RESEARCH ARTICLE

Journal of Sociotechnical Inquiry
Volume 1, Issue 2, 2026, pp. 24–33

What national surveys can see of app-based work: allocation, schedules and pay in the 2017 Contingent Worker Supplement and the 2024 SHED

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ABSTRACT

App-based work is work in which a smartphone app or website matches a worker to a task or customer, and often sets and processes the pay. This article asks what U.S. national surveys reveal about such work and about the app as an allocator of labour. It analyses two public microdata files. The May 2017 Contingent Worker Supplement (48,145 employed respondents) holds the answers both as collected and after the Bureau of Labor Statistics removed false positives. The 2024 Survey of Household Economics and Decisionmaking (12,295 adults) randomly assigned two question wordings. In 2017 the collected answers put app-based work at 3.3% of the employed; recoding cut this to 1.0% by removing 69% of the yes answers, almost all of them about main jobs. Recoding also raised the odds ratios for Black, foreign-born and contract workers. In 2024, 4.3% of adults (about 11.1 million) got short tasks through an app or website, and a quarter of them were found only by a follow-up probe. App-based workers were younger, more often Black or Hispanic and more often on low incomes; almost half of those in work held several jobs. They were more likely than other task workers to say the work gives flexible hours (77% versus 62%) and also more likely to wish the pay were more consistent (62% versus 45%). Surveys capture the flexibility the app offers but see little of how it sets pay and assigns work.

Keywords: platform work, algorithmic management, survey measurement, gig economy, Contingent Worker Supplement, SHED

1. Introduction

Ride-hailing, food delivery and online task platforms run on software that decides which worker sees which job, at what price and when. Researchers call this algorithmic management: the use of software to direct, evaluate and discipline workers in place of a human supervisor (Kellogg et al., 2020). Field studies of drivers, couriers and online freelancers show the app matching people to tasks, setting fares and hiding the information workers would need to judge an offer (Rosenblat, 2018; Wood et al., 2019). These studies are rich but cover single platforms or single cities. Policy debates in the United States lean instead on national labour-force surveys to say how many people do this work, who they are and whether they want it.

National surveys, however, meet the app only through the respondent. A household survey cannot observe a dispatch decision or a pay rule; it can only ask people to recognise their own work in a question. That makes the survey question itself a piece of technology placed between the app and the public record. The U.S. Bureau of Labor Statistics (BLS) learned this in 2017, when four new questions on electronically mediated work in the Contingent Worker Supplement (CWS) produced so many wrong yes answers that BLS recoded the data by hand before publishing (U.S. Bureau of Labor Statistics, 2018). A national expert panel later called for better measures of platform work (National Academies of Sciences, Engineering, and Medicine, 2020).

This article treats the survey and the app as two linked systems. The app allocates tasks, sets pay and shapes schedules; the survey classifies workers by asking them how the app touched their work. I ask three research questions:

RQ1. How large is app-based work in the United States, and how much do the estimate and the profile of who does it depend on how a survey asks and edits the question?

RQ2. Who does app-based work, and how does it fit with workers' other jobs, hours and employment arrangements?

RQ3. What can survey data reveal about the app as a labour-allocation system, in particular how tasks arrive, how schedules are set and how pay is experienced, and how do app-based workers judge the work?

I define app-based work as paid work in which an app or website connects the worker with a task or customer. The 2017 CWS adds a second condition: the company also arranges the payment. BLS calls this electronically mediated work (EMW), and I keep that term when I report CWS results. The 2024 Survey of Household Economics and Decisionmaking (SHED) asks about short-term tasks obtained through an app or website, which I call app-based task work.

The study makes three contributions. First, it uses the public CWS file to compare the collected and recoded answers person by person, which shows where the 2017 questions failed and how recoding changed the estimated correlates of app work. Second, it uses a randomised split-sample design in the 2024 SHED to show how much the estimate depends on wording and on a follow-up probe. Third, it uses SHED items on how the next task arrives and on workers' judgements to show a gap between two measures of the same system. App-based workers credit the app with flexible hours, while the same workers are more likely

to want steadier pay and benefits. Surveys that ask only whether workers prefer their arrangement record the first and miss the second.

A note on data is needed at the start. The July 2023 CWS included new questions on digital platform work and on schedule control. As of October 2026, BLS had not published estimates from these questions, and its public-use microdata file had not been released (U.S. Bureau of Labor Statistics, 2024). I therefore use the 2017 CWS microdata, the published 2023 CWS tables for alternative arrangements, and the 2024 SHED microdata as the most recent public national data on app-based work.

2. Related work and framing

2.1 What platforms do: matching, pricing and control

Vallas and Schor (2020) argue that platforms are a distinct way of organising work, neither market nor firm, in which the company keeps control of pricing and access while shifting cost and risk to workers. Three functions of the app recur in the literature. The first is matching: the app decides which worker is offered which task. Möhlmann et al. (2021) show that on online labour platforms matching is also a form of control, because the same algorithm that pairs workers with clients rewards some behaviour and punishes other behaviour. The second is pay setting. Ride-hailing apps set fares and change them in real time, and drivers often cannot see how a fare was computed (Rosenblat, 2018). The third is control over time. Apps offer workers the choice of when to log on but steer them through bonuses, ratings and acceptance targets (Shapiro, 2018; Griesbach et al., 2019).

Labour process studies describe this mix as autonomy combined with algorithmic control. Wood et al. (2019) found that remote gig workers valued flexibility and task variety but also faced long and irregular hours, overwork and sleep loss driven by platform ratings and competition. Veen et al. (2020) show food-delivery apps hiding information from couriers while monitoring them closely. Rahman (2021) shows how opaque rating systems make workers guess at the rules, and Cameron (2022) shows drivers making games out of the app's efficiency demands to keep a sense of control. Gandini (2019) places these findings within labour process theory, where the app replaces the supervisor as the point of control. Duggan et al. (2020) use the term app-work for work in which an app directly mediates the employment relationship.

2.2 Flexibility, dependence and who does the work

A strand of economics values the flexibility that apps provide. Using Uber records, Chen et al. (2019) estimate that drivers gain substantial surplus from being able to choose their hours, and Hall and Krueger (2018) report that most drivers cite flexibility as a main reason for driving. Mas and Pallais (2017) find, in contrast, that the average job seeker places little value on flexible scheduling set by the worker but strongly dislikes schedules set by the employer at short notice. Koustas (2019) finds that many people take up gig work to smooth income after a fall in other earnings.

Sociologists stress dependence. Schor et al. (2020) show that workers who rely on a platform for their main income report less autonomy and more precarity than those who use it to supplement other earnings. In a Canadian national survey, Glavin et al. (2021) find that gig workers report more powerlessness and isolation than other workers. Kalleberg (2009) frames such work within a wider shift towards precarious employment, in which risk moves from employers to workers. Kuhn and Maleki (2017) distinguish micro-entrepreneurs, dependent contractors and workers with few other options, a reminder that the same app can carry very different meanings for different people. Cook et al. (2021) show that even a gender-blind pay algorithm produced a 7% earnings gap among drivers through differences in driving speed, experience and where people chose to drive.

2.3 Measuring app-based work

Survey measurement of nonstandard work long predates apps (Kalleberg, 2000). Katz and Krueger (2019) documented a rise in alternative work arrangements from 1995 to 2015 and found that online intermediaries accounted for a small part of it. Abraham et al. (2019, 2021) showed that household surveys and tax records disagree on the size and growth of gig work. Respondents often do not think of occasional task work as a job, and household surveys miss it, while tax records capture payments but not the work. The underlying problem is old: answers depend on how questions are worded and on what respondents think the question is about (Schwarz, 1999).

Science and technology studies offer a frame for this. Classification systems are infrastructures that make some activities visible and others invisible, and the categories embed choices about what counts (Bowker & Star, 1999). Turning varied experiences into a single count is a social process of commensuration with its own rules (Espeland & Stevens, 1998). A survey question about apps is such a classifier. It decides whether a ride-hailing driver, a bank executive who uses an app or a person who sells crafts online counts as an app-based worker. This study asks what that classifier sees of the app's work as an allocator of labour, and what it misses.

3. Data and methods

3.1 The 2017 Contingent Worker Supplement

The CWS is a supplement to the Current Population Survey (CPS), the monthly household survey that produces official U.S. employment statistics. The May 2017 supplement asked employed respondents two new questions about the reference week of 7 to 13 May 2017. The first asked about short in-person tasks found through companies that connect workers with customers using a website or mobile app and that coordinate payment, with examples of driving, delivering and household errands. The second asked about short online tasks selected from lists kept by companies that coordinate payment, with examples of data entry, translation, web development and graphic design. Each yes was followed by a question on whether the work was for the main job, a second job or additional work for pay (U.S. Bureau of Labor Statistics, 2018).

BLS found many yes answers that conflicted with the respondent's job description, such as surgeons, police officers and bank vice presidents reporting app-mediated work. Using confidential verbatim job descriptions, employer names and

other items, BLS recoded obvious false positives to no. It could check main jobs but had little information on second jobs and none on additional work for pay, so yes answers about side work were mostly left unchanged (U.S. Bureau of Labor Statistics, 2018). The public file released by the Census Bureau contains both versions. I use both, which lets me treat the recoding as a measurable intervention.

The analysis sample is all employed civilians aged 16 and over who completed the supplement: 48,145 people. I weight by the supplement weight and compute standard errors with the 160 successive-difference replicate weights released with the file (variance scale 4/160). As a check, my weighted estimates reproduce the published BLS figures: 1.0% of the employed (1.6 million people) did recoded EMW, 0.6% in person and 0.5% online, and 6.9% were independent contractors on their main job.

I group respondents by recoded status: EMW on the main job, EMW as side work only (second job or additional work for pay) and no EMW. Covariates are age group, sex, race and Hispanic ethnicity, education, nativity, multiple jobholding, usual weekly hours across all jobs, self-employment and the main-job arrangement. Arrangement follows BLS: independent contractor; on-call worker; paid by a temporary help agency; provided by a contract firm; or traditional. For self-employed people and independent contractors, the CWS also asked whether they would prefer to work for someone else and their main reason for their arrangement.

3.2 The 2024 SHED

The SHED is an annual online survey of U.S. adults run for the Federal Reserve Board on a probability-based panel. The 2024 wave, fielded in October 2024, has 12,295 respondents and includes a module on gig and task work. The Federal Reserve split the sample at random. One half (6,145 adults) was asked whether in the past month they had done any freelance or gig work. The other half (6,150 adults) was asked whether they earned money by obtaining short-term tasks or projects. Those who said yes were asked whether they used an app or website to get these tasks. Those who said no were asked a probe: whether they had used an app or website to select projects, pick tasks or connect directly with customers.

I define app-based task work, in the task-wording half, as a yes or sometimes to the app question or a yes to the probe; 247 respondents meet this definition. Task workers who did not use an app (262) form the comparison group. All task workers were asked how they get the next task once one is done (a boss, supervisor or dispatcher assigns it; they line up work on their own; they go to an app or website; something else; or only one task). They were also asked their usual weekly hours on the task work, whether it was the job they had reported earlier in the survey, and whether they agreed with six statements about it. I use the main SHED weight. The Federal Reserve does not release replicate weights or design variables, so standard errors are linearisation estimates that treat the weights as fixed; they are likely to understate uncertainty somewhat.

3.3 Published 2023 CWS tables

For the change between 2017 and 2023 in alternative arrangements, I take 2023 shares from BLS published Table A and preference shares from Table 9 of the November 2024 release (U.S. Bureau of Labor Statistics, 2024) and compare them with my own 2017 estimates. BLS notes three differences between the waves: the 2023 survey ran in July rather than May, the questionnaire was shortened and revised, and the 2017 EMW items were replaced with new questions on digital platform work. BLS judges the main-job arrangement estimates broadly comparable. BLS does not publish standard errors for these tables, so I report the 2023 figures as published and do not test the differences.

3.4 Analysis

For each data set I estimate weighted shares with 95% confidence intervals. To find the correlates of app-based work I fit survey-weighted logistic regressions. In the CWS I fit the same model to the recoded and the collected measures, with age, sex, race and ethnicity, education, nativity, multiple jobholding, part-time hours and main-job arrangement as predictors. Comparing the two sets of odds ratios shows how the recoding changed the estimated profile of app workers. In the SHED I model app-based task work among all adults in the task-wording half, with age, sex, race and ethnicity, education, metropolitan residence, whether the person worked for pay last month and family income below $25,000. Income and work status may be consequences as well as causes of app work, so I read all odds ratios as descriptive associations, not causal effects. For SHED task workers I compare app users with non-users on each item using weighted linear probability models and report differences in percentage points.

4. Findings

4.1 How much app-based work, and how the instrument shapes the count

Figure 1 sets the estimates side by side. In the 2017 CWS, 3.3% of employed people (95% CI 3.0–3.6) answered yes to at least one EMW question, which corresponds to about 5.1 million workers. After recoding, the share fell to 1.0% (0.9–1.2), or 1.6 million workers. Recoding cut the in-person estimate from 2.0% to 0.6% and the online estimate from 1.9% to 0.5%. The unweighted count of yes answers fell from 1,582 to 462. Among recoded EMW workers, 61.5% (55.7–67.3) did in-person tasks and 43.6% (37.9–49.3) did online tasks; the two shares sum to more than 100 because some people reported both, for example for two different jobs.

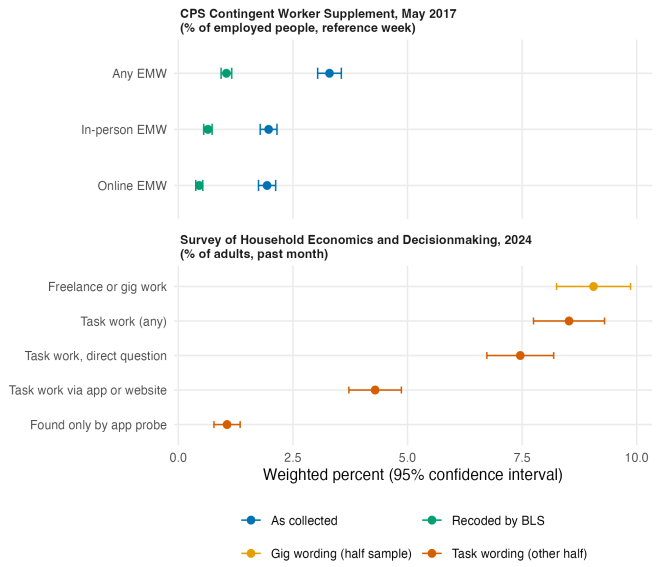


Figure 1. Estimated prevalence of app-based work under different survey instruments. Top: May 2017 CPS Contingent Worker Supplement, share of employed people doing electronically mediated work (EMW) in the reference week, as collected and after BLS recoding. Bottom: 2024 SHED, share of adults in the past month under two randomly assigned wordings; the task-wording estimates include a follow-up probe about apps. Bars show 95% confidence intervals.

Figure 2 shows where the collected answers failed. Recoding removed 68.9% of all collected yes answers. The removals fell almost entirely on main jobs: 73.8% of yes answers about the main job were recoded to no, compared with 2.9% of yes answers about a second job or additional work. This gap reflects what BLS could check, not where errors occurred. Among main-job answers, the share removed was highest in sales (88.4%), management, business and financial occupations (86.3%) and office and administrative support (83.4%). It was lowest in transportation and material moving (37.0%), the occupation group that contains most drivers and couriers. The questions worked best for the in-person driving and delivery work their examples described, and worst for office workers who use apps and online systems every day.

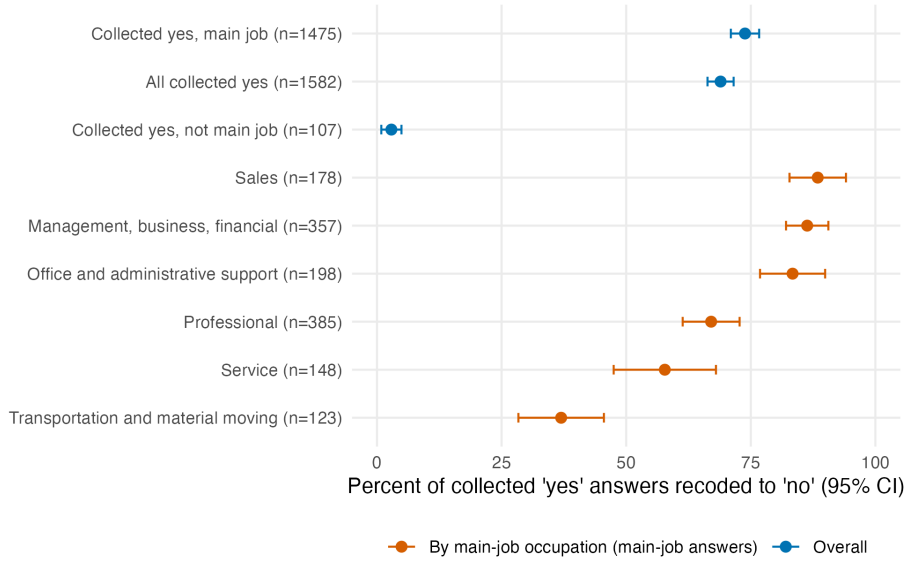


Figure 2. Share of collected yes answers to the 2017 EMW questions that BLS recoded to no, overall, by whether the answer referred to the main job, and by main-job occupation for main-job answers (groups with at least 100 collected yes answers). Weighted, with 95% confidence intervals from replicate weights.

Recoding changed who appeared to do app-based work as well as how many. Table 2 compares the two CWS models. With the collected measure, Black workers did not differ from White workers (odds ratio 1.12, 95% CI 0.90–1.40), and foreign-born workers did not differ from the native born (1.16, 0.91–1.48). With the recoded measure, both associations became clear: 1.56 (1.10–2.22) for Black workers and 1.76 (1.18–2.63) for the foreign born. Part-time hours had no association with the collected measure (0.97) but did with the recoded one (1.53, 1.18–1.99). The odds ratio for independent contractors rose from 3.60 to 9.10. The removed answers came disproportionately from managerial, sales, office and professional jobs, and their removal sharpened the link between app-based work and the groups that field studies describe.

The 2024 SHED shows a different measurement effect. Among adults asked about freelance or gig work, 9.1% (8.3–9.9) said yes. Among those asked about short-term tasks or projects, 7.5% (6.7–8.2) said yes to the direct question, and the app probe raised task work to 8.5% (7.8–9.3). In this half, 4.3% of adults (3.7–4.9) did task work through an app or website in the past month, about 11.1 million adults (95% CI 9.6–12.6 million). Among adults who worked for pay last month, the share was 5.8% (4.9–6.7). A quarter of app-based task workers (24.8%, 18.9–30.6) were found only by the probe. They had said no to the question about short-term tasks but yes when the question named the app and its functions of selecting projects, picking tasks and connecting with customers. Some people who work through apps do not recognise their work in a generic description of task work. The 2017 CWS problem ran the other way: some respondents read a question about apps as a question about any work involving an app.

The 2017 and 2024 figures are not a time series. They differ in

population (employed people versus all adults), reference period (one week versus one month), survey mode and wording. They show instead that the measured size of app-based work moves by a factor of three or more with the instrument, within a single survey.

4.2 Who does app-based work and how it fits with other work

Table 1 describes app-based workers in both surveys. In 2017, recoded EMW workers whose main job was app-based were concentrated in self-employment (42.6% versus 9.9% of all employed), in independent contracting (41.9% versus 6.9%) and in transportation and utilities (25.3% versus 5.1%). They were more often foreign born (21.8% versus 16.8%) and more often held a bachelor's degree (44.7% versus 37.6%). The degree share reflects online EMW, which drew more graduates than in-person EMW.

Table 1. Characteristics of app-based workers and comparison groups (weighted percent).

Characteristic	Comparison group	App-based group	Other group
CPS CWS, May 2017 (employed)	All employed	EMW, main job	EMW, side work only
Age 16–24	12.4	9.2	14.1
Age 55 and over	23.1	19.6	14.6
Women	46.8	47.3	41.4
Black, non-Hispanic	11.4	13.7	20.9
Hispanic	16.6	17.1	14.4
Bachelor's degree or higher	37.6	44.7	54.9
Foreign born	16.8	21.8	24.9
Multiple jobholder	5.3	11.2	52.1
Usually under 35 hours, all jobs	16.5	27.2	13.0
Usual hours vary	6.3	13.8	12.2
Self-employed, main job	9.9	42.6	18.9
Independent contractor, main job	6.9	41.9	20.8
Transportation and utilities, main job	5.1	25.3	9.9
Unweighted n	48,145	354	108
SHED 2024 (adults, task-wording half)	No task work	App-based task work	Task work without app
Age 18–29	19.1	35.7	28.6
Age 60 and over	32.7	9.5	24.8
Women	51.9	47.2	42.9
Black, non-Hispanic	11.7	23.5	11.4
Hispanic	17.7	23.7	20.2
Bachelor's degree or higher	37.7	33.2	34.1
Family income under $25,000	18.4	33.8	26.3
Finding it difficult or just getting by	25.2	44.1	38.5
Worked for pay last month	57.2	79.9	79.1
More than one job (those who worked)	15.5	45.9	50.6
Self-employed, main job (those who worked)	9.0	27.2	26.1
Unweighted n	5,641	247	262

App-based work was mostly a main job in 2017, by the CWS measure. Of recoded EMW workers, 77.1% (72.3–81.9) reported it for their main job, 11.4% for a second job and 11.7% as additional work for pay. This split must be read alongside Figure 2: recoding removed three in four main-job yes answers but hardly any side-work answers, so the side-work share is less filtered and may still contain false positives. Those doing EMW only as side work look very different from main-job EMW workers. Half (52.1%) were multiple jobholders, against 5.3% of all employed, and their usual hours across all jobs averaged 46.6 (42.7–50.6), compared with 39.4 for workers without EMW. Main-job EMW workers worked slightly fewer hours on average (37.1, 35.2–39.1). They were more likely to work under 35 hours (27.2% versus 16.5%) and twice as likely to say their hours vary (13.8% versus 6.3%).

Figure 3 shows the overlap with other alternative arrangements. In 2017, 5.6% of independent contractors did recoded EMW, compared with 0.6% of workers in traditional arrangements. Rates for temporary help agency workers (3.4%) and on-call workers (2.6%) were also above the traditional rate, although these estimates rest on small numbers. The hollow points show the collected rates. For traditional workers, the collected rate (2.8%) was more than four times the recoded rate, which again places most false positives among standard employees.

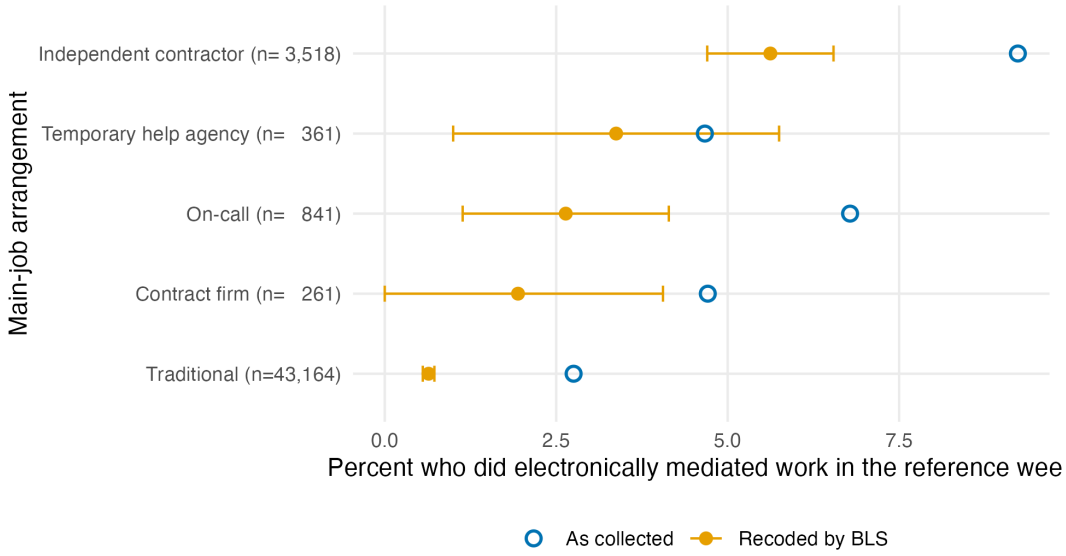


Figure 3. Share of workers doing electronically mediated work (EMW) in the reference week, by main-job arrangement, May 2017. Filled points: recoded by BLS, with 95% confidence intervals from replicate weights; hollow points: as collected. Unweighted sample sizes in brackets.

App-based work sits inside a wider set of alternative arrangements that changed little between 2017 and 2023. In my 2017 estimates, independent contractors made up 6.9% of the employed on their main job (6.6–7.2), on-call workers 1.7%, temporary help agency workers 0.9% and contract firm workers 0.6%; 3.8% were contingent under the broadest definition. BLS published figures for July 2023 of 7.4%, 1.7%, 0.6%, 0.5% and 4.3% (U.S. Bureau of Labor Statistics, 2024). In 2023, 80.3% of independent contractors preferred their arrangement and 8.3% would have preferred a traditional job. Whether app-based work grew within this stable total cannot be answered from the published 2023 tables.

The 2024 SHED gives a fuller demographic profile because it covers all adults (Table 1, lower panel). App-based task workers were younger than adults who did no task work: 35.7% were aged 18 to 29, against 19.1%, and only 9.5% were 60 or older, against 32.7%. They were more often Black (23.5% versus 11.7%) and Hispanic (23.7% versus 17.7%). A third (33.8%) lived in families with incomes under $25,000, against 18.4%, and 44.1% said they were finding it difficult to get by or just getting by, against 25.2%. Among those who worked for pay, 45.9% held more than one job, three times the rate of adults without task work (15.5%). Task workers who did not use an app resembled app users on job holding and self-employment but were older and more often White.

The regression results in Table 2 hold these patterns with other factors fixed. Black adults had 2.72 times the odds of app-based task work (1.88–3.93) and Hispanic adults 1.60 times (1.08–2.37), compared with White adults. Adults aged 60 and over had much lower odds (0.35). Every education group had higher odds than high school graduates, with the largest odds ratio for those without a high school diploma (2.45). Family income under $25,000 was associated with 1.83 times the odds (1.22–2.76). Women did not differ from men in either survey. In the 2017 recoded model, holding more than one job was the strongest personal correlate (odds ratio 3.89, 2.86–5.28), apart from main-job arrangement. The 2017 recoded model and the 2024 model agree on the direction of the age, race and labour-market associations, which gives some confidence that the recoded CWS measure and the SHED measure capture related populations.

Table 2. Survey-weighted logistic regressions of app-based work: odds ratios (95% confidence intervals).

Predictor	CWS 2017, EMW recoded	CWS 2017, EMW as collected	SHED 2024, app-based task work
Age 16–24 (CWS) / 18–29 (SHED)	1.11 (0.72<e2><80><93>1.72)	0.88 (0.68<e2><80><93>1.14)	1.15 (0.78<e2><80><93>1.70)
Age 25–34 (CWS)	1.18 (0.88<e2><80><93>1.57)	1.00 (0.86<e2><80><93>1.16)	
Age 45–59 (SHED)			0.73 (0.50<e2><80><93>1.06)
Age 55+ (CWS) / 60+ (SHED)	0.62 (0.44<e2><80><93>0.85)	0.82 (0.68<e2><80><93>0.98)	0.35 (0.21<e2><80><93>0.58)
Women	0.97 (0.78<e2><80><93>1.21)	1.05 (0.95<e2><80><93>1.16)	0.90 (0.68<e2><80><93>1.20)
Black, non-Hispanic	1.56 (1.10<e2><80><93>2.22)	1.12 (0.90<e2><80><93>1.40)	2.72 (1.88<e2><80><93>3.93)
Hispanic	1.07 (0.72<e2><80><93>1.59)	1.13 (0.89<e2><80><93>1.42)	1.60 (1.08<e2><80><93>2.37)
Asian, non-Hispanic	0.77 (0.41<e2><80><93>1.45)	0.80 (0.55<e2><80><93>1.17)	1.14 (0.54<e2><80><93>2.41)
Less than high school	0.51 (0.30<e2><80><93>0.87)	0.73 (0.54<e2><80><93>0.99)	2.45 (1.22<e2><80><93>4.91)

Some college or associate degree	1.27 (1.17<e2><80><93>2.11)	1.43 (1.20<e2><80><93>1.70)	2.04 (1.31<e2><80><93>3.19)
Bachelor's degree or higher	1.57 (1.17<e2><80><93>2.11)	1.74 (1.48<e2><80><93>2.05)	1.62 (1.02<e2><80><93>2.57)
Foreign born	1.76 (1.18<e2><80><93>2.63)	1.16 (0.91<e2><80><93>1.48)	
Multiple jobholder	3.89 (2.86<e2><80><93>5.28)	1.83 (1.49<e2><80><93>2.26)	
Usually under 35 hours, all jobs	1.53 (1.18<e2><80><93>1.99)	0.97 (0.83<e2><80><93>1.15)	
Independent contractor, main job	9.10 (7.12<e2><80><93>11.64)	3.60 (3.08<e2><80><93>4.21)	
On-call worker, main job	3.83 (2.05<e2><80><93>7.16)	2.61 (1.83<e2><80><93>3.72)	
Temporary help agency, main job	5.10 (2.44<e2><80><93>10.68)	1.84 (1.01<e2><80><93>3.36)	
Contract firm, main job	3.15 (1.00<e2><80><93>9.93)	1.74 (0.89<e2><80><93>3.42)	
Worked for pay last month			2.59 (1.74<e2><80><93>3.87)
Family income under $25,000			1.83 (1.22<e2><80><93>2.76)
Lives in a metropolitan area			0.76 (0.50<e2><80><93>1.17)
Unweighted n (yes)	48,145 (462)	48,145 (1,582)	6,150 (247)

4.3 What the surveys show about the app as an allocator

The CWS says little directly about how the app allocates work. Its EMW questions build the allocation function into the definition: the company connects the worker with customers and coordinates payment. Beyond that, the survey records only outcomes that might reflect the app's role, such as variable hours and self-employment. The SHED goes further by asking task workers how they get their next task. Figure 4 shows the answers.

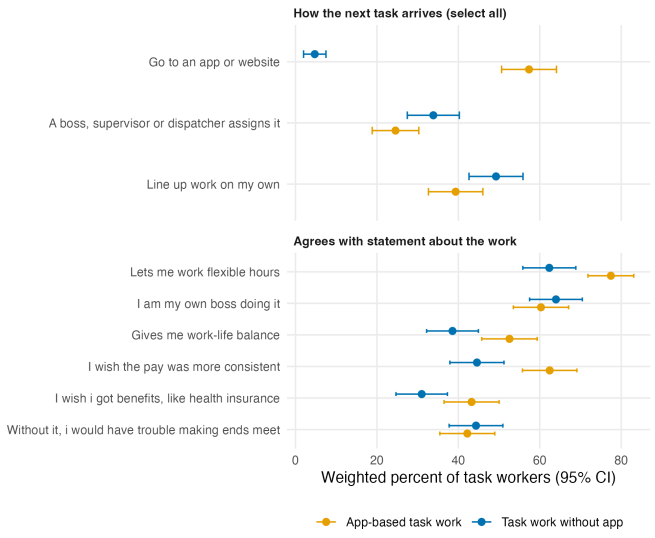


Figure 4. How task workers get their next task and how they judge the work, by whether they obtain tasks through an app or website, 2024 SHED (task-wording half; app-based n = 247, without app n = 262). Weighted percentages with 95% confidence intervals. Respondents could select more than one way of getting the next task.

Among app-based task workers, 57.4% (50.6–64.1) said they go to an app or website to get the next task, compared with 4.7% of other task workers. That leaves 43% of app users who did not name the app as the source of their next task, even though they had said they use one to get tasks. A quarter (24.6%) said a boss, supervisor or dispatcher assigns the next task, and 39.3% said they line up work on their own. Respondents could choose more than one answer, so many combine the app with other channels. The app is the main allocator for a majority of app-based task workers but not for all, and some workers experience app dispatch as assignment by a boss or dispatcher.

The answers on time and pay point in two directions. App-based task workers were 15.1 percentage points more likely than other task workers to agree that the work lets them work flexible hours (77.5% versus 62.3%; difference 95% CI 6.5–23.7). They were 14.0 points more likely to agree that it gives them work-life balance (52.6% versus 38.6%). The same group was 17.9 points more likely to agree that they wish the pay were more consistent (62.4% versus 44.6%; CI 8.4–27.3), and 12.3 points more likely to wish they got benefits such as health insurance (43.3% versus 31.0%). The two groups did not differ on being their own boss (60.3% versus 64.0%) or on needing the work to make ends meet (42.2% versus 44.3%). The same pattern appears in the other half of the sample, which was asked about freelance or gig work: 78.6% agreed that the work lets them work flexible hours and 62.3% wished the pay were more consistent. The pairing of flexible hours with unsteady pay therefore does not depend on the task wording.

The hours data fit a picture of mostly part-time task work. Among app-based task workers, 14.8% usually spent less than one hour a week on it, 34.9% one to four hours and 31.8% five to 19 hours. Only 18.4% (13.2–23.6) usually spent 20 or more hours a week, compared with 13.3% of other task workers, a difference that is not statistically clear. For most app users, the app fills gaps around other work rather than structuring a full working week. About half of those who worked (50.8% of app users, 46.7% of others) said the task work was the job, or the main job, they had reported earlier in the survey.

The CWS gives an earlier view of preferences. Among self-employed people and independent contractors whose main job

was EMW, 17.0% (10.9–23.1) would have preferred to work for someone else, twice the 8.4% (7.4–9.5) of other self-employed people and contractors. Flexibility of schedule was the main reason for their arrangement for 35.6% of them, compared with 24.6% of others. Among full-time workers, the median weekly earnings on the main job were $700 (622–840) for main-job EMW workers and $865 for workers without EMW, though this estimate rests on only 109 EMW workers.

5. Discussion

5.1 The survey question as a classifier

The first finding concerns the survey as a technology. The 2017 CWS questions described what the app does: it connects workers with customers and coordinates payment. Many respondents did not read them that way. Office workers, managers and professionals who use apps and websites in their jobs answered yes, and BLS judged about two in three yes answers to be wrong. The questions worked best for drivers and couriers, whose work matched the examples given. In the language of Bowker and Star (1999), the classifier was tuned to one image of platform work, the ride-hailing driver, and it absorbed everyone else whose work passed through a screen.

Recoding fixed much of this, but with the confidential job descriptions that only BLS can see, and only for main jobs. The resulting public estimate therefore mixes two levels of checking. Main-job answers were edited by trained staff; side-work answers mostly were not. Any finding about app work as a side job in 2017 inherits this asymmetry. The 2024 SHED shows the opposite error. A generic question about short-term tasks missed a quarter of app-based task workers, who appeared only when a probe named the app's functions. Abraham et al. (2021) argued that household surveys undercount gig work because respondents do not see it as a job. These results suggest the direction and size of the error depend on whether the question describes the work or the technology.

The choice matters for policy because the error is not random. In the 2017 data the false positives came disproportionately from managerial, sales, office and professional jobs. Before recoding, the measure suggested that app-based workers looked much like other workers; after recoding, they were more often Black, foreign born, part time and independent contractors. Counts built on weak classifiers can therefore hide the very inequalities that field studies of platform work report (Schor et al., 2020; Vallas & Schor, 2020).

5.2 Flexibility recorded, pay instability missed

The second finding is a gap between two kinds of evidence on the same workers. App-based task workers credit the work with flexible hours and work-life balance more often than other task workers do, in line with evidence from platform records that drivers value control over when they work (Chen et al., 2019; Hall & Krueger, 2018). The same workers are more likely to want steadier pay and benefits. The app gives workers the choice of when to log on, while keeping control over the price and the flow of tasks. Field studies describe this split (Shapiro, 2018; Wood et al., 2019), and here it appears in a national probability sample.

This gap is the point at which the system is evaluated on one set of measures and experienced on another. Platforms and much economic analysis evaluate the app on the flexibility it offers, and a survey that asks only whether workers prefer their arrangement will mostly confirm that. In the 2023 CWS, 80.3% of independent contractors preferred their arrangement. Workers' experience of the app also includes pay that varies from week to week, set by rules they cannot see (Rosenblat, 2018; Rahman, 2021). A preference question compresses the two into a single answer. The SHED items separate them, and they show that the extra flexibility and the extra pay instability come together for the same group.

The 2017 CWS points the same way. Main-job EMW workers who were self-employed or contractors were twice as likely as other self-employed people to prefer working for someone else, even though more of them chose their arrangement for its flexible schedule. Workers can value control over their hours while still wanting the steadier income of a standard job. This matches Mas and Pallais (2017), who find that workers value avoiding employer-set schedules more than they value choosing their own hours. The 2024 profile also matches Schor et al. (2020) and Koustas (2019): app-based task workers are more often on low incomes, more often struggling financially and often combine the work with other jobs.

5.3 What the surveys cannot see

Neither survey observes the app's allocation decisions. Neither records how many tasks a worker was offered or declined, how pay per task was set or changed, or how ratings shaped access to work. These are the mechanisms that research on algorithmic management places at the centre (Kellogg et al., 2020; Möhlmann et al., 2021). The SHED item on how the next task arrives is the closest any national survey comes. Even this item shows that respondents describe the same app as an app, a dispatcher or their own effort, so worker reports are an uncertain guide to who or what allocates the work. Linking survey data to platform records or tax data, as Abraham et al. (2021) propose, is the clearest route to seeing both sides. The 2023 CWS questions on platform work and schedule control may help when they are released; their value will depend on whether the wording avoids the 2017 errors.

5.4 Implications for measuring platform work

Three practical lessons follow for the agencies that will field the next round of questions. First, a question should name the app's functions in the worker's own terms. The 2024 SHED probe asked whether the respondent used an app or website to select projects, pick tasks or connect with customers. It found a quarter of app-based task workers whom a generic question on short-term tasks had missed. The 2017 CWS questions named the same functions but were read by many office workers as a question about any use of an app at work. Wording that ties the app to how the respondent got the work, rather than to how the respondent does the work, appears to separate the two groups better.

Second, the follow-up items matter as much as the screener. The

SHED item on how the next task arrives is a simple, low-cost way to observe allocation from the worker's side. It showed that 43% of app users did not name the app as their source of new work, a result that a single yes or no screener cannot reveal. Items on the regularity of pay, on whether the worker can see the price before accepting a task and on whether the app has limited their access to work would bring the survey closer to the mechanisms that field studies describe (Veen et al., 2020; Rahman, 2021).

Third, editing rules should be published with the data. The 2017 recoding was careful and transparent, and BLS released both versions of the answers. The recoding still changed the estimated correlates of app work, for example raising the odds ratio for independent contractors from 3.60 to 9.10. Users of the public file who do not compare the two versions will not see that change. The same applies to the 2023 platform items when they appear. Releasing the collected answers next to any edited version lets researchers see how much of a finding comes from the work and how much from the classifier.

6. Limitations

The study has several limits. The CWS data are from 2017, before the growth of app-based delivery during the pandemic, and the newer 2023 platform items were not public at the time of writing. The 2017 recoded measure still contains unknown errors, especially for side work, and my comparison cannot say which collected answers were correct. The SHED is an online panel survey with a modest number of app-based workers (247), and its released weights do not allow full design-based variance estimates, so its intervals are probably too narrow. The SHED app question asks about obtaining tasks through an app or website and does not require that the app process payment, so it is broader than the CWS definition and may include people who use online listings. The two surveys differ in population, period and wording, so I do not compare their levels over time. All regression results are associations; they do not show that any characteristic causes app-based work. Finally, many CWS subgroup estimates, including earnings and preferences, rest on fewer than 200 respondents.

7. Conclusion

App-based work allocates labour through software that matches, prices and schedules. National surveys see this system only through questions that ask workers to classify their own work, and those questions are themselves systems that include some workers and exclude others. In 2017 the CWS counted three times as many app workers as BLS could confirm, and the errors hid the over-representation of Black, foreign-born and contract workers. In 2024 a generic question on task work missed a quarter of app users. Where the surveys do reach app-based workers, they show a younger, lower-income and more often Black and Hispanic group that combines the work with other jobs. These workers value the flexible hours and want steadier pay. Measurement that asks only about the arrangement will record the flexibility and miss the pay instability. Questions on how tasks arrive and how pay varies, released with the 2023 CWS data, would let national statistics capture the second as well.

Declaration of conflicting interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship and/or publication of this article.

Funding

This research received no external funding.

Ethics statement

This study is a secondary analysis of publicly available, de-identified data. No human participants were contacted, and no ethics approval was required.

Data availability statement

All data are public. May 2017 CPS Contingent Worker Supplement public-use microdata and replicate weights (U.S. Census Bureau): https://www2.census.gov/programs-surveys/cps/datasets/2017/supp/ (files may17pub.zip and may17rep.zip), with documentation at https://www2.census.gov/programs-surveys/cps/techdocs/cpsmay17.pdf, accessed October 2026. 2024 Survey of Household Economics and Decisionmaking public-use data and codebook (Board of Governors of the Federal Reserve System): https://www.federalreserve.gov/consumerscommunities/shed_data.htm, accessed October 2026. Contingent and Alternative Employment Arrangements, July 2023, news release tables (U.S. Bureau of Labor Statistics): https://www.bls.gov/news.release/conemp.toc.htm, accessed October 2026. The analysis code will be deposited in a public repository on acceptance; it is withheld during review only to keep the review anonymous.

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Received: 30 August 2026. Accepted: 1 October 2026. Published: 8 October 2026.

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