.06	0.27	0.000
Emp., Wage/Salary Full-Time (%)	45.60	43.18	46.57	-0.07	0.000
Emp., Wage/Salary Part-Time (%)	9.86	18.84	6.25	0.42	0.000
Emp., Unemployed (%)	14.17	12.68	14.77	-0.06	0.000
Emp., Retired/Disabled (%)	19.63	6.67	24.85	-0.46	0.000
Partner Emp., Self-Emp. Full-Time (%)	4.98	8.06	3.74	0.20	0.000
Partner Emp., Self-Emp. Part-Time (%)	1.43	3.08	0.77	0.20	0.000
Partner Emp., Wage/Salary Full-Time (%)	27.20	29.84	26.14	0.08	0.000
Partner Emp., Wage/Salary Part-Time (%)	4.44	7.26	3.30	0.19	0.000
Partner Emp., Unemployed (%)	8.60	8.50	8.64	-0.01	0.000
Partner Emp., Retired/Disabled (%)	12.57	5.43	15.44	-0.30	0.000
Partner Emp., No Spouse/Partner (%)	40.78	37.83	41.97	-0.08	0.000
Observations	4,757	1,364	3,393		

Table 2. Descriptive Statistics, by COVID-19 Job/Income Loss (Propensity Score Weighted)

Characteristic	COVID-19 Job/Income Loss	No COVID-19 Job/Income Loss	Standardized Differences	p-value
Total	46.99	53.01		
Age, Mean (SD)	45.8 (16.6)	47.0 (16.7)	-0.07	0.070
Gender, Female (%)	49.10	50.62	0.03	0.409
Race, White (%)	62.59	61.57	0.02	0.545
Race, Black (%)	10.55	12.56	-0.06	0.545
Race, Hispanic (%)	5.35	5.49	0.03	0.545
Race, Asian (%)	18.48	17.37	-0.01	0.545
Race, Other (%)	3.03	3.02	0.00	0.545
Children, 0 (%)	72.86	75.03	-0.05	0.494
Children, 1 (%)	13.69	12.28	0.04	0.494
Children, 2 (%)	9.86	9.28	0.02	0.494
Children, 3+ (%)	3.60	3.42	0.01	0.494
Student, Full-Time (%)	16.30	14.44	0.05	0.166
Student, Part-Time (%)	6.08	5.39	0.03	0.166
Student, No (%)	77.62	80.17	-0.06	0.166
Ed, Less than HS (%)	0.87	0.93	-0.01	0.978
Ed, HS Degree (%)	27.09	27.60	-0.01	0.978
Ed, Two-Year Degree (%)	13.27	13.41	0.00	0.978
Ed, Bachelor's Degree (%)	37.04	35.92	0.02	0.978
Ed, Graduate Degree (%)	21.73	22.15	-0.01	0.978
Housing, Own w/ Mortgage (%)	40.60	40.19	0.01	0.408
Housing, Own In Full (%)	24.70	27.22	-0.06	0.408
Housing, Rent (%)	29.61	27.78	0.04	0.408
Housing, Neither Own/Rent (%)	5.09	4.80	0.01	0.408
Health, Excellent/Very Good (%)	52.92	52.26	0.01	0.732
Health, Good (%)	34.75	34.42	-0.03	0.732
Health, Poor (%)	12.34	13.32	0.01	0.732
Health Insurance, Yes (%)	93.82	94.63	-0.04	0.296
Vehicle, Yes (%)	88.26	88.80	-0.02	0.623
HH Income in 2019, Mean (SD)	87157.9 (69552.4)	88230.5 (70042.1)	0.02	0.662
HH Income in 2019, Median	71000.0	70000.0		
Liq. Assets pre-COVID, Mean (SD)	25782.0 (55876.2)	28281.5 (60599.3)	-0.04	0.255
Liq. Assets pre-COVID, Median	5500.0	5800.0		
Bank Account, Yes (%)	97.08	96.97	0.01	0.845
Credit Cards, 0 (%)	9.07	9.53	-0.02	0.326
Credit Cards, 1 (%)	15.80	17.59	-0.05	0.326
Credit Cards, 2 (%)	22.17	22.99	-0.02	0.326
Credit Cards, 3+ (%)	52.96	49.89	0.06	0.326
Emp., Self-Emp. Full-Time (%)	7.85	7.11	0.03	0.048
Emp., Self-Emp. Part-Time (%)	4.07	3.09	0.05	0.048
Emp., Wage/Salary Full-Time (%)	46.45	45.79	0.01	0.048
Emp., Wage/Salary Part-Time (%)	11.06	9.37	0.06	0.048
Emp., Unemployed (%)	14.26	14.24	0.00	0.048
Emp., Retired/Disabled (%)	16.32	20.40	-0.10	0.048
Partner Emp., Self-Emp. Full-Time (%)	5.27	4.78	0.02	0.246
Partner Emp., Self-Emp. Part-Time (%)	1.64	1.11	0.04	0.246
Partner Emp., Wage/Salary Full-Time (%)	29.25	27.36	0.04	0.246
Partner Emp., Wage/Salary Part-Time (%)	5.07	4.17	0.04	0.246
Partner Emp., Unemployed (%)	8.41	8.56	-0.01	0.246
Partner Emp., Retired/Disabled (%)	10.84	13.08	-0.07	0.246
Partner Emp., No Spouse/Partner (%)	39.52	40.93	-0.03	0.246
Observations	2,236	2,521		

Table 2 presents the characteristics of the sample after the use of generalized boosted regression modeling to estimate propensity score weights for the likelihood of experiencing a COVID-19-related job/income loss. We observe that the application of propensity score weights was highly effective at balancing the two groups on observable characteristics. The largest standardized difference was -0.1—well below the typical threshold—and all other indicators have even smaller standardized differences.

The Impact of COVID-19-Related Job and Income Loss on Financial Distress

Having demonstrated that the use of propensity score weights substantially improved balance, we turn now to addressing our first research question concerning the extent to which job and income losses due to COVID-19 are associated with a greater likelihood of experiencing financial distress, which we operationalize through measures of households falling behind on their expenses or using high-cost financial resources. Table 3 presents the results of this analysis. Across all eight outcome measures—skipping essential bill payments, carrying credit card debt from month-to-month, falling behind or going into collections on credit card debt, overdrafting bank accounts, using payday loans, using title loans, using pawn shops, and selling blood plasma—we see that COVID-19-related job and income losses are significantly associated with increases in these outcomes. In many cases, the effects are quite large. COVID-19-related job and income loss functionally doubled the rate of skipping essential bill payments (from 8.4% to 18.0%; $p < 0.001$), falling behind on credit card debt (from 5.9% to 12.2%; $p < 0.001$), selling blood plasma (from 4.4% to 8.3%; $p < 0.001$), and using a pawn shop (from 5.4% to 11.0%; $p < 0.001$). The impacts of COVID-19-related job and income loss on the other measured outcomes is somewhat more attenuated, but remain both large and statistically significant.

Table 3. Financial Distress Outcomes, by COVID-19 Job/Income Loss (Propensity Score Weighted)

Outcome	COVID-19 Job/Income Loss	No COVID-19 Job/Income Loss	p-value
Hardship and Debt Outcomes			
Skipped Essential Bills, Past 3 Months (%)	17.99	8.39	0.000
Carried Credit Card Debt, Past 3 Months (%)[a]	37.30	29.83	0.000
Behind/In Collections on Credit Card Debt, Now (%)[a]	12.16	5.86	0.000
Account Overdraft, Past 3 Months (%)	13.52	8.92	0.000
High-Cost Financial Resource Usage			
Auto Title Loan, Past 3 Months (%)	9.97	7.64	0.017
Payday Loan, Past 3 Months (%)	8.78	5.97	0.002
Blood Plasma Sales, Past 3 Months (%)	8.33	4.42	0.000
Pawn Shop, Past 3 Months (%)	10.98	5.41	0.000
Weighted Observations	2,236	2,521	

[a]Restricted to households with credit cards (n=4,276)

The Role of Liquid Assets in Moderating the Impacts of COVID-19-Related Job and Income Loss

To address our final two research questions concerning the moderating role of liquid assets, we estimate a series of propensity score-weighted linear probability models. Tables 4 and 5 present the results of these estimates across the study outcomes. Each measured outcome has two sets of model estimates. The first set estimates the effects of COVID-19 job/income loss and liquid assets on each outcome independently, corresponding to Equation 1 above. The second set estimates the moderation effect of liquid assets on the impacts of COVID-19-related job/income loss by interacting the two variables, corresponding to Equation 2 above.

Table 4. The Impact of COVID-19-Related Job/Income Loss and Liquid Assets on Hardship and Debt Outcomes, Linear Probability Model

Outcome	Skipped Essential Bills	Skipped Essential Bills	Carried CC Debt[a]	Carried CC Debt[a]	Behind on CC Debt[a]	Behind on CC Debt[a]	Account Overdrafts	Account Overdrafts
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
COVID-19 Job/Income Loss	0.092***	0.144***	0.063***	0.088**	0.058***	0.095***	0.040***	0.051*
	(0.011)	(0.024)	(0.016)	(0.030)	(0.009)	(0.023)	(0.010)	(0.021)
Liquid Assets, 2nd Quartile	-0.042*	-0.050**	-0.034	-0.043	-0.053***	-0.044**	-0.056***	-0.065***
	(0.018)	(0.015)	(0.024)	(0.025)	(0.015)	(0.014)	(0.015)	(0.015)
Liquid Assets, 3rd Quartile	-0.123***	-0.062***	-0.208***	-0.195***	-0.111***	-0.073***	-0.099***	-0.086***
	(0.014)	(0.014)	(0.022)	(0.023)	(0.012)	(0.013)	(0.014)	(0.015)
Liquid Assets, 4th Quartile	-0.100***	-0.044**	-0.305***	-0.263***	-0.088***	-0.062***	-0.102***	-0.083***
	(0.015)	(0.014)	(0.022)	(0.022)	(0.013)	(0.014)	(0.014)	(0.015)
COVID-19 Job/Income Loss*2nd Q LA		0.013		0.017		-0.020		0.019
		(0.036)		(0.049)		(0.031)		(0.030)
COVID-19 Job/Income Loss*3rd Q LA		-0.130***		-0.027		-0.081**		-0.027
		(0.028)		(0.043)		(0.025)		(0.026)
COVID-19 Job/Income Loss*4th Q LA		-0.121***		-0.092*		-0.057*		-0.041
		(0.027)		(0.039)		(0.026)		(0.025)
Constant	0.602***	0.576***	0.512***	0.496***	0.577***	0.555***	0.596***	0.590***
	(0.102)	(0.101)	(0.123)	(0.125)	(0.097)	(0.097)	(0.087)	(0.087)
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Financial Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Propensity Score Weighting	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,757	4,757	4,276	4,276	4,276	4,276	4,757	4,757
R-squared	0.180	0.189	0.218	0.220	0.175	0.178	0.152	0.153

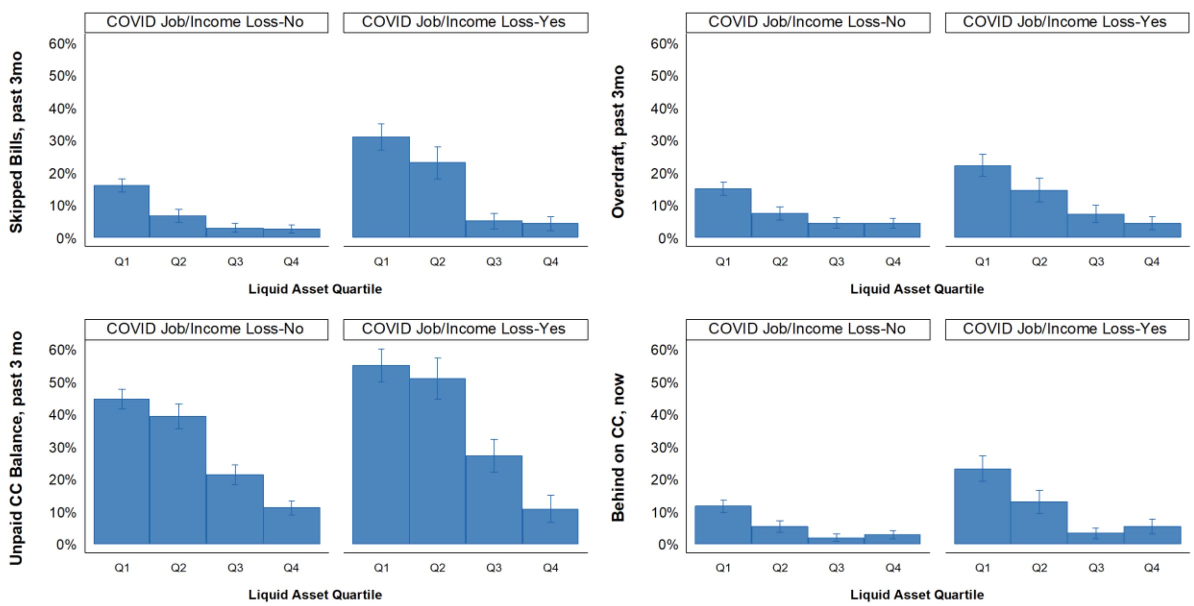
[a]Restricted to households with credit cards

Table 4 presents model estimates for hardship and debt outcomes. Estimates of Equation 1 are in odd-numbered columns, and estimates of Equation 2 are in even-numbered columns. We observe that, almost universally, higher levels of liquid assets are associated with significant and substantial reductions in the probability of experiencing a measured hardship or debt outcome. Relative to being in the bottom quartile of liquid assets, respondents in higher liquid asset quartiles tend to report experiencing these outcomes at lower rates, and those in the third and fourth quartiles tend to experience better outcomes than those in the second.

We also observe that, in many cases, liquid assets moderate the relationship between COVID-19-related job and income loss and modeled outcomes. For example, households in the third quartile of liquid assets prior to the pandemic who experienced a COVID-19-related job/income loss were 13 percentage points less likely to report skipping essential bills than households in the bottom liquid asset quartile who experienced a job/income loss ($p < 0.001$). However, liquid assets only appear to have a protective effect on falling behind on credit card debt in the event of a COVID-19-related job/income loss if respondents were in the fourth liquid asset quartile prior to the pandemic ($\beta = -0.092$; $p < 0.05$), and they were less likely to report carrying credit card debt in the event of a job loss if they were in the third ($\beta = -0.081$; $p < 0.01$) or fourth ($\beta = -0.057$; $p < 0.05$) liquid asset quartiles. Liquid assets did not appear to have any protective effect on the likelihood of account overdrafts in the event of a job or income loss.

To give a better sense of the magnitude of these relationships, Figure 1 presents the marginal probability of experiencing a given financial distress measure, conditional on the experience of COVID-19-related job loss and the household's pre-pandemic liquid asset quartile. This figure demonstrates both how precarious the financial lives of the asset poor are, and the extent to which high levels of liquid assets protect households. Taking the rate of skipping essential bills during the pandemic as an example, after correcting for differential propensities to experience a COVID-19-related job/income loss and applying covariate controls we estimate that 31% of households in the bottom liquid asset quartile who had a COVID-19-related job/income loss skipped essential bills , as compared to 16% of households in the lowest liquid asset quartile who did not experience a job/income loss. By contrast, households in the third and fourth liquid asset quartiles experienced these measured outcomes at similar rates, regardless of whether or not they had a COVID-19-related job/income loss.

Figure 1. Predicted Probabilities of Experiencing Expense or Debt Hardships, by Liquid Asset Quartile and COVID-19-Related Job/Income Loss (Propensity Score Weighted)



Note: This figure presents the predicted probabilities of the models from the even-numbered columns in Table 4, which examine the interaction between COVID-19-related job/income loss, liquid assets, and hardship and debt outcomes. N=4,757 for skipped bills and account overdrafts; N=4,276 for unpaid credit card calances and being behind on credit card debt. CC=credit card.

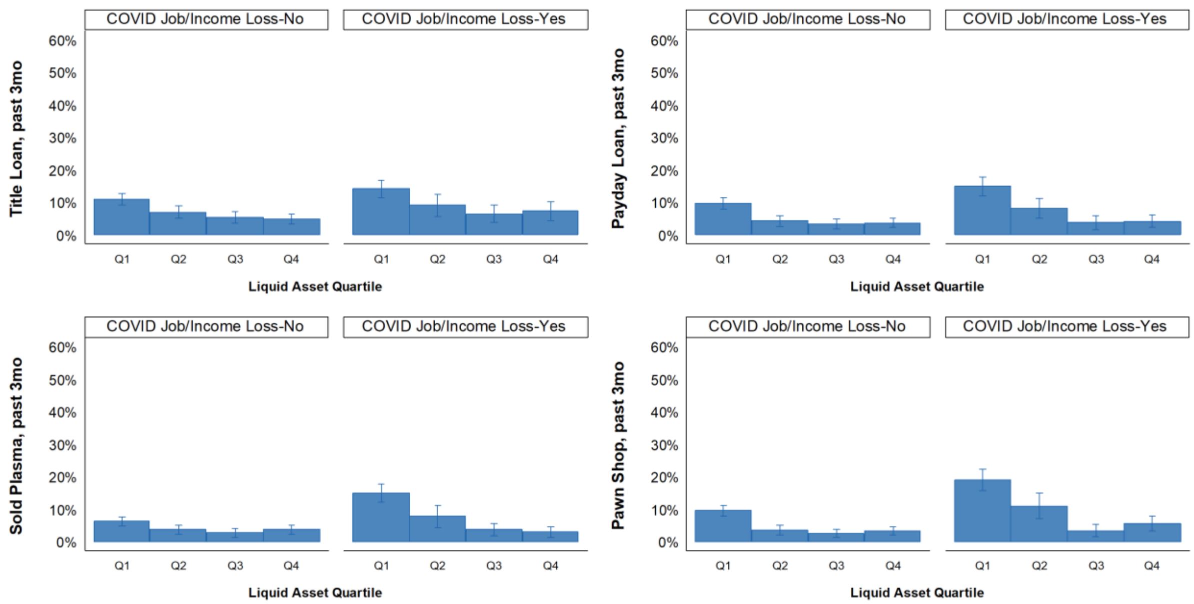
In Table 5, we estimate the same two models for high-cost financial resource usage. In these models, we again observe that higher amounts of prepandemic liquid assets are correlated with lower rates of using high-cost financial resources, relative to those in the bottom quartile of liquid assets, and that those in the third and fourth liquid asset quartiles tend to be less likely to draw on these resources than those in the second quartile. However, we also see that prepandemic liquid assets only moderate the impact of COVID-19-related job/income loss for certain high cost resources, namely selling blood plasma and pawning items. Liquid assets do not significantly moderate the relationship between COVID-19-related job/income loss and payday loan usage or auto title loan usage.

Figure 2 presents the marginal probabilities of using high cost financial resources, conditional on prepandemic liquid asset quartile and the experience of COVID-19-related job loss. In this figure, the moderating effect of liquid assets is clear when examining blood plasma sales and pawn shop usage. For example, 15 percent of households in the bottom liquid asset quartile and 8 percent of households in the second liquid asset quartile who had a COVID-19-related job/income loss reported selling blood plasma over the prior 3 months, as compared to 6 percent and 4 percent of those in the bottom and second quartiles who did not experience a job/income loss, respectively. However, this difference between the groups disappears among households in the top two pre-pandemic liquid asset quartiles.

Table 5. The Impact of COVID-19-Related Job/Income Loss and Liquid Assets on High-Cost Financial Resource Usage, Linear Probability Model

Outcome	Auto Title Loan	Auto Title Loan	Payday Loan	Payday Loan	Sold Blood Plasma	Sold Blood Plasma	Pawn Shop	Pawn Shop
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
COVID-19 Job/Income Loss	0.017	0.005	0.024**	0.029	0.035***	0.067***	0.053***	0.077***
	(0.009)	(0.016)	(0.008)	(0.017)	(0.008)	(0.016)	(0.009)	(0.019)
Liquid Assets, 2nd Quartile	-0.035**	-0.043**	-0.042***	-0.048***	-0.036**	-0.026*	-0.046**	-0.045***
	(0.013)	(0.014)	(0.013)	(0.012)	(0.013)	(0.011)	(0.014)	(0.012)
Liquid Assets, 3rd Quartile	-0.063***	-0.065***	-0.069***	-0.057***	-0.055***	-0.030**	-0.082***	-0.049***
	(0.013)	(0.014)	(0.011)	(0.012)	(0.011)	(0.011)	(0.011)	(0.012)
Liquid Assets, 4th Quartile	-0.062***	-0.078***	-0.063***	-0.058***	-0.056***	-0.025*	-0.063***	-0.044***
	(0.014)	(0.014)	(0.013)	(0.013)	(0.012)	(0.012)	(0.013)	(0.013)
COVID-19 Job/Income Loss*2nd Q LA		0.017		0.011		-0.023		-0.002
		(0.026)		(0.025)		(0.025)		(0.028)
COVID-19 Job/Income Loss*3rd Q LA		0.005		-0.025		-0.054**		-0.069**
		(0.023)		(0.022)		(0.020)		(0.022)
COVID-19 Job/Income Loss*4th Q LA		0.035		-0.011		-0.068***		-0.041
		(0.024)		(0.021)		(0.020)		(0.024)
Constant	0.649***	0.657***	0.620***	0.618***	0.511***	0.495***	0.613***	0.602***
	(0.076)	(0.076)	(0.076)	(0.076)	(0.081)	(0.080)	(0.094)	(0.093)
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Financial Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Propensity Score Weighting	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,757	4,757	4,757	4,757	4,757	4,757	4,757	4,757
R-squared	0.158	0.158	0.176	0.177	0.166	0.169	0.189	0.192

Figure 2. Predicted Probabilities of High-Cost Financial Resource Usage, by Liquid Asset Quartile and COVID-19-Related Job/Income Loss (Propensity Score Weighted)



Note: This figure presents the predicted probabilities of the models from the even-numbered columns in Table 5, which examine the interaction between COVID-19-related job/income loss, liquid assets, and high-cost financial resource usage. N=4,757.

Robustness Check

Most of the dependent variables in this study ask about household experiences over the 3 months prior to the survey. While this time period covers the early stages of the COVID-19 pandemic (from late January to mid-May, depending on when the respondent took the survey), these outcomes do not necessarily capture the extent to which a given outcome occurred as a result of the pandemic. For example, a household could have missed an essential bill payment in the 3 months prior to the survey for reasons not related to COVID-19 (e.g., inattention to the bill's due date). As noted earlier, if respondents reported experiencing 7 of the 8 outcomes in this study (all outcomes except carrying credit card debt from month-to-month), we then asked if they experienced a given outcome as a result of the COVID-19 pandemic. To confirm that the relationships we observed in the main analysis were due to the COVID-19 pandemic, we re-ran all of the models in the main analysis using these COVID-19-specific outcomes as dependent variables instead of the main analysis' more general outcomes. Overall, the results of these supplemental models were highly similar to those of the main model. The significant relationships we observe in the main analysis remain significant, though the magnitudes of the relationships differed somewhat—the coefficients on job/income loss and the interaction between job/income loss and liquid assets were often somewhat stronger (though not exclusively), while the coefficients on liquid assets were often somewhat weaker (though not exclusively). As such, we are confident that the relationships we observed in the main analysis were due to COVID-19.[6]

DISCUSSION

The COVID-19 pandemic has wreaked economic havoc on many U.S. households. In this study, we examine the association of liquid assets with financial distress, comparing households that have and have not experienced job and/or income losses related to COVID-19. Regarding our first research question, we find that, unsurprisingly, households that have experienced job and/or income losses due to COVID-19 reported greater signs of financial distress such as bank account overdrafts and selling blood plasma. These differences hold for all eight distress indicators after controlling for a host of household demographic and financial characteristics and using propensity score weighting. Regarding our second research question, we find that households with liquid assets in the upper 75% of the distribution (roughly $2,000 and above) have significantly lowered risk for all eight types of distress compared to households with assets in the first quartile. Regarding our third research question, we find that liquid assets significantly

[6] Full results available upon request.

moderate the relationship between the majority of our measured financial distress indicators and COVID-19-related job or income loss, but that this moderation effect was only present for those in the top two quartiles of liquid assets (roughly $8,000 and above).

Though extensive research has demonstrated the value of liquid assets in helping households avoid hardship and promoting a general sense of financial well-being, our research shows that these protective effects translate to the specific context of the COVID-19 pandemic and the accompanying economic turmoil. This distinction is not trivial. Research on the protective effects of liquid assets generally occurs in the context of relatively normal or stable economic conditions. In these conditions, a household faced with a job or income loss has the option of looking for work, finding other sources of income, and relying on family and friends to help with expenses, in addition to using liquidity to smooth consumption. In the early days of the COVID-19 pandemic—during which the data for our study were collected—seasonally adjusted unemployment claims increased by a factor of more than 10; an economic shock that was unprecedented in both magnitude and rapidity. Given that these job losses were accompanied in many cases by stay-at-home orders restricting travel and business hours, it was unlikely that households had the option of seeking out additional work to make ends meet, meaning their pre-pandemic liquid asset buffer may have taken on particular importance during the pandemic.

Implications

Much of the current policy discussions surrounding preparation for future pandemics or large-scale shocks concerns "building back better" and ensuring that our public health, governmental, and economic institutions are better equipped to support the health and well-being of the U.S. population in the event of a future crisis. Our research indicates that developing a strategy to shore up the often anemic emergency savings and liquidity options of U.S. households should be central to these discussions. We briefly discuss three ways of doing so.

First, policy goals concerning financial inclusion should better emphasize access to and use of savings accounts (e.g., the Consumer Financial Protection Bureau's "Start Small, Save Up" program) to help households build an emergency buffer. The focus on savings accounts specifically is valuable, as money held in accounts earmarked for savings tends to be stickier than money held in consumption accounts or as cash (Thaler, 1999). Further, roughly a quarter of U.S. households lack savings accounts (Federal Deposit Insurance Corporation, 2018) and, despite efforts like Bank On and the FDIC Model Safe Account template, many banks fail to offer affordable products and are unlikely to do so without regulatory changes.

Second, encouraging private sector innovation can help households develop emergency savings. Financial technology platforms like Chime offer affordable checking and savings accounts, while platforms like SaverLife and Onward encourage and facilitate saving for emergencies. Employers can also play an important role by offering employees' the ability to split their direct deposits into dedicated emergency savings funds; in essence offering a short-term savings equivalent of employer-sponsored retirement accounts that have benefited middle- and upper-income workers.

However, expanded savings account access is necessary but insufficient in helping households—and low-income households in particular—save. These households tend to face a high degree of budgetary constraint that makes even meeting essential expenses difficult, and saving for the future is harder still. These households need savings incentives and policy supports such as a higher minimum wage and universal basic income, which can help households meet immediate consumption needs and build liquid assets to be more financially resilient.

Absent these large-scale policy reforms, policymakers could help expand existing economic supports to help households build savings. For example, the tax refund is often the single largest payment that low-income households receive in a given year (Roll, Russell, Perantie, & Grinstein-Weiss, 2019) and presents an opportunity for tax filers to build their savings, yet savings deposit rates at tax filing remain low (Roll, Grinstein-Weiss, Gallagher, & Cryder, 2019). Policymakers could help households better capitalize on their tax refund by offering savings incentives, such as those proposed by the Refund to Rainy Day Act.

Though helping households, and low-income households in particular, build liquid assets is essential to support their well-being and a tangible way to confront rising wealth inequality, these efforts can also help increase the population's resiliency to future pandemics. Following stay-at-home orders, social distancing, and minimize the risk of exposure and transmission of a virus require individuals to be able to afford to stay home. Increasing households' liquid assets are a direct way to do that, and to help families avoid the terrible choice of risking their health or risking hunger, eviction, and an array of other hardships.

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