Gig Work and the Pandemic: Looking for Good Pay from Bad Jobs During the COVID-19 Crisis

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Abstract
COVID-19 led to work hour reductions and layoffs for many Americans with wage/salary jobs. Some gig work, however, which is usually considered precarious, remained available. We examine whether people doing gig microtasks right before the pandemic increased their microtask hours during COVID-19 and whether those changes helped them financially. Using data from workers on Amazon’s Mechanical Turk platform from February, March, and April of 2020, we find that roughly one third of existing workers increased their microtask hours. Increases were larger for people who lost household income or wage/salary hours. Spending more time on microtasks, however, did little to help workers financially. Furthermore, the people most reliant on microtasks before the pandemic had worse financial outcomes than others. In short, even though microtask work might seem like a good way for people to recoup lost income during the pandemic, it was of limited utility even for the experienced workers in our sample.
Keywords
gig, platform, COVID-19, pandemic, Amazon Mechanical Turk, MTurk, microtask, crowdwork

Gig work does not have the best reputation. Microtask platforms like Amazon’s Mechanical Turk (MTurk), freelance platforms like Upwork, and transportation platforms like Instacart and Uber may offer flexible work locations, schedule control, and the opportunity to supplement primary earnings, but they fall short on features commonly seen as defining elements of “good” jobs: high pay, fringe benefits, stable hours, job security, and other workplace protections that reduce uncertainty (Kalleberg, 2018). Gig work is thus precarious. It may appeal to workers who prioritize flexibility or want supplemental income, but under normal circumstances, it is often considered a “bad” work arrangement compared to traditional wage/salary work (Kalleberg & Dunn, 2016).

However, in the context of the COVID-19 crisis, gig work’s drawbacks may have been diluted or even outweighed by some of its advantages. COVID-19 posed a public crisis unprecedented in recent history. By the end of 2020, Americans reported around 20 million COVID-19 cases, causing a massive health crisis. Furthermore, even for workers who managed to avoid getting sick, COVID-19 created crises related to mobility and finances. Lockdowns and the threat of infection created a need for remote work and schedules that accommodated heightened childcare needs and virtual school. COVID-19 also led to a huge spike in the unemployment rate, creating a financial crisis. As these different crises unfolded, microtask work, which is considered highly precarious under normal circumstances, may have been unusually appealing and useful, at least in theory.

Workers doing microtasks on platforms like MTurk just before the pandemic were in a unique position to benefit from that work. They could potentially: avoid the virus by working from home, accommodate changes in family schedules and childcare, and begin to recoup lost household income through a platform they already used. These workers may therefore have been in a good position to weather the early months of COVID-19. Many workers whose entire earnings came from wage/salary jobs, in contrast, suffered serious financial hardships during the pandemic (Karpman et al., 2020). We examine the extent to which people working on microtask platforms increased their hours and whether that helped them financially.

We are not suggesting that microtask work suddenly became a “good” job during the pandemic, but it may have provided enough income to serve as a financial life raft. This paper addresses that possibility by examining two
research questions: 1) How did workers registered on MTurk prior to the pandemic alter their microtask hours when the pandemic hit? 2) To what extent did microtask work help these workers financially during the pandemic? To answer these questions, we draw on a new panel study that surveyed a large sample of Americans who were active on MTurk in February, March, and April of 2020.

We make both empirical and conceptual contributions to the literature. Most existing literature on paid work and the pandemic has focused on wage/salary jobs (e.g., Fan & Moen, 2021), and the little research addressing gig work and financial crises has been largely about rideshare platforms. We therefore supplement these literatures by examining how COVID-19 affected the use and utility of microtask work. This question is particularly important because microtask work was one of the most safe, flexible, and accessible forms of gig work during the pandemic. We also encourage a new perspective on gig work by highlighting a frequently overlooked link between the gig economy and the conventional economy: the people who work in both. Furthermore, we show how dependance on gig work shapes its risks and opportunities (Schor et al., 2020) by comparing people who were working in both economies when the pandemic hit to those doing gig work exclusively. This comparison contributes to broader theoretical debates around gig work in a “risk society.”

**Gig Work as Precarious Work**

Precarity is at the heart of many sociological frameworks for understanding contemporary social life. Bourdieu (1998) considered précarité as a fundamental source of social problems in the twenty-first century, including the “exploitation” of work. Giddens (1991) suggests the modern world is characterized by great “ontological insecurity” as actors increasingly realize that their rituals are conditional and arbitrary. Beck (1992, 2000) and Hacker (2006) highlight how modernization, globalization, and individualization have given rise to a “risk society” in which individuals are now responsible for navigating and managing myriad risks once handled by and shared among governments and organizations/corporations. This risk society is characterized by the rise of “precarious work” in which workers receive fewer protections/benefits and must accept greater risks of insecurity, uncertainty, and instability (Kalleberg, 2018; Kalleberg & Vallas, 2018).

Gig work is often considered the “epitome” (Ravenelle et al., 2021) or “apogee” (Schor et al., 2020) of precarious work. Gig work comes in many forms. It can be low- or high-skill, allow much or little worker control, and may or may not involve face-to-face interactions (Kalleberg & Dunn, 2016; Spreitzer et al., 2017). Gig workers might write computer code for
clients found on freelancer.com, drive for Uber, do yardwork through TaskRabbit, or deliver groceries for Instacart. The microtask workers we study can do their work from anywhere, at any time, in small or large quantities, and they do not need a car or specialized skills.

Underlying the diversity of gig work, however, are two defining characteristics: gig work depends on digital platforms or apps and is organized around “gigs,” the short-term engagements between workers and employers/customers (Kalleberg & Dunn, 2016). Although the digital component of gig work is relatively new, short-term, informal engagements between workers and employers/customers were actually quite common before 1950 (Kalleberg & Dunn, 2016). Gig work is thus a new incarnation of a very old approach to employment.

It is also important to recognize that the risks and rewards of gig work are highly variable and contextual. It can be attractive to students, homemakers, retirees, and others who prioritize flexibility over job security or fringe benefits (Kalleberg, 2018). The risks and rewards also depend on the kind of gig work. High-skill work through platforms like freelancer.com tends to pay more than microtask work through platforms like MTurk (Kalleberg & Dunn, 2016; Vallas & Schor, 2020). Furthermore, the risks and rewards depend on whether gig work is combined with other types of work (Schor et al., 2020). Finally, the risks and rewards of different gig arrangements depend on context. The pandemic heightened the need for well-paid gig work, but it also made many types of gig work risky.

Changes in Microtask Work During COVID-19: A Pandemic Pivot?

Few studies have examined how people doing gig work altered their gig hours in response to COVID-19 (but see Ravenelle et al., 2021). We are not aware of any studies that examine how individuals doing gig work on microtask platforms altered those hours during the pandemic. Furthermore, countervailing pressures make it hard to predict if there would be a pivot toward or away from microtask work at the aggregate level.

There are some good reasons to expect an increase in the average hours spent on microtask platforms amid the public health crisis, mobility crisis, and financial crisis caused by the pandemic. In the wake of the public health crisis, people needed work that did not expose them to the virus. Microtask work met this criterion: workers can access MTurk from home. In the wake of the mobility crisis (e.g., lockdowns, school/daycare closures), people needed flexible schedules that could accommodate new demands of
family life (e.g., children suddenly at home 24/7). Microtask work also met this criterion: MTurk work can be completed at any time in small or large amounts. Furthermore, in the wake of the financial crisis, many people needed ways to compensate for the loss of income in wage/salary jobs. Microtask work also met this criterion: MTurk workers are often paid quickly, and the supply of microtask work was fairly stable during the pandemic (AppJobs, 2020; Moss, 2021). Furthermore, people already doing microtask work before the pandemic were in a particularly good position to maximize the opportunities on such platforms. Existing MTurk workers did not need to request an account, wait three business days for approval, learn to navigate the platform, wait ten more days for the cap on daily tasks to be removed, or develop strategies for finding good-paying tasks.

There are also good reasons, however, to expect that many people would maintain or reduce their microtask hours during the pandemic. Microtask work might be a safe, convenient, and accessible way to earn money, but it does not pay well (Hara et al., 2018). Moreover, money was not the only thing people needed during the pandemic. People also needed extra time and energy to deal with other effects of the pandemic (e.g., sick family members, daycare closures, on-line schooling, working from home, fluctuating public-health mandates, supply chain disruptions, etc.). These new demands might have convinced many people to put microtask work lower on their list of priorities.

In short, it is not clear whether the pandemic pushed people already doing microtasks toward that work or away from it. At the aggregate level, the answer to this question will depend on the cumulative effects of the factors pushing and pulling people in different directions. When it comes to the factors that influence individuals, existing research provides some good guidance.

**Factors Fostering a Pandemic Pivot: Decreases in Wage/Salary Hours and Household Income**

Based on previous research, we expect that people will be especially likely to make a “pandemic pivot” toward microtask work (i.e., do more of it) under two conditions. First, because gig work, including MTurk work, is often motivated by low or unstable earnings from other sources (Abraham & Houseman, 2019; Bajwa et al., 2018; Berg et al., 2018), we expect people to do more of it when household income decreases or their own work hours in wage/salary jobs are cut. Many people experienced these things during the pandemic.

During spring of 2020, the unemployment rate in the U.S. soared, millions of people dropped out of the U.S. labor force (Kochhar & Bennett, 2021), and
those who remained working often worked fewer hours—especially women with young children (Collins et al., 2021). Consequently, many Americans needed to make up for reduced wage/salary income. Past research offers some evidence of a compensatory relationship between wage/salary work and other types of gig work (Berg et al., 2018; Farrell & Greig, 2016; Koustas, 2019). At the macro level, for instance, more people do gig work when the unemployment rate is high (Farrell & Greig, 2017; Huang et al., 2020). At the micro-level, Koustas (2019) found that among Uber/Lyft drivers, drops in non-gig household income were followed by increases in gig income. Recently, Ravenelle et al. (2021) showed that a similar dynamic was visible during the pandemic: when conventional work dried up, gig workers in New York City often turned (or returned) to work as ride-share and delivery drivers, dog-walkers, shoppers, and household assistants. When asked directly, people also say that gig work helps them compensate for income fluctuations (Smith, 2016). In short, when opportunities for wage/salary work shrink, people seem to do more in-person gig work. No study we know of, however, has examined if this relationship extends to gig work on microtask platforms.

H1. Decreases in household income will be associated with increases in microtask hours.

H2. Decreases in wage/salary or self-employed hours will be associated with increases in microtask hours.

Factors Limiting a Pandemic Pivot: Family-to-Work Conflict

While hour reductions and income losses brought on by COVID-19 could lead workers to increase their microtask hours, other factors may have limited workers’ ability to make this “pandemic pivot.” During the pandemic, school and daycare closures increased family responsibilities for many workers, especially mothers (Heggeness & Fields, 2020). Unsurprisingly, many people experienced increases in family-to-work conflict (Vaziri et al., 2020). Given that microtask pay is low and the majority of people on MTurk use the money for non-essential expenses (Moss, Rosenzweig, Robinson, Jaffe, et al., 2020), microtask work may be one of the first activities that people reduce if personal/family demands increase (Dunn et al., 2020). Indeed, many people do microtask work so they can accommodate family responsibilities (Berg et al., 2018, p. 38; Moss, Rosenzweig, Robinson, Jaffe, et al., 2020).

H3. Increases in family-to-work conflict will be associated with decreases in microtask hours.
Beneﬁts and Risk of Gig Work During COVID-19

A second unresolved issue is whether pivoting toward microtask work helped people earn the money they needed. For years, scholars have questioned whether the disadvantages of gig work outweigh its advantages. We do not attempt to settle that question here. Rather, we contribute to this debate by focusing on whether doing microtask work helped people financially during the COVID-19 crisis. Examining the usefulness of gig work during a crisis is particularly important given that in a risk society like the U.S., the social safety net is weak (Hacker, 2006). In the absence of a strong social support system, it is possible that gig work was a financial life raft for some workers (see Ravenelle et al., 2021).

Freedom and Flexibility

There are some reasons to expect that microtask work may have had important financial benefits during the pandemic. A “freedom and flexibility” perspective offers an optimistic view of gig work’s potential to help workers financially (Anwar & Graham, 2021; Kagondu, 2014). Proponents of this view suggest that workers have the “freedom and flexibility” to work as much as they want. Perhaps for this reason, Kagondu (2014) suggests that gig work “offers significant income earning potential for those who can successfully navigate the platforms.” An important assumption of this perspective, however, is that there is enough gig work for everyone who wants it.

Platforms’ algorithms do streamline the process of finding consumers/customers (Edelman & Geradin, 2015) thus making it easier to find gig work opportunities. Furthermore, because demand for gig workers can vary dramatically across occupations (Stephany et al., 2020), it is possible that demand for microtask workers remained stable or increased even if demand in other types of gig work dropped (Stephany et al., 2021). Indeed, some MTurkers say that COVID-19 did not negatively disrupt their work (Toxtli et al., 2021), and there is some evidence that the demand for survey takers and research participants increased substantially in Spring 2020 (AppJobs, 2020; Moss, 2021). Thus, even though around 45% of MTurk workers say there is not enough work in normal times (Berg et al., 2018), the pandemic may have actually increased the demand for microtask workers.

Moreover, even if increased demand was not accompanied by better pay, a little money can make a big difference to people in need (Abraham & Houseman, 2019). Nearly 75% of people doing gig work during the pandemic said it was “as important or more important” for their financial security during the pandemic compared to before it (Davinci Payments, 2021).
Pre-pandemic research suggests that income from gig transportation work can help workers compensate for other lost income (Koustas, 2019). The “freedom and flexibility” to do microtask work anywhere, anytime, and (potentially) as much as desired may, therefore, have helped people avoid financial hardship and generate new income during the pandemic.

H4a: Increases in microtask hours will help workers cover their expenses.
H4b: Increases in microtask hours will increase household income.

**Precarity and Platform-Dependence**

A “precarity” perspective offers a more pessimistic view of gig work’s potential to help workers financially. Gig work is often precarious work: it tends to offer low pay, few fringe benefits, an unreliable supply of work, limited promotion opportunities, low job security, and limited legal protections (Kalleberg, 2018). Among different types of gig work, microtask work is particularly precarious. Some tasks last only minutes before workers must return to their dashboards for more work, and even when plenty of work is available, it is often severely underpaid because MTurk has no minimum wage requirements. Workers are also not paid for time spent reading information to understand the task or messaging HIT Requestors for clarification (Toxtli et al., 2021). They are also not paid if a HIT (i.e., task) “times out” before they finish or if a Requestor chooses to reject their work (Toxtli et al., 2021). Some estimates suggest that only 4% of workers on MTurk earn more than $7.25 per hour (Hara et al., 2018). Moss, Rosenzweig, Robinson, Jaffe, et al. (2020) and Moss, Rosenzweig, Robinson, Litman (2020) estimated that the average MTurk worker earned $6.85 per hour in 2019. Others suggest median pay is as little as $2.83 (Toxtli et al., 2021). Moreover, as independent contractors, workers on MTurk and other gig platforms are not covered by most labor laws.

The precarity facing those who do gig work is often contrasted with the experiences of the seemingly separate population of workers with conventional wage/salary jobs. Some studies draw this contrast by detailing how gig arrangements differ from standard work arrangements (Kalleberg, 2018; Kalleberg & Dunn, 2016). Others examine how the workers differ in terms of wages, hours, and satisfaction (Katz & Krueger, 2019). Finally, some studies ask people doing gig work if they would prefer standard employment arrangements (Berg et al., 2018; Manyika et al., 2016; Moss, Rosenzweig, Robinson, Jaffe, et al., 2020). All these comparisons can foster the impression that few gig workers have other jobs.

In reality, however, many people doing gig work have income from other sources including wage/salary jobs (e.g., Farrell et al., 2018; Manyika et al.,
2016; Ravenelle, 2019), and it is the subset of gig workers who depend on gigs for their income who are most affected by its precarity. Rooted in a recognition of this fact, a “platform-dependence” perspective suggests that the risks of gig work are contingent on the degree to which one is dependent on it (Glavin & Schieman, 2022; Schor et al., 2020). Those who rely on it as their sole source of personal income may suffer more from its precarity than those who also have other jobs (Schor et al., 2020). Financial reliance on microtask work may act as a “disciplinary device” (Schor et al., 2020) that leads those without other income to do even the lowest-paying work, or accept tasks from “requesters” with poor track records of “approving” (i.e., paying for) the work. MTurk Requesters can also take up to 30 days to pay, which may leave workers who rely on that income in a particularly undesirable position. Gig workers who have wage/salary jobs, in contrast, tend to have more control over their working conditions and schedules and report greater satisfaction and earnings in their gig work (Keith et al., 2019; Manyika et al., 2016; Schor et al., 2020). For these workers, the freedom and flexibility of gig work may outweigh the risks.

Based on these insights, we answer calls for research guided by the platform-dependance perspective (Schor et al., 2020), by distinguishing between MTurk workers whose personal incomes come solely from microtasks (henceforth “gig-only” workers) and workers who also have non-gig jobs (henceforth “gig+” workers). Based on the platform-dependance perspective, we suspect that even after accounting for their pre-pandemic financial situation, those who were reliant on microtasks fared worse during the pandemic:

**H5a:** Workers who were gig-only at Wave 1 will be more likely to have trouble covering expenses.

**H5b:** Workers who were gig-only at Wave 1 will have lower household incomes.

**Data**

We test our hypotheses with data from our panel study of U.S. residents who were working on the MTurk platform, one of the largest and best known microtask platforms in the U.S. (Berg et al., 2018), in February 2020, just before the pandemic began. The study’s original aim was to collect data about all the paid work respondents did and examine how their overall work schedules (that could involve both gig and conventional work) fit with the demands of their personal lives. The timing of the first wave, however, provided an unexpected opportunity to examine changes in work schedules across the early months of the COVID-19 crisis. Our respondents’
experiences during the pandemic should offer a best-case scenario for the use and utility of microtask work. Rarely have Americans been so restricted in terms of mobility while also in such financial need, thus making microtask work an unusually attractive strategy for earning money. In short, the pandemic highlighted the platforms’ best features. Furthermore, because our respondents were already registered on and familiar with MTurk when COVID-19 hit, they were in a good position to use and benefit from the platform. If the platform was not a financial life raft for them, it is unlikely to have been one for those who joined later.¹

In contrast to many researchers who sample MTurk workers, our goal is not to generalize from our sample to the adult population of the United States. We sampled MTurk workers based on theoretical interests in them and the paid work they do. In this way, we follow other studies that have relied on purposive samples to study gig work (Berg, 2015; Koustas, 2019; Schor et al., 2020). Due to the diverse range of skills, working conditions, and work-types in the gig economy, we also do not attempt to generalize to all gig workers. Rather, we focus on people who do microtask gig work.

Although Amazon’s restrictions make it impossible to get a probability sample of MTurk workers (Difallah et al., 2018), our recruitment procedures were designed to ensure that the sample reflected the overall MTurk population better than many previous samples. First, we recruited respondents by posting surveys every three hours for seven consecutive days. This ensured that people who are typically on MTurk on particular days or times could still participate (Berg et al., 2018). Second, we adjusted the number of surveys in each batch to reflect the estimated activity levels at different times of day (Hitlin, 2016). This helps compensate for variations in the number of people working at particular times of day. Finally, although many researchers restrict their samples to workers who have completed at least 100 HITs, (Robinson et al., 2019), we allowed both experienced and inexperienced users to participate. These steps should help our sample reflect the MTurk population. See Appendix A for additional steps taken to guard against multiple submissions and ensure data quality.

We collected Wave 1 in the last week of February 2020, before the pandemic disrupted life in the U.S. We collected Wave 2 at the end of March as the Trump Administration’s initial pandemic response (i.e., the “15 Days to Slow the Spread” effort) expired. At that time, the financial relief provided by the CARES Act, which became law on March 27, 2020, had not yet reached Americans (Equifax, 2021). We collected Wave 3 in early May. Workers were invited to participate in Waves 2 and 3 even if they were no longer working for pay (on MTurk or elsewhere).² The study’s panel structure and timing make it ideal for studying pandemic-driven shifts from one
work-type to another and examining whether doing more microtask work helped people financially. Although Wave 1 yielded 1,560 usable surveys, pandemic-related changes are central to our research questions. Thus, we restricted our sample to the 1,169 respondents who also participated in at least one other wave. Dropping 44 respondents for missing data leaves 1,125 respondents who provide 3,065 observations.

**Variables**

**Focal Variables**

To examine factors related to changes in microtask hours, we rely on measures of microtask hours, household income (H1), wage/salary hours or self-employed hours (H2), and family-to-work conflict (H3).

**Microtask hours and wage/salary or self-employed hours:** At each wave, we asked about various types of gig work (e.g., microtasks, online freelancing, rideshares, etc.), wage/salary employee work, and self-employment (as an independent business owner, a franchise owner, or direct salesperson). Roughly 36% of respondents worked on other microtask platforms besides MTurk, but relatively few did other gig work. Roughly 16% sold items through platforms like eBay or Craigslist, and only 2% combined MTurk with rideshare work. At Wave 1, we asked how many hours per week respondents usually spent on each type of work. At later waves, we asked how many hours they spent on each type of work in the previous week.

**Household income:** At Wave 2, we asked respondents, “What were your total household earnings, from all sources of work in the past year? (Prior to taxes or other deductions).” At waves 2 and 3, we also asked, “Up to this point, how has the coronavirus affected your household income?” (Reduced it, Had no effect, Increased it). Depending on their answer we then asked, “What percent of your regular household income have you lost?” or “By what percent has your regular household income increased?” This allowed respondents to describe changes in household income without having to know their exact monthly income, which can be difficult to calculate/estimate and more prone to respondent error. Using this measure of household income as a percent of pre-COVID income, we also created a time-varying measure of household income in dollars by adjusting the Wave 1 total earnings based on the reported percent increase/decrease. To aid interpretation, we sometimes divide this last measure by 12 (to represent monthly earnings). This changes the scale of the variable but has no effect on its correlation with other variables.

**Family-to-work conflict:** At each wave we asked, “This past week, how much did the demands of your personal/family life interfere with
your work (of all types)?” The choices ranged from 1 “Not at all” to 10 “A great deal.”

To examine financial outcomes associated with microtask work, we explore respondents’ own subjective perceptions of MTurk’s importance as a financial resource during COVID-19. We also examine difficulty covering expenses and household income (H4a and H4b), and microtask platform-dependance (i.e., gig-only vs. gig +) (H5a and H5b).

**Perceived importance of MTurk:** At Waves 2 and 3, we asked “How much have you relied on the things below to meet your financial needs since the start of the Covid-10 pandemic?” The choices ranged from 1 “Not at all” to 10 “A great deal.” The items were “Pre-COVID employers,” “MTurk,” “Savings,” “Government support,” “Credit cards,” “Other gig work,” “Relatives,” “Friends,” “Bank loans,” “New employers,” and “Charities.”

**Difficulty covering expenses:** At Wave 1, we asked, “In the last 12 months, did any of the following happen to you because of a shortage of money?” The four items included, “Could not pay electric or gas bills on time,” “Could not pay mortgage or rent on time,” “Went without meals,” and “Was unable to pay phone bill on time.” We asked the same questions at Wave 3 but inquired about “the last four weeks” to capture experiences in the early months of the pandemic.

**Microtask platform-dependance:** As discussed above, we operationalize “gig-only” (i.e., platform-dependent) workers as those who do not combine microtask work with wage-salary work or self-employment and “gig +” workers as those who have non-gig jobs.

**Other Variables**

During the analysis, we also use other variables. We use continuous measures of respondents’ total weekly work hours, percent of household income from microtask work, and age. We use a set of indicator variables to identify respondents who had no spouse/partner, a spouse/partner not working for pay, a spouse/partner working less than 35 hours per week, or a spouse/partner working 35 or more hours per week. We use indicator variables (1 = Yes 0 = No) to identify respondents who were men, had resident children, had a bachelor’s degree, or were sick in the previous week. We also classify respondents as White (non-Hispanic), Black (non-Hispanic), Hispanic, or other.

In the fixed-effects regressions predicting microtask hours, we use indicator variables (1 = Yes 0 = No) to control for whether respondents had a wage/salary job they were doing at home, whether their childcare duties increased, and whether they have a spouse/partner who was: unemployed, laid-off, or
worked for an organization that had closed. We also use variables about the pandemic-context in respondents’ geographic area. We use a crosswalk connecting zip and fips codes (Andagostino, 2018) with data from the Johns Hopkins COVID-19 Case Tracker (Associated Press, 2020) to measure COVID cases per 100k people in a respondent’s county. We also calculate the number of days since the respondents’ state issued a stay-at-home order (Mervosh et al., 2020) and the unemployment rate in the state (BLS, 2022).

Analytic Strategy

To address our first research question (if there was a pandemic pivot toward microtask work), we examine how respondents’ work hours changed after COVID-19 hit. This involves a wave-by-wave accounting of the hours they spent in microtask and non-gig work (Tables 2 and 3, and Figure 1). To examine why people changed their microtask hours (H1, H2, and H3), we use linear fixed-effects models to control for all time-invariant factors while examining how changes in microtask hours are related to changes in household income, wage/salary or self-employment hours, and family-to-work conflict (Table 4).

To address our second research question (if microtask work helped people financially), we do three analyses. First, we examine respondents’ perceptions regarding the importance of microtask work for meeting expenses during the pandemic. Second, we draw on the subset of respondents who provided information about difficulties paying a variety of expenses (i.e., utilities, rent, meals, phone) at Wave 3. We used logistic regressions to assess if spending more hours on microtask work helped respondents cover these expenses (H4a) and whether the gig-only and gig+ respondents differed in their ability to cover these expenses (H5a). Third, because our measures of expenses are not exhaustive, we also examine how microtask hours and being gig-only influence household income (H4b and H5b). For this step of the analysis, we estimate a cross-lagged panel model with fixed effects, which we describe in more detail later.

In supplemental analyses, we re-estimated all final regressions with weights to see if the results were affected by respondent attrition. Before accounting for missing data, there were 1560 respondents at Wave 1, 1076 at Wave 2, and 931 at Wave 3. Following current advice (Hernán & Robins, 2020; Metten et al., 2022) we tried both inverse probability weights and stabilized inverse probability weights. We also tried calculating each kind of weight by predicting attrition with just the control variables from our analysis and with an expansive set of predictors that included all our independent variables plus information about MTurk experience.
and the number of minutes respondents spent completing our surveys. Because the cross-lagged panel model (used to test H4b and H5b) does not allow weights, we instead adjusted for attrition with full-information maximum likelihood (FIML) (Seaman & White, 2013). Any variables relevant for our hypotheses that were significant in unweighted analyses were also significant when using weights (or FIML); thus, we present unweighted results.

**Findings**

Table 1 provides descriptive statistics about gig-only and gig + respondents. As detailed in the top of the table, gig-only respondents are the minority: they only account for 26% of the sample. As the rest of the rows in the table show, the two groups differ in several ways. In total, gig + respondents work roughly twice as many hours per week as gig-only respondents but spend significantly less time on microtask work. The gig + group also earns more, gets a smaller percentage of income from gig work, and is less likely to have trouble paying basic expenses. Gig + respondents are also more likely to have a spouse/partner who does not work for pay, and they are less likely to have resident children.

In the first months of the pandemic, respondents’ work situations changed radically. Initially, 74% were in the gig + group and roughly 26% were in the
gig-only group (See Figure 1). Between Wave 1 (February 2020) and Wave 2 (March 2020), however, the percentage of respondents combining gig work with wage/salary work dropped to 46%. The percentage of respondents doing only gig work, in contrast, climbed nearly 20 percentage points. Furthermore, just over 4% of the sample had stopped working altogether. These trends continued into Wave 3 (April 2020), when the percentage of gig+ respondents was less than 20%, the gig-only group exceeded 70%, and more than 7% had stopped working. This is striking evidence of a contraction in the conventional economy and increased reliance on gig work.

### Table 1. Means and Proportions by Worker Type at Wave 1.

| Situation at wave 1:          | Gig-only | Gig+ |
|-------------------------------|----------|------|
| N                             | 288      | 837  |
| Proportion of sample          | 0.26     | 0.74 |
| Mean:                         |          |      |
| Total weekly hours            | 26.1     | 53.5 |
| Weekly hours in microtask work| 23.2     | 15.0 |
| 2019 Household income in $1,000s\(^a\) | 55.8  | 64.0 |
| % of household income from microtask work\(^b\) | 0.35 | 0.16 |
| Age                           | 37.2     | 37.6 |
| Proportion:                   |          |      |
| No spouse or partner          | 0.31     | 0.36 |
| Spouse/partner who does not work for pay | 0.03 | 0.07 |
| Spouse/partner works <35 h per week | 0.15 | 0.13 |
| Spouse/partner works 35+ hours per week | 0.51 | 0.44 |
| Resident children             | 0.52     | 0.44 |
| Man                           | 0.52     | 0.58 |
| Bachelor’s degree+            | 0.56     | 0.60 |
| White, non-Hispanic           | 0.71     | 0.74 |
| Black, non-Hispanic           | 0.09     | 0.09 |
| Hispanic                      | 0.12     | 0.09 |
| Other                         | 0.08     | 0.08 |
| Trouble paying utilities at wave 1 | 0.22 | 0.16 |
| Trouble paying rent/mortgage  | 0.19     | 0.11 |
| Trouble paying for meals      | 0.14     | 0.09 |
| Trouble paying phone bill     | 0.24     | 0.14 |

\(^a\)Calculated from midpoints of income ranges. The top midpoint is derived from a Pareto midpoint estimator (see Hout, 2004). Household income was missing for 48 respondents at wave 1, and % household income from microtask work was missing for 67.
Tracing transitions among work situations shows the flow of respondents more explicitly. Roughly 31% of respondents who were in the gig + group at Wave 1 were only doing gig work by Wave 2 (Table 2 Panel A). Respondents who were in the gig-only group at Wave 1, in contrast, were much less likely to change work situations. Approximately 86% kept doing gig work exclusively. The flow of respondents from the gig + to a gig-only situation was even more pronounced between Waves 2 and 3. Roughly 68% of the respondents still combining gig work with other work at Wave 2 were only doing gig work by Wave 3. Again, respondents in the gig-only situation tended to remain in that situation. Also 39% of the respondents who were not working at Wave 2, were doing gig work by wave 3 (Table 2 Panel B).

To examine the evidence of a “pandemic pivot” (research question 1) more closely, we compare the usual weekly hours spent in each type of work at Wave 1 (February 2020) with the weekly hours spent in each type of work at Waves 2 and 3 (March and April 2020). We make these comparisons by tracking the mean hours for each work-type, calculated among respondents who did that type of work at Wave 1. Figure 2 shows changes in work hours for respondents who were gig-only at Wave 1 and respondents who

**Table 2. Transitions among Work Combinations Across Waves.**

**Panel A. Wave 1 to 2 (row percentages)**

| Wave 2       | Gig+ | Gig-only | Only non-gig | Not working |
|--------------|------|----------|--------------|-------------|
| Gig+         | 60%  | 31%      | 6%           | 3%          |
| Gig-only     | 5%   | 86%      | 0%           | 9%          |

**Panel B. Wave 2 to 3 (row percentages)**

| Wave 3       | Gig+ | Gig-only | Only non-gig | Not working |
|--------------|------|----------|--------------|-------------|
| Gig+         | 27%  | 68%      | 1%           | 4%          |
| Gig-only     | 9%   | 84%      | 1%           | 6%          |
| Only non-gig | 6%   | 53%      | 8%           | 33%         |
| Not working  | 7%   | 39%      | 0%           | 54%         |

*Note: All respondents did MTurk at wave 1, and most combined it with non-gig work, i.e., wage-salary or self-employment. Only 27% also did other kinds of gig work, most often, selling items through platforms like eBay. Only 2% combined MTurk with gig transportation work (e.g., Uber, Grubhub).*
were gig+ at Wave 1. The red line shows the change in mean weekly micro-
task hours among gig-only respondents. There is only one line because they
only did one kind of work initially. Respondents in the gig + group, however,
initially combined microtask work with wage/salary work or self-
employment. Thus, the three blue lines show changes in mean weekly
hours for those three types of work among respondents who were gig+ at
Wave 1. Overall, Figure 2 provides additional evidence of increasing reliance
on gig work. Among gig + respondents, wage/salary hours plummeted from
almost 40 at Wave 1 to roughly seven at Wave 3. Mean hours in self-
employment also dropped substantially. Mean hours in microtask work, in
contrast, were fairly stable for both gig + and gig-only respondents. Further
examination, however, shows that the mean microtask hours hide important
variation.

Although mean microtask hours did not change much between waves,
increases and decreases in microtask hours were both common and large.
Roughly half of respondents in the gig-only and gig + groups at Wave 1
pivoted away from the Mturk platform and did less microtask work by
Wave 2. On average, gig-only and gig + respondents reduced their weekly
microtask work by 11.6 and 11.2 hours, respectively (See Table 3). These
wide-spread reductions were not obvious in Figure 2 because they were coun-
terbalanced by a pivot toward the platform. Around one-third of respondents
increased their microtask hours. On average, both the gig-only and gig +
groups added about 11 microtask hours. Almost no one pivoted toward wage-salary work. For instance, only 8% of respondents in the gig + group increased their hours in wage-salary jobs between Wave 1 and Wave 2. Thus, while the pivot toward microtask work was far from universal, it was far more common than a pivot toward conventional work, and it was the primary way our respondents found more work during this period.

To learn more about the factors associated with changes in microtask hours, we turn to fixed-effects regressions. The significant negative coefficients on our focal variables suggest that increases in monthly income, wage/salary or self-employment hours, and family-to-work conflict are all associated with reductions in microtask hours (Table 4 Model 2). During the pandemic, however, most people experienced decreases (not increases) in income and wage/salary or self-employment hours. Therefore, rather than relying on these conventional coefficients, which assume that the changes associated with increases and decreases in the independent variables are equal and opposite, we estimate asymmetric fixed-effects models (Allison, 2019). This allows us to obtain separate estimates of change in the dependent variable for increases and decreases in the independent variables. The results confirm that decreases in income and non-gig hours are associated with increases in microtask hours while increases in family-to-work conflict are associated with decreases in microtask hours (Table 4 Model 3). All these relationships remain after introducing a number of controls (Table 4 Model 4), thus supporting Hypotheses 1, 2, and 3.

Although it is not possible to include time-invariant variables in standard fixed effects regressions, they can be interacted with time-varying variables in

| Table 3. Changes in Microtask Hours Between Wave 1 and 2 by Worker Type. |
|--------------------------|--------------------------|--------------------------|--------------------------|
|                          | Direction of Change      | Mean Change              |                          |
|                          | Gig Only | Gig+ | Gig Only | Gig+ |                          |
| Microtask hours:         |          |      |          |      |
| Increased                | 30%      | 36%  + | 11.6     | 11.2 |
| No change                | 18%      | 14%  | NA       | NA   |
| Decreased                | 52%      | 50%  | −14.1    | −9.3 ***|
| Wage-salary hours        |          |      |          |      |
| Increased                | 1%       | 8%  *** | 28.5     | 12.0  + |
| No change                | 99%      | 35%  *** | NA       | NA   |
| Decreased                | NA       | 58%  | NA       | −26.0 |

Significant differences between gig-only and gig + respondents are marked as follows +p < .1, *p < .05, **p < .01, ***p < .001.
Table 4. Linear Fixed-Effects Models Predicting Changes in Weekly Microtask Hours.

|                                | Model 1 | Model 2 | Model 3a | Model 4a | Model 5a |
|--------------------------------|---------|---------|----------|----------|----------|
| Household income as % of pre-covid income |         |         | −0.05 *** |          |          |
| Weekly wage & salary + self-employed hours |         |         | −0.09 *** |          |          |
| Family-to-work conflict |         |         | −0.32 **  |          |          |
| Separate coef. for increases & decreases |         |         |          |          |          |
| Increases in income | −0.06 * | −0.06 * | −0.06 * |          |          |
| Decreases in income |          |          | 0.04 *** | 0.05 *** | 0.05 *** |
| Increases in wage & salary / self-emp. hours | −0.01 | −0.03 | −0.02 |          |          |
| Decreases in wage & salary / self-emp. hours | 0.10 *** | 0.10 *** | 0.09 *** |          |          |
| Increases in family-to-work conflict | −0.53 *** | −0.55 *** | −0.37 * |          |          |
| Decreases in family-to-work conflict | 0.01 | 0.01 | 0.01 |          |          |
| Controls |          |         |          |          |          |
| Wage-salary job now majority at home |         |         | 1.16 | 0.86 |          |
| Increased childcare duties |         |         | 0.45 | 0.41 |          |
| Partner is unemployed/laid off/org closed |         |         | −0.40 | −0.32 |          |
| Covid cases per 100k in county |         |         | −0.00 | −0.00 |          |
| Days since state began lockdown |         |         | 0.08 | 0.08 |          |
| Unemployment rate in state |         |         | −0.02 | −0.03 |          |

(continued)
Table 4. Continued.

|                     | Model 1 | Model 2 | Model 3<sup>a</sup> | Model 4<sup>a</sup> | Model 5<sup>a</sup> |
|---------------------|---------|---------|----------------------|----------------------|----------------------|
| Wave 2              | −1.33 *** | −2.81 *** | −2.41 *** | −3.00 *** | −2.77 *** |
| Wave 3              | −2.48 *** | −5.07 *** | −4.34 *** | −6.87 *** | −6.35 *** |
| Gig only at wave 1 × increased family-to-work conflict |          |   | −0.67 *  |          |          |
| Constant            | 17.11 *** | 25.16 *** | 17.10 *** | 17.13 *** | 17.18 *** |
| N                   | 3065     | 3065    | 3065     | 3065     | 3065     |
| R² within            | 0.018    | 0.054   | 0.055    | 0.058    | 0.061    |

<sup>a</sup>Models 3, 4, and 5 are asymmetric fixed-effects models (see Allison, 2019).

+<i>p</i> < 0.1, *<i>p</i> < 0.05, **<i>p</i> < 0.01, ***<i>p</i> < 0.001.
the model. We used this technique to examine if our focal variables had different effects for gig-only and gig + respondents. We present the one significant interaction in Model 5, which shows that increases in family-to-work conflict reduce microtask hours even more among gig-only respondents than among gig + respondents. This heightened reaction to family-to-work conflict is consistent with evidence that some people prefer gig work over conventional employment because it allows them to prioritize family responsibilities (Moss, Rosenzweig, Robinson, Jaffe, et al., 2020).

Predicted values help connect these results to experiences people had during the pandemic. On average, across all waves gig + respondents in Model 5 did 14.4 hours of microtasks each week. Gig-only respondents did 20.4. We examine three scenarios that could change that. Scenario 1: If family-to-work conflict increased substantially between waves (e.g., by 6 points on our scale), but household income and wage-salary hours remained the same, Model 5 predicts that gig-only respondents would reduce their weekly microtask time by 2.9 hours (14%) and gig + respondents would reduce it by 8.3 hours (58%). Scenario 2: If gig + respondents experienced no change in family-to-work conflict, but they lost 40 hours of non-gig work and their entire household income, they would increase their microtask work by 8.3 hours (58%). Scenario 3: If gig + respondents experienced a substantial increase in family-to-work conflict and also lost 40 hours of non-gig work and their entire household income, they would make almost no change to their microtask hours.

To examine if microtask work helped respondents financially (research question 2), we first examine respondents’ own perceptions. Respondents in the gig-only group at Wave 1 considered MTurk their most important source of financial support—considerably more important than savings, government support, credit cards, other gig work, relatives, friends, bank loans, and charities. Respondents who were gig + at Wave 1 provided similar answers, rating MTurk second only to their pre-COVID employers (Figure 3).

The objective evidence that microtask work helped respondents financially, however, is far weaker than the subjective evidence. By Wave 3 (April 2020), respondents who only did gig work before the pandemic were significantly more likely than those who also did other work to have trouble paying for utilities, rent, and meals (Table 5). Importantly, this pattern is present while controlling for pre-pandemic household income and difficulty paying these expenses in the year before the pandemic. The odds of being unable to pay a utility bill in the last four weeks were 87% larger for gig-only respondents than for respondents who had done both gig and non-gig work at Wave 1. The odds ratio for gig-only in the rent model is also significant and even larger. The p-value on the odds ratio for gig-only in the meals model is larger than 0.5 in the two-tailed test;
however, it is significant in a one-tailed test, which is appropriate given that H5a is a directional hypothesis. These results all suggest that pre-COVID reliance on gig work put people at higher risk of financial difficulties during the pandemic, thus supporting H5a. The odds ratios for changes in microtask hours, in contrast, are often less than one (Table 5 Row 2), suggesting that doing more microtask work reduced trouble covering expenses; however, the relationships are not significant. This suggests that doing more microtask work may not reduce financial difficulties as predicted in H4a.

Our analysis of overall household income echoes the findings from the analysis of specific expenses. For the analysis of household income, we rely on a cross-lagged panel model with fixed effects. In contrast to a standard fixed effects model, this allows for lagged reciprocal causation (i.e., the likely possibility that microtask hours are affected by prior levels of household income) and the inclusion of time-invariant variables (Allison et al., 2017; Leszczensky & Wolbring, 2019). The coefficient for gig-only is negative and significant, indicating that respondents who were gig-only at Wave 1 had lower household incomes even after controlling for their income at the previous wave (Table 6). The coefficient for weekly microtask hours at the previous wave, in contrast, is nonsignificant, suggesting that they have little effect on current household income. H4b is thus not supported but

**Figure 3.** Sources of financial support during COVID by worker type.
Note: Respondents were asked: How much have you relied on the things below to meet your financial needs since the start of the Covid-19 pandemic? (0=Not at all 10=A great deal).
H5b is. These directional hypotheses, which justify one-tailed tests, are still supported after adding additional controls (Table 6, Model 2). In summary, although respondents felt that microtask work was an important financial resource during the pandemic, increasing the hours they spent on it did not help alleviate trouble paying the expenses we examined or significantly increase household income.

If doing more microtask work did not help respondents financially, why did they consider it so important for meeting their financial needs? A closer look at

Table 5. Odds Ratios from Logistic Regressions Predicting Inability to Cover Expenses at Wave 3.

|                        | Utilities | Rent | Meals | Phone |
|------------------------|-----------|------|-------|-------|
| Gig-only at wave 1     | 1.87 *    | 2.17 * | 1.93 + | 1.39  |
| Change in weekly microtask hrs since last wave | 0.99 | 1.00 | 1.00 | 0.99 |

Controls

|                        | Utilities | Rent | Meals | Phone |
|------------------------|-----------|------|-------|-------|
| Household income (k) at wave 1 | 0.99 +    | 0.99 | 0.99 | 0.99 **|
| Percent of wave 1 household income lost | 1.03 *** | 1.03 *** | 1.02 *** | 1.02 ***|
| Age                    | 1.00      | 0.98 | 0.98 | 0.97 +|
| Spouse/partner not working for pay | 0.79 | 1.87 | 0.86 | 0.92 |
| Spouse/partner works <35 h/week | 2.56 * | 2.82 ** | 2.87 * | 1.98 +|
| Spouse/partner works 35+ hrs/week | 0.69 | 0.99 | 0.78 | 0.58 |
| Man                    | 0.89      | 1.07 | 1.17 | 1.22  |
| BA+                    | 1.23      | 1.38 | 0.90 | 1.49  |
| Resident children      | 1.51      | 1.15 | 0.87 | 1.31  |
| Increased childcare duties | 1.43 | 1.22 | 0.77 | 2.29 *|
| Was sick in past week  | 1.59      | 1.29 | 2.14 | 1.10  |
| Black non-Hispanic     | 1.60      | 2.92 ** | 0.83 | 1.36  |
| Hispanic               | 1.97      | 3.69 *** | 1.43 | 1.50  |
| Other                  | 0.15 +    | 0.54 | 0.66 | 0.39  |
| Had trouble paying for this pre-COVID | 10.82 *** | 7.43 *** | 20.54 *** | 7.38 ***|

N 841 841 841 841

+p < .1, *p < .05, **p < .01, ***p < .001.
The reference category for the spouse/partner variables is no spouse/partner and the reference category for race is White.
MTurk earnings across waves provides some clues. Respondents completed the surveys for Waves 1, 2, and 3 near the end of February, March, and April 2020, respectively. At Wave 3, we asked respondents to report monthly earnings from the MTurk dashboard for each of those months. Using the subset of 848 respondents who provided that information, we calculated changes in monthly MTurk income for each respondent between waves.

The vertical scatter in Figure 4 shows that monthly MTurk earnings can vary dramatically. The magnitude of the changes varies somewhat by quadrant, but across all observations, the mean absolute change is nearly $125. This is very large considering that mean earnings were $335 and median earnings were only $250. A $125 drop in income could mean that respondents are only earning about half of what they earned the previous month.

### Table 6. Cross-Lagged Panel Model with Fixed Effects Predicting Current Household Income in Thousands of Dollars.

| Model 1 | Model 2 |
|---------|---------|
| Gig-only at wave 1 | −0.367 * | −0.339 + |
| Weekly microtask hours (at previous wave) | 0.006 | 0.005 |
| **Controls** | | |
| Household income at previous wave | 0.416 ** | 0.352 ** |
| Wage & salary + self-emp hours | 0.006 * | 0.006 * |
| Spouse/partner not working for pay | −0.052 | −0.043 |
| Spouse/partner working <35 h/week | 0.312 | 0.314 |
| Spouse/partner working 35 + hrs/week | 0.784 ** | 0.777 ** |
| Increased childcare duties | 0.063 | 0.069 |
| Age | | 0.003 |
| Man | | 0.171 |
| BA | | 1.089 *** |
| Black non-Hispanic | | −0.399 |
| Hispanic | | −0.192 |
| Other | | 0.177 |
| Constant | 2.144 * | 1.670 ** |

| N | 862 | 862 |
| RMSEA | 0.041 | 0.029 |
| CFI | 0.997 | 0.998 |
| TLI | 0.989 | 0.993 |

+p < .1, *p < .05, **p < .01, ***p < .001.

# of units = 862. # of periods = 3. First dependent variable is from period 2. Constants are free to vary across time periods. The reference category for the spouse/partner variables is no spouse/partner and the reference category for race is White. Household income is divided by 12 to represent monthly rather than yearly income.
The overall scatter in Figure 4 suggests that although microtask hours and earnings sometimes moved together in intuitive ways, they often did not, making microtask hours an unreliable predictor of MTurk income. The top right quadrant (blue) where work hours and earnings both increased between waves contains 20% of the observations. The bottom left quadrant (green) where work hours and earnings both decreased contains roughly 24% of the observations. These two quadrants provide evidence of a positive association between work hours and income. However, even among these observations, changes in hours and income are only loosely connected. For instance, respondents who worked an additional 10, 20, 30, or 40 hours per week might all earn $200 more than in the previous month. Similarly, respondents who worked 10, 20, 30, or 40 hours fewer per week might all earn $200 less. The large number of respondents in the top left and bottom right quadrants (55% of cases) provide even more striking evidence of a disconnect between work hours and earnings. Respondents in the top left quadrant (orange) had surprising increases in income: they worked the same or fewer hours but earned around $114 more. Respondents in the bottom right quadrant (red) had surprising reductions in income: they worked the same or more hours but earned around $127 less than in the previous month. This bivariate relationship should be evaluated with caution. Although

![Figure 4. Changes in microtask hours and MTurk income.](image)

Note: Based on 1655 obs and 848 respondents. We dropped two observations where respondents reported modest changes in work hours (12-15 hrs) but income losses of more than $2,000.
respondents reported total MTurk income for each month, they only reported microtask hours for one week at the end of each month. This is only a proxy for the hours they spent on microtasks during the other weeks that month. Still, the patterns echo our regression results, which indicated that microtask hours were also only loosely connected to overall household income.

So why would respondents still indicate that earnings from MTurk were an important financial resource during the pandemic? Perhaps because any income can be helpful for people in need, even if it is small and unpredictable. The USDA estimated that in 2021, a “thrifty food plan” for a single male 20–50 years old cost about $267 per month (USDA, 2021). Therefore, although fewer than half of our respondents would be able to cover the cost of food for one adult using their MTurk income, it could still cover a substantial portion of that expense. We suspect that during this time period, when health, mobility, and financial crises made many types of work risky, inaccessible, or hard-to-find, our respondents valued the ability to earn money through MTurk even if their earnings were often meagre and volatile.

Discussion

The pandemic sharply reduced the supply of wage-salary work, but it altered life in ways that could have pushed people toward or away from gig work on microtask platforms. In our sample of people who had been working on Amazon’s MTurk platform prior to the pandemic, we find a modest pivot toward microtask work: nearly one-third of our respondents increased the number of hours they spent on microtasks. As hypothesized, increases in microtask hours at the individual level were related to decreases in household income (Hypothesis 1) and decreases in time devoted to wage/salary jobs or self-employment (Hypothesis 2). Family-to-work conflict, in contrast, was associated with a reduction in microtask hours, as predicted by Hypothesis 3.

We also find that although respondents perceived MTurk as an important financial resource during the pandemic, people who devoted more hours to it were not better able to cover basic expenses or boost their household income. Our analysis thus failed to support Hypothesis 4a or 4b. Furthermore, although microtask hours were more stable during the pandemic than hours in wage/salary jobs or self-employment, people who only did gig work before the pandemic were less able to cover basic expenses or boost income than those who had combined gig work with conventional employment. This provides support for Hypotheses 5a and 5b. Our findings also suggest that hours and earnings in microtask work are only loosely connected: many individuals who spent more time on microtasks did not earn more money.
Conclusion

In the COVID-19 pandemic, millions of Americans lost jobs or had work hours cut. Some forms of gig work, however, were more stable. We examined if microtask gig work that is precarious in normal times was, paradoxically, an attractive and useful source of income during the pandemic. Our analysis builds on research about the utility of doing gig delivery, transportation, and personal service work during periods of unemployment (Berg et al., 2018; Farrell & Greig, 2016; Koustas, 2019; Ravenelle et al., 2021) and on studies of changes in conventional work hours during the pandemic (Collins et al., 2021; Fan & Moen, 2021). We followed a large sample of Americans active on Amazon’s MTurk platform in February 2020 into the early months of the pandemic. Our study is the first we know of to examine how and why people changed the hours they spent on microtasks and whether that work served as a financial life raft.

Collectively, our findings suggest that for many people who were doing microtask work when COVID-19 hit, its freedom and flexibility were overshadowed by its precarious pay. Consistent with the platform-dependance (Schor et al., 2020) and precarity (Kalleberg, 2018) perspectives, our analysis indicates that doing microtask work is a financially risky strategy for surviving a crisis, especially for people without other sources of income. As a fairly unreliable and inadequate primary source of income, gig work on microtask platforms is not a financial life raft that can be sufficiently inflated in an emergency. Perhaps this is why the number of people on the MTurk platform did not increase substantially during the pandemic (Moss, 2021).

Due to data limitations, we were not able to make all the comparisons we would like. We cannot compare our respondents, who were on the MTurk platform before the pandemic began, with workers who joined the platform after the start of the pandemic. However, because of the learning curve and restrictions new workers face (e.g., the probationary period), our analysis represents a best-case scenario for workers’ financial opportunities on the platform. If the workers in our sample did not earn enough to stabilize or improve their finances, workers who joined the platform after the start of the pandemic likely fared even worse (Toxtli et al., 2021).

Our analysis contributes to existing research on gig work in several ways. First, some studies show a connection between unemployment and gig transportation work, but there is almost no prior research on the extent to which people turn to microtask platforms in times of financial need. This is a crucial oversight because microtask platforms are especially easy to access. We address this oversight by examining changes in microtask work during the pandemic, when it was one of the few accessible and safe ways to earn
money quickly. Second, while previous studies have focused on how gig work might help the unemployed, we examined if it helped people who experienced a reduction in earnings more generally. The unemployed are only a subset of the people facing financial hardship. Focusing too narrowly on them obscures the range of people who might pivot toward gig work and thus its potential utility as a financial life raft. Third, we show the individual-level connection between microtask work and conventional employment in the U.S. We find that when workers’ conventional employment hours drop, they spend more hours on microtask work. Fourth, by studying microtask work during the pandemic, when the conventional economy contracted, we seized an opportunity to see the risks and benefits of that gig work more clearly (Spurk & Straub, 2020) and develop a nuanced understanding of how workers who rely on it now (or in the future) may fare financially. Finally, our analysis corroborates the platform-dependance perspective which suggests that workers who depend on gig work face greater risks than those who combine it with more conventional employment (Schor et al., 2020).

Our results also have a number of policy implications. Some researchers have praised the performance of the gig economy during the pandemic and encouraged policymakers to support its growth (Umar et al., 2020). We recommend greater caution. Microtask work may not be as bad as some feared (Moss, Rosenzweig, Robinson, Jaffe, et al., 2020), but our work suggests that for many people, this highly accessible form of gig work was not an adequate or stable source of income during the pandemic. We are thus inclined to agree with others who warn that gig work is not a viable substitute for the social safety net (Ravenelle et al., 2021; Rubery et al., 2018). Other forms of gig work (e.g., freelancing, rideshare work) may offer better rewards, but because they require more skills or resources, they are also less accessible. In this way, the inequalities of the gig economy mirror the conventional labor market: the most accessible jobs are rarely the “good” jobs. This does not mean that gig work can never be helpful, or that it cannot be reformed to better compensate and protect workers (Rubery et al., 2018). Given the low barriers to entry, microtask work may be a particularly useful place to focus such efforts. Governments could impose reforms, but improvements could also emerge from collective agreements, codes of conduct, etc. (International Labour Organization, 2021). Some gig platforms have even begun adding worker protections on their own (Fairwork, 2021). If these reforms continue, microtask work could evolve to become both accessible and higher quality. Ultimately, the key to understanding how the risks and rewards of gig work vary and change is more research on when and why people do gig work, how they combine it with conventional employment, and how the effort they put into gig work is rewarded.
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Notes
1. It is worth noting that the pandemic had little effect on the number of people joining MTurk or the demographics of MTurk workers (Moss, 2021; Moss, Rosenzweig, Robinson, & Litman, 2020).
2. To the best of our knowledge, MTurk workers do not generally delete their accounts; they just stop using them. Amazon does not seem to delete inactive accounts either. We were able to contact MTurk workers who completed a survey for us even if they were no longer working on MTurk regularly.

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**Appendix A**

**Efforts to Guard Against Multiple Submissions and Ensure Data Quality**

We did two things to prevent MTurkers from submitting more than one initial survey. First, we used the Unique Turker service (https://uniqueturker.myleott.com/) to generate a custom script that we included in the HTML code for all the HITs posted during the week we recruited respondents into the study. This script was designed to prevent people from completing more than one assignment even if they were in different HITs. Second, we used the features in Qualtrics to “prevent ballot-stuffing,” thus adding an additional layer of protection. Even if a worker registered multiple accounts, a cookie placed in their browser upon completion would allow Qualtrics to detect that they had already completed the survey and prevent them from participating a second time. These steps guarded against multiple submissions.
We also did several things to ensure the quality of the data. We had a question in the survey that was designed to detect bots and another that was designed to catch respondents not paying attention. We also collected information that could be combined to identify problem cases. For instance, we asked for the number of hours usually worked each day of the week and also usual total weekly hours. We also included some questions with short text answers to check for respondents who completed the questionnaires with an automated script. Through this kind of careful scrutiny, we identified and dropped six respondents from this analysis who provided inconsistent answers or gave nonsensical answers on open-ended questions.
Table A1. Descriptive Statistics for Variables in Table 4

| Variable                              | Gig Only          |                |                | Gig+              |                |                |
|---------------------------------------|-------------------|----------------|----------------|-------------------|----------------|----------------|
|                                       | Mean  | s.d.  | s.d._b | s.d._w | Mean  | s.d.  | s.d._b | s.d._w |
| Microtask hours per week              | 14.43 | 11.63 | 9.55   | 6.72   | 20.45 | 15.01 | 12.28  | 8.69   |
| Household income as % of pre-covid income | 90.04 | 22.22 | 15.27  | 16.07  | 91.89 | 22.14 | 14.71  | 16.60  |
| Weekly wage & salary + self-empoyed hours | 22.77 | 19.53 | 11.55  | 15.93  | 1.04  | 6.14  | 3.99   | 4.79   |
| Family-to-work conflict               | 3.16  | 2.57  | 2.10   | 1.53   | 3.99  | 2.81  | 2.23   | 1.71   |
| Wage-salary job now at home           | 0.18  | 0.38  | 0.25   | 0.29   | 0.01  | 0.11  | 0.07   | 0.09   |
| Increased childcare duties            | 0.13  | 0.34  | 0.24   | 0.23   | 0.12  | 0.32  | 0.23   | 0.22   |
| Partner is unemployed/laid off/org closed | 0.08  | 0.26  | 0.19   | 0.19   | 0.09  | 0.28  | 0.19   | 0.20   |
| Covid cases per 100k in county        | 127.12 | 346.66 | 203.07 | 277.82 | 87.95 | 260.56 | 153.96 | 207.35 |
| Days since state began lockdown       | 11.67 | 16.20 | 5.74   | 15.30  | 11.01 | 16.06 | 6.64   | 14.80  |
| State unemployment rate               | 7.33  | 5.00  | 1.86   | 4.69   | 7.27  | 4.95  | 2.14   | 4.54   |
| N (person-years)                      | 2299  |      |        |        | 766   |      |        |        |
| n (respondents)                       | 837   |      |        |        | 288   |      |        |        |
| Mean person-years per respondent      | 2.75  |      |        |        | 2.66  |      |        |        |

Note: Mean is the overall mean across all person-years; s.d. is the standard deviation across all person-years; s.d._b is the standard deviation between the variation of the means across respondents; s.d._w is the standard deviation within: the mean variation across person-years within a respondent.
| Variable                                      | Gig Only |       |       |       | Gig+ |       |       |       |
|-----------------------------------------------|----------|-------|-------|-------|------|-------|-------|-------|
|                                               | Mean     | s.d.  | Min   | Max   | Mean | s.d.  | Min   | Max   |
| Could not pay utility bill                    | 0.09     | 0.28  | 0.00  | 1.00  | 0.15 | 0.36  | 0.00  | 1.00  |
| Could not pay rent/mortgage                   | 0.08     | 0.27  | 0.00  | 1.00  | 0.16 | 0.37  | 0.00  | 1.00  |
| Went without meals                            | 0.05     | 0.21  | 0.00  | 1.00  | 0.09 | 0.29  | 0.00  | 1.00  |
| Could not pay phone bill                      | 0.08     | 0.28  | 0.00  | 1.00  | 0.13 | 0.34  | 0.00  | 1.00  |
| Change in microtask hrs in last month         | −0.90    | 11.33 | −43.00| 50.00 | −2.55| 13.61 | −40.00| 40.00 |
| Percent of wave 1 family income lost          | 16.33    | 25.52 | 0.00  | 100.00| 13.13| 23.57 | 0.00  | 100.00|
| No spouse/partner                             | 0.39     | 0.49  | 0.00  | 1.00  | 0.34 | 0.48  | 0.00  | 1.00  |
| Spouse/partner not working for pay            | 0.16     | 0.36  | 0.00  | 1.00  | 0.18 | 0.38  | 0.00  | 1.00  |
| Spouse/partner works <35 h/week               | 0.19     | 0.39  | 0.00  | 1.00  | 0.21 | 0.41  | 0.00  | 1.00  |
| Spouse/partner works 35+ hrs/week             | 0.26     | 0.44  | 0.00  | 1.00  | 0.27 | 0.44  | 0.00  | 1.00  |
| Resident children                             | 0.36     | 0.48  | 0.00  | 1.00  | 0.36 | 0.48  | 0.00  | 1.00  |
| Increased childcare duties                    | 0.22     | 0.41  | 0.00  | 1.00  | 0.20 | 0.40  | 0.00  | 1.00  |
| Was sick in past week                         | 0.01     | 0.10  | 0.00  | 1.00  | 0.01 | 0.10  | 0.00  | 1.00  |

| N                                             | 640      | 201   |