DEMOCRATIZING THE ECONOMY OR INTRODUCING ECONOMIC RISK? GIG WORK DURING THE COVID-19 PANDEMIC

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Abstract

Though the growth of the gig economy has coincided with increased economic precarity in the new economy, we know less about the extent to which gig work (compared with other self-employment arrangements and non-gig work) may fuel economic insecurity among American households. We fill this gap in the literature drawing on a sample of 4,756 workers from a unique national survey capturing economic hardships among non-standard workers like app-and platform-based gig and other self-employed workers during the COVID-19 pandemic. Results from generalized boosted regression modeling, utilizing machine learning to account for potential endogeneity, demonstrated that gig workers experienced significantly greater economic hardship than non-gig and other self-employed workers during the pandemic. For example, gig workers were more likely to experience food insecurity, eviction, and skipped-medical treatment compared with non-gig and other self-employed workers during the pandemic. While household liquid assets endowment prior to the pandemic reduced the effect of gig work on experiencing economic hardships, having dependent children in the household increased this effect. Thus, contrary to democratizing entrepreneurship opportunities, these findings suggest that the expansion of the gig economy may exacerbate labor market inequality, with wealth-endowed families being protected against adverse economic consequences of the gig economy. We discuss the implications of these findings for inequality-reducing labor market policies, including policies that account for the interconnectedness of family and the labor market.

1 INTRODUCTION

In recent years, the number of self-employed workers and size of the gig economy have both increased significantly in the United States and many other advanced economies (Boeri et al. 2020; Conen and Schippers 2019). Proponents of the sharing economy situate gig work within a "future of work" narrative (Lin et al. 2019), depicting it as broadening the entrepreneurial ecosystem and providing opportunities for workers to earn unlimited income and build wealth by being their own bosses (Schor 2020; Vallas and Schor 2020; Ravenelle 2019a). Though research has suggested that some gig economy and other self-employed workers might gain sufficient earnings for them and any dependents to maintain a decent standard of living (Ravenelle 2019a), for many workers, gig work and other self-employment activities are results of blocked labor market opportunity, thereby constituting a survival mechanism (Wassink and Hagan 2018; Ravenelle 2019a). Yet, partly due to the difficulty in precisely distinguishing between entrepreneurial and subsistence self-employment and gig work (Boeri et al. 2020), it has been challenging for empirical analyses drawing on commonly-used survey data to fully capture the extent to which gig work is associated with economic insecurity as compared with other self-employment arrangements. Beyond a recent ethnographic study conducted in New York (Ravenelle 2019b), existing quantitative studies provide a limited account on how social risk and economic insecurity associated with self-employment differ across different categories of self-employed workers in the gig economy.

We fill this gap in the literature on gig work by drawing on unique national survey data capturing the experience of economic hardship during the COVID-19 pandemic among non-standard workers like app-and platform-based gig and other self-employed workers. In doing so, we also examine the degree to which workers' financial standing prior to the COVID-19 pandemic and the composition of their households matter for whether gig employment predicts chances of experiencing economic hardship due to the pandemic. This is particularly important because even before the COVID-19 pandemic, large segments of American households faced increasing financial insecurity, with half of U.S. households experiencing at least some difficulty covering regular expenses and nearly half lacking sufficient emergency savings (Lin et al. 2019), and about 40 to 50 percent of households reporting that they would borrow money or sell something to pay for a $400 emergency expense, respectively (Board of Governors of the Federal Reserve System 2019). Households' limited pre-pandemic savings may have left them vulnerable to the acute economic shocks that characterized the early months of the pandemic. In particular, lower-income households with limited liquid assets are at higher risk for material hardship amidst financial shocks (Despard et al. 2018). Another group disproportionately exposed to economic risks from the pandemic was families with children, and mothers in particular, who faced higher rates of unemployment than the general population (Heggeness 2020) while their children experienced disproportionate increases in food insecurity (Coleman-Jensen et al. 2021). Similarly, drawing on data from Panel Study of Income Dynamics, Hacker (2019) found that economic instability has risen in the U.S., with family income becoming increasingly volatile since the 1970s. Accordingly, we examine four key questions regarding the link between gig employment and economic insecurity during the COVID-19 pandemic. First, to what extent did gig workers experience economic hardship due to the COVID-19 pandemic compared with non-gig workers? Second, to what extent did gig workers experience economic hardship due to the COVID-19 pandemic compared with other self-employed workers? Third, to what extent did the level of household financial endowment prior to the COVID-19 pandemic influence the degree to which gig and non-gig workers experienced economic hardship due to the COVID-19 pandemic? Fourth, to what extent did household composition, such as the presence of dependent children in the household, influence the degree to which gig and non-gig workers experienced economic hardship during the COVID-19 pandemic?

Results from generalized boosted regression modeling, utilizing machine learning to account for potential endogeneity, show that gig workers experienced significantly greater economic hardship than non-gig and other self-employed workers during the COVID-19 pandemic. For instance, gig workers were significantly more likely to experience job or income volatility, food insecurity, eviction, and to skip medical treatment compared with non-gig and other self-employed workers. However, households' liquid assets endowment prior to the pandemic diminished the effect of gig work on the experience of economic hardship, whereas having dependent children in the household increased this effect. Thus, contrary to democratizing entrepreneurship opportunity, these findings suggest that the proliferation of gig work in the new economy may exacerbate labor market inequality, with wealth-endowed families being protected against adverse economic consequences of the gig economy. In addition, the fact that gig workers with dependent children are particularly vulnerable to experiencing economic insecurity stresses the interconnectedness of workers' standing in the labor market and their family dynamics.

In the rest of the paper, we summarize relevant research on the gig economy, self-employment and precarious work and develop hypotheses linking gig work and economic hardship during the COVID-19 pandemic. Next, we describe the data and methods we use to evaluate our argument, followed by the presentation of the results. In the final section, we discuss the results and their implications for future research, and policy initiatives aimed at reducing labor market inequalities.

2 REVIEW OF RELEVANT LITERATURE AND HYPOTHESES

2.1 The prevalence and promise of gig work in the new economy

Research shows that about 20% of the working-age population in North America have performed work in the gig economy (Angus Reid Institute 2019)), which is consistent with a recent survey showing that 20% of all workers in in New York state had a gig job of some kind in 2021 (Lew, Chatterjee, and Torres 2021). Large portions of gig workers, such as food delivery and ride-hailing drivers, home repair and care workers, perform their work via apps and online platforms, while incurring the cost of operating the services (Vallas and Schor 2020). Some gig workers are identified as content producers and influencers as they create content for social media platforms (Vallas and Schor 2020), whereas others provide professional consulting services in areas like graphic design, computer programming and journalism (Christin 2018; Osnowitz 2010). Thus, proponents of the sharing economy contend that the prevalence of app-and platform-enabled gig work has broadened entrepreneurship opportunity by providing people with flexible work schedules, work autonomy, and the potential for unlimited earnings (Goods, Veen, and Barratt 2019; Vallas and Schor 2020; Wood, Lehdonvirta, and Graham 2018), thereby branding gig work platforms as business incubators (Vallas and Schor 2020).

2.2 The precarity of gig work in the new economy

Gig workers in the sharing economy lack the social protections associated with standard employment arrangements, which protect workers against dangerous working conditions, exploitation, unfair treatment, unemployment and poverty in old age, as well as often providing workers health insurance and parental leave (Conen and Schippers 2019). Compared to full-time standard employment, non-standard employment arrangements (like app- and platform-enabled gig work) tend to be insecure and dependent on short term fluctuations in employer demand (Conen and Schippers 2019). Contrary to the autonomous and entrepreneurial self-employment branding of the proliferation of app- and platform-based gig work, the sharing economy is largely dominated by short-term, on-demand, and independent contracting jobs. Scholars classify these jobs as precarious due to their uncertain, unstable and insecure nature, and the fact that employees bear the risks of work (as opposed to businesses or the government), while receiving very limited or no social benefits and statutory entitlements (Kalleberg 2018). To make matters worse, because gig workers are classified as independent contractors by companies like Uber they must pay the employer share (7.65% of wages; in addition to the employee share of 7.65%) of Social Security and Medicare taxes on income up to $142,500. Gig platforms increase workers' precarity via low wages, risky workplaces, and temporary work that may last as short as a few minutes (Kaine and Josserand 2019; Vallas and Schor 2020; Ravenelle 2019a). Drawing on 78 ethnographic interviews with platform workers, Ravenelle (2017) found that digital platforms increase workers' vulnerability when platform designs, services offered, and algorithms suddenly change.

Many gig workers in the sharing economy adopt emotional and cognitive self-protective practices to defend themselves against physical, emotional and economic costs associated with completing their job. For instance, analyzing data from interviews with 32 Uber and Lyft drivers in New York City and Boston, research finds that some Uber and lift drivers are forced to carry weapons in their cars, while others try to stand up against clients' hostile behavior or try to remain composed even when they are experiencing abuses. Drivers also tried to protect themselves by installing cameras in their cars to collect data, rejecting negative customer reviews and complaints, and as well as monitoring payments to prevent them from being rescinded (Ladegaard, Ravenelle, and Schor 2022).

Though a large share of the gig work activities are in the service sector, where precarious, involuntary and low-pay gig work is prevalent (Kautonen et al. 2010; Stone 2006; Westerveld 2012; Buschoff and Schmidt 2009), work precarity is also prevalent among high status gig workers. Recent research, based on in-depth interviews and surveys of 35 high socioeconomic status gig workers, showed that these workers experienced job and income volatility and had little control on their work due to a constant need to market themselves (Ravenelle, Janko, and Kowalski 2021). In addition, regardless of their socioeconomic status, gig workers are vulnerable to experiencing unemployment without being laid off because they are independent contractors. As a result, job and income volatility is likely to have increased among gig workers during the COVID-19 pandemic because they may automatically become unemployed because of decrease in demand due to the pandemic (Lew, Chatterjee, and Torres 2021).

Yet, the extent of the precarity of gig work also varies by social groups (Aronson and Belous 1991; Cappelli and Keller 2013; Kalleberg, Reskin, and Hudson 2000), job types, individuals, and the household and communities in which individuals and jobs are embedded (Vosko 2006). Some people use gig work income to supplement their full-time wage-and-salary income. Others use gig work only as side income because they depend on earnings from other family members or they have other sources of income such as savings and equity investment to maintain an adequate standard of living. However, for many workers in the sharing economy, gig work is their primary job, while they say that they will prefer having a more permanent and full-time job.

2.3 Gig work and entrepreneurship

Contrary to proponents' claims that gig work promotes entrepreneurship, gig work fails to provide workers the necessary conditions for the development of successful ventures such as human capital development at work, the network of coworkers for the sharing of new ideas, and financial capital. Successful entrepreneurs are often high wealth, high human capital endowment people (Conen and Schippers 2019), and come from high-resourced environments (Frid, Wyman, and Coffey 2016). In contrast, many gig workers undertake gig work due to blocked labor market mobility and underemployment, hence they tend to have low-financial and human (education and work experience) capital, and are often from low-resourced environments (Boeri et al. 2020). Embedded in low-resourced environments, many gig workers have few resource-rich people on which they could depend in the early stages of the entrepreneurial process (Conen and Schippers 2019), as social networks are crucial for start-up development and success (Aldrich and Ruef 2006). In addition, the gig economy shifts the responsibility of production from employers and government to gig workers, while simultaneously allowing employers to exert significant control over workers (Vallas and Schor 2020). Data from qualitative interviews and demographic surveys with 41 contract workers from TaskRabbit and KitchenSurfing show that gig workers see themselves as part-time employees as opposed to entrepreneurs as advertised by the proponents of the gig economy (Ravenelle 2019b). A recent study of elite platform gig workers found that though high-skilled platform-based gig workers identify as entrepreneurs and their self-employment activities are often incorporated, they do not describe their platform-based work as entrepreneurship (Ravenelle, Janko, and Kowalski 2021). In addition, the conditions that produce prosperous and growth-oriented self-employment generally differ from precarious working conditions that a large proportion of gig workers face in the sharing economy (Ravenelle 2017; Vosko 2006; Lew, Chatterjee, and Torres 2021; Ravenelle 2019a; Ravenelle 2019b).Yet, non-standard jobs are not always associated with economic precarity as some non-standard employment arrangements, such as entrepreneurial self-employment, may provide sufficient earnings for the worker and any dependent to maintain a decent standard of living (Moulton and Scott 2016; Vermeylen et al. 2021). Under entrepreneurship-enabling conditions, self-employment can be prosperous and innovative, thereby leading to socioeconomic mobility. For instance, research examining the experience of self-employed nurses in Canada, drawing on ethnographic data, found that even though self-employed nurses experienced difficulty in starting their own health care businesses due to a lack of business knowledge, nearly all of them were financially successful (Wall 2015). Other research shows that among higher socioeconomic groups, self-employment is often motivated by access to economic opportunity (Solinge 2014). Examining gender and class differences in the experience of self-employment using the 1979 to 1998 waves of the National Longitudinal Survey of Youth, Budig (2006) found that self-employment increased men's earnings compared to wage-and-salary employment.

In sum, branding the growth of the sharing economy as the broadening of entrepreneurship opportunities masks the precarious nature of gig work with respect to employment arrangements, job quality, and opportunities for successful small business launches. Thus, in assessing financial insecurity in relation to non-standard employment arrangements, it is important to differentiate gig work and entrepreneurial self-employment.

2.4 Pandemic-induced economic hardship, gig work, traditional employment and non-gig self-employment

Given the precarious nature of gig employment, one may expect that economic hardship caused by the COVID-19 pandemic to be particularly stark among gig workers. During the COVID-19 pandemic, many gig workers say they undertook gig work because they lost their job due to the pandemic and had no other option, therefore gig work is their primary source of income (Lew, Chatterjee, and Torres 2021). While many employers allowed their employees to work from home due to the COVID-19 pandemic, app-based gig workers (such as Uber and Lyft drivers, and Door Dash and Instacart food delivery workers) continued to work outside, exposing themselves and their families to the risk of COVID-19 infection. Indeed, research conducted by Community Service Society of New York found that about 40 percent of app-based gig workers or a family member were infected with the coronavirus, compared with 26 percent of those with a standard job, and 21 percent of non-gig self-employed workers (Lew, Chatterjee, and Torres 2021). Utilizing a survey of low-and moderate-income households and difference-in-difference regression analysis, a recent study found that increased availability of app-and platform-mediated gig work decreased take-home pay among low-and moderate-income workers (Daniels and Grinstein-Weiss 2018). A survey of 500 app-based gig workers (such as Uber and Lift ride-hailing and Door Dash food delivery drivers) in New York showed that gig workers earn below New York $15 per hour minimum wage, earning between $6.57 and $7.87 per hour after deducting the money they used to purchase their own smartphones, electric bikes and other necessary equipment (McGeehan 2021).

Yet, the extent of the experience of economic hardship varies by households' resource endowments. For instance, research conducted at the Federal Reserve Bank of St. Louis found that households with home equity, retirement savings, and other equities like stocks are, respectively, 44%, 25% and 21% less likely to experience financial delinquency compared to those lacking these assets (Ricketts and Boshara 2020). In addition, the presence of dependent children in households affected the degree of economic insecurity during the pandemic as research found that households with dependents were at least two months behind on a current loan obligation compared to those with no dependents (Ricketts and Boshara 2020). More specifically, the chances of a family experiencing serious financial delinquency increased by 17% for each child in the family (Ricketts and Boshara 2020).

Food and housing insecurity were among the main challenges that gig workers faced in the U.S. during the COVID-19 pandemic. In New York for example, app-enabled gig workers were three times more likely than traditional employees to experience some type of housing hardship such as falling behind on their rent or mortgage, experiencing a utility shut-off for missing payment, or facing potential eviction or foreclosure (Lew, Chatterjee, and Torres 2021). More specifically, about 43% of app-based gig workers said that they were unable to pay their rent or mortgages compared to 17% of those with a traditional job, and they were two times as likely as traditional employees to not have health insurance or to delay medical care (Lew, Chatterjee, and Torres 2021). Overall, about 55 percent of app-mediated gig workers in the state reported experiencing three or more hardships since the start of the pandemic, a number that doubles the proportion that the traditional employees reported (Lew, Chatterjee, and Torres 2021).

2.5 Study Purpose and Hypotheses

Research has suggested that scholars pay closer attention to the link between work arrangement and the actual and perceived quality of employment arrangement (Vosko 2006). Building on previous research (Vosko 2006), we examine the extent of economic hardship among non-standard employment arrangement workers by assessing differences between gig workers, non-gig self-employed workers and traditional employment workers. Our empirical analysis includes a measure of income adequacy, and an array of other employment arrangements to account for workers who use income from gig work to complement earning from regular full-time employment as well as those who rely on other sources of income, such as saving and/or income from other members of the family to live as opposed to income from their gig work. Based on the above argument, we formulate the following hypotheses:

Hypothesis 1: Gig workers experience greater economic hardship due to the COVID-19 pandemic compared with non-gig workers.

Hypothesis 2: Gig workers experience greater economic hardship due to the COVID-19 pandemic compared with other self-employed workers.

Hypothesis 3: Household financial endowment prior to the COVID-19 pandemic reduces the likelihood of experiencing economic hardship, whereas the presence of dependent children in the household increases this likelihood.

Hypothesis 4: Household financial endowment prior to the pandemic decreases the effect of gig work on the experience of economic hardship due to the COVID-19 pandemic.

Hypothesis 5: Having dependent children in the household increases the effect of gig work on the experience of economic hardship due to the COVID-19 pandemic.

3 METHODS

3.1 Data and Sample

The data used in this study come from the Socio-Economic Impacts of COVID-19 survey, while was fielded during the early stage of the pandemic (April 27 to May 12, 2020) using Qualtrics online panels (Roll et al. 2021). This survey was designed to take roughly 30 minutes and aimed to document changes in household behaviors and well-being during the pandemic including their employment, balance sheets, hardship experiences, and personal experiences with COVID-19.[1] Respondents to the survey were recruited via email, and we employed quota-based sampling procedures to ensure the survey sample reflected the U.S. population in terms of income, race/ethnicity, age, and gender. Prior research has found that recruiting online, non-probability samples through Qualtrics panels produces samples that closely approximate those of the General Social Survey (Zack, Kennedy, and Long 2019), both in terms of demographic indicators and indicators for individual perceptions and beliefs. The response rate to the survey was 10.8%,[2] and our main analytical sample includes all survey respondents. After sample exclusions due to data quality checks and quota requirements, our main analytical sample included 4,756 respondents.

As a supplemental analysis, we examined the relationship between participation in the gig economy and household hardship only for self-employed households. To conduct this analysis, we restricted the sample to respondents who reported that either they or their spouse/partner (if applicable) were self-employed on either a full- or part-time basis. This sub-sample included 676 respondents.

3.2 Measures

The dependent variables in this study capture eight different indicators of household financial distress. These indicators were measured by asking respondents if their household (1) had skipped any bills in the past 3 months; (2) was currently behind on their credit card payments; (3) currently had an unpaid credit card balance; (4) had lost a job or income due to the pandemic; (5) had skipped a housing payment in the past 3 months; (6) had been forced to move by a bank or landlord (which we term as 'eviction') in the past 3 months; (7) had skipped essential medical care in the past 3 months; and (8) had experienced food insecurity in the past 3 months. All of these indicators were structured as binary yes/no questions with the exception of the food insecurity measure. To measure food insecurity, we used the USDA's six-item food insecurity screener (Bickel et al. 2000) and subsequently created a binary food insecurity variable capturing if respondents answered affirmatively to any of the six items.[3]

[Insert Table 1 here]

[1] Survey participants received a completion incentive that varied based on how participants were recruited into the broader survey panel. As a result, some participants received cash payments while others received cash-equivalent payments (e.g., airline miles). Qualtrics set the amount of the incentive at a level commensurate with the time required to complete the survey.

[2] Response rates were calculated using the American Association of Public Opinion Research's RR2 measure (AAPOR, 2016).

[3] Because the survey was administered between April 27, 2020, and May 12, 2020, the three-month timeframe used for most of these outcomes covered the time immediately prior to the pandemic through the large unemployment spike in April and May.

The main independent variable in this study, participation in the gig economy, was based on the measure of gig employment that has been used by the Federal Reserve's Survey of Household Economics and Decisionmaking for several years (Board of Governors of the Federal Reserve System 2021). This measure asked about their household's participation in different types of gig work over the prior 3 months, including (1) child or elder care services; (2) dog walking, feeding pets, or house sitting; (3) house cleaning, yard work, or other property maintenance work; (4) driving or ride-sharing; (5) paid tasks online (not including online surveys); (6) personal tasks such as deliveries, grocery shopping, running errands, or helping people move; (7) selling goods at flea markets or garage sales; (8) selling goods at consignment shops or thrift stores; (9) selling goods on-line; (10) renting out property, such as a car or house; (11) other paid personal tasks they had not already mentioned in the survey. If respondents indicated that they or anyone in their household participated in any of these types of work, they were coded as gig workers.

We are also interested in the extent to which household financial endowment and the presence of children in the household moderate the relationship between gig employment and household hardship. To measure household financial endowment, which we operationalize through a measure of liquid assets, we asked respondents to provide the dollar value of their cash, checking, and savings accounts three months prior to the survey (i.e., before the pandemic). We then divided the value of these accounts into quartiles. The 1st quartile ranged from $0 to $2,000 in pre-pandemic liquid assets, the 2nd quartile from $2,001 to $8,250, the 3rd quartile from $8,251 to $28,900, and the 4th quartile included anyone with more than $28,900 in liquid assets.[4] We also asked respondents how many children under the age of 18 were in their household, and created a categorical variable with four levels (0, 1, 2, and 3 or more children) based on their responses.

Finally, we include an array of control variables in this study to account for both differential selection into gig employment and to address potential confounding between our independent/moderating variables and our outcomes. These variables include age, race/ethnicity, educational attainment, housing status (e.g., owning, renting), access to health insurance, household income in 2019 (before the pandemic), access to a bank account, credit card ownership, respondent's employment status, spouse/partner's employment status, marital/living with a partner status, and Census region of residence.[5]

3.3 Data analysis

The primary challenge in estimating the relationship between gig employment and household hardship during the pandemic is that selection into the gig economy is not random, and the factors that may predict gig employment may also predict household hardship. For example, households with children may be attracted to gig employment because it allows one parent to earn money on a flexible schedule while the other parent works full-time, but these households may also be more exposed to pandemic-related hardships such as the loss of income or food insecurity because of the need to decrease work to care for children during school closures or the increased costs of having extra mouths to feed. We use a propensity score estimation technique known as generalized boosted regression modeling (GBM) to account for this potential endogeneity. This nonparametric approach to propensity score estimation allows us to statistically balance gig workers and non-gig workers on observed covariates—which include the array of control variables described above—by using machine learning to identify propensity score weights that minimize the overall mean effect size differences between these covariates (McCaffrey, Ridgeway, and Morral 2004). To identify the optimal propensity score weights to balance gig and non-gig workers, we re-estimated our propensity model over 10,000 iterations.

We then estimated the relationship between gig employment and household hardship outcomes using linear probability models of the following general form:

[4] Both liquid asset and income variables in this study are top coded at the 99th percentile.

[5] Most variables used in this study, and all the dependent, independent, and moderating variables, use the household as the unit of analysis. For example, the question on gig employment asks whether anyone in their household has earned income in any of the gig employment categories we list. However, some variables in our array of controls are measured at the individual (or respondent) level, including age, gender, race/ethnicity, and educational attainment. Employment status is also measured at the individual level, though our inclusion of the spouse/partner's employment status a control gives us a strong proxy for a household level measure of employment.

$$y_i = \beta_0 + \beta_1 GigWorker_i + \beta_2 LiqQuartile_i + \beta_3 NumKids_i + \gamma_i \pi + \varepsilon_i$$

where y is a given household hardship outcome for respondent i, *GigWorker* is an indicator capturing whether or not someone in the respondent's household was employed in the gig economy, LiqQuartile is a categorical variable capturing the quartile of liquid assets a respondent's household occupies, and *NumKids* is a categorical variable capturing the number of children in the respondent's household. γ is a vector of controls, and ε is an error term. In addition to this main model, we also examined the extent to which household financial endowment (i.e., liquid assets) and the presence of children moderated the relationship between gig employment and household hardship by re-estimating Equation 1 with, separately, interactions between liquid assets and gig employment and the number of children and gig employment. This approach, in which we use the same array of variables to construct our propensity score weights as we use for covariate controls in our outcome models is known as "doubly robust" estimation (Bang and Robins 2005; Huppler-Hullsiek and Louis 2002), and is a technique for minimizing the mean square error of estimated relationships.[6]

4 RESULTS

4.1 Descriptive Analysis

About 29% of our sample earned some money from gig work in the three months prior to the survey.[7] Tables 1 and 2 show the demographic characteristics and socioeconomic standing of gig workers and non-gig workers in our sample. The results in Table 1 are unweighted, meaning that they do not account for the differences in the propensity to select into gig work among workers in our sample, whereas the results in Table 2 are weighted to account for differential selection into gig work. Table 1 shows that there are significant differences in many demographic factors between gig workers and non-gig workers. For instance, the average age among gig workers is 39.11 years compared with 50 years for non-gig workers, but there is no statistically significant gender difference in the proportion of gig workers and non-gig workers. About 50% of gig workers are female compared with 51% of non-gig workers. Table 1 also shows that 12% of gig workers are full-time self-employed compared with 5% of non-gig workers, and that 16% of gig workers are unemployed compared with 13% of non-gig workers. Yet, many of these demographic differences become statistically non-significant after applying propensity score weights in Table 2. For example, Table 2 shows that there is no statistically significant age differences between gig workers and non-gig workers as the average age among gig workers is 46.13 years compared with 47.28 years among non-gig workers.

[Insert Table 2 here]

Given that our key interest is to understand differences in the experience of economic hardship between gig and non-gig workers, we now describe these differences drawing on the analyses that account for the propensities of selecting into gig work (Table 3). Table 3 shows statistically significant differences in the experience of economic hardship due to the COVID-19 pandemic between gig and non-gig workers with a p-value < 0.000 for the differences in all of economic hardship indicators. About 21% of gig workers reported that they skipped bills in past three months compared with 8% of non-gig workers, and 18% of gig workers said they were currently behind on credit card payment, while 33% reported that they had unpaid credit card balance compared with, respectively, 4% and 28% of non-gig workers. Table 3 also shows that

[6] As a robustness test, we also estimated our models using logistic regression rather than linear probability modeling, though we had to use a more limited set of control variables to account for small cell sizes within the regression. Results were broadly similar to those using the linear probability models, and can be seen in Tables 9-14 in the Appendix.

[7] This proportion is similar to the proportion observed in the Federal Reserve's 2020 Survey of Household Economics and Decision-making, which used a nearly identical question on gig employment (BGFRS, 2021). In that survey, which asked about gig employment of respondents in the prior month, 27% of respondents said they earned money from gigs.

40%, 15%, 9%, 20% and 40% of gig workers, respectively, experienced job and income loss, skipped housing payment in the last three months, had been evicted in the past three months, skipped medical care due to financial hardship in the past three months and experienced food insecurity in past three months compared with 24%, 15%, 1%, 6% and 19% of non-gig workers. These results support some recent research using in-depth interviews (Ravenelle, Kowalski, and Janko 2021), and survey data with gig workers in some states such New York and Boston (Ladegaard, Ravenelle, and Schor 2022), showing that gig workers experienced significant economic hardship during the pandemic. In addition to examining differences in economic insecurity between gig workers and non-gig workers (Ladegaard, Ravenelle, and Schor 2022), our analysis investigates potential differences in the experience of economic hardship between gig workers and other non-standard workers such self-employed workers. To this end, we now turn to the multivariate analysis, which accounts for the array of demographic and labor market variables that we describe in Tables 1 and 2.

[Insert Table 3 here]

4.2 Multivariate Analysis

Models 1-8 in Table 4 examine the effect of gig employment on the experience of income or job volatility and budget constraint during the COVID-19 pandemic compared with non-gig workers, as well as the protective effect of liquid assets on the experience of economic hardship due to the COVID-19 pandemic. To facilitate interpretation, we also graph these results in Figures 1-6. Further, we evaluate our second hypothesis that gig workers will experience greater economic hardship during the COVID-19 pandemic compared with other self-employed workers by reducing our analytical sample to only self-employed people (Table 7).

Model 1, which examines the relationship between gig work, liquid assets, and COVID-19-related job and income loss, shows that the coefficient for gig worker is 0.082 and statistically significant ($p < 0.001$), indicating that gig workers have an 8.2 percentage point increase in experiencing income or job volatility due to the COVID-19 pandemic compared with non-gig workers (Figure 1). This result is consistent with our argument that gig workers are likely to experience greater job or income volatility due to the pandemic compared with non-gig workers. Models 2-8 analyze the outcomes related to household budget constraints, including skipped bills, falling behind on credit card payments, having unpaid credit card balances, skipped housing payment, experiencing eviction, skipped medical treatment, and to experiencing food insecurity. Models 2 and 3, respectively, show that gig workers are 9.4 percentage points and 9 percentage points more likely to have skipped bills in the past three months and to have fallen behind on credit card payments compared with non-gig workers ($p < 0.001$). Models 4 to 6, respectively, show that gig workers have a 4.3 percentage point ($p < 0.01$), 6.9 percentage point ($p < 0.001$), and 4.4 percentage point ($p < 0.001$) greater chance of having an unpaid credit card balance, of skipping a housing payment in the past three months, and of being evicted in the past three months compared with non-gig workers. Models 7 and 8, respectively, demonstrate that gig workers have a 9.5 percentage point and 12.2 percentage point greater likelihood of skipping medical treatment and experiencing food insecurity in the prior three months than their non-gig counterparts ($p < 0.001$). These results support our first hypothesis that gig workers will experience greater economic hardship due to the COVID-19 pandemic compared with non-gig workers (Hypothesis 1).

[Insert Table 4 here]

[Insert Figure 1 here]

[Insert Figure 2 here]

In Table 4, Models 1-8 also analyze the effect of having liquid assets on the experience of income volatility (Model 1) and budget constraint because of the COVID-19 pandemic (Models 2-8). Model 1 shows that having liquid assets protects people against the experience of economic hardship caused by the pandemic. It shows that people with \$2,001 to \$8,250 are 5.34 percentage points less likely to experience job or income loss ($p < 0.05$). Model 2 shows that people in the 2nd quartile (\$2,001 to \$8,250), 3rd quartile (\$8,251 to \$28,900), and 4th quartile (\$28,901 or more) of liquid assets have, respectively, a 4.5 percentage point, 11.3 percentage point and 10.10 percentage point lower chance of skipping a bill in the past three months compared with those in the lowest quartile of liquid assets (\$0 to \$2,000) ($p < 0.05$ and $p < 0.001$). People in the 2nd, 3rd, and 4th liquid assets quartiles are, respectively, 5.5 percentage points, 10.8 percentage points, and 9.6 percentage points less likely than those in the bottom quartile to be behind on credit card payments (Model 3, $p < 0.001$).

Model 4 shows a similar difference in the experience of economic hardship by levels of liquid assets endowment. Households with liquid assets in the 2nd, 3rd, and 4th quartiles have, respectively, a 5.3 percentage point, 18.9 percentage point, and 29.7 percentage point lower chance of having unpaid credit card balance relative to those in the bottom quartile ($p < 0.05$, $p < 0.001$). In Model 5, those in the 2nd, 3rd, and 4th liquid asset quartiles are, respectively, 8.2 percentage points and 7.2 percentage points less likely to skip housing payment than those in the bottom quartile ($p < 0.001$). Similarly, Model 6 demonstrates that compared to those in the bottom liquid asset quartile, households in the 2nd, 3rd, and 4th liquid asset quartiles have, respectively, a 2.7 percentage point, 4.5 percentage point, and 4.3 percentage point lower chance of being evicted in the past three months due to the pandemic ($p < 0.001$). Households in the 2nd, 3rd, and 4th liquid asset quartiles also have, respectively, a 4.3 percentage points, 9.10 percentage points and 9.9 percentage point lower chance of skipping medical treatment (Model 7), and a 8.3 percentage point, 15.8 percentage point, and 17.4 percentage point lower chance of experiencing food insecurity (Model 8) than those with liquid assets in the bottom quartile ($p < 0.05$ and $p < 0.001$). These results support our argument that financial endowment prior to the COVID-19 will protect people against the experience of economic hardship due to the COVID-19 pandemic (Hypothesis 3).

In Table 4, Models 1-8 also analyze the effect of having dependent children in the household on the likelihood of experiencing income volatility (Model 1) and budget constraint due to the COVID-19 pandemic (Models 2-8). In Model 1, the coefficients on the number of children are not statistically significant, suggesting that there are not substantial differences in the likelihood of experiencing job or income volatility between households with dependent children and those without dependent children. Yet, households with one, two, and three or more dependent children have, respectively, a 5.5 percentage points, 10 percentage points, and 7.9 percentage point greater chance of skipping bills in the past three months (Model 2, $p < 0.05$, $p < 0.001$), and a 6.6 percentage points, 10.30 percentage points, and 7.10 percentage point higher chance of being behind on credit card payment compared with households without dependent children (Model 3, $p < 0.05$, $p < 0.001$). Model 4 shows that households with one and two dependent children are, respectively, 5.7 and 7.1 percentage points more likely to have unpaid credit card balance, and have a 6.8 and 6.7 percentage point greater chance of skipping housing payments in the past three months compared with households with no dependent children (Model 5, $p < 0.05$, $p < 0.01$, $p < 0.001$). Households with one, two, and three or more dependent children also have, respectively, a 4.5 and 7.3 percentage point greater chance of being evicted in the past three months compared with those without dependent children (Model 6, $p < 0.05$, $p < 0.001$). Model 7 also shows that households with one and two dependent children are, respectively, 6 and 5.10 percentage points more likely to skip medical treatment in the past three months, as well as having a 7.3 and 8.8 percentage point greater chance than those with no dependents to experience food insecurity (Model 8, $p < 0.05$, $p < 0.01$, $p < 0.001$). These results corroborate our argument that family composition, such as having dependent children in the household, may influence the risk of experiencing economic hardship during the COVID-19 pandemic (Hypothesis 3).

4.3 Moderating effect of liquid assets on the relationship between gig work and the experience of economic hardship during the pandemic

Models 9-16 in Table 5 evaluate the extent to which households' endowment of liquid assets prior to the COVID-19 pandemic attenuated the effect of gig work on the experience of economic hardship during the pandemic. To ease interpretation, we present these interactions in Figures 3 and 4. Model 9 shows that gig workers in the 3rd quartile of liquid assets have a 9.1 percentage point lower chance of experiencing job loss or income volatility compared with gig workers in the bottom quartile of liquid assets ($p < 0.05$). Model 10 shows that gig workers with liquid assets in the 3rd or 4th quartiles have, respectively, a 7.1 and 9 percentage point decrease in the likelihood of skipping bills in the past three months, as well as 6.7 and 5.7 percentage point decrease in the likelihood of being behind on credit card payments compared gig workers in the bottom quartile of liquid assets ($p < 0.05$, $p < 0.01$, $p < 0.001$). Yet, Model 12 shows that liquid assets do not significantly moderate the relationship between gig employment and having an unpaid credit card balance. However, gig workers with liquid assets in the 3rd and 4th quartiles, respectively, are 7.6 and 7.7 percentage points less likely to skip a housing payment in the prior three months relative to those in the bottom liquid asset quartile (Model 13, $p < 0.01$, $p < 0.001$). Model 14 indicates that gig workers with liquid assets in the 2nd, 3rd, and 4th quartiles have, respectively, a 4.4, 5.1, and 5.1 percentage point lower chance of being evicted in the prior three months relative to those in the bottom liquid asset quartile ($p < 0.01$, $p < 0.001$). Gig workers in the 3rd and 4th liquid asset quartiles are also, respectively, 8 and 10.8 percentage points less likely to report skipping medical treatment in the prior 3 months than gig workers in the bottom liquid asset quartile (Model 15, $p < 0.01$, $p < 0.001$), whereas gig workers in the top liquid asset quartile have a 13.6 percentage point lower likelihood of experiencing food insecurity in the prior three months compared with gig workers in the bottom quartile (Model 16, $p < 0.001$). These results corroborate our argument that household financial endowment prior to the pandemic would reduce the extent to which gig workers would experience economic hardship during the pandemic (Hypothesis 4).

[Insert Table 5 here]

[Insert Figure 3 here]

[Insert Figure 4 here]

4.4 Moderating effect of having dependent children in the household on the relationship between gig work and the experience of economic hardship during the pandemic

Models 17-24 in Table 4 examine the extent to which having dependent children in the household modifies how gig work affects chances of experiencing economic hardship during the COVID-19 pandemic. We have graphed these results to improve interpretation (Figures 5 and 6). Model 17 shows that having dependent children in the household does not have a significant moderating effect on the likelihood of experiencing job or income loss due to the pandemic for gig workers, whereas gig workers from a household with one, two and three or more dependent children have, respectively, a 7, 14 and 16 percentage points greater likelihood of skipping bills in the past three months (Model 18, $p < 0.05$, $p < 0.001$). Gig workers from households with one and two dependent children are also, respectively, 10.4 and 15.5 percentage points more likely to be behind on credit card payment than households with no dependent children (Model 19, $p < 0.01$; $p < 0.001$). Yet, Model 20 shows that gig workers from households with two and three or more dependent children have, respectively, a 12.4 and 16 percentage point greater likelihood of holding an unpaid credit card balance ($p < 0.05$, $p < 0.01$). Moreover, gig workers from families with one and two dependent children have a 9 percentage point higher likelihood of skipping housing payments in the past three months compared to those without any dependent children in the household (Model 21, $p < 0.05$, $p < 0.01$). Model 22 shows that gig workers with one, two and three or more dependent children in the household are, respectively, 10.8, 11.7, and 8.8 percentage points more likely to be evicted in the past three months compared to those without any dependent children in the household ($p < 0.05$, $p < 0.001$). In addition, gig workers with one and two dependent children in the household have, respectively, a 10.9 and 9.7 percentage point greater likelihood of skipping medical treatment compared to gig workers without any dependent children in the household (Model 23, $p < 0.01$). Yet, Model 24 shows that gig workers with two and three or more dependent children in the household have, respectively, a 12.5 and 15.3 percentage point greater likelihood of experiencing food insecurity during the COVID-19 pandemic compared to gig workers without any dependent children in the household ($p < 0.05$, $p < 0.01$). These results support our hypothesis that gig workers with dependent children will be particularly vulnerable to economic adversity during the pandemic (Hypothesis 5).

[Insert Table 6 here]

[Insert Figure 5 here]

[Insert Figure 6 here]

Finally, Table 7 shows the results from the analyses using only the sample of self-employed people. In Models 25-32, gig-workers are significantly more likely than other self-employed workers to experience economic hardship, supporting our second hypothesis. For instance, in Models 25, 26, 27 and 28, the coefficients for gig workers indicate that they are, respectively, 10.4 percentage, 14.7 percentage, 22.3 percentage and 14.2 percentage points more likely to experience job or income loss, skip their bill in the past three months, be behind on credit card payment, and to have unpaid credit card balances compared with other self-employed workers ($p < 0.05$, $p < 0.001$). In Models 29, 30, 31 and 32, the coefficients for the gig workers indicate that they have a 13.2, 13.2, 17.6, and 18.7 percentage point greater chances of, respectively, skipping housing payment, being evicted, skipping medical care, and experiencing food insecurity ($p < 0.001$). Together, these results demonstrate that gig-workers endured substantially greater economic adversity during the COVID-19 pandemic than other self-employed workers.[8]

[Insert Table 7 here]

5 DISCUSSION AND CONCLUSION

The sharing economy is argued to broaden entrepreneurship opportunities, thereby enabling people to build wealth by being their own boss. However, research has shown that the increased prevalence of gig work in the sharing economy has coincided with increased economic precarity among American workers, thereby failing to deliver to workers the entrepreneurship promise advertised by proponents of the sharing economy. Though some sharing economy workers may fit the profile of entrepreneurs and innovators (Vallas and Schor 2020; Ravenelle 2019a) due to difficulty in differentiating gig work from entrepreneurial self-employment with growth potential, current research has been unable to capture differences in economic standing among self-employed workers in the new economy. We fill this gap in the literature by utilizing a unique survey that collected information separately on gig economy workers and non-gig self-employed workers. We examine the extent to which American workers experienced economic hardship during the COVID-19 pandemic, focusing on differences among gig workers compared with non-gig workers and other self-employed workers. Given the well-documented uncertain, instable, and volatile nature of gig employment in the new economy, we hypothesize that gig workers would be more likely to experience economic hardship during the COVID-19 pandemic. Yet, we also contend that given the protective power of wealth in society, family wealth endowment should reduce the risk that gig workers would experience economic hardship during the pandemic, whereas having dependent children in the household should increase that risk.

We find support for our key argument that economic hardship is starker among gig workers compared with non-gig and other self-employed workers. The analysis shows that gig workers experience significantly greater difficulty paying for their expenses (such as missing credit card and housing payments) and are more likely to be evicted, skip medical treatment and experience food insecurity during the pandemic

[8] Notably, the models in Table 7 do not control for employment status, as our sample is restricted only to those who have someone in the household identifying as self-employed. However, it is possible that household-level employment dynamics may be influencing our findings. For example, a household where the respondent is self-employed but their spouse or partner is unemployed may have a different experience of hardship than a household where the spouse or partner is self-employed and the respondent is part-time employed. As a robustness test, we re-estimated the models in Table 7 while controlling for employment status. The results are similar to those in the main analysis, and can be seen in Tables 13 and 14 in the Appendix.

compared with non-gig and other self-employed workers. The results also corroborate our argument that wealth endowment and family composition should explain variation in economic hardship experienced by gig workers (compared with non-gig other self-employed workers) during the COVID-19 pandemic. More specifically, we find that gig workers with liquid assets of $8,251 to $28,900, and $28,900 or more had a significantly lower chance of skipping bills and medical treatment, as well as of being evicted or experiencing food insecurity during the pandemic. In contrast, the presence of dependent children in the household significantly increased the chances that gig workers would fail to pay their bills, skip medical treatment, and experience eviction, food insecurity and income or job loss. Below we discuss three key implications of these findings for research on the future of work in the new economy, and the consequences of the changing nature of work for economic mobility, as well as for government policy initiatives aimed at improving working conditions in the new economy.

5.1 Implications for future research and labor market policy

First, our finding that people who engage in gig work (compared with non-gig workers and other self-employed) experienced significantly greater economic hardship during the COVID-19 pandemic suggests that the growth of the gig economy is associated with distinct labor mechanisms that heighten economic insecurity among gig workers compared with non-gig workers and other self-employed workers. This implies that, in order to fully capture the extent to which the proliferation of gig work in the new economy shapes labor market inequality and social stratification as a whole, research needs to develop a new conceptualization of gig work distinct from commonly used framework that treats self-employment as entrepreneurship. A key conceptual difference is that, for gig workers, the decisions about the direction of their work lie in the hands of the app and platform managers, whereas non-gig self-employed workers have full autonomy over the direction and strategies they can use to develop and grow their self-employment activities, within the boundaries of the resources and opportunity made available to them by their environment. Yet, gig workers lack the autonomy inherent to entrepreneurial self-employment as their work is controlled by the apps and online platforms and bear the cost of conducting business (as opposed to the employer). For instance, unpredictable changes by app and platform managers in platform designs, algorithms and services offered can increase the vulnerability of gig workers (Ravenelle 2017), causing them to feel powerless, regardless of their economic standing (Glavin, Bierman, and Schieman 2021).

Another key reason to treat gig work separately in regard to the mechanisms by which it relates to economic precarity in the new economy is that gig work is generally a solo activity with low potential to scale. Further, solo self-employment activities are characterized by underemployment, low earning and high liquidity constraint compared to self-employed workers with employees (Boeri et al. 2020). In addition, solo self-employed workers have lower hourly earnings and work fewer hours. Indeed, research found that solo self-employed workers are more likely to say they would cover a $400 emergency expense by borrowing or selling something (Boeri et al. 2020). In contrast, many entrepreneurial self-employment activities have employees and high growth potential, providing a viable path to social mobility for the self-employed. For instance, many successful businesses, such as Amazon and Apple, started as a solo self-employment activity with growth potential. In this regard, our analysis supports Vosko's (2006) conclusion that scholars need to pay greater attention to the link between work arrangements and their actual quality.

Second, these findings also suggest that policy initiatives aimed at reducing labor market adversity should be coupled with actions that reduce barriers to wealth building, such as access to home ownership, mainstream financial institutions, and financial and equity markets. The fact that having liquid assets (funds held in cash, checking/savings accounts, or money market accounts) prior to the pandemic protects gig workers against experiencing economic hardship during the pandemic lends support to our argument. Our finding highlights the enduring, transcendent, and extensive power of wealth in protecting people against the experience of economic hardship. Our conclusion is also consistent with research conducted at the Federal Reserve Bank of St. Louis showing that people with home equity, retirement savings, and equities were, respectively, 44%, 25%, and 21% less likely than people without those assets to experience financial delinquency during the COVID-19 pandemic (Ricketts and Boshara 2020). Thus, our analysis corroborates the well-established segmented labor market argument that people's socioeconomic position shapes the extent to which they can weather labor market shocks and adversities caused by cyclical economic change or unpredictable events like the COVID-19 pandemic.

The third implication of our findings is that to fully understand the link between the expansion of the gig economy and economic insecurity and, accordingly, design policies to remedy labor market-induced economic insecurity, policy makers should approach labor market stability and family economic wellbeing as interconnected issues. In other words, policy makers should acknowledge the extent to which family structures affect the link between work and economic wellbeing. Our finding that gig workers with dependent children are particularly vulnerable to experiencing economic insecurity compared with other self-employed workers corroborate our conclusion. This finding also suggests that policy initiatives aiming at improving labor market outcomes for workers, for instance, may not be separated from family-focused policies such as government programs enabling workers to provide care for dependent children.

Further, we find that gig workers experience significantly greater economic hardship compared with non-gig workers, despite that the pool of workers eligible for unemployment benefits was broadened to include gig workers. This finding suggests that existing labor market related social policy, like unemployment benefits, may be insufficient to address increased economic insecurity associated with the gig economy. In fact, research found that during the pandemic many gig workers did not apply for unemployment benefits because they did not know they were eligible, whereas others refrained from participating due to stigma associated with many poverty-reducing government social programs (Ravenelle, Kowalski, and Janko 2021, p. 19). Thus, we suggest that policy makers may address the limitation of unemployment benefits to protect workers against the precarity of the gig economy by expanding the Earned Income Tax Credit for single filers, as well as making the expanded Child Tax Credit permanent for households with children. Finally, the implication of our analysis is that the extent to which workers experience the increased employment precarity in the new economy is linked to non-economic factors, such as the composition of a worker's family.

5.2 Limitations of the study and suggestions for future research

Career history, such as prior occupations and work experience, are key predicting factors of people's standing in the labor market. Though our survey does not provide information on individuals' career history, it is possible that the extent to which gig work predicts economic hardship during the pandemic is conditioned by people's paths to self-employment, such as prior work experience, occupations and unemployment. When data is made available, building on our findings that household's financial endowment moderates the extent to which gig-work predicts economic hardship, future research may advance extant research by examining the degree to which an individual's prior work experience and occupation are consequential for the degree to which gig-work signals economic insecurity. Further, due to data limitations, we were unable to assess how much increased economic hardship during the pandemic has contributed to increased economic inequality and whether the prevalence of gig-work may be implicated in increased inequality. Thus, future studies may improve our knowledge in this area by investigating the degree to which the prevalence of gig work contributes to, for example, income and wealth inequality. While further research may improve our understanding of the link between employment history, gig-work and economic inequality, our findings demonstrate that household wealth and family composition matter for whether gig-work is associated with economic hardship.

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Table 1: Descriptive Statistics, by Gig Employment Status (Unweighted)

Characteristic	Sample	Gig Worker	Non-Gig Worker	Standardized Differences	p-value
Total	100.00	28.55	71.45		
Age, Mean (SD)	46.9 (16.8)	39.11 (15.32)	50 (16.4)	-0.65	0.000
Gender, Female (%)	0.50	0.51	0.50	0.03	0.309
Race, Asian (%)	0.05	0.04	0.06	-0.09	0.000
Race, Black (%)	0.12	0.09	0.14	-0.16	0.000
Race, Hispanic (%)	0.17	0.17	0.17	0.00	0.000
Race, White (%)	0.62	0.67	0.60	0.15	0.000
Race, Other (%)	0.03	0.03	0.03	-0.02	0.000
Children, 0 (%)	0.74	0.63	0.78	-0.35	0.000
Children, 1 (%)	0.13	0.17	0.11	0.18	0.000
Children, 2 (%)	0.10	0.15	0.08	0.25	0.000
Children, 3+ (%)	0.03	0.05	0.03	0.11	0.000
Ed, Less than HS (%)	0.01	0.01	0.01	0.01	0.003
Ed, HS Degree (%)	0.28	0.31	0.27	0.09	0.003
Ed, Two-Year Degree (%)	0.13	0.12	0.14	-0.08	0.003
Ed, Bachelor's Degree (%)	0.36	0.37	0.36	0.04	0.003
Ed, Graduate Degree (%)	0.22	0.19	0.23	-0.08	0.003
Housing, Own w/ Mortgage (%)	0.40	0.39	0.40	-0.02	0.000
Housing, Own In Full (%)	0.27	0.23	0.29	-0.13	0.000
Housing, Rent (%)	0.28	0.30	0.27	0.07	0.000
Housing, Neither Own/Rent (%)	0.05	0.07	0.04	0.16	0.000
Health Insurance, Yes (%)	0.94	0.93	0.95	-0.11	0.001
Vehicle, Yes (%)	0.89	0.88	0.89	-0.03	0.327
HH Income in 2019, Mean (SD)	87012.0	84573.6	87986.5	-0.05	0.142
	(70250.7)	(73882.8)	(68732.6)		
HH Income in 2019, Median	70000.0	65000.0	72000.0		
Liq. Assets pre-COVID, Mean (SD)	27469.9	25392.0	28300.3	0.00	0.963
	(59481.7)	(58532.2)	(59845.3)		
Liq. Assets pre-COVID, Median	4450.0	4450.0	6000.0		
Bank Account, Yes (%)	0.97	0.97	0.97	0.00	0.889
Credit Cards, 0 (%)	0.10	0.10	0.09	0.04	0.437
Credit Cards, 1 (%)	0.17	0.17	0.18	-0.01	0.437
Credit Cards, 2 (%)	0.23	0.24	0.22	0.03	0.437
Credit Cards, 3+ (%)	0.50	0.49	0.51	-0.04	0.437
Emp., Self-Emp. Full-Time (%)	0.07	0.12	0.05	0.27	0.000
Emp., Self-Emp. Part-Time (%)	0.03	0.06	0.03	0.19	0.000
Emp., Wage/Salary Full-Time (%)	0.45	0.45	0.46	-0.01	0.000
Emp., Wage/Salary Part-Time (%)	0.10	0.13	0.09	0.15	0.000
Emp., Unemployed (%)	0.14	0.16	0.13	0.07	0.000
Emp., Retired/Disabled (%)	0.20	0.08	0.24	-0.42	0.000
Partner Emp., Self-Emp. Full-Time (%)	0.05	0.09	0.01	0.09	0.000
Partner Emp., Self-Emp. Part-Time (%)	0.01	0.02	0.40	0.09	0.000
Partner Emp., Wage/Salary Full-Time (%)	0.27	0.27	0.27	-0.01	0.000
Partner Emp., Wage/Salary Part-Time (%)	0.04	0.04	0.05	-0.02	0.000
Partner Emp., Unemployed (%)	0.09	0.09	0.09	0.00	0.000
Partner Emp., Retired/Disabled (%)	0.13	0.06	0.16	-0.29	0.000
Partner Emp., Single (%)	0.41	0.44	0.40	0.09	0.000
Region, Midwest	0.21	0.20	0.21	-0.02	0.948
Region, Northeast	0.20	0.20	0.21	-0.02	0.948
Region, South	0.35	0.35	0.35	0.01	0.948
Region, West	0.23	0.24	0.23	0.02	0.948
Region, Other	0.01	0.01	0.01	0.01	0.948
Observations	4756	1358	3398		

Table 2: Descriptive Statistics, by Gig Employment Status (Weighted)

Characteristic	Gig Worker	Non-Gig Worker	Standardized Difference	p-value
Total	28.55	71.45		
Age, Mean (SD)	46.13 (16.56)	47.28 (16.77)	-0.07	0.073
Gender, Female (%)	0.51	0.51	0.01	0.796
Race, Asian (%)	0.05	0.06	-0.04	0.786
Race, Black (%)	0.12	0.13	-0.02	0.786
Race, Hispanic (%)	0.18	0.17	0.02	0.786
Race, White (%)	0.62	0.62	0.02	0.786
Race, Other (%)	0.03	0.03	0.01	0.786
Children, 0 (%)	0.74	0.75	-0.03	0.732
Children, 1 (%)	0.13	0.12	0.01	0.732
Children, 2 (%)	0.10	0.09	0.03	0.732
Children, 3+ (%)	0.04	0.03	0.01	0.732
Ed, Less than HS (%)	0.01	0.01	-0.02	0.830
Ed, HS Degree (%)	0.27	0.28	-0.01	0.830
Ed, Two-Year Degree (%)	0.13	0.14	-0.03	0.830
Ed, Bachelor’s Degree (%)	0.38	0.36	0.04	0.830
Ed, Graduate Degree (%)	0.22	0.22	0.00	0.830
Housing, Own w/ Mortgage (%)	0.40	0.40	0.00	0.578
Housing, Own In Full (%)	0.25	0.27	-0.04	0.578
Housing, Rent (%)	0.29	0.28	0.03	0.578
Housing, Neither Own/Rent (%)	0.06	0.05	0.03	0.578
Health Insurance, Yes (%)	0.94	0.95	-0.02	0.456
Vehicle, Yes (%)	0.89	0.89	0.00	0.970
HH Income in 2019, Mean (SD)	84573.6 (73882.8)	87986.5 (68732.6)	-0.02	0.550
HH Income in 2019, Median	65000.0	72000.0		
Liq. Assets pre-COVID, Mean (SD)	25392.0 (58532.2)	28300.3 (59845.3)	-0.02	0.533
Liq. Assets pre-COVID, Median	4450.0	6000.0		
Bank Account, Yes (%)	0.97	0.97	0.02	0.624
Credit Cards, 0 (%)	0.10	0.10	0.00	0.971
Credit Cards, 1 (%)	0.17	0.18	-0.01	0.971
Credit Cards, 2 (%)	0.23	0.23	-0.01	0.971
Credit Cards, 3+ (%)	0.51	0.50	0.02	0.971
Emp., Self-Emp. Full-Time (%)	0.07	0.07	0.02	0.557
Emp., Self-Emp. Part-Time (%)	0.04	0.03	0.02	0.557
Emp., Wage/Salary Full-Time (%)	0.46	0.46	0.02	0.557
Emp., Wage/Salary Part-Time (%)	0.11	0.10	0.03	0.557
Emp., Unemployed (%)	0.14	0.14	-0.01	0.557
Emp., Retired/Disabled (%)	0.18	0.20	-0.06	0.557
Partner Emp., Self-Emp. Full-Time (%)	0.05	0.01	0.02	0.904
Partner Emp., Self-Emp. Part-Time (%)	0.02	0.41	0.03	0.786
Partner Emp., Wage/Salary Full-Time (%)	0.27	0.28	-0.02	0.904
Partner Emp., Wage/Salary Part-Time (%)	0.04	0.05	0.00	0.904
Partner Emp., Unemployed (%)	0.08	0.09	-0.02	0.904
Partner Emp., Retired/Disabled (%)	0.12	0.13	-0.02	0.904
Partner Emp., Single (%)	0.42	0.41	0.03	0.904
Region, Midwest	0.21	0.21	0.00	0.902
Region, Northeast	0.19	0.20	-0.03	0.902
Region, South	0.35	0.35	0.02	0.902
Region, West	0.24	0.23	0.02	0.902
Region, Other	0.01	0.01	-0.01	0.902
Observations	1358	3398		

Table 3: Financial Distress Outcomes, by Gig Employment Status (Propensity Score Weighted)

Outcome	Sample %	Gig Worker	Non-Gig Worker	p-value
Skipped Bills, Past 3 Months	0.12	0.21	0.08	0.000
Behind on Credit Card, Now	0.08	0.18	0.04	0.000
Unpaid Credit Card Balance, Now	0.30	0.33	0.28	0.006
Lost Job/Income due to COVID-19	0.29	0.40	0.24	0.000
Skipped Housing, Past 3 Months	0.07	0.15	0.15	0.000
Evicted, Past 3 Months	0.03	0.09	0.01	0.000
Skipped Medical Care, Past 3 Months	0.10	0.20	0.06	0.000
Food Insecurity, Past 3 Months	0.25	0.40	0.19	0.000
Weighted Observations	4756	1358	3398	

Table 4: Linear Probability Regressions of Household Hardship on Gig Work

Notes: Suppressed demographic controls include age, gender, marital/partner status, and education. Suppressed financial controls include spousal employment, health insurance, homeownership, vehicle ownership, and bank account ownership. Suppressed geographic controls include Census region. * p < 0.05; ** p < 0.01; *** p < 0.001.

	Model 1	Model 2	Model 3	Model 4
	Lost Job/Income, COVID	Skipped Bills, past 3 months	Behind on CC, Now	Unpaid CC Balance, Now
Gig Employment (Ref. = Non-Gig Worker)				
Gig Worker	0.082***	0.094***	0.090***	0.043**
	(0.016)	(0.011)	(0.010)	(0.015)
Employment Status (Ref. = Self-Employed Full-Time)				
Self-Employed Part-Time	0.082	-0.111**	-0.132***	-0.153***
	(0.051)	(0.036)	(0.031)	(0.042)
Wage+Salary Full-Time	-0.168***	-0.109***	-0.131***	-0.089**
	(0.032)	(0.025)	(0.024)	(0.030)
Wage+Salary Part-Time	0.094*	-0.087**	-0.112***	-0.098**
	(0.041)	(0.032)	(0.028)	(0.035)
Unemployed	-0.189***	-0.069*	-0.105***	-0.118***
	(0.037)	(0.031)	(0.027)	(0.033)
Liquid Asset Quartile (Ref. = 1st Quartile, $0 - $2,000)				
2nd Quartile ($2,001 - $8,250)	0.053*	-0.045*	-0.055***	-0.053*
	(0.021)	(0.017)	(0.015)	(0.022)
3rd Quartile ($8,251 - $28,900)	0.022	-0.113***	-0.108***	-0.189***
	(0.022)	(0.014)	(0.013)	(0.022)
4th Quartile ($28,901+)	-0.005	-0.101***	-0.096***	-0.297***
	(0.024)	(0.014)	(0.013)	(0.022)
Race/Ethnicity (Ref. = White)				
Black	-0.031	0.011	0.036	0.108***
	(0.026)	(0.020)	(0.019)	(0.027)
Asian	-0.018	-0.013	0.015	-0.088**
	(0.039)	(0.019)	(0.021)	(0.030)
Hispanic	0.006	0.012	-0.004	0.038
	(0.021)	(0.017)	(0.014)	(0.021)
Other Race	0.008	0.023	-0.047**	0.036
	(0.016)	(0.012)	(0.010)	(0.016)
Number of Children (Ref. = 0 Children)				
1 Child	0.020	0.055**	0.066***	0.057*
	(0.023)	(0.018)	(0.016)	(0.023)
2 Children	0.009	0.100***	0.103***	0.071**
	(0.028)	(0.022)	(0.019)	(0.025)
3+ Children	-0.014	0.079*	0.071*	0.069
	(0.040)	(0.035)	(0.030)	(0.038)
Other Controls				
Demographic	Yes	Yes	Yes	Yes
Financial	Yes	Yes	Yes	Yes
Geographic	Yes	Yes	Yes	Yes
Observations	4,756	4,756	4,756	4,756
R-squared	0.122	0.152	0.144	0.213

Table 5: Linear Probability Regressions of Household Hardship on Gig Work (continued)
Notes: Suppressed demographic controls include age, gender, marital/partner status, and education. Suppressed financial controls include spousal employment, health insurance, homeownership, vehicle ownership, and bank account ownership. Suppressed geographic controls include Census region. * p < 0.05; ** p < 0.01; *** p < 0.001.

	Model 5	Model 6	Model 7	Model 8
	Skipped Housing, past 3 months	Evicted, past 3 months	Skipped Medical, past 3 months	Food Insecurity, past 3 months
Gig Employment (Ref, = Non-Gig Worker)				
Gig Worker	0.069***	0.044***	0.095***	0.122***
	(0.010)	(0.005)	(0.011)	(0.014)
Employment Status (Ref, = Self-Employed Full-Time)				
Self-Employed Part-Time	-0.134***	-0.100***	-0.171***	-0.149***
	(0.031)	(0.021)	(0.034)	(0.044)
Wage+Salary Full-Time	-0.107***	-0.090***	-0.130***	-0.188***
	(0.023)	(0.018)	(0.025)	(0.029)
Wage+Salary Part-Time	-0.111***	-0.080***	-0.113***	-0.164***
	(0.027)	(0.019)	(0.030)	(0.036)
Unemployed	-0.113***	-0.106***	-0.126***	-0.161***
	(0.026)	(0.018)	(0.029)	(0.033)
Liquid Asset Quartile (Ref. = 1st Quartile, $0 - $2,000)				
2nd Quartile ($2,001 - $8,250)	-0.025	-0.027***	-0.043*	-0.083***
	(0.015)	(0.008)	(0.017)	(0.022)
3rd Quartile ($8,251 - $28,900)	-0.082***	-0.045***	-0.091***	-0.158***
	(0.013)	(0.007)	(0.015)	(0.020)
4th Quartile ($28,901+)	-0.072***	-0.043***	-0.099***	-0.174***
	(0.014)	(0.008)	(0.015)	(0.020)
Race/Ethnicity (Ref. = White)				
Black	0.015	-0.000	-0.008	0.016
	(0.018)	(0.009)	(0.020)	(0.027)
Asian	0.019	0.001	0.018	0.086**
	(0.026)	(0.013)	(0.026)	(0.033)
Hispanic	0.014	0.003	0.010	0.071***
	(0.014)	(0.008)	(0.016)	(0.021)
Other Race	-0.002	-0.014	0.026	0.017
	(0.010)	(0.006)	(0.011)	(0.015)
Number of Children (Ref. = 0 Children)				
1 Child	0.068***	0.045***	0.060**	0.073***
	(0.016)	(0.011)	(0.019)	(0.021)
2 Children	0.067***	0.073***	0.051*	0.088***
	(0.018)	(0.015)	(0.020)	(0.024)
3+ Children	0.052	0.043*	0.003	0.036
	(0.029)	(0.022)	(0.029)	(0.037)
Other Controls				
Demographic	Yes	Yes	Yes	Yes
Financial	Yes	Yes	Yes	Yes
Geographic	Yes	Yes	Yes	Yes
Observations	4,756	4,756	4,756	4,756
R-squared	0.106	0.139	0.133	0.219

Table 6: The Interaction between Gig Work, Financial Endowment, and Household Hardship (Linear Probability Models)

Notes: Suppressed demographic controls include age, gender, marital/partner status, and education. Suppressed financial controls include spousal employment, health insurance, homeownership, vehicle ownership, and bank account ownership. Suppressed geographic controls include Census region. * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

	Model 9	Model 10	Model 11	Model 12	Model 13	Model 14	Model 15	Model 16
	Lost Job/Income, COVID	Skipped Bills, past 3 months	Behind on CC, Now	Unpaid CC Balance, Now	Skipped Housing, past 3mo	Evicted, past 3mo	Skipped Medical, past 3mo	Food Insecurity, past 3mo
Gig Employment (Ref. = Non-Gig Worker)								
Gig Worker	0.116***	0.131***	0.122***	0.029	0.110***	0.075***	0.147***	0.169***
	(0.026)	(0.024)	(0.020)	(0.026)	(0.021)	(0.012)	(0.023)	(0.027)
Liquid Asset Quartile (Ref. = 1st Quartile)								
2nd Quartile ($2,001 - $8,250)	0.055*	-0.038*	-0.040**	-0.048*	-0.007	-0.006	-0.015	-0.066**
	(0.022)	(0.016)	(0.012)	(0.023)	(0.013)	(0.007)	(0.015)	(0.021)
3rd Quartile ($8,251 - $28,900)	0.066**	-0.078***	-0.075***	-0.225***	-0.045***	-0.020**	-0.052***	-0.132***
	(0.023)	(0.014)	(0.011)	(0.021)	(0.012)	(0.007)	(0.013)	(0.020)
4th Quartile ($28,901+)	0.025	-0.057***	-0.069***	-0.295***	-0.035**	-0.018*	-0.046***	-0.108***
	(0.024)	(0.014)	(0.011)	(0.021)	(0.013)	(0.007)	(0.013)	(0.020)
Gig Worker-Liquid Asset Interaction								
Gig*2Q Liq. Assets	-0.003	-0.013	-0.030	-0.011	-0.039	-0.044**	-0.057	-0.034
	(0.043)	(0.036)	(0.028)	(0.044)	(0.030)	(0.016)	(0.034)	(0.044)
Gig*3Q Liq. Assets	-0.091*	-0.071*	-0.067**	0.075	-0.076**	-0.051***	-0.080**	-0.051
	(0.042)	(0.029)	(0.025)	(0.041)	(0.024)	(0.014)	(0.029)	(0.038)
Gig*4Q Liq. Assets	-0.062	-0.090***	-0.057*	-0.003	-0.077***	-0.051***	-0.108***	-0.136***
	(0.033)	(0.028)	(0.016)	(0.023)	(0.024)	(0.011)	(0.026)	(0.032)
Other Controls								
Demographic	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Financial	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Geographic	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4756	4756	4756	4756	4756	4756	4756	4756
R-squared	0.124	0.156	0.146	0.214	0.110	0.143	0.137	0.222

Table 7: The Interaction between Gig Work, Children, and Household Hardship (Linear Probability Models)

Notes: Suppressed demographic controls include age, gender, marital/partner status, and education. Suppressed financial controls include spousal employment, health insurance, homeownership, vehicle ownership, and bank account ownership. Suppressed geographic controls include Census region. * p < 0.05; ** p < 0.01; *** p < 0.001.

	Model 17	Model 18	Model 19	Model 20	Model 21	Model 22	Model 23	Model 24
	Lost Job/Income, COVID	Skipped Bills, past 3mo	Behind on CC, Now	Unpaid CC Balance, Now	Skipped Housing, past 3mo	Evicted, past 3mo	Skipped Medical, past 3mo	Food Insecurity, past 3mo
Gig Employment (Ref. = Non-Gig Worker)								
Gig Worker	0.075***	0.066***	0.060***	0.017	0.046***	0.016***	0.071***	0.098***
	(0.019)	(0.013)	(0.010)	(0.018)	(0.010)	(0.004)	(0.012)	(0.017)
Number of Children (Ref. = 0 Children)								
1 Child	0.006	0.022	0.015	0.022	0.025	-0.007	0.007	0.048
	(0.027)	(0.017)	(0.014)	(0.023)	(0.014)	(0.005)	(0.017)	(0.025)
2 Children	-0.004	0.031	0.026	0.010	0.023	0.015	0.003	0.027
	(0.033)	(0.024)	(0.019)	(0.030)	(0.021)	(0.017)	(0.022)	(0.029)
3+ Children	-0.027	0.000	0.047	-0.010	0.006	0.001	-0.000	-0.039
	(0.047)	(0.032)	(0.032)	(0.045)	(0.026)	(0.015)	(0.031)	(0.042)
Gig-Child Interaction								
Gig*1 Child	0.029	0.070*	0.104**	0.071	0.090**	0.108***	0.109**	0.054
	(0.045)	(0.035)	(0.032)	(0.043)	(0.032)	(0.022)	(0.036)	(0.042)
Gig*2 Children	0.027	0.140***	0.155***	0.124**	0.090*	0.117***	0.097**	0.125**
	(0.051)	(0.041)	(0.036)	(0.046)	(0.035)	(0.031)	(0.037)	(0.045)
Gig*3+ Children	0.026	0.160*	0.051	0.160*	0.093	0.088*	0.009	0.153*
	(0.078)	(0.066)	(0.058)	(0.073)	(0.056)	(0.041)	(0.055)	(0.070)
Other Controls								
Demographic	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Financial	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Geographic	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4756	4756	4756	4756	4756	4756	4756	4756
R-squared	0.123	0.158	0.153	0.216	0.111	0.157	0.137	0.222

Table 8: Linear Probability Regression of Household Hardship on Gig Work and Among Self-Employed Households

Notes: Suppressed demographic controls include age, gender, marital/partner status, and education. Suppressed financial controls include spousal employment, health insurance, homeownership, vehicle ownership, and bank account ownership. Suppressed geographic controls include Census region. * p < 0.05; ** p < 0.01; *** p < 0.001.

	Model 25	Model 26	Model 27	Model 28	Model 29	Model 30	Model 31	Model 32
	Lost Job/Income, COVID	Skipped Bills, past 3months	Behind on CC, Now	Unpaid CC Balance, Now	Skipped Housing, past 3 months	Evicted, past 3 months	Skipped Medical, past 3 months	Food Insecurity, past 3 months
Gig Employment (Ref. = Non-Gig Worker)								
Gig Worker	0.104*	0.147***	0.223***	0.142***	0.132***	0.132***	0.176***	0.187***
	(0.042)	(0.031)	(0.027)	(0.036)	(0.028)	(0.021)	(0.031)	(0.035)
Liquid Asset Quartile (Ref. = 1st Quartile, $0 - $2,000)								
2nd Quartile ($2,001 - $8,250)	0.012	-0.037	-0.027	-0.046	-0.037	-0.059	-0.068	-0.076
	(0.058)	(0.047)	(0.041)	(0.053)	(0.043)	(0.033)	(0.046)	(0.052)
3rd Quartile ($8,251 - $28,900)	-0.001	-0.159***	-0.187***	-0.196***	-0.157***	-0.151***	-0.152***	-0.164**
	(0.060)	(0.041)	(0.034)	(0.054)	(0.036)	(0.026)	(0.043)	(0.052)
4th Quartile ($28,901+)	-0.004	-0.126**	-0.152***	-0.386***	-0.129**	-0.117***	-0.187***	-0.196***
	(0.062)	(0.047)	(0.037)	(0.052)	(0.041)	(0.034)	(0.045)	(0.051)
Race/Ethnicity (Ref. = White)								
Black	-0.117	0.131*	0.108*	0.172**	0.037	-0.002	0.052	0.117*
	(0.065)	(0.054)	(0.046)	(0.059)	(0.044)	(0.034)	(0.049)	(0.057)
Asian	-0.023	0.008	0.164**	0.007	0.012	0.044	0.074	0.193**
	(0.080)	(0.053)	(0.056)	(0.066)	(0.049)	(0.052)	(0.062)	(0.065)
Hispanic	-0.004	0.029	0.020	0.087	0.053	-0.007	0.095*	0.052
	(0.056)	(0.043)	(0.038)	(0.050)	(0.040)	(0.025)	(0.045)	(0.048)
Other Race	-0.009	-0.112*	-0.042	0.068	-0.089*	-0.031	-0.014	-0.027
	(0.123)	(0.055)	(0.042)	(0.103)	(0.036)	(0.027)	(0.063)	(0.104)
Number of Children (Ref. = 0 Children)								
1 Child	0.088	0.129**	0.148***	0.143**	0.112**	0.093**	0.157**	0.185***
	(0.056)	(0.045)	(0.043)	(0.050)	(0.040)	(0.033)	(0.049)	(0.048)
2 Children	0.126	0.202***	0.288***	0.208***	0.174**	0.166***	0.188**	0.222***
	(0.068)	(0.061)	(0.054)	(0.058)	(0.054)	(0.050)	(0.059)	(0.057)
3+ Children	-0.119	0.100	0.026	0.033	0.106	0.043	0.052	0.128
	(0.098)	(0.074)	(0.063)	(0.079)	(0.078)	(0.050)	(0.078)	(0.075)
Other Controls								
Demographic	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Geographic	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	676	676	676	676	676	676	676	676
R-squared	0.101	0.226	0.356	0.293	0.257	0.328	0.257	0.334

Figure 1: Probability of Experiencing Economic Hardship Among Gig and Non-Gig Workers

Note: These results correspond to the regression results in Table 4. The bracketed lines on each plot correspond to the 95 percent confidence interval of the point estimate.

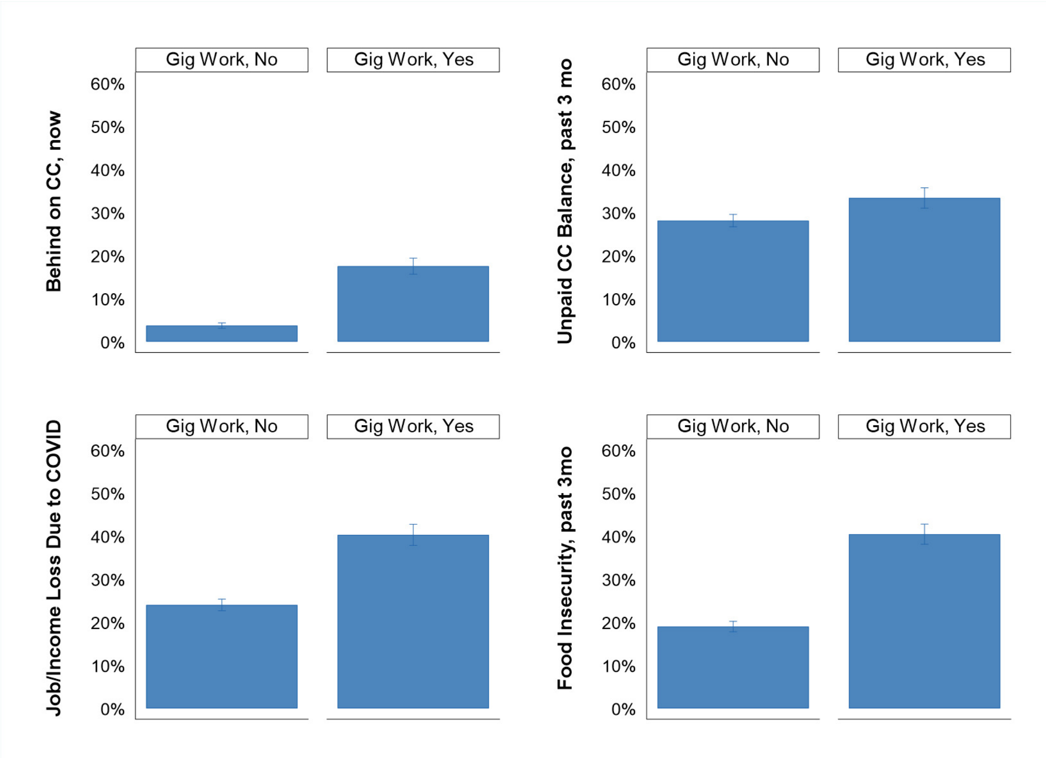

Figure 2: Probability of Experiencing Economic Hardship Among Gig and Non-Gig Workers (continued)

Note: These results correspond to the regression results in Table 4. The bracketed lines on each plot correspond to the 95 percent confidence interval of the point estimate.

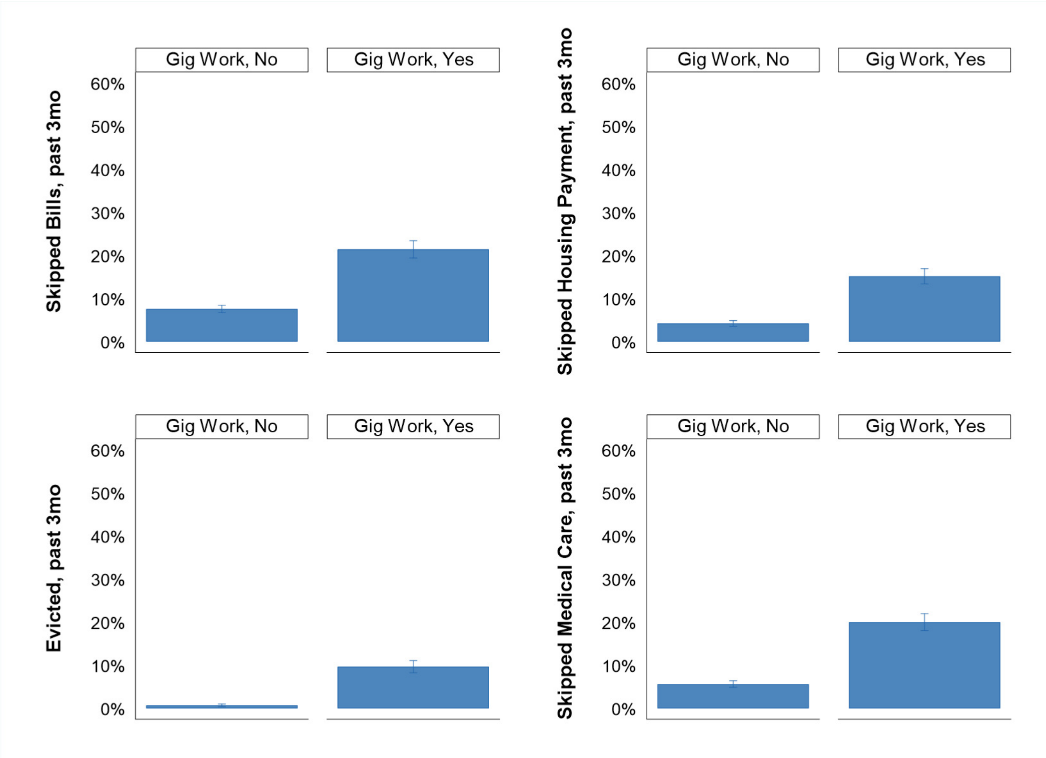

Figure 3: Probability of Experiencing Economic Hardship Among Gig and Non-Gig Workers by Liquid Asset Endowment

Note: These results correspond to the regression results in Table 5. The bracketed lines on each plot correspond to the 95 percent confidence interval of the point estimate.

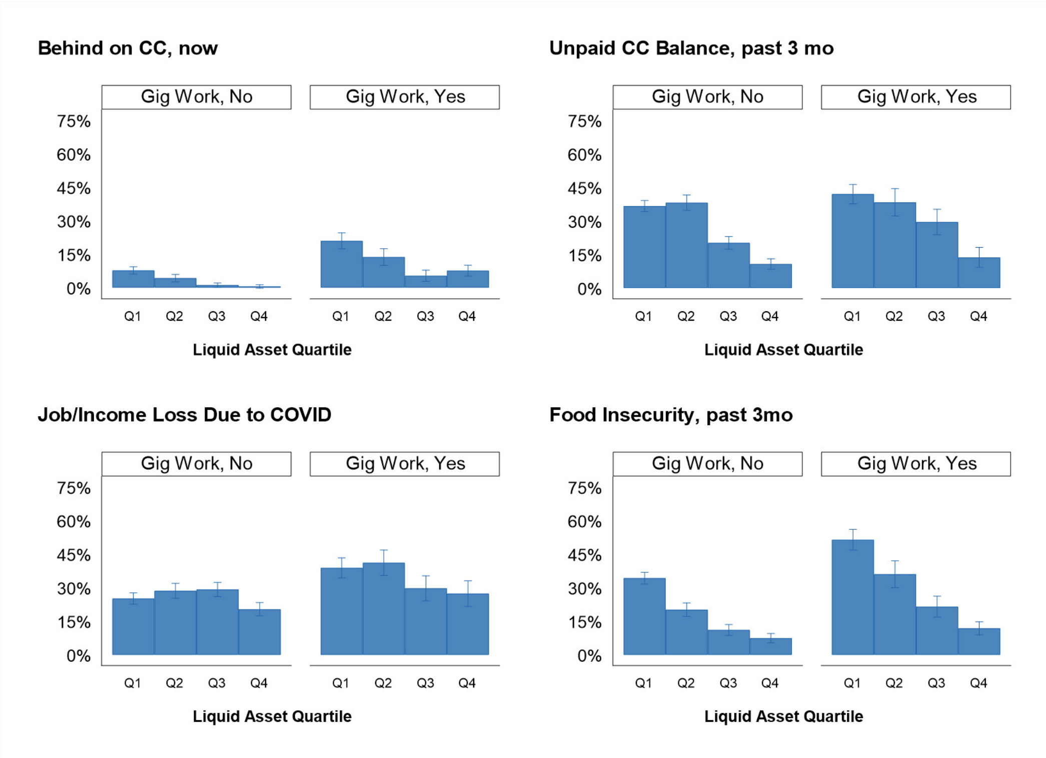

Figure 4: Probability of Experiencing Economic Hardship Among Gig and Non-Gig Workers by Liquid Asset Endowment (continued)

Note: These results correspond to the regression results in Table 5. The bracketed lines on each plot correspond to the 95 percent confidence interval of the point estimate.

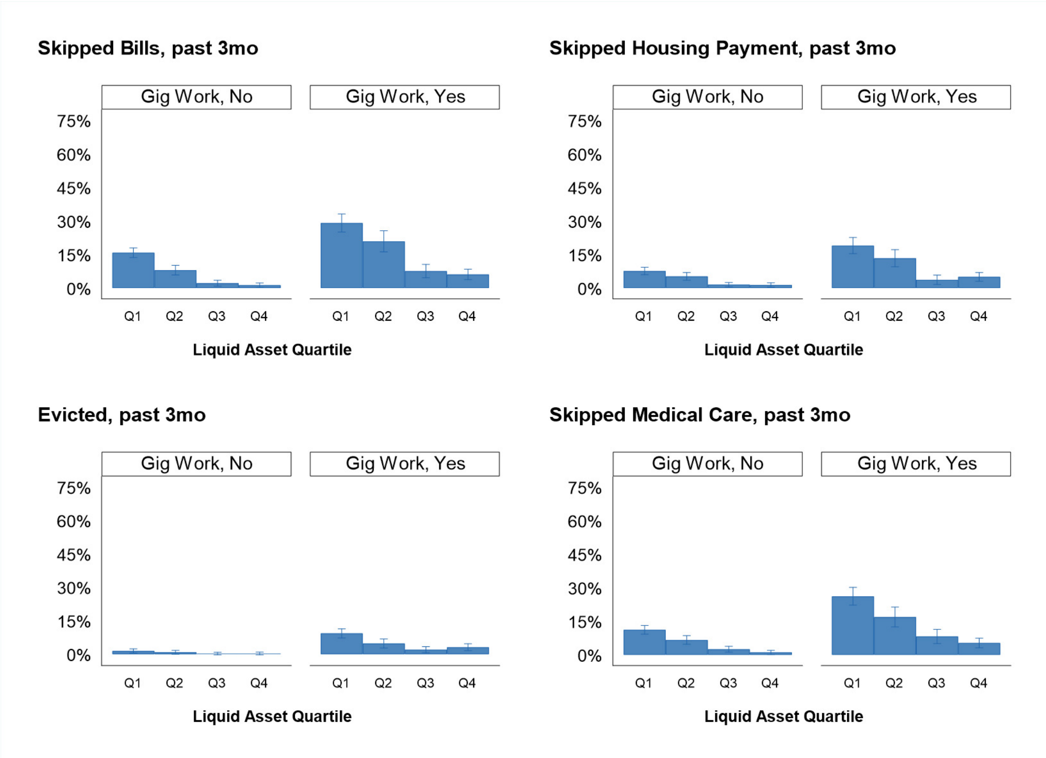

Figure 5: Probability of Experiencing Economic Hardship Among Gig and Non-Gig Workers by Number of Dependent Children in the Household

Note: These results correspond to the regression results in Table 6. The bracketed lines on each plot correspond to the 95 percent confidence interval of the point estimate.

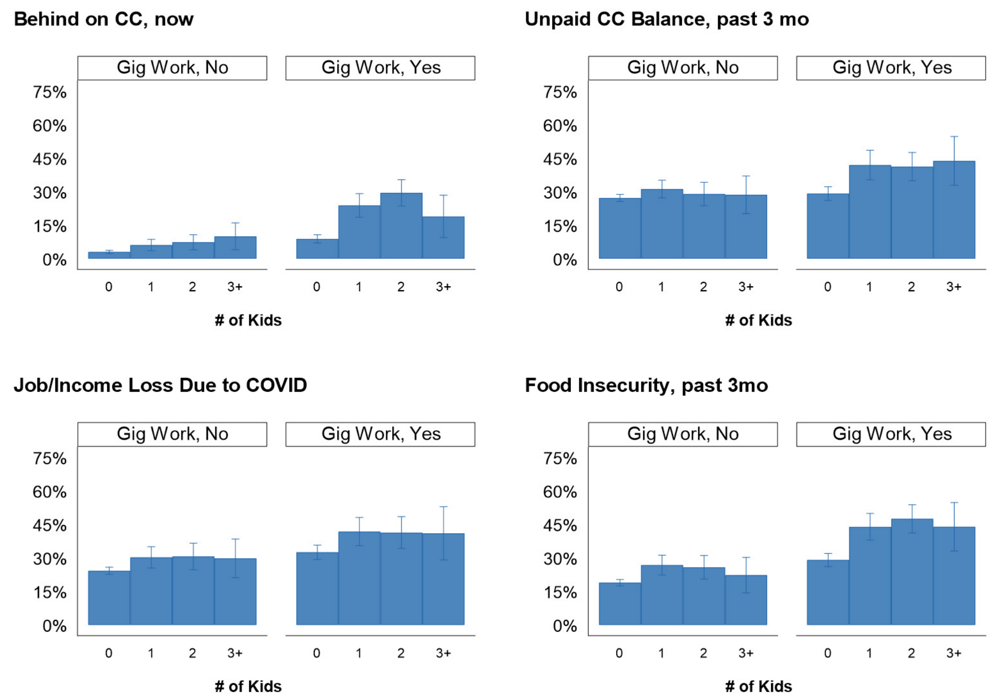

Figure 6: Probability of Experiencing Economic Hardship Among Gig and Non-Gig Workers by Number of Dependent Children in the Household (continued)

Note: These results correspond to the regression results in Table 6. The bracketed lines on each plot correspond to the 95 percent confidence interval of the point estimate.

APPENDIX

Table 9: Gig Work and Household Hardship (Logistic Regression)

Notes: Suppressed demographic controls include age, gender, and education. Suppressed financial controls include household income in 2019, and health insurance. Suppressed geographic controls include Census region. * p < 0.05; ** p < 0.01; *** p < 0.001.

	Model 1	Model 2	Model 3	Model 4
	Lost Job/Income, COVID	Skipped Bills, past 3mo	Behind on CC, Now	Unpaid CC Balance, Now
Gig Employment (Ref. = Non-Gig Worker)				
Gig Worker	1.540***	2.644***	3.795***	1.272**
	(0.124)	(0.293)	(0.510)	(0.107)
Employment Status (Ref. = Self-Employed Full-Time)				
Self-Employed Part-Time	1.318	0.395***	0.297***	0.442***
	(0.280)	(0.109)	(0.100)	(0.098)
Wage+Salary Full-Time	0.434***	0.401***	0.266***	0.599***
	(0.057)	(0.071)	(0.049)	(0.082)
Wage+Salary Part-Time	1.289	0.412***	0.300***	0.497***
	(0.213)	(0.097)	(0.078)	(0.089)
Unemployed	0.375***	0.503**	0.309***	0.397***
	(0.061)	(0.106)	(0.071)	(0.066)
Not in Labor Force	0.154***	0.124***	0.118***	0.241***
	(0.035)	(0.041)	(0.054)	(0.047)
Liquid Asset Quartile (Ref. = 1st Quartile, $0 - $2,000)				
2nd Quartile ($2,001 - $8,250)	1.307*	0.702*	0.591**	0.969
	(0.140)	(0.099)	(0.101)	(0.102)
3rd Quartile ($8,251 - $28,900)	1.073	0.262***	0.217***	0.520***
	(0.123)	(0.053)	(0.053)	(0.061)
4th Quartile ($28,901+)	0.889	0.226***	0.266***	0.210***
	(0.116)	(0.049)	(0.059)	(0.031)
Race/Ethnicity (Ref. = White)				
Black	0.825	1.194	1.575	1.596***
	(0.122)	(0.212)	(0.367)	(0.221)
Asian/Other	0.983	1.128	1.015	0.816
	(0.171)	(0.280)	(0.274)	(0.134)
Hispanic	1.086	1.256	1.128	1.372**
	(0.120)	(0.199)	(0.216)	(0.149)
Number of Children (Ref. = 0 Children)				
1 Child	1.217	1.726***	2.332***	1.481***
	(0.134)	(0.271)	(0.412)	(0.168)
2 Children	1.212	2.566***	3.139***	1.537***
	(0.151)	(0.412)	(0.546)	(0.191)
3+ Children	1.061	2.249**	2.549**	1.560*
	(0.203)	(0.597)	(0.748)	(0.301)
Other Controls				
Demographic	Yes	Yes	Yes	Yes
Financial	Yes	Yes	Yes	Yes
Geographic	Yes	Yes	Yes	Yes
Observations	4,756	4,756	4,756	4,756

Table 10: Gig Work and Household Hardship (Logistic Regression, Continued)

Notes: Suppressed demographic controls include age, gender, and education. Suppressed financial controls include household income in 2019, and health insurance. Suppressed geographic controls include Census region. * p < 0.05; ** p < 0.01; *** p < 0.001.

	Model 5	Model 6	Model 7	Model 8
	Skipped Housing, past 3 months	Evicted, past 3 months	Skipped Medical, past 3 months	Food Insecurity, past 3 months
Gig Employment (Ref. = Non-Gig Worker)				
Gig Worker	2.819***	7.025***	3.046***	2.126***
	(0.382)	(1.953)	(0.364)	(0.187)
Employment Status (Ref. = Self-Employed Full-Time)				
Self-Employed Part-Time	0.246***	0.193***	0.198***	0.382***
	(0.089)	(0.094)	(0.072)	(0.090)
Wage+Salary Full-Time	0.305***	0.164***	0.291***	0.316***
	(0.057)	(0.044)	(0.051)	(0.047)
Wage+Salary Part-Time	0.250***	0.183***	0.311***	0.316***
	(0.071)	(0.073)	(0.074)	(0.062)
Unemployed	0.278***	0.075***	0.309***	0.343***
	(0.065)	(0.031)	(0.064)	(0.059)
Not in Labor Force	0.123***	0.247	0.254***	0.290***
	(0.054)	(0.233)	(0.088)	(0.068)
Liquid Asset Quartile (Ref. = 1st Quartile, $0 - $2,000)				
2nd Quartile ($2,001 - $8,250)	0.722	0.448**	0.644**	0.586***
	(0.128)	(0.133)	(0.104)	(0.070)
3rd Quartile ($8,251 - $28,900)	0.210***	0.201***	0.320***	0.356***
	(0.055)	(0.072)	(0.067)	(0.047)
4th Quartile ($28,901+)	0.252***	0.220***	0.201***	0.249***
	(0.062)	(0.077)	(0.047)	(0.036)
Race/Ethnicity (Ref. = White)				
Black	1.368	1.260	1.001	1.229
	(0.321)	(0.531)	(0.212)	(0.196)
Asian/Other	1.410	1.407	1.469	1.703**
	(0.451)	(0.667)	(0.394)	(0.298)
Hispanic	1.379	1.676	1.263	1.671***
	(0.262)	(0.455)	(0.225)	(0.204)
Number of Children (Ref. = 0 Children)				
1 Child	2.333***	4.854***	1.938***	1.548***
	(0.413)	(1.453)	(0.315)	(0.188)
2 Children	2.415***	6.774***	1.916***	1.826***
	(0.454)	(1.942)	(0.329)	(0.246)
3+ Children	2.142*	5.391***	1.253	1.316
	(0.646)	(2.393)	(0.372)	(0.277)
Other Controls				
Demographic	Yes	Yes	Yes	Yes
Financial	Yes	Yes	Yes	Yes
Geographic	Yes	Yes	Yes	Yes
Observations	4,756	4,756	4,756	4,756

Table 11: The Interaction between Gig Work, Financial Endowment, and Household Hardship (Logistic Regression)

Notes: Suppressed demographic controls include age, gender, and education. Suppressed financial controls include household income in 2019, and health insurance. Suppressed geographic controls include Census region. * p < 0.05; ** p < 0.01; *** p < 0.001.

	Model 9	Model 10	Model 11	Model 12	Model 13	Model 14	Model 15	Model 16
	Lost Job/Income, COVID	Skipped Bills, past 3mo	Behind on CC, Now	Unpaid CC Balance, Now	Skipped Housing, past 3months	Evicted, past 3months	Skipped Medical, past 3months	Food Insecurity, past 3mo
Gig Employment (Ref. = Non-Gig Worker)								
Gig Worker	1.827***	2.277***	3.215***	1.231	2.831***	7.578***	2.929***	2.152***
	(0.240)	(0.332)	(0.578)	(0.156)	(0.524)	(2.815)	(0.468)	(0.283)
Liquid Asset Quartile (Ref. = 1st Quartile)								
2nd Quartile ($2,001 - $8,250)	1.342*	0.606**	0.575*	1.086	0.761	0.694	0.698	0.588***
	(0.162)	(0.108)	(0.140)	(0.117)	(0.168)	(0.422)	(0.138)	(0.075)
3rd Quartile ($8,251 - $28,900)	1.385**	0.177***	0.140***	0.421***	0.213***	0.179*	0.259***	0.329***
	(0.168)	(0.055)	(0.058)	(0.052)	(0.070)	(0.148)	(0.077)	(0.050)
4th Quartile ($28,901+)	1.032	0.136***	0.075***	0.207***	0.218***	0.191*	0.134***	0.300***
	(0.142)	(0.050)	(0.040)	(0.032)	(0.083)	(0.157)	(0.056)	(0.054)
Gig Worker-Liquid Asset Interaction								
Gig Worker*2Q Liquid Assets	0.956	1.267	1.048	0.792	0.925	0.590	0.889	0.993
	(0.199)	(0.335)	(0.339)	(0.167)	(0.290)	(0.397)	(0.257)	(0.225)
Gig Worker*3Q Liquid Assets	0.607*	1.774	1.785	1.506	0.976	1.141	1.349	1.138
	(0.133)	(0.718)	(0.902)	(0.330)	(0.455)	(1.035)	(0.524)	(0.278)
Gig Worker*4Q Liquid Assets	0.757	1.998	4.556**	1.033	1.215	1.168	1.707	0.736
	(0.177)	(0.875)	(2.621)	(0.272)	(0.545)	(1.021)	(0.818)	(0.191)
Other Controls								
Demographic	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Financial	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Geographic	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,756	4,756	4,756	4,756	4,756	4,756	4,756	4,756

Table 12: The Interaction between Gig Work, Children, and Household Hardship (Logistic Regression)

Notes: Suppressed demographic controls include age, gender, and education. Suppressed financial controls include household income in 2019, and health insurance. Suppressed geographic controls include Census region. * p < 0.05; ** p < 0.01; *** p < 0.001.

	Model 9	Model 10	Model 11	Model 12	Model 13	Model 14	Model 15	Model 16
	Lost Job/Income, COVID	Skipped Bills, past 3mo	Behind on CC, Now	Unpaid CC Balance, Now	Skipped Housing, past 3months	Evicted, past 3months	Skipped Medical, past 3months	Food Insecurity, past 3mo
Gig Employment (Ref. = Non-Gig Worker)								
Gig Worker	1.516***	2.160***	3.225***	1.103	2.358***	4.330***	2.616***	1.889***
	(0.149)	(0.299)	(0.573)	(0.114)	(0.419)	(1.658)	(0.393)	(0.204)
Number of Children (Ref. = 0 Children)								
1 Child	1.183	1.429	1.791*	1.166	1.782*	0.929	1.364	1.420*
	(0.160)	(0.280)	(0.490)	(0.149)	(0.415)	(0.739)	(0.328)	(0.216)
2 Children	1.183	1.586	2.105*	1.180	1.821	4.992**	1.376	1.337
	(0.197)	(0.405)	(0.633)	(0.191)	(0.629)	(2.963)	(0.419)	(0.245)
3+ Children	1.021	1.243	2.856**	1.132	1.409	3.404	1.377	0.819
	(0.240)	(0.458)	(1.084)	(0.276)	(0.658)	(2.821)	(0.518)	(0.232)
Gig-Child Interaction								
Gig Worker*1 Child	1.056	1.357	1.449	1.610*	1.495	6.532*	1.694	1.178
	(0.228)	(0.396)	(0.502)	(0.356)	(0.490)	(5.524)	(0.541)	(0.280)
Gig Worker*2 Children	1.047	2.163*	1.763	1.678*	1.525	1.460	1.653	1.781*
	(0.255)	(0.704)	(0.641)	(0.406)	(0.629)	(0.959)	(0.611)	(0.479)
Gig Worker*3+ Children	1.075	2.655	0.821	1.876	1.882	1.750	0.848	2.386*
	(0.401)	(1.382)	(0.446)	(0.715)	(1.142)	(1.672)	(0.471)	(1.001)
Other Controls								
Demographic	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Financial	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Geographic	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,756	4,756	4,756	4,756	4,756	4,756	4,756	4,756

Table 13: Gig Work and Household Hardship Among Self-Employed Households
(Linear probability models with additional controls for household employment status)

Notes: Suppressed demographic controls include age, gender, marital/partner status, race/ethnicity, and education. Suppressed financial controls include spousal employment, health insurance, homeownership, vehicle ownership, and bank account ownership. Suppressed geographic controls include Census region.
* p < 0.05; ** p < 0.01; *** p < 0.001.

	Model 1	Model 2	Model 3	Model 4
	Lost Job/Income, COVID	Skipped Bills, past 3mo	Behind on CC, Now	Unpaid CC Balance, Now
Gig Employment (Ref. = Non-Gig Worker)				
Gig Worker	0.109**	0.147***	0.223***	0.138***
	(0.041)	(0.030)	(0.026)	(0.036)
Employment Status (Ref. = Self-Employed Full-Time)				
Self-Employed Part-Time	0.069	-0.108**	-0.107***	-0.142***
	(0.051)	(0.034)	(0.031)	(0.041)
Wage+Salary Full-Time	-0.155*	-0.171**	-0.241***	-0.094
	(0.067)	(0.052)	(0.045)	(0.060)
Wage+Salary Part-Time	-0.163	-0.162	-0.436***	-0.375*
	(0.166)	(0.141)	(0.067)	(0.146)
Unemployed	-0.076	-0.110	-0.076	-0.158
	(0.116)	(0.096)	(0.074)	(0.092)
Not in Labor Force	-0.397*	-0.248***	-0.229***	-0.174
	(0.172)	(0.063)	(0.052)	(0.152)
Spouse/Partner Employment Status (Ref. = Self-Employed Full-Time)				
Self-Employed Part-Time	0.170*	-0.021	0.081	0.061
	(0.077)	(0.055)	(0.051)	(0.065)
Wage+Salary Full-Time	-0.069	-0.043	-0.071	-0.077
	(0.073)	(0.055)	(0.054)	(0.064)
Wage+Salary Part-Time	0.024	-0.129	-0.122	-0.257*
	(0.108)	(0.081)	(0.065)	(0.101)
Unemployed	-0.098	-0.048	-0.044	-0.117
	(0.095)	(0.080)	(0.067)	(0.084)
Not in Labor Force	-0.088	-0.157**	-0.081	0.022
	(0.133)	(0.059)	(0.050)	(0.104)
Liquid Asset Quartile (Ref. = 1st Quartile, $0 - $2,000)				
2nd Quartile ($2,001 - $8,250)	0.015	-0.022	-0.015	-0.049
	(0.057)	(0.046)	(0.039)	(0.051)
3rd Quartile ($8,251 - $28,900)	0.009	-0.140***	-0.167***	-0.178**
	(0.060)	(0.040)	(0.034)	(0.054)
4th Quartile ($28,901+)	0.009	-0.108*	-0.142***	-0.377***
	(0.063)	(0.045)	(0.037)	(0.052)
Number of Children (Ref. = 0 Children)				
1 Child	0.043	0.089	0.128**	0.117*
	(0.057)	(0.046)	(0.041)	(0.051)
2 Children	0.086	0.157**	0.263***	0.192***
	(0.069)	(0.058)	(0.053)	(0.057)
3+ Children	-0.157	0.065	0.005	0.032
Other Controls				
Demographic	Yes	Yes	Yes	Yes
Financial	Yes	Yes	Yes	Yes
Geographic	Yes	Yes	Yes	Yes
Observations	676	676	676	676
R-squared	0.101	0.226	0.356	0.293

Table 14: Gig Work and Household Hardship Among Self-Employed Households
(Linear probability models with additional controls for household employment status)

Notes: Suppressed demographic controls include age, gender, marital/partner status, race/ethnicity, and education. Suppressed financial controls include spousal employment, health insurance, homeownership, vehicle ownership, and bank account ownership. Suppressed geographic controls include Census region. * p < 0.05; ** p < 0.01; *** p < 0.001.

	Model 5	Model 6	Model 7	Model 8
	Skipped Housing, past 3 months	Evicted, past 3 months	Skipped Medical, past 3 months	Food Insecurity, past 3 months
Gig Employment (Ref. = Non-Gig Worker)				
Gig Worker	0.132***	0.130***	0.176***	0.188***
	(0.027)	(0.020)	(0.031)	(0.034)
Employment Status (Ref. = Self-Employed Full-Time)				
Self-Employed Part-Time	-0.126***	-0.081***	-0.164***	-0.142**
	(0.030)	(0.021)	(0.033)	(0.045)
Wage+Salary Full-Time	-0.213***	-0.169***	-0.170**	-0.248***
	(0.049)	(0.042)	(0.052)	(0.055)
Wage+Salary Part-Time	-0.142	-0.214***	-0.236*	-0.330*
	(0.115)	(0.060)	(0.096)	(0.145)
Unemployed	-0.243***	-0.232***	-0.157	-0.176*
	(0.069)	(0.041)	(0.108)	(0.087)
Not in Labor Force	-0.211***	-0.150***	-0.205***	-0.248**
	(0.057)	(0.043)	(0.061)	(0.078)
Spouse/Partner Employment Status (Ref. = Self-Employed Full-Time)				
Self-Employed Part-Time	-0.070	-0.082*	-0.101*	-0.001
	(0.046)	(0.033)	(0.050)	(0.059)
Wage+Salary Full-Time	-0.185***	-0.134**	-0.101	-0.115*
	(0.050)	(0.042)	(0.055)	(0.058)
Wage+Salary Part-Time	-0.170*	-0.185***	-0.157	0.030
	(0.075)	(0.042)	(0.083)	(0.103)
Unemployed	-0.152*	-0.176**	-0.085	-0.094
	(0.070)	(0.058)	(0.077)	(0.076)
Not in Labor Force	-0.030	-0.120**	-0.099	-0.101
	(0.108)	(0.039)	(0.054)	(0.080)
Liquid Asset Quartile (Ref. = 1st Quartile, $0 - $2,000)				
2nd Quartile ($2,001 - $8,250)	-0.025	-0.049	-0.052	-0.059
	(0.043)	(0.031)	(0.045)	(0.051)
3rd Quartile ($8,251 - $28,900)	-0.125***	-0.125***	-0.130**	-0.147**
	(0.034)	(0.024)	(0.042)	(0.052)
4th Quartile ($28,901+)	-0.114**	-0.103**	-0.167***	-0.179***
	(0.039)	(0.032)	(0.044)	(0.050)
Number of Children (Ref. = 0 Children)				
1 Child	0.089*	0.075*	0.132**	0.170***
	(0.041)	(0.032)	(0.051)	(0.050)
2 Children	0.147**	0.145**	0.156**	0.198***
	(0.050)	(0.046)	(0.055)	(0.056)
3+ Children	0.080	0.023	0.022	0.094
Other Controls				
Demographic	Yes	Yes	Yes	Yes
Financial	Yes	Yes	Yes	Yes
Geographic	Yes	Yes	Yes	Yes
Observations	676	676	676	676
R-squared	0.257	0.328	0.257	0.334