How Much Can You Make?
Misprediction and Biased Memory in Gig Jobs*

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Abstract

Flexibility is an increasingly prominent feature of many jobs. In the gig economy, workers can choose their work hours and face wages that vary across hours and weeks. This increased complexity adds challenges to predicting and understanding job outcomes. Incomplete information or behavioral biases can then lead to inaccurate beliefs about pay and labor supply. We test this hypothesis by collecting novel survey data on 454 delivery and ride share gig workers in the United States. Comparing gig workers' beliefs with data on their actual job performance, we find they overestimate their predictions (43%) and their recalls (31%) of weekly pay, despite it being reported prominently in their earnings statements. Furthermore, gig workers underestimate expenses and overestimate hours worked. The results are consistent with selective recall: when forming and updating their beliefs in noisy environments, workers overweight past high-paying periods. We then examine how biased beliefs affect labor market decisions. We derive predictions from a behavioral labor supply model and test them using survey data and a randomized de-biasing intervention. We find that job choices and labor supply decisions are significantly affected by mistaken beliefs in flexible gig jobs.

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Many jobs have some level of flexibility, with work hours and pay that vary from month to month. Examples include shift choices and tipping in service sector jobs and short-term contracts with piece rate pay in developing countries. A more prominent case are gig economy jobs, which have surged in popularity in the past decade (Collins et al., 2019). Over 9 percent of adults in the United States worked in a gig job for an online platform such as Uber, DoorDash, Instacart or TaskRabbit during the last 12 months (Pew Research Center, 2021). According to the gig economy literature (Chen et al., 2019; Koustas, 2018), flexible jobs generate surpluses of thousands of dollars per year, as workers are able to adjust work hours to accommodate changes in reservation wages and in demand.

Standard economic models assume that agents have accurate expectations of their labor market outcomes. Yet, the extra complexity involved in understanding and predicting pay and work hours in flexible jobs may lead workers to hold incorrect beliefs. For example, workers may not fully comprehend how predictable supply and demand shocks influence variation in earnings and hours. In this case, labor market decisions will not be optimal and prior estimates of worker surplus created by flexibility may no longer hold. For instance, a worker who misperceives how much they make may choose a sub-optimal number of total work hours and allocate them inefficiently across the month. Furthermore, they might misunderstand expected pay differentials across jobs and make incorrect job choices. Inefficient selection can also occur: workers who overvalue flexible jobs may stay at them longer.

In this paper, we examine whether workers in flexible jobs misperceive their labor market outcomes and analyze how this impacts their decisions. We collect novel data from 454 ride share and delivery gig workers in the United States in three online surveys. We begin by eliciting recalls and forecasts of key outcomes such as pay, hours, and expenses. We then collect actual job performance data by asking workers to submit screenshots from the gig platform app. We measure errors in remembering and predicting job outcomes by comparing workers' stated beliefs with their actual outcomes.

We find that gig workers overestimate their job performance by economically meaningful amounts. We first consider gross weekly pay, which is an important outcome for gig workers and is featured prominently in earnings statements. On average, gig workers overestimate a forecast (incentivized for accuracy with a bonus of up to $5) of next week's weekly pay by 43.7%. Likewise, a recall of weekly pay of either the last week or the last month is overestimated by, on average, 31.3%. These errors amount to $85 to $100 per week. More than 70% of our sample overestimates each measure. We show that forecast and recall mistakes are strongly correlated, suggesting a link between prediction errors and biased memory.

Gig workers' perceptions of their *post-expenses* pay is what should guide consumption choices and other decisions. Thus, to have a better understanding of mistaken beliefs, we estimate drivers' expected costs when doing ride share and delivery gig work. Our measure is a function of a car's category, such as small sedan or medium SUV, and age. We consider only variable costs, including maintenance and repair, and make conservative assumptions regarding taxes. Using our estimate of expenses, we find that recalls of net weekly pay are exaggerated by, on average, 46.3%.

Mistaken beliefs about net weekly pay can be broken down into three components. Indeed, the net weekly pay is the product of the average gross hourly pay, an expenses discount, and hours worked per week. We find that overestimation of labor supply and underestimation of expenses are the most influential factors in explaining aggregate errors. Misperceptions of gross hourly pay play only a minor role. In particular, gig workers over-recall work hours by, on average, 33.1% or 5.8 hours, while underestimating expenses by 22%. In addition, a majority of gig workers report ignoring several categories of costs, including depreciation and expected repairs, when calculating their take home pay.

The next step is to investigate why gig workers misperceive their job outcomes. The explanation should provide a reason for pay being consistently *over*-estimated, rather than equally misunderstood in both directions. We propose motivated beliefs (Bénabou and Tirole, 2002; Bénabou and Tirole, 2016) as a likely mechanism. In this theory, agents hold incorrect beliefs due to hedonic utility or as a motivation tool. For instance, a person might derive direct utility from believing they are highly paid or productive.

Our finding that forecast and recall errors are correlated suggests that memory biases are important in the development of overoptimistic beliefs. Accordingly, we show evidence of selective recall. In other words, gig workers' recalls are influenced more by high-paying than low-paying periods, despite the fact that they should be equally significant. Indeed, a pay increase of $100 in the highest-earning week out of the last four is associated with a rise in recall of weekly pay of $57, compared to $26 in the lowest-earning week. In this way, a motivated belief that gig work is highly paid can be justified.

Similarly, we show gig workers update their pay beliefs asymmetrically, reacting more after realizations of weekly pay that are greater than their previous belief. This finding provides a rationale for the persistence of mistaken beliefs over time. Accordingly, we document that there is a positive correlation between gig work experience and overestimation of pay. That is, gig workers who are experienced overestimate their pay by *more*. We show this striking result reflects both incomplete learning and a selection of biased workers in gig jobs.

When labor market outcomes are noisier, there is additional leeway for selecting unrepresentative memories that more easily justify motivated beliefs. Consistent with this, we show that overestimation is increasing in the variance of previous realizations of weekly pay. Increasing the coefficient of variation (standard deviation over the mean) of the four previous weeks by 0.1 is associated with a statistically significant rise in weekly pay over-recalling of $9. This result supports the view that the flexibility of gig jobs is the key aspect behind misperception of job outcomes. It can also explain why full-time salaried workers do not overestimate their earnings (Moore et al., 2000; Rothbaum, 2015): there is no way in these settings to select memories of being paid above the usual salary.

Misperceptions about job outcomes will likely not reduce gig workers' welfare unless their labor market decisions are affected. To this end, we discuss the labor market consequences of mistaken beliefs in gig jobs. We derive predictions from a simple behavioral labor supply model. According to our model, gig workers who overestimate their net hourly pay (in our data, this is 20.7%, on average) will: (i) sometimes not choose a higher-paying alternative job; (ii) backload work inefficiently over the pay cycle, since they earn less than expected at the beginning of the cycle and have to pay bills at its end; (iii) relative to the rational benchmark, work either too few hours (if the relevant margin is satisfying the household budget) or too many hours (if the relevant margin is weighting consumption benefits from work versus the effort cost of additional work hours).

We test these predictions with observational data and a randomized de-biasing intervention embedded in our surveys. We start by examining whether biased workers make mistakes when choosing a job. We find that 45% of workers in our sample move from being above to being below their stated reservation wage when we use their actual (rather than perceived) net hourly pay. This number is probably an overestimate and can be partially explained by other factors. Nevertheless, even in our most conservative specification, we find that 17% of gig workers would be put below their outside option if they knew their actual take home pay. Thus, we find evidence that biased gig workers make sub-optimal employment choices.

Next, we examine if work hours are under-smoothed across the household budget cycle. We elicit up to two days in the month in which workers have to pay major bills. Using this information, we find that gig labor supply is higher close to when bills are due. Gig workers in our sample work, on average, 40 percent (or 3 hours per week) more when a major bill is near due, compared to when it is at least 3 weeks away. In our model, this can be explained by workers earning less than expected at the beginning of the budget cycle, as they over-predict their pay. In order to pay the bills, they then need to work more hours than planned. This leads to a loss in welfare if effort costs are convex.

We further investigate how misperceiving job outcomes affects gig workers by implementing a randomized de-biasing treatment as part of our surveys. In this intervention, we show the treatment group a comparison between their beliefs and their actual expected net hourly pay. By doing so, we make gig workers aware of their mistaken beliefs. If workers become less biased as a result, this should push them to make different labor market choices.

We are underpowered to detect small to moderate effects. However, we find suggestive evidence that financially secure gig workers reduce work hours after learning they make less money than originally thought. On the other hand, de-biased gig workers facing stronger budget constraints tend to work the same or more. Treatment effects are larger for workers whose pay is initially underestimated. This is consistent with our discussion of motivated beliefs: it is more difficult to dissuade workers from believing they are highly paid.

Our paper builds on the behavioral economics literature on the existence and persistence of biased beliefs such as overconfidence.[1] In particular, we closely relate to the theoretical (Bénabou and Tirole, 2002; Bénabou and Tirole, 2016; Köszegi, 2006) and empirical (Eil and Rao, 2011; Godker et al., 2022; Gottlieb, 2010; Moebius et al., 2022; Saucet and Villeval, 2019; Sial et al., 2022; Zimmermann, 2020) literature linking mistaken beliefs to the functioning of memory.[2] We contribute to this literature by being one of the first to apply these ideas to the labor market (Hoffman and Burks, 2020; Huffman et al., 2022), by emphasizing the importance of flexibility in generating mistaken beliefs, and by documenting more thoroughly the implications of mistaken beliefs on labor market decisions.

This paper also relates to a growing literature in labor economics documenting how workers lack information about several variables necessary to make optimal labor supply decisions. For instance, they can have biased beliefs about their outside options (Jäger et al., 2022) and job market prospects (Bandiera et al., 2022; Banerjee and Sequeira, 2020; Conlon et al., 2018; Cortes et al., 2022; Mueller et al., 2021), as well as how their performance (Huffman et al., 2022) and compensation compare with that of their peers (Card et al., 2012; Cullen and Perez-Truglia, 2022). These beliefs have been shown to affect their search behavior, employment decisions (Bergman and Jenter, 2007; Larkin and Leider, 2012; Oyer and Schaefer, 2005) and other labor market choices. We contribute to this literature by

[1] See, for instance, Camerer and Lovallo (1999), Grubb and Osborne (2015), Healy and Moore (2007), Malmendier and Tate (2015), Puri and Robinson (2007) and Sharot (2011).

[2] In addition, see Adler and Pansky (2020), Carlson et al., (2020), Chammat et al. (2017), Di Tella et al. (2015), Enke et al. (2020), Maréchal (2020), Mischel et al. (1976) and Schacter (2008).

investigating a parallel under-explored question: whether workers have accurate beliefs about their inside option – i.e., their current job.

Our work also contributes to the literature on flexible jobs (Camerer et al., 1997; Crawford and Meng, 2011; Farber, 2015; Fehr and Goette, 2007; Thakral and Tô, 2021) and the gig economy (Angrist et al. 2017; Bernhard et al., 2022; Chen et al., 2019; Collins et al., 2019; Cook et al., 2021; Hall et al., 2021; Katz and Krueger, 2019; Koustas, 2018; Mas and Pallais, 2017; Parrott and Reich, 2020). These jobs allows workers to choose their work schedule and are characterized by pay that fluctuates over time. A key question in this literature is how labor supply decisions are made. Our paper provides additional insight into this topic by finding that workers misunderstand key job outcomes in this setting, and that these biases influence labor supply choices.

The paper is structured as follows. Section 2 presents the survey design and describes the data. Section 3 presents the baseline results on mistakes in recalls and forecasts of job outcomes. Section 4 shows that these mistakes can be explained by a combination of motivated beliefs and selective recall. Section 5 derives and tests the empirical predictions of a simple behavioral labor supply model in which workers have mistaken beliefs. Section 6 concludes and shows directions for future work.

2 Survey Design and Data

We study ride share and delivery gig workers for online platforms in the United States. These jobs are characterized by the use of platform apps to accept gigs, pay that varies with demand and skill, full flexibility in hours and a responsibility for workers of paying for most expenses. We only consider companies for which the earnings page in the gig platform app includes not only information on pay but also on hours worked. This choice, made to increase the range of outcomes we observe at these jobs, implies we do not study gig work done for Postmates, Amazon Flex, Shipt, and others.

We consider in our data work done for five gig economy companies: Uber, Lyft, Uber Eats, DoorDash and Instacart. Uber and Lyft combine to be almost the entirety of the ride share market, while DoorDash and Uber Eats represent over 80% of the food delivery market in the United States. Finally, Instacart has a market share of around 45% of the American grocery delivery market (Bloomberg Second Measure, 2022).

We collected online survey data from gig workers from April to November of 2022. We recruited participants to our study using social media posts, social media ads, and gig economy newsletters. We invited participants with the following prompt: "*If you're a driver in the gig economy, answer our online survey to get $10 and a personalized report*".[3] Only people who worked in the past 3 months for at least one of the five gig companies we consider could take part in our study.

If a participant finishes our baseline survey, we invite them through email to answer two follow-up surveys: the midline and the endline surveys. The midline happens 1 to 2 weeks after the baseline, depending on when the first full week (starting on a Monday) following the baseline survey ends. The endline, in turn, happens 2 to 5 months after the baseline survey. We collected all endline surveys in October and November of 2022. Figure 1 summarizes the design of our surveys. We paid participants $10 for participating in our baseline and midline surveys and $20 for answering our endline survey.[4]

2.1 Belief Elicitation

Unless otherwise noted, all beliefs of job outcomes elicited over our three surveys refer exclusively to the gig company that the worker worked the most for in the previous 3 months.

[3]We also used other similar formulations: "*Drivers in the gig economy: Join our online academic study and receive a $10 gift card.*", "*Do you do food delivery or rideshare gig work? Participate in our online survey to receive at least $10.*" and "*Complete a 15 min survey from a UC Berkeley graduate student researcher for US drivers of DoorDash, Uber Eats, Instacart, Uber or Lyft. Receive a $10 Amazon gift card and see how you compare to other drivers.*"

[4]Participants that answered our follow-up surveys were also given a personalized report summarizing (i) their own pay and (ii) the average pay in our sample at their gig company. As described below and detailed in Appendix E, half of participants actually received information (i) at the end of the baseline survey in the form of a randomized information treatment.

We start the baseline survey by eliciting recalls from workers about their job outcomes. We ask two thirds of respondents for a recall of the last month they worked for the gig company and the other one third for a recall of the last week. In our setting, weeks are defined to always start on a Monday and end on a Sunday. We vary the recall period to test how the accuracy of beliefs differs depending on the time frame they refer to.

We focus on recalls of gross weekly pay, weekly expenses, weekly hours, gross hourly pay and net hourly pay. We construct the recall of net weekly pay by subtracting the recall of weekly costs from the recall of weekly gross pay. We calculate the recall of expenses share out of total pay by dividing the recall of weekly costs by the recall of weekly pay. Appendix Figure A1 shows an example of our recall belief elicitation questions.

Next, we ask workers to forecast their job outcomes in the next week (starting on the following Monday) after the baseline survey. We only ask for forecasts of workers who say they are very or somewhat likely to work during this week, which is around 85% of our sample. The forecast for gross weekly pay is incentivized. In particular, we use a Quadratic Scoring Rule to define a payoff based on accuracy, with a bonus that goes up to \$5 and is \$0 if the absolute value of the prediction error is equal to around \$160 or higher. Thus, workers have an incentive for truth-telling.[5] Forecasts for weekly hours and gross hourly pay are also elicited but are not incentivized. Figure A2 shows an example of our forecast belief elicitation questions. The final part of the baseline survey is the randomized information treatment. We provided half of the sample with information on whether they correctly assess their net hourly pay. We detail our information treatment in Appendix E.

Both the midline and the endline surveys are simplified versions of the baseline. In the midline survey, we measure the accuracy of the forecasts elicited in the baseline. We again elicit recalls for key job outcomes. The recall period is the same week as the forecasts

[5]We used the Quadratic Scoring Rule (QSR) due to its simplicity. In particular, the payoff function is defined as $\max\left\{5 - \frac{(X-\tilde{X})^2}{5000}, 0\right\}$, where X is the actual weekly pay for the relevant week and $\tilde{X}$ is its forecast. Participants have to click a button to see an example and the formula of the payoff function. The QSR has been shown to not be robust to risk-aversion, but we believe more complex alternatives would be more problematic, as discussed in Danz et al. (2020) and Charness and Gneezy (2021).

refer to. We then show participants how their forecast of weekly pay matched reality, and inform them of their accuracy bonus. For the information treatment group, we repeat the information we gave them on the baseline survey.

In the endline survey, we elicit recalls referring to the average of the four previous weeks in which participants worked for the gig company. This survey was mainly designed to measure the medium-run effects of the information treatment. Those in the control group receive the information treatment at end of the endline survey. We only elicit beliefs about the baseline gig company during the follow-up surveys if participants report doing work for that company during the relevant time period. Throughout all surveys, we gather a rich set of covariates referring to demographics, job market history, work habits, and other secondary beliefs.

2.2 Labor Market Outcomes

We obtain information on labor market outcomes by asking workers to submit screenshots of the weekly earnings page from the gig company app. As with beliefs, this gig company is the one they worked the most for in the past three months. In all three surveys, we ask for these screenshots only *after* gig workers state their beliefs, and have no possibility of modifying them. Figure 2 shows examples of the screenshots we request. They have information on, among other variables, weekly hours and gross weekly pay for a particular week. Each screenshot prominently displays the gross weekly pay in large font at the top. We require participants to submit at least one screenshot to complete each survey.

As part of the baseline survey, we ask workers to upload a screenshot of their last week of working for the gig company. Participants receive a bonus of $2 if they agree to submit an additional three screenshots, referring to their three previous weeks working for the gig company. In the midline survey, we ask for a screenshot of the weekly earnings page for the forecast week. In the endline survey, we ask workers to upload screenshots of the weekly earnings page for up to twelve weeks in the period between the midline and endline surveys. In this survey, we pay participants a bonus of $1 per screenshot submitted beyond the first one.[6]

Our measure of weekly hours is the total amount of hours spent online in the app (that is, time spent actively on gigs plus time spent waiting for gigs) in a given week. This is the same definition of labor supply as some of the previous literature on the gig economy (Chen et al., 2019; Angrist et al., 2021; Cook et al., 2021). It is also a measure available for all the gig companies we consider. In addition, this measure captures the nature of a standard job, in which only part of the time is spent actively working. We calculate the average gross hourly pay by dividing the gross weekly pay by weekly hours.

2.3 Accounting for Expenses

We do not observe work expenses for gig workers in our sample. As a result, we use an estimate of expected costs of driving to do gig work to calculate the expected actual net pay, a measure relevant for consumption decisions. We take a conservative approach and only consider the main variable costs, which are: fuel, maintenance and repair, variable depreciation and taxes. Our cost measures for maintenance, repair and variable depreciation are based on the AAA Your Driving Costs 2022 guide. Fuel costs are an average of gas prices, also from AAA, in the three months before the baseline survey.

Using survey information on which car is used to do gigs, we estimate expected expenses across 27 groups, combining 9 car categories and 3 car age groups (0-5, 5-10 and 10+). Estimates from the AAA Your Driving Costs guide apply only to the first 5 years of owning a car. We adjust for variation of maintenance, repair and depreciation costs over a car's lifespan by using information from CarEdge. In particular, we find the ratio of how (i) depreciation and (ii) maintenance and repair costs compare for a car that is either 5 to 10 or over 10 years old and a car that is between 0 and 5 years old. We then apply this ratio to the estimates from the AAA guide.

[6] In some cases, workers are asked for recalls referring to the past month but only agree to submit screenshot information referring to one week. When studying mistaken beliefs about job outcomes, we use this one week as a proxy for the last four.

We apply the IRS mileage rate deduction in 2022 ($.585/mile) to calculate self-employment taxes. We estimate federal income taxes by combining reported yearly household income, an estimate of gig income over the year and by applying the standard deduction. We ignore state income taxes for simplicity. Appendix Table B1 shows an example of our calculation of expected expenses. We do not estimate expenses for workers who rent a car to do gig work or that use a bike or a scooter. We discuss additional details of our expenses estimation in Appendix B.

2.4 Sample Selection and Descriptive Statistics

We screen out non-active gig workers from our sample by only including participants who submit valid screenshots from the gig company app. For a screenshot to be considered valid, it has to satisfy three conditions: (i) weekly pay is visible and legible, (ii) the screenshot is not findable on reverse image search, and (iii) the week at the top of the screenshot is at most 3 months before to when the baseline survey was taken. A total of 13 survey responses with identical emails or identical screenshots as other responses were also excluded from our sample.

When we make these restrictions, we end up with 454 baseline survey responses. 51% of workers in our sample have DoorDash as their main gig company for the past three months. This number is 20% for Instacart, 13% for Uber Eats, 10% for Uber and 5% for Lyft. Furthermore, we have 210 midline survey responses and 202 endline survey responses. These numbers imply a response rate of 46% at the midline survey and of 50% at the endline survey. We trim the top and bottom 1% of all forecasts, recalls and actual job outcomes. Our results are robust to changing this trimming cut-off to 2% or 3%.

Summary statistics for our baseline survey sample are presented in Table 1. In Panels A through C, we present information for our main covariates. The vast majority of gig workers in our sample are between 18 and 54 years old. They are over 70% white and majority female. Around 38% of them have at least a complete college degree, and a little over half of our sample has a household income of \$40,000 per year or less. We find that 42% of respondents are struggling financially and 83% of them consider the pay from their gig work to be essential.

Over half of gig workers in our sample has another job – either a gig or a non-gig one. Around 10% were unemployed before starting doing gigs, while 36% had a full-time job. In addition, 23% of workers have at least a year of gig ride share experience, while that number is 57% for gig delivery experience. The five most common cars that gig workers in our sample drive are: Hyundai Elantra, Toyota Corolla, Honda Civic, Honda Accord and Hyundai Sonata. About 80% of participants drives either a small sedan, a medium sedan, a compact SUV or a medium SUV. In addition, the median car age is 8 years old.

In Panels D through F of Table 1, we present summary statistics for our main outcome variables. Gross pay is, on average, \$18 per hour and \$284 per week. Average hours worked is equal to 17 per week. Note this includes only weeks with a positive amount of work hours. Our estimated expected expenses share is, on average, 32% of total gross earnings.

We observe that, generally, recalls and forecasts have higher averages than actual job outcomes. As in the rest of the paper, we pool together recalls for the past week and the past month. For instance, the average forecast of gross weekly pay is around \$376/week, while the average recall of weekly hours is around 22 hours per week. In addition, recalls and forecasts of job outcomes are very similar. Outcome variables vary widely across workers, reflecting the nature of flexible gig work.

We analyze selective attrition across our three surveys in Appendix Table A1 and Appendix Table A2. There is some indication that participants in our follow-up surveys are more likely to be more college educated and are perhaps a little richer. However, taken broadly, we cannot reject that the mean observable characteristics are overall the same across the surveys.

Appendix Table A3(A) compares the share of workers in our sample who have done any gigs for different gig companies to how many people each of those companies contract in the United States. We find evidence that DoorDash workers, and delivery workers more broadly, are over-represented in our sample relative to Uber and Lyft drivers. Appendix Table A3(B) shows how key summary statistics in our sample of gig workers compares to recent previous surveys on the gig economy (Parrott and Reich, 2020; Pew Research Center, 2021; Doordash, 2021). We find suggestive evidence that our sample is younger, more white and more educated. In addition, participants in our study appear to work more hours than the median gig economy worker.

3 Mistaken Beliefs about Job Outcomes

3.1 Forecasting Errors

In this section, we explore whether job outcomes are misperceived by gig workers. We begin by looking at forecasts of gross weekly pay for the next week. This is a consequential belief, essential for labor supply and consumption choices. Weekly pay is also the most salient job variable when checking the gig platform app, as the screenshots in Figure 2 show. Furthermore, our sample of gig workers had a special incentive to get this prediction right, as we provided them with an accuracy bonus of up to $5.

Figure 3(A) shows a scatter plot comparing the forecast and the actual gross weekly pay for each gig worker. The forecast refers to the first week following our baseline survey. We only include participants who answered our midline survey, as otherwise we cannot measure the accuracy of their forecast.[7] We draw a 45 degree line to represent the case where forecasts exactly match actual realizations. Points above this line indicate overestimation, while points below this line imply underestimation of gross weekly pay.

Due to noise and variation in gig pay over time, points are unlikely to be positioned neatly

[7]We include workers in both the treatment and control groups of our information treatment in this analysis, as we asked them both to forecast their job outcomes. We allowed treated individuals to review their forecast of weekly pay after the information treatment. Mistakes are larger when we only the control group is considered.

on the 45 degree line even if workers' beliefs are correctly calibrated. However, in the absence of systematic biases, points should be positioned *symmetrically* around this line. Looking at the results, we find that points are concentrated above the 45 degree line, indicating that the majority of the sample over-predicted their weekly pay. Furthermore, this asymmetry holds across most of the distribution, and is not dependent on outliers.

We define overestimation of a job outcome (either for a recall or a forecast) as the belief minus the actual realization. We say a worker underestimates a job outcome if this measure is negative. We present statistics using this variable in Table 2 Panel A. We find that overestimation of forecasts of gross weekly pay is significant: it is 43% of the actual weekly pay, or around $110, on average. 72% of our sample is identified as overestimating their forecast. These measures are statistically significant at 1% against the null of no overestimation. As seen in Figure 3(A), the slope of a linear regression of forecasts on the actual weekly pay is around 0.8. This implies that forecasts are significantly related to actual outcomes and that overestimation is, broadly, decreasing on actual weekly pay.

3.2 Recall Errors

We have shown that workers make large mistakes when they predict their weekly pay. Nevertheless, forecasting job outcomes is by nature a complex task in flexible jobs. As such predictions require taking into account a complex set of shocks and understanding their exact relationship with hours and pay, it might not be surprising that workers can fail to do them correctly.

We now tackle a much simpler problem: *recalling* gross weekly pay. A gig worker has easy access to the actual value of this variable for all periods in which they worked for the company. That is, they can know their exact gross total pay in every week. Consequently, errors in recall will indicate additional difficulties in understanding gig pay.

We pool recalls of the previous week and month before the baseline survey. On Figure 3(B), we see a similar pattern as with forecasts: points are concentrated above the 45 degree line, and most participants seem to over-recall their weekly pay. The statistics in Table 2 confirm this suspicion. Overestimation of recalls is both statistically and economically significant. We find that gig workers exaggerate their actual weekly pay by over 30%, or around $90/week. Over 70% of gig workers in our sample overestimate their recall of weekly pay. These measures are statistically significant at 1% against the null of no overestimation.

Thus, biases in forecasting and recalling weekly pay are similar in magnitude. This is true despite the fact that weekly pay predictions included incentives for accuracy while recalls did not. This is consistent with workers stating their true beliefs even without being incentivized. The similarity between recall and forecast errors may also indicate that mistaken beliefs about the future are tied to incorrectly remembering the past.

This suspicion is tested in Figure 4(B) by graphing, at the individual level, forecast overestimation against recall overestimation for weekly pay. The slope coefficient of the regression between these two types of mistakes is 0.51, which is statistically significant at 1%. Figure 4(A) re-does this analysis for forecast versus recall *beliefs*. Here, the relationship is even stronger (coefficient of 0.9), suggesting that gig workers see these two beliefs as nearly equivalent.

We elicited recalls and forecasts at different points in the survey and on pages with very different layouts, as one can see by comparing Appendix Figure A1 and Appendix Figure A2. Therefore, confusion is not likely to be the cause for this result. From now on, we will sometimes focus on recalls as a short-hand for both types of errors due to the similarity between them and to allow us to take advantage of a larger sample size.

3.3 Gross versus Net Pay

The previous sections have documented that gig workers overestimate their future and past weekly pay. However, we have not taken into account the expenses and taxes associated with gig work. Costs are a significant margin at these jobs, since workers are generally responsible for paying them. This adds a new layer of complexity to understanding pay. At the same time, the net weekly pay, which represents the amount of income from gig work left over for consumption, is likely to be of special importance to workers.

Taking expenses into account is also relevant when thinking about the consequences of errors in understanding job outcomes in gig work. For instance, a gig worker that overestimates both gross weekly pay and expenses can end up holding correct beliefs about their expected net weekly pay. In this scenario, their mistaken beliefs might not result in sub-optimal labor supply and consumption decisions.

As previously mentioned, we calculate a measure of expected costs by car category and car age group, taking into account variable operating expenses and taxes (see Appendix B for more details). Our estimates will likely not reflect true costs at the individual level in particular weeks, but they should be close to reality on average. We calculate the actual expected net weekly pay by discounting the gross weekly pay by our measure of the expected expenses share.[8]

We find more evidence of mistaken beliefs after adjusting for expenses. In Table 2, we see that workers significantly overestimate their recall of net weekly pay by about 46%, or around $90 per week. As shown in Appendix Figure A3, a scatter plot relating beliefs and the actual expected net weekly pay reveals a sizable grouping of individuals above the 45 degree line, where recalls are greater than the expected net pay.[9]

3.4 Decomposition of Mistakes

Net weekly pay is the product of three factors: average gross hourly pay, an expenses discount and weekly hours worked. This allows us to decompose total errors in understanding this outcome into individual errors along these three dimensions. Prior to discussing this decomposition, we examine the average overestimation for each outcome separately. Table 2 Panel B summarizes recall results once again. First, note that sample sizes differ across

[8]Our estimated expected expenses share is, on average, 32% of total gross earnings.

[9]Note that our error in capturing variations in expenses across time partially explains the dispersion seen in this graph.

outcomes. The reason for this is a combination of trimming, that not all screenshots contain hours information, and that, as mentioned before, we do not calculate expected expenses for certain types of gig workers, such as those who use bikes or scooters.

Overestimation of weekly hours is around 6 hours a week, or 31% of actual hours worked. Gig workers underestimate expenses by, on average, about 22% or 7 percentage points. Gross hourly pay is overestimated only by a small non-statistically significant magnitude. However, this analysis is based on recalling the average hourly pay over entire weeks. Our finding does not imply that workers are able to recall or predict variation in gross hourly pay over particular hours, for instance. Finally, we find that net hourly pay is over-recalled by, on average, 20.7%.

Table 2 Panel A shows forecast errors for these outcomes. Weekly hours are overestimated by about 8 hours, or 63% of actual hours driven. Once again, gross hourly pay is overestimated by only a small, non-significant amount. For both recalls and forecasts, about 70 percent of gig workers overestimate (or underestimate in the case of expenses) each individual outcome, with the exception of average gross hourly pay. These shares are statistically different from 50% at the 1% significance level. Thus, we find strong evidence of significant overestimation in recalls and forecasts across most job outcomes in gig jobs.[10]

We now decompose the total error in recalling net weekly pay into three categories: average gross hourly pay, the expenses discount and weekly hours worked. Multiplying the recall for each of these components gives us the *implied* recall of net weekly pay. The average gig worker overestimates this implied measure by 53.3% of the expected actual net weekly pay. This is greater by about $50/week to what we found using another definition of net weekly pay recall (recall of gross weekly pay minus recall of weekly expenses).

In the next step, we replace each element of the implied net weekly pay recall with its

[10] Appendix Figure A3 and Appendix Figure A4 present additional scatter plots relating beliefs to actual job outcomes. Appendix Table A4 shows that overestimation is generally positively correlated across different job outcomes, with the exception being hourly pay and hours. Appendix Figure A5 and Appendix Figure A6 show a significant relationship between forecast and recall errors and forecast and recall beliefs for both gross hourly pay and weekly hours. This means that the strong ties between the two types of beliefs extend beyond weekly pay.

correct equivalent. For instance, we replace the recall of gross hourly pay by its actual value, while keeping recalls of expenses and hours in place. A comparison between this multiplication and the original implied belief reveals the importance of gross hourly pay errors *only*.

Figure 5 shows the results of this exercise. In this figure, we show the average pay for four possibilities related to this decomposition of net weekly pay: (i) implied recall, (ii) correct gross hourly, (iii) correct weekly hours; and (iv) correct expenses. By replacing recalls by their actual equivalent for each individual outcome, net weekly pay drops by 57% for hours, 36% for expenses and 11% for gross hourly pay. Hence, underestimation of expenses and overestimation of hours explain most of why workers overestimate their take home weekly pay. Therefore, both hours and net pay flexibility can cause misperceptions.

3.5 Additional Results and Heterogeneity Analysis

In our baseline survey, we asked people to recall either the last week or the last month in which they worked for the gig company. Appendix Table A5 shows that overestimation is generally larger when workers are asked to recall an average of the last 4 weeks, compared with just last week. Appendix Figure A7 shows the results of regressions of recall beliefs for the past month on the last four weeks of actual realizations of the same outcome, ordered by recency, and a constant. For gross weekly pay, we find that recent periods influence beliefs more than older ones. These findings are consistent with individuals having a more difficult time remembering events that happened further ago in the past.

Appendix C details our analysis of beliefs about the average worker at the same gig company. We elicited these beliefs in all three of our surveys for a sub-sample. Workers believe the average gig worker works more hours but earns a similar amount per hour, both before and after expenses. We find no evidence of overplacement (Healy and Moore, 2007). That is, workers' belief about their pay differential relative to the average gig worker is not higher than the actual difference in earnings between the two.

In Appendix Table A6, we examine whether overestimation is heterogeneous by worker characteristics. Within each table, we regress our measure of recall overestimation for different job outcomes on variables summarizing key attributes. In Panel (A), we divide the sample into (i) workers who are entirely or somewhat certain of their recall beliefs and (ii) workers who are neither certain nor uncertain, somewhat uncertain, or not certain at all of their recall beliefs. We find some evidence that overestimation is larger for workers more certain of their recalls. This is problematic because this group may be less likely to obtain information about their actual gig pay and work hours.

Panel (B) examines whether errors vary by whether workers are full-time gig workers or not. Full-time gig work is defined as working at least 30 hours per week, on average. In our sample, 23% of workers satisfy this definition. The results indicate that full-time gig workers overestimate their hourly wages by more, but underestimate their weekly hours. The combination of these effects implies the same amount of overestimation of weekly pay recalls.

Panel (C) of Appendix Table A6 focuses on financial need. Results show that workers who rely more on gig pay tend to overestimate their hours and weekly pay by more. This is significant, since these workers are likely to face more consequences from not knowing their pay. In Panel (D), we examine demographic characteristics (age, gender, race, education, and household income). Overall, we find no statistically significant correlation between these characteristics and mistakes in recalling job outcomes. In Panel (E), looking at labor market information, we show that gig workers previously employed full-time overestimate their weekly pay and hours by more.

Finally, in Table 3, we examine how misestimation varies with gig work experience. We find that gig workers with more than one year of experience in both rideshare and delivery overestimate their weekly pay by around \$70 *more* than inexperienced ones.[11] Thus, not only is experience not associated with gig workers holding more accurate beliefs, it is correlated

[11]We provide an alternative analysis in Appendix Table A7, by separately considering delivery and ride share experience. We also include other job outcomes. We find very similar results.

with larger errors. As we discuss below, this result reflects a mix of incomplete learning and selection of biased workers over time at these jobs.

3.6 Robustness

In this section, we discuss alternative explanations for some of our findings and conduct robustness checks. We categorize possible issues into three categories: selection, measurement of beliefs, and measurement of outcomes. We address each set of potential problems in turn.

We first argue against the concern that our overestimation results come from disproportionally selecting biased workers into our sample. First, our sample is likely to be more sophisticated and more informed than the average gig worker, as we partially recruited participants from gig worker groups and gig economy newsletters. Additionally, Appendix Table A3(B) indicates our sample is more educated than the median gig worker. Previous research has found that education is negatively correlated with behavioral biases (Stango and Zinman, 2020).

Next, our heterogeneity analysis in Appendix Table A6 has shown that mistakes are widespread across a wide range of demographic and other characteristics. For this reason, selection along many common dimensions would not be enough to reproduce our findings. Finally, a pilot study conducted without monetary incentives and with no information treatment found overestimation of job outcomes of a similar magnitude to what we document here. This variation in incentives to answer our survey likely attracted different types of gig workers. Nevertheless, the fact that both of them produced similar results reinforces our conclusions that sample selection cannot explain our results.

We believe our findings are not the result of measuring recall and forecast beliefs incorrectly. First, we explicitly ask gig workers to consider all elements of pay, including tips, bonuses and platform fees. Another possibility is that workers round up their beliefs when answering our survey. Appendix Table A8(B) shows that considering only workers with beliefs that are not round numbers implies qualitatively similar overestimation results.

We elicit beliefs about job outcomes only for one gig company. However, a significant number of gig workers in our sample (42%) worked for more than one platform in the previous three months. If workers do not correctly understand our survey questions, they might report total pay and hours across multiple companies. Appendix Table A8(A) shows overestimation of job outcomes is still economically and statistically significant if we only consider the group who worked for only one gig company.

As a result of social desirability bias, workers may intentionally overstate their beliefs. We do not believe this is driving our results for a number of reasons. First, remember that predictions of weekly pay were incentivized with a monetary bonus for accuracy. This raises the costs of inflating beliefs and should make beliefs more accurate in the presence of a desire to impress researchers. Nevertheless, we found substantial overestimation in weekly pay forecasts. Second, work hours are less likely to be overstated in this way. Indeed, working additional hours implies a lower hourly pay and does not clearly carry a self-image benefit (required for social desirability bias). We have shown, however, that workers significantly overestimate their hours worked.[12]

Finally, during the midline and endline surveys, workers are aware that we might ask them to later submit screenshots containing their job performance. As such, inflating beliefs for the sake of impressing researchers makes less sense, since participants can infer that their answers can be directly compared to reality. Appendix Table E3 shows that, in the follow-up surveys, gig workers in the control group of the information treatment still significantly overestimate job outcomes.

We discuss robustness checks for our measurement of job outcomes, including a discussion on the distinction between online and active hours, in Appendix D. To test the robustness of our measure of expected gig work costs, we now propose an alternative formulation of

[12] Appendix C documents that gig workers in our sample do not believe they earn more than the average gig worker. This piece of evidence is also inconsistent with the standard formulation of the social desirability bias.

errors in understanding this outcome. We first ask workers which categories of costs they consider when calculating their net pay. Results are shown in Appendix Figure A8. Many gig workers report ignoring types of costs such as maintenance (45%), taxes (65%) and depreciation (83%).

Based on this information, we calculate an implied measure of belief about expenses. Specifically, we assume drivers use only the cost categories they self-report to take into account. We then input *our own* expenses estimates for each of these categories. In this alternate estimate, only errors resulting from ignoring some types of expenses are considered. In reality, errors also arise from wrong beliefs about the expected cost of repairs, for instance. Using this measure, we still find that gig drivers underestimate expenses by about 5 percentage points, or 15%. In other words, mistaken beliefs about expenses are not due to our estimates of actual costs of different types.

4 Explaining Mistaken Beliefs

In the previous section, we documented that gig workers overestimate both their prior and future earnings by significant margins. This section attempts to understand why these errors occur. The proposed mechanism should be able to explain why beliefs are biased toward overestimation, rather than being inaccurate in both directions. In addition, we found before that forecasting and recall errors are correlated. In light of this, we must also take into account the connection between inaccurate memories and wrong beliefs about the future.

We consider motivated beliefs (Bénabou and Tirole, 2002; Bénabou and Tirole, 2016) to be a likely explanation for the patterns we observe. In this framework, agents hold incorrect beliefs due to hedonic utility or as a motivational tool. For instance, a person might enjoy believing they are highly paid, smart or productive.

Motivated beliefs are developed and maintained by selective recall: favorable memories are more easily accessed than unfavorable ones. By relying on a biased memory, forward-looking beliefs used in making decisions are distorted. For example, a person with selective recall may remember days when they exercised more readily than other days. By doing so, one reinforces the desirable perception of being healthy and active. However, this may taint predictions regarding future gym attendance. Mistakes will occur even if the agent has a correct function for inferring forecasts from recalls. Indeed, the key error lies in failing to appreciate that recalls are partially chosen to justify particular beliefs.

In the same way, new information does not necessarily lead to more accurate beliefs: updating is not Bayesian, but it reacts disproportionately to positive news, which have a more lasting effect on beliefs. Therefore, incorrect views can persist over time and additional experience may not make mistakes disappear. There are limits to belief manipulation in this framework. Nevertheless, these constraints can be relaxed when signals are less informative and the environment is noisier, since this allows for additional leeway in choosing unrepresentative memories.

Recent empirical literature finds extensive evidence for overly optimistic beliefs tied to selective memory. Many domains have been studied, including investment decisions (Godker et al., 2022), intelligence (Zimmermann, 2020; Moebius et al., 2022), beauty (Eil and Rao, 2011), and generosity and altruism (Saucet and Villeval, 2019; Di Tella et al., 2015; Carlson et al., 2020).

4.1 Evidence of Motivated Beliefs

We now apply the predictions of this theory to our setting. Gross weekly pay is the main outcome we consider in our analysis. Assume gig workers want to believe they are highly paid. A favorable memory, such as a period with high pay, will support this belief, while an unfavorable memory will contradict it. Unless otherwise noted, we use only data from the baseline survey.

First, we examine whether high-paying periods influence recalls more than low-paying ones. This may happen if gig workers remember high-paying weeks more easily. This analysis only includes workers asked to recall the average of the last four weeks. Our first specification regresses recalls of gross weekly pay on the maximum and the minimum of the last four actual realizations. In the absence of biases, a one-unit increase to either the maximum or the minimum should affect recalls equally. Indeed, the recall *should* be a simple average of the weekly pay in the last four weeks. We find that this is not the case. Results are shown in the first column of Table 4(A).[13] Increasing pay in the workers' highest paying week by $100 is associated with a rise in recall of $57, compared to $26 for a similar increase in the lowest paying week.

In column (3), we regress the recall of weekly pay on both the actual mean of the past 4 weeks and the maximum of these same weeks. If workers rationally form their beliefs, the coefficient on the maximum week should equal 0, since the mean is a sufficient statistic for the recall. Yet, we find that not to be the case. Indeed, the maximum week has a statistically significant coefficient that is half as large as the coefficient on the mean. Thus, the best periods seem to be overweighted by gig workers in belief formation, as predicted by selective recall of favorable information.

We now evaluate whether workers update their beliefs asymmetrically when presented with new information about their pay. We estimate how the weekly pay recall at the midline survey relates to the relative comparison of (1) the actual weekly pay in the week that the recall refers to, and (2) the previous recall belief, elicited in the baseline survey. We expect workers to update more strongly to positive than to negative news.

We apply this idea in a simplified way by dividing weekly pay realizations into two: those above or equal to the previous recall, and those below. We then run regressions of the midline weekly pay recall on the previous recall and two binary variables, equal to one when the actual weekly pay realization is (i) above or equal to or (ii) below the original recall belief.

[13] Appendix Table A11 shows the same set of results, but for forecasts.

Results are shown in Table 4(B). We find that gig workers update their beliefs more strongly after a positive realization. The recall of weekly pay is estimated to increase by $208 when the actual weekly pay is above or equal to the previous belief, and to fall by only $48 when the opposite is true. This asymmetric in reacting to new information can justify the persistence of biased beliefs.

These findings are consistent with the previously discussed Table 3, which examines how mistaken beliefs vary with gig work experience. We found that not only is gig experience not associated with gig workers holding more accurate beliefs, it is correlated with larger errors. Our correlational estimates of experience effects are influenced by both selection and learning. Workers may become significantly better at measuring their job outcomes over time. Nonetheless, there may be a stronger countervailing effect caused by overconfident individuals who stay at gig jobs longer, precisely because they believe their pay is higher than it is.

We can test whether this is the case by examining the average levels of overestimation in our endline survey, which was conducted two to five months after our initial survey. We ask for a recall of the past 4 weeks. By comparing mistaken beliefs from this survey with errors in the baseline survey, we can estimate learning effects. Appendix Table E3 shows the results. The average level of overestimation across job outcomes is 30% to 40% lower at the endline survey (compared to one month recalls shown in Appendix Table A5). Thus, while there is some degree of learning, it is insufficient to counter the likely selection of overconfident gig workers at these jobs.

We now evaluate whether more variation in job outcomes, by relaxing the constraints on belief manipulation, leads to more overestimation of weekly pay. Indeed, more uncertainty in outcomes might make it easier to select unrepresentative memories and base one's beliefs on them. The same mechanism might also explain why workers in non-flexible jobs do not appear to overestimate their earnings.[14] In fact, studies comparing survey data with tax data

[14] See, for instance, Appendix Figure C.4 in Cullen and Perez-Truglia (2022).

reveal a slight *under*-reporting of labor income in surveys (Moore et al., 2000; Rothbaum, 2015).

We measure noisiness in weekly pay realizations across four weeks as the coefficient of variation, which is the standard deviation divided by the mean. Results are presented in Table 5. We find that a higher coefficient of variation leads to more overestimation: increasing this variable by 0.1 (mean of 0.48) is associated with an increase in weekly pay recall overestimation of around $9, which is statistically significant at 1%. This result supports the view that the flexibility of gig jobs is the key aspect behind overestimation of job outcomes.

We re-do our previous analyses for weekly hours and gross hourly pay in Appendix Table A9 and Appendix Table A10. Generally, the results are similar for hours. One possible interpretation is that believing one works long hours helps the belief that weekly pay is high. Our results for hourly pay are generally consistent with a lack of significant overestimation in this variable, as we don't find much evidence for the mechanisms discussed above. Alternatively, this can be explained by each realization of hourly pay in our data being only its weekly average, not allowing us to not incorporate intra-week variation.

We have not discussed the mechanisms underlying underestimation of gig job expenses. This is because we do not observe variation in actual expenses over time at the individual level. We believe it is reasonable to assume similar mechanisms than the ones just discussed are at play. For instance, when forming their beliefs, gig workers may overlook periods when their car broke down or when they had to pay taxes.

There is one last point we want to make before moving on. Overestimation of weekly pay following the patterns predicted by the theory of motivated beliefs with selective recall is another argument in favor of us identifying true mistakes. Indeed, any suggested confounder is now also required to explain why overestimation in our settings fits the predictions of this theory.

5 Consequences of Mistaken Beliefs

In this last section, we explore the consequences of workers consistently overestimating key job outcomes, such as gross and net pay. This is critical, as these mistakes will be less important if they do not lead to welfare-reducing labor market decisions. We derive potential implications from mistaken beliefs by developing a simple behavioral labor supply model. We then test the model's predictions using survey data as well as a randomized de-biasing information treatment, in which workers are informed of their mistakes in understanding their net wages.

5.1 A Model of Labor Supply

Consider a model in which a worker first chooses a job, consumes (c) and works (h) over two periods, and then leaves some amount of savings (s) for the future. The worker can freely borrow and save across both periods, which can be thought of as the first and the second halves of the household budget cycle.

At the Job Choice Stage, the worker decides between a gig job G and a non-gig job O, which are identical in all dimensions besides net hourly wages. The gig job has a fixed net wage of w_G, which the worker mistakenly believes to be $\tilde{w}_G = w_G \cdot (1 + \theta)$. The parameter $\theta \geq 0$ is the degree of net hourly pay overestimation. As previous discussed, θ is around 0.2 in our sample.[15] The non-gig job has a fixed net wage of w_O, which we assume the worker correctly assess. Assume that w_O possibly includes the difference in non-wage amenities between the two jobs.

Denote the job choice by $J \in \{G, O\}$. Given our setup, the worker will choose the job with the highest perceived wage: $J = G$ if $w_G \cdot (1+\theta) \geq w_O$ and $J = O$ otherwise. Let $\tilde{w}$ be the *perceived* wage, where $\tilde{w} = \max\{w_G \cdot (1+\theta), w_O\}$, and let w be the *actual* hourly wage, such that $w = 1\{J = G\} \cdot w_G + 1\{J = O\} \cdot w_O$.

[15] We make the simplifying assumption that the worker's only bias lies in misunderstanding the net hourly pay in a gig job, where before we also shown evidence for the overestimation of work hours.

After choosing a job, in Period 1 the worker maximizes his perceived value function by choosing c_1 and h_1, while making plans for c_2, h_2 and s:

$$\max_{c_1,c_2,h_1,h_2,s} u(c_1) + u(c_2 - \bar{c}) + V(s) - c(h_1) - \delta c(h_2) \tag{1}$$

such that

$$c_1 + c_2 + s = \tilde{w} \cdot h_1 + \tilde{w} \cdot h_2 + M \tag{2}$$

Where $u(c_1)$ is a concave period 1 consumption utility function and $u(c_2 - \bar{c})$ is a Stone-Geary utility function defined over period 2 consumption. This implies a subsistence condition of $c_2 \geq \bar{c}$, where $\bar{c}$ is a minimum level of consumption needed to pay household bills in period 2. In addition, $c(h)$ is the convex cost of effort function, s is the leftover (potentially negative) savings to be used after period 2, and $V(s)$ is the continuation value of s, with $dV(s)/ds > 0$. Furthermore, M is non-labor income. For simplicity, we assume no time discounting and zero interest rates between periods 1 and 2. Represent Period 1 choices by $\tilde{c}_1^*, \tilde{h}_1^*$ and Period 1 plans by $\tilde{c}_2^p, \tilde{h}_2^p$ and s^p.

At the start of Period 2, the worker learns the *actual* amount of money leftover after Period 1 $(w \cdot \tilde{h}_1^* - \tilde{c}_1^* + M)$, which is potentially negative. When $\theta > 0$ and $J = G$, the worker will be negatively surprised by this information. For simplicity and to match evidence from previous sections, we assume there is no learning of overestimation θ from this fact. After this, still in Period 2, the worker has an opportunity to revise their plans for c_2 and h_2. In particular, they maximize the perceived value function by choosing c_2, h_2 and making plans for s:

$$\max_{c_2,h_2,s} = u(c_2 - \bar{c}) + V(s) - c(h_2) \tag{3}$$

such that

$$c_2 + s = (M + \tilde{w} \cdot \tilde{h}_1^* - \tilde{c}_1^*) + \tilde{w} \cdot h_2 \tag{4}$$

Represent choices by $\tilde{c}_2^*$ and $\tilde{h}_2^*$. Finally, at the end of Period 2, the worker learns the *actual* amount of money saved (or borrowed) after Period 2, $\tilde{s}$:

$$\tilde{s} = w \cdot \tilde{h}_1^* + w \cdot \tilde{h}_2^* + M - \tilde{c}_1^* - \tilde{c}_2^* \tag{5}$$

This is accompanied by the continuation value $V(s)$, which is a reduced form way of considering how increased savings or borrowing affect the worker's future, which we don't explicitly model. Variation in the shape of this function across workers can reflect, for instance, borrowing constraints.

Overestimating net pay ($\theta > 0$) can lead to three categories of mistakes for a gig worker:[16]

1. *Incorrect choice of employer.* A gig worker will not choose a higher-paying outside job when overestimation θ is enough to move the perceive gig wage $\tilde{w}_G$ from below to above the outside job wage w_O. This happens when $w_G \cdot (1+\theta) > w_O > w_G$.

2. *Under-smoothing of labor supply.* A gig worker with $\theta > 0$ believes their period 1 labor income is higher than it actually is by $\theta \cdot w_G \cdot \tilde{h}_1^*$. Realizing this fact at the start of Period 2 is equivalent to an unexpected negative wealth shock. This unexpectedly increases $u'(c_2 - \bar{c})$, the marginal utility of consumption in period 2, causing the gig worker to re-optimize by working more than originally planned ($\tilde{h}_2^* - \tilde{h}_2^p > 0$). The gig worker then inefficiently works too much in Period 2 and too little in Period 1.

3. *Incorrect choice of hours.*

   (a) *Works too much.* If gig income is not essential to fulfill the household budget (M is large enough relative to $\bar{c}$), the relevant margin in deciding labor supply is the marginal benefit of consumption. Biased gig workers then work more hours than optimal.

   If $c_2 \geq \bar{c}$ (which is guaranteed for large M), gig workers decide labor supply in

[16] As previously mentioned, we do not incorporate errors in understanding labor supply into our model. Two of our predictions below, incorrect job choice and wrong labor supply allocation across the pay cycle, are exacerbated if we consider this additional bias.

Period 1[17] by equating

$$c'(h_1) = c'(h_2) = \tilde{w}_G \cdot u'(c_1) = \tilde{w}_G \cdot u'(c_2 - \bar{c}) = \tilde{w}_G \cdot V'(s) \qquad (6)$$

As $\tilde{w}_G > w_G$ when $\theta > 0$, a biased gig worker believes the benefits of additional consumption and savings of working one additional hour are higher than they actually are. Due to the assumed convexity of $c(\cdot)$, this implies they will work too many hours relative to when $\theta = 0$.

(b) *Works too little.* If gig income is essential to fulfill the household budget (M is not large relative to $\bar{c}$ and $\bar{c}$ is sufficiently high), the relevant margin in deciding labor supply is consuming enough in Period 2 to reach the subsistence level $\bar{c}$. Biased gig workers then work less than needed to optimally satisfy the subsistence restriction.

To isolate this mechanism, consider a version of our model with only Period 2 and $s = 0$. In this case, the first-order condition implies a choice of hours equal to h. However, if $\tilde{w}_G \cdot h + M < \bar{c}$, the subsistence condition is not satisfied and the optimal labor supply choice will be such that $\tilde{w}_G \cdot \tilde{h}^* + M = \bar{c}$. In this case, $\tilde{h}^*$ is decreasing on the overestimation parameter θ, such that a more biased agent works fewer hours.[18]

In Figure 6, we solve our model numerically and further illustrate the consequences of overestimation. We do comparative statics by varying the overestimation parameter θ. Details of our parametrization and calibration are provided in the notes of this figure.

We show in Panel (A) the number of hours worked in period 1 and period 2 for different values of θ. In this graph, our model is parametrized so that the gig job is not chosen if the bias θ is low enough. As a result, workers with low θ accurately predict their pay and work the same number of hours in both periods. However, at higher values of θ, the worker

[17] The same logic holds for Period 2 decisions.

[18] The same logic holds for our full model for sufficiently high values of $\bar{c}$, despite countervailing adjustments in c_1 and s when the subsistence restriction does not hold.

chooses the gig job, committing an error in job choice. This results in a larger labor supply for period 2 than for period 1. The difference in work hours between both periods is also increasing on θ. Thus, this illustrates our second mechanism, the inefficient under-smoothing of labor supply in the presence of overestimation.

In Panel (B), we plot the difference between total labor supply of a biased and a rational ($\theta = 0$) worker as overestimation θ increases. We plot two separate lines, one for a low value of non-labor income M and another for a high value of M. For this graph, we assume the outside job is considered an inferior choice for all values of $\theta \geq 0$. As discussed above, we find that a behavioral gig worker works less than the optimal amount when non-gig labor income M is low (relative to $\bar{c}$). In contrast, if M is sufficiently high, the behavioral gig worker supplies too much labor relative to the rational benchmark.

5.2 Empirical Evidence

We begin by testing our first prediction: biased gig workers will sometimes not choose a superior outside option. Our measure of the reservation wage is equal to workers' self-reported lowest acceptable net hourly pay to keep working in their current gig job. Figure 7 shows scatter plots relating the reservation wage to the net hourly pay, for either its recall (left panel) or its actual expected value (right panel). We find that, as we move from the recall to the actual expected net hourly pay, many gig workers are moved under the 45 degree line. In other words, their net pay falls below their reservation wage.

This impression is confirmed in Table 6. First, we find that 23 percent of workers have a higher reservation wage than recall of net hourly pay. This relatively high percentage may reflect a mix of noise in beliefs and actual job outcomes, confusion over the outside option, and perhaps real plans to stop working for the gig company in the future. When comparing the reservation wage with the *actual* expected net hourly pay, however, this percentage increases substantially, to 68%.

In other words, 45 percent of gig workers move from being above to being below their reservation wage when their actual net hourly pay is considered, versus their belief of it. In our model, gig workers for whom this is true are characterized as making a mistake in job choice. We find similar qualitative results by looking at the averages (Appendix Table A12) or the share of workers $5 below their stated reservation wage.

Our analysis thus far contains some caveats. To this end, the other rows of Table 6 provide robustness checks to our results. First, we may exaggerate the magnitude of gig workers not choosing the best available job if they also overestimate their outside options. To address this, we first consider workers less likely to have another gig job – where mistaken beliefs are more likely to occur – as their outside option. Specifically, we focus on workers who did not work a gig job before or in addition to their main gig company. Next, we assume that the reservation wage is reported with an error equal to half of the error related to understanding the net hourly pay. Our results remain when using these alternate measures.

We then re-run our analysis using a different proxy for the reservation wage. We use the worker's gross hourly wages in either a previous job or in another current job. This measure is elicited in 5-dollar bins, for which we take the midpoint. The magnitude of gig workers earning below this wage is significant, even relative to their beliefs of gig pay. In any case, we still find an increase in the group positioned under this proxy of outside option of approximately 20 percentage points when using the actual expected net hourly pay.

Next, fluctuations in gig pay may temporarily place workers below their reservation wages, even if this is not the case over longer periods of time. We provide a robustness check to this by assuming the actual pay is the highest average net hourly pay over the four previous weeks. We find that our conclusions are similar when we run this analysis: the share of workers predicted to hold a sub-optimal job is 31%.

Finally, we should keep in mind that the outside option for the gig work we consider might be to work for another gig company. Consequently, workers who quit their current gig jobs after being de-biased would not necessarily leave the gig economy. On the other hand, our job choice analysis ignores errors in valuing gig work stemming from the overestimation of labor supply. Due to this channel, gig income will likely be lower than expected, lowering the value of gig work. With these caveats in mind, our findings indicate that a significant share of gig jobs are sustained by mistaken beliefs about pay.

Our model predicts that gig workers will work more hours in the second half of the household budget cycle. In our framework, this happens because workers are surprised by their gig income being less than expected in the first half of the cycle. As they need to pay bills at the end of the cycle, they work more than originally planned. Alternatively, procrastination or a failure to anticipate future bills would also predict this labor supply pattern. Having a convex cost of effort function makes this pattern welfare-reducing.

We now see whether this prediction is borne out in practice. First, we ask workers to report two days each month when they have to pay major bills (Appendix Figure A9). As we only observe total weekly hours and not their division day-by-day, we make the simplifying assumption that hours are driven uniformly across the week. Importantly, this assumption will weaken the relationship between work hours and the budget cycle, in particular at the end or the beginning of the cycle. Following that, we calculate the number of total hours worked in intervals of seven days, based on the distance from paying a major bill.

Results are shown in Figure 8. Gig workers in our sample work, on average, 40 percent (or 3 hours per week) more when a major bill is close to due, compared to when it is at least 3 weeks away. Thus, gig workers work more at the end of the household budget cycle. Note that our analysis is based only on correlations. Thus, we cannot rule out that unobservable characteristics related to which days gig workers pay their bills partially explain our findings. Nevertheless, we find evidence that overestimation of pay in gig jobs is connected to under-smoothing of work hours across the household budget cycle.

As a further test of our model's predictions, we examine the effects of our randomized information treatment.[19] In this intervention, we inform gig workers in the treatment group (during our baseline survey) what their *actual* expected net hourly pay is. Then, we compare

[19]See Appendix E for more details.

this number to their recall of net hourly pay, informing participants if their beliefs are incorrect. Appendix Figure E1 shows an example of our information treatment. The effects of this intervention should be similar to moving our model's overestimation parameter θ towards zero. Note that we provide gig workers with an informative signal. However, that signal is not fully accurate at the individual level due to noise in measuring actual expenses.

In general, we are under-powered to identify small to moderate effects. This is primarily due to a small sample size, since we need to observe workers at our follow-up surveys to estimate treatment effects on labor market decisions. In addition, we previously documented that gig workers have incomplete learning of their job outcomes, possibly due to biased updating and selective recall. Thus, fundamentally changing workers' beliefs can be difficult, especially if they overestimate their pay. Nevertheless, we find suggestive evidence that we are able to influence beliefs about gig job outcomes, especially expenses, through our information treatment.[20]

We expect our information treatment to affect job choices and labor supply decisions when misperceptions about gig pay exist. However, the effects should be heterogeneous based on the direction of gig workers' mistaken beliefs. In other words, treatment effects should differ depending on whether we tell gig workers they overestimate (bad signal) or underestimate (good signal) their net hourly pay. Accordingly, we estimate treatment effects separately based on whether initial overestimation is positive or negative.

In Table 7, we estimate the effect of the information treatment on labor supply and on the probability of holding a job outside the gig company. Effects are measured at the endline survey, distributed between two to five months after the treatment. Labor supply is an average of the weekly hours worked for the gig company for all available weeks after the baseline survey. It includes zeroes for those no longer working for the gig company.

Following the predictions of our model, we estimate effects on labor supply separately by financial need, using information on whether the worker's household is struggling finan-

[20]We discuss these results in Appendix E.

cially.[21] We find that treated workers who initially overestimate their net pay and are more budget constrained slightly increase their workers worked. In contrast, more financially secure workers reduce their average weekly labor supply by around 3 hours per week after our information treatment. These effects are, however, not statistically significant at standard levels.

Next, we find that gig workers in the treatment group initially overestimating their net hourly pay are 5 percentage points more likely to hold another job, which is, again, not statistically significant. In general, we find larger and statistically significant effects – in the opposite direction – among treated workers who initially underestimate their net pay. This is consistent with the mechanisms we discussed in Section 4, which imply that people incorporate positive information more readily than negative information.

6 Conclusion

In this study, we examine whether gig workers correctly understand their job outcomes. First, we collected data on beliefs and on actual job performance. When comparing the two, we find that gig workers consistently overestimate recalls and forecasts of their gross and net weekly pay. We then document that recall errors and forecast errors are strongly correlated. In addition, overestimation of labor supply and underestimation of expenses are key drivers of aggregate mistakes.

We show that our findings are consistent with motivated beliefs supported by selective recall. According to this theory, errors stem from biased formation and updating of beliefs, do not necessarily improve with experience and increase with the noisiness of job outcomes. We find evidence for these implications in our setting. Then, we develop a simple behavioral labor supply model and derive predictions of the consequences of overestimating pay in gig jobs. The magnitude of the errors we identify is enough to move a significant share of gig

[21] Struggling financially is defined as reporting to be receiving calls from collectors, contemplating bankruptcy, or struggling to pay the bills.

workers below their stated reservation wage, indicating potential mistakes in job choices. We also document that gig labor supply choices and allocation across the budget cycle are affected by overestimation of gig job outcomes, leading to sub-optimal decisions.

Our findings imply that the economic modeling of flexible jobs needs to incorporate behavioral biases in understanding pay and hours. Otherwise, welfare calculations and predictions may be inaccurate. Moreover, our work motivates policies that provide summarized job performance information to workers in flexible jobs. By doing so, mistakes in understanding job outcomes can be reduced. However, we see challenges in doing this, and we believe that changing worker beliefs may be difficult. As technological advances allow for greater flexibility across a wider range of jobs, these issues become more relevant.

Our study can be interpreted as saying that flexible gig jobs are less valuable than previously thought. In spite of this, we believe these jobs may still provide significant surpluses, especially to individuals with strong preferences for flexibility. A quantitative welfare analysis of the consequences of the mistakes we identify here is left for future research. The same is true for a study of how mistaken beliefs affect firms' decisions and their market power.

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Tables

Table 1: Summary statistics

Baseline Survey	**Full Sample**	
	Mean	Std. Dev.
Panel A: Demographics (%)		
Age 18-34	42.07	(49.42)
Age 35-54	47.14	(49.97)
White	72.69	(44.61)
Male	41.19	(49.27)
College Degree	38.55	(48.72)
Panel B: Financial Situation (%)		
Household Income \$0-\$40k	54.19	(49.88)
No Household Budget	21.59	(41.19)
Struggling Financially	42.73	(49.52)
Gig Pay is Essential	83.48	(37.18)
Panel C: Labor Market (%)		
Has Other Gig Job	35.68	(47.96)
Has Non-Gig Job	17.18	(37.76)
Employed Full-Time Prior to Gig	36.34	(48.15)
Employed Part-Time Prior to Gig	20.26	(40.24)
Unemployed Prior to Gig	10.13	(30.21)
Experience Delivery (12+ mo.)	57.49	(49.49)
Experience Rideshare (12+ mo.)	23.57	(42.49)
Panel D: Actual Outcomes		
Weekly Pay	284.2	(250.4)
Weekly Hours	17.41	(14.81)
Hourly Pay	17.94	(7.515)
Expected Expenses Share	32.19	(5.188)
Panel E: Recall Outcomes		
Weekly Pay	372.8	(265.8)
Weekly Hours	22.69	(13.63)
Hourly Pay	18.85	(6.251)
Panel F: Forecast Outcomes		
Weekly Pay	376.8	(324.9)
Weekly Hours	23.24	(14.05)
Hourly Pay	19.36	(6.798)

Notes: Sample of delivery and ride share gig workers in the United States from our baseline survey ($N = 454$). The mean and standard deviation are shown for each variable. Variables in Panels A-C are measured in percentage units. *Struggling Financially* is defined as receiving calls from collectors, contemplating bankruptcy, or struggling to pay the bills. Panel D shows actual job outcomes, collected from screenshots of the gig economy apps that workers submit. *Expenses Share* is an estimation of expected expenses by car category and car age group. Panel E presents pooled recalls of job outcomes for the previous week and month. Panel F shows information on forecasts about the first week (starting on a Monday) after the baseline survey.

Table 2: Forecast and recall overestimation of main job outcomes

	N	Mean of Actual	Overestimation (Belief - Actual) Mean	Mean (%)	Share
Panel A: Forecast					
Weekly Pay	155	$260	$113.7***	43.7%	.72***
Weekly Hours	142	13.5	8.4***	62.3%	.8***
Hourly Pay	125	$20.2	$.5	2.4%	.54
Panel B: Recall					
Weekly Pay	434	$284.2	$88.9***	31.3%	.73***
Net Weekly Pay	408	$198.8	$92.1***	46.3%	.74***
Expenses Share	396	32.2p.p.	-7.1p.p***	-22%	.29***
Weekly Hours	392	17.4	5.8***	33.1%	.75***
Hourly Pay	386	$17.9	$.7*	3.9%	.53
Net Hourly Pay	338	$12.4	$2.6***	20.7%	.68***

Notes: Panel A shows errors in forecasting job outcomes for the first full week (starting on a Monday) after the baseline survey. Panel B shows pooled errors in recalling the week and the month before the baseline survey. We include, for each variable, the number of observations used for calculating overestimation. This number varies across variables due to trimming and a subset of submitted screenshots having incomplete information. *Mean of Actual* is the mean of the actual job outcome. Overestimation is defined as the recall or forecast belief minus the actual job outcome. *Mean* is the mean overestimation (including negative values) for each outcome. *Mean (%)* overestimation is the ratio of the mean overestimation and the mean actual job outcome in our sample. *Share* is the share of workers for whom overestimation is positive. We test whether the average overestimation is equal to 0 and the share overestimating is equal to 50%. Stars are used to denote the statistical significance of these tests (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$). *Expenses Share* recall is defined as the ratio of recalls for weekly costs and weekly pay. Actual *Expenses Share*, *Net Weekly Pay* and *Net Weekly Pay* use an estimation of expected expenses by car category and car age group.

Table 3: Correlation of gig work experience with overestimation of job outcomes

	Overestimation (Belief - Actual)	
	(1)	(2)
	Weekly Pay	Net Weekly Pay
Inexperienced (Less than 6 Months)	40.2*	64.3***
	(22.0)	(22.2)
Some Experience (Between 6 and 12 Months)	87.2***	93.6***
	(8.57)	(8.90)
Experienced (Over 12 Months)	132.0***	104.7***
	(18.7)	(18.4)
Observations	439	400
p-value(Some Experience = Inexperienced)	0.047	0.22
p-value(Experienced = Inexperienced)	0.0016	0.16

Notes: We regress the overestimation of weekly pay on binary variables for experience in gig work. The regressions do not have a constant term. Overestimation of each outcome is defined as the recall belief minus the actual job outcome for the same time period. We pool recalls of the week and the month before the baseline survey. *Inexperienced* is equal to 1 if a gig worker has less than six months of experience in both delivery and ride share. *Experienced* is equal to 1 if a gig worker has more than one year of experience in both delivery and ride share. *Some Experience* is equal to 1 if both *Inexperienced* and *Experienced* are equal to 0. Robust standard errors in parentheses. Stars are used to denote the statistical significance of each coefficient (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$). Under each regression,we present the p-value for a test of whether (i) the coefficients on *Experienced* and *Inexperienced* are equal, and (ii) the coefficients on *Some Experience* and *Inexperienced* are equal.

Table 4: Predictions from motivated beliefs theory: selective recall and updating

	Recall Belief Weekly Pay			
	(1)	(2)	(3)	(4)
Last 4 Weeks (Actual)				
Maximum	0.57***	0.55***	0.24**	0.22*
	(0.058)	(0.059)	(0.12)	(0.12)
Minimum	0.26***	0.26***		
	(0.086)	(0.087)		
Mean			0.60***	0.59***
			(0.14)	(0.14)
Observations	320	320	320	320
Demographic Controls		✓		✓
p-value(Max=Min)	0.026	0.039		

(A) Selective Recall

	Belief_t Weekly Pay	
	(1)	(2)
Belief_{t-1}	0.69***	0.67***
	(0.049)	(0.053)
$1\{\text{Actual}_t \geq \text{Belief}_{t-1}\}$	208.3***	166.5**
	(33.6)	(69.6)
$1\{\text{Actual}_t < \text{Belief}_{t-1}\}$	-47.5*	-81.8
	(25.9)	(68.6)
Observations	155	155
Demographic Controls		✓
p-value(Above=Below)	0.0016	0.53

(B) Belief Updating

Notes: Robust standard errors in parentheses. Stars are used to denote the statistical significance of each coefficient (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$). Our set of demographic controls consists of binary variables for male, white, age between 18-34, age between 35-54, at least a college degree and household income below $40,000/year. Outcome variables in Panel (A) are recalls referring to the month before the baseline survey. Panel (A) shows regressions of recalls of weekly pay on functions of the 4 previous weeks of actual weekly pay. We define the minimum, the maximum and the mean for this set of four weeks. We present the p-value for a test of whether the coefficients for the maximum and the minimum variables are the same. In Panel (B), only participants that replied to our midline survey are included. $Belief_t$ is the recall of weekly pay of the first full week (starting on a Monday) after the baseline survey. $Belief_{t-1}$ is the pooled recall for each job outcome for the week or the month before the baseline survey. $Actual_t$ refers to the actual job outcome (obtained from a screenshot submitted from the gig platform app) of the first full week after the baseline survey. Each column shows the result of the regression of $Belief_t$ on $Belief_{t-1}$ and two binary variables: a variable equal to 1 if $Actual_t$ is above or equal to $Belief_{t-1}$, and a variable equal to 1 if $Actual_t$ is below $Belief_{t-1}$. There is no constant term in the regressions in Panel (B). We present the p-value for a test of whether the coefficients for the two indicator variables are the same.

Table 5: Predictions from motivated beliefs theory: variance of outcomes

	Overestimation (Belief - Actual) Weekly Pay	
	(1)	(2)
Last 4 Weeks (Actual)		
Coefficient of Variation (CV)	0.85***	0.94***
	(0.30)	(0.31)
Constant	62.3***	60.3
	(17.4)	(45.7)
Observations	232	232
Demographic Controls		✓
Average CV (SD/Mean)	0.48	0.48

Notes: Robust standard errors in parentheses. Stars are used to denote the statistical significance of each coefficient (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$). Overestimation of a job outcome is defined as the recall belief minus the actual job outcomes for the same time period. We allow for negative values of this variable. We show regressions of the overestimation of weekly pay on the coefficient of variation for the 4 previous weeks of weekly pay. The coefficient of variation is the standard deviation over the mean. We normalize this variable so that a 1 unit increase is equal to an increase of 1 percentage point. We present the average coefficient of variation underneath each column. Our set of demographic controls consists of binary variables for male, white, age between 18-34, age between 35-54, at least a college degree and household income below $40,000/year.

Table 6: Relationship of net hourly pay with reservation wage

	Net Hourly Pay		
	Belief	Actual	Difference (SE)
	(1)	(2)	(2) - (1)
Panel A: Share with Pay below Reservation Wage			
Full Sample	23%	68%	45% (2.6)
Alternative Calculations:			
Outside Option Not Gig Work	22%	57%	35% (4.6)
Overestimated Outside Option	23%	55%	32% (2.5)
Maximum Actual Net Hourly Pay	23%	54%	31% (2.4)
Wage at Other or Previous Jobs	61%	78%	17% (3.3)
Panel B: Share with Pay $5 or More below Reservation Wage			
Full Sample	6%	29%	22% (2.2)
Alternative Calculations:			
Outside Option Not Gig Work	4%	22%	18% (3.6)
Overestimated Reservation Wage	6%	21%	15% (1.9)
Maximum Actual Net Hourly Pay	6%	22%	16% (1.9)
Wage at Other or Previous Jobs	32%	51%	20% (3.6)

Notes: Belief of net hourly pay is the pooled net hourly pay recall of the week and the month before the baseline survey. The actual net hourly pay refers to the same period. Our reservation wage proxy is the answer to the following question: "What is the lowest acceptable hourly pay after taxes and expenses that would accept to keep working for [gig company]?". In the two panels, we calculate the share of workers for whom the reservation wage proxy is above the net hourly pay by either 0 or 5 dollars. The final column shows the difference between these shares when the belief and actual net hourly pay are used. The first row includes our full sample and is our base measure. For *Outside Option Not Gig Work*, we include only workers that did not do gigs before their current gig job and that do not work for other gig companies. For *Overestimated Reservation Wage*, we assume the reservation wage is measured with half as much error as the net hourly pay. For *Wage at Other or Previous Jobs*, we use the worker's gross hourly wages in either a previous job or in another current job as the reservation wage proxy. This measure is elicited in 5-dollar bins, for which we take the midpoint. For *Maximum Actual Net Hourly Pay*, we assume the actual net hourly pay is the maximum weekly average of the net hourly pay in the past 4 weeks.

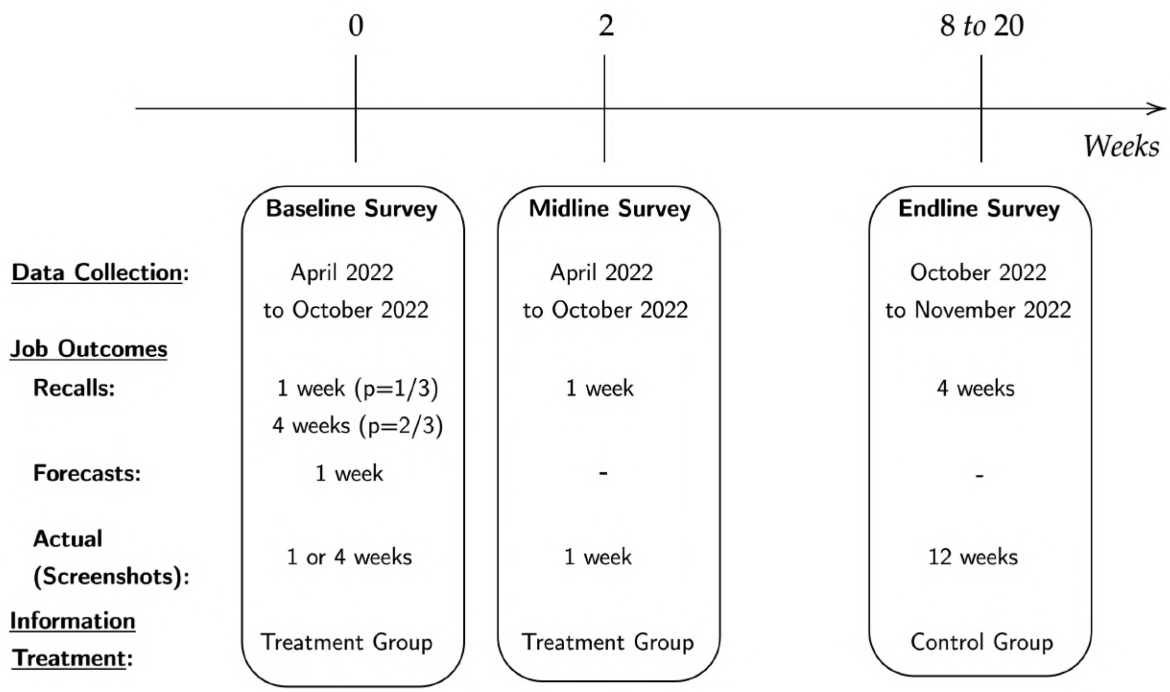
Table 7: Effects of randomized information treatment on labor market decisions

	Other Jobs		**Weekly Hours**	
	(1)	(2)	(3)	(4)
Good Signal	-0.28**	-0.28**		
	(0.11)	(0.12)		
Bad Signal	0.037	0.055		
	(0.083)	(0.082)		
Good Signal × Less Financial Need			2.77	4.23**
			(2.87)	(2.14)
Bad Signal × Less Financial Need			-0.59	-2.99
			(2.05)	(2.02)
Good Signal × More Financial Need			1.32	-1.16
			(7.71)	(4.76)
Bad Signal × More Financial Need			0.53	1.63
			(2.95)	(3.54)
Observations	168	168	162	153
Baseline Outcome		✓		✓
Demographic Controls		✓		✓
p-value(Treatment No Effect)	0.041	0.045	0.90	0.16

Notes: Robust standard errors in parentheses. Stars are used to denote the statistical significance of each coefficient (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$). In models (1) and (2), we estimate versions of $y_{it} = \beta_0 + \beta_1 Over_i + \beta_2 Bad\,Signal_i + \beta_3 Good\,Signal_i + X_{i0}\Gamma + \varepsilon_{it}$, where y_{it} is whether individual i at the endline survey reports having a job other than one for the main gig company. $Over_i = 1$ if initial overestimation of net hourly pay is positive and 0 otherwise. Our two variables of interest here are $Bad\,Signal_i$ and $Good\,Signal_i$: $Bad\ Signal_i$ is equal to 1 if an individual is in the treatment group and $Over_i = 1$; $Good\ Signal_i$ if an individual is in the treated group and $Over_i = 0$. Individuals in the treatment group were told whether they misestimated their actual net hourly pay (see Appendix E for more details). We test whether all treatment variables are jointly significant and provide a p-value for this test for each model. X_{i0} is the covariates matrix. Our set of demographic controls consists of binary variables for male, white, age between 18-34, age between 35-54, at least a college degree and household income below $40,000/year, in addition to the outcome variable in the baseline survey. In models (3) and (4) we replace $Over_i$, $Bad\ Signal_i$ and $Good\ Signal_i$ by their interaction with two dummies: $Less\,Financial\,Need$ and $More\,Financial\,Need$. *More Financial Need* (*Less Financial Need*) is equal to 1 if the gig worker is in a household that is (not) struggling financially and 0 otherwise. *Struggling Financially* is defined as receiving calls from collectors, contemplating bankruptcy, or struggling to pay the bills. In addition, we add a binary variable of $More\ Financial\ Need$ to our model. The dependent variable for models (3) and (4) is a simple average of the weekly hours worked for the main gig company for all available weeks prior to the endline but after the baseline survey (including zeroes).

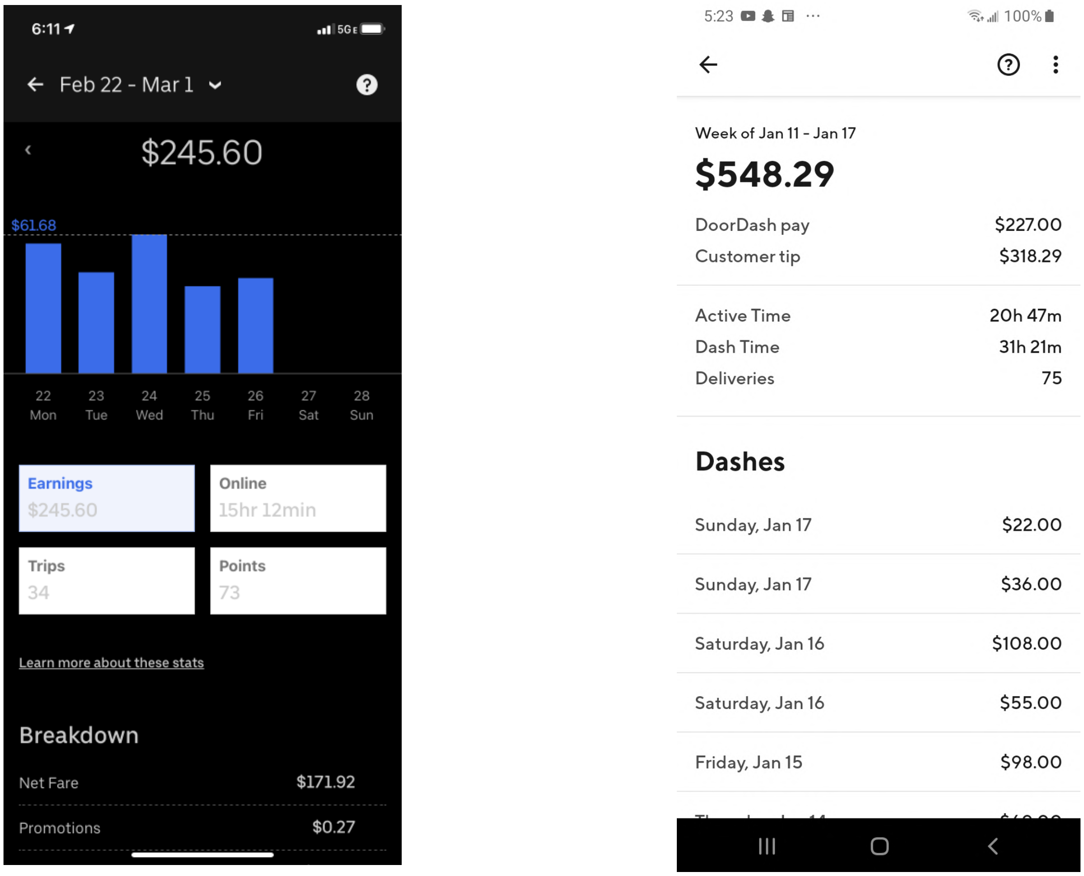
Figures

Figure 1: Survey timeline



Notes: We survey gig workers in three occasions: the baseline, midline and endline surveys. For 2/3 of the sample, we elicit a 1 month recall in the baseline survey, while for another 1/3 we ask about the previous week. Beliefs refer to full weeks, from Monday to Sunday. We elicit a one week recall in the midline survey and a 4 weeks recall in the endline survey. In the baseline survey, we obtain information on 1 or 4 weeks of actual job outcomes based on screenshots from the gig platform app. In the midline survey, we obtain information on 1 week of actual job outcomes based on screenshots. In the endline survey, we obtain information on up to 12 weeks of actual job outcomes based on screenshots. The information treatment group receives information, at the both the baseline and the midline surveys, about their actual net hourly pay and sees an example of how to calculate expenses. The control group is presented this information at the end of the endline survey.

Figure 2: Examples of valid screenshots from gig platform apps

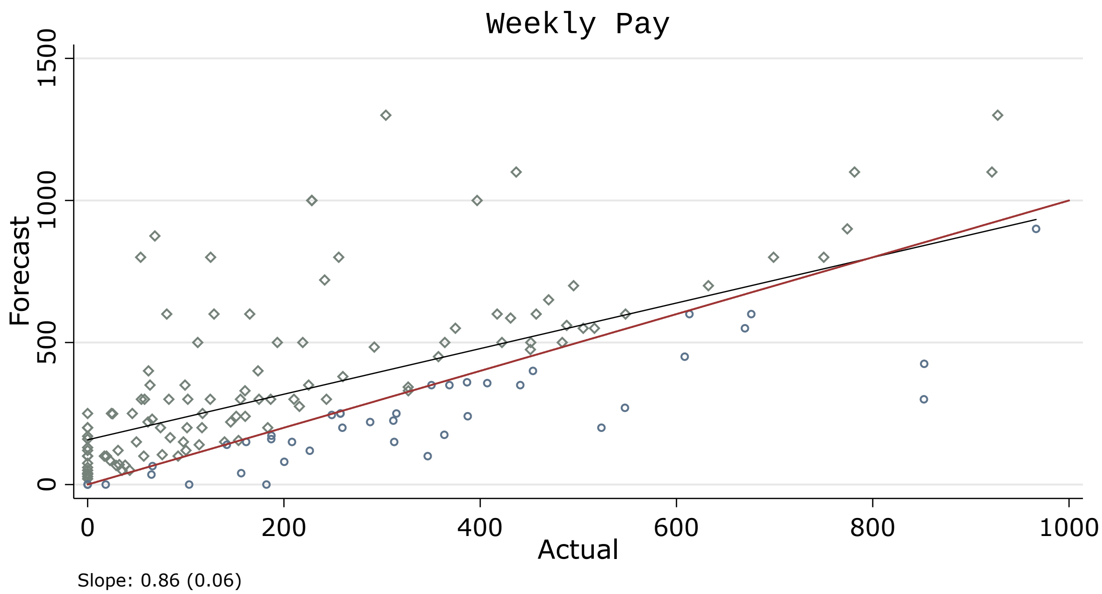


(A) Uber/Uber Eats

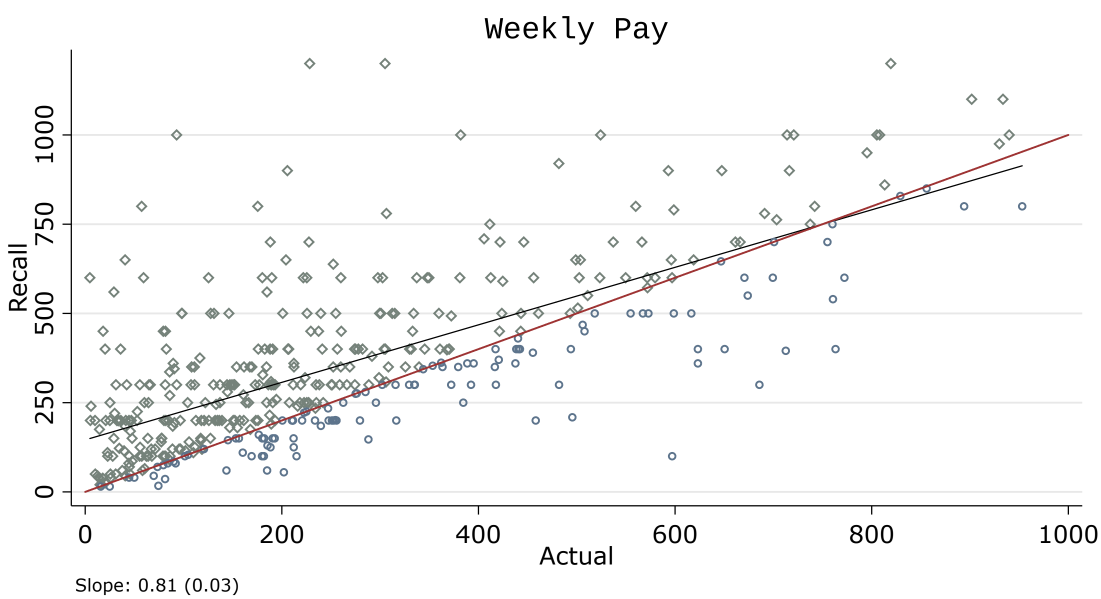
(B) Doordash

Notes: We show examples of valid screenshots from the weekly earnings page in the gig platform app. Panel (A) is an example of an Uber or Uber Eats screenshot, while Panel (B) is an example of a DoorDash screenshot. In each screenshot, among other things, we have information on the gross weekly pay on top (including tips, bonuses and platform fees), one or two measures of work hours and information on the week that the screenshot refers to.

Figure 3: Scatter plots relating beliefs to actual gross weekly pay



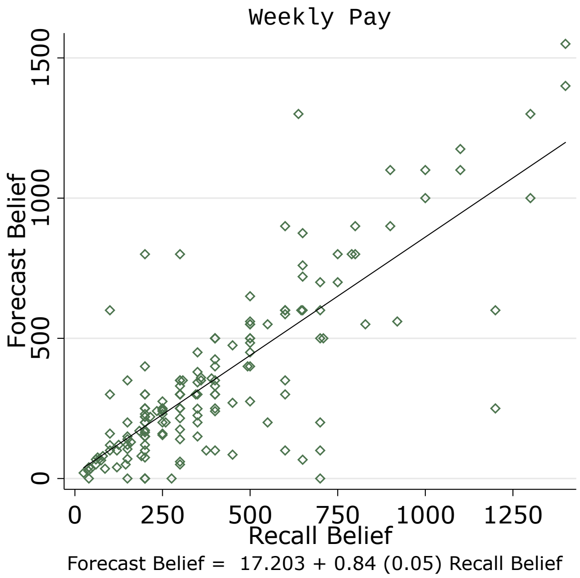
(A) Forecast



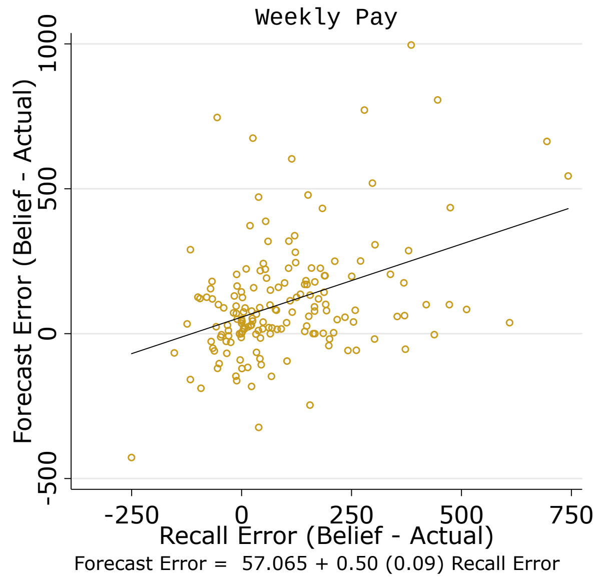
(B) Recall

Notes: In each graph, we draw a 45 degree line and the estimated slope of the regression of the belief on the actual weekly pay. Underneath each graph, we present the slope from the regression of the actual outcome versus its recall or forecast belief, with the associated standard error in parentheses. We exclude some outliers from each graph. Points above the 45 degree line indicate overestimation, whereas points below the 45 degree line indicate underestimation of weekly pay. Panel (A) shows forecasts for the first full week (starting on a Monday) after the baseline survey. In Panel (B),we pool recalls of the week and the month before the baseline survey. The actual weekly pay refers to the same time period as this forecast or recall and are obtained using information from screenshots from gig platform apps.

Figure 4: Relationship between forecasts and recalls of weekly pay



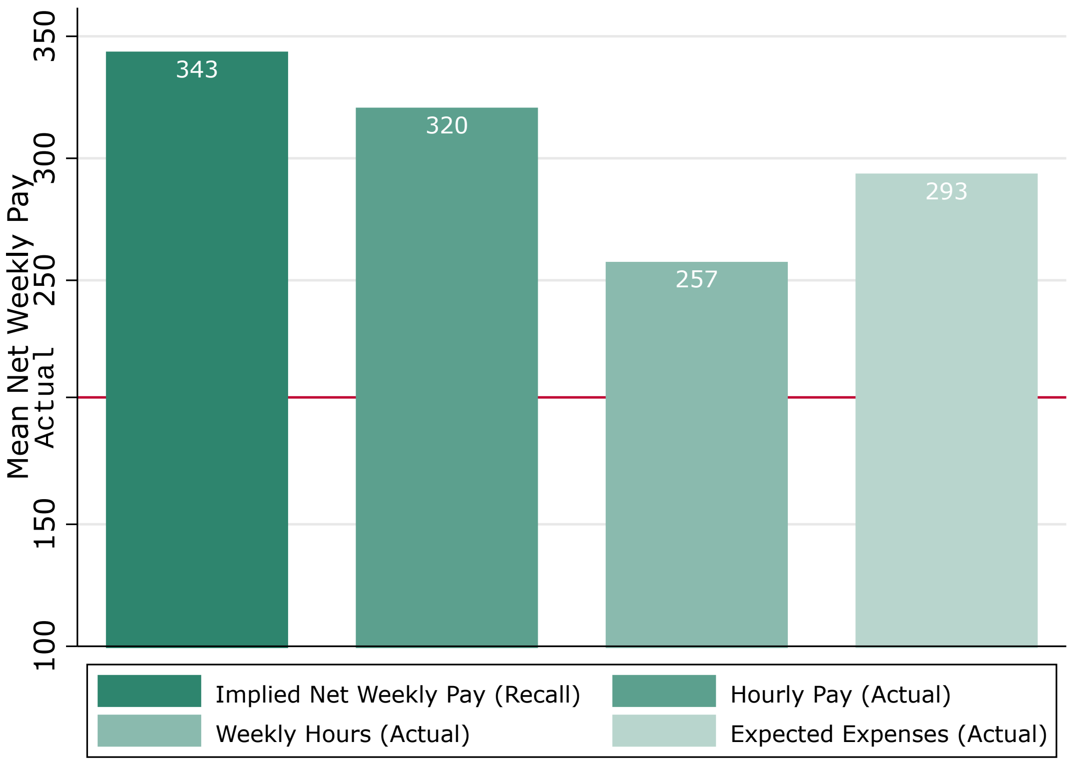
(A) Beliefs



(B) Errors (Belief - Actual)

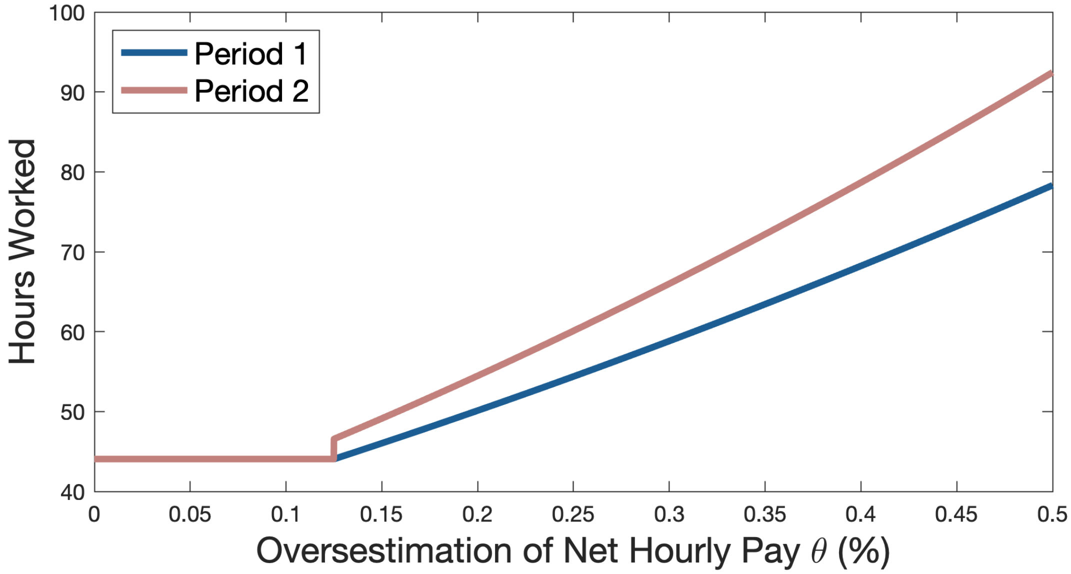
Notes: In Panel (A), we draw the fitted line of the regression relating the recall belief and the forecast belief of weekly pay. In Panel (B), we show the fitted line of the regression relating the forecast overestimation and the recall overestimation of weekly pay. The estimated equation is shown underneath each plot. Overestimation is measured as the recall or forecast minus the actual job outcome. We exclude some outliers from each plot. We pool recalls of the week and the month before the baseline survey. The forecast refers to the first full week (starting on a Monday) following the baseline survey.

Figure 5: Decomposing factors that explain errors in recalling net weekly pay

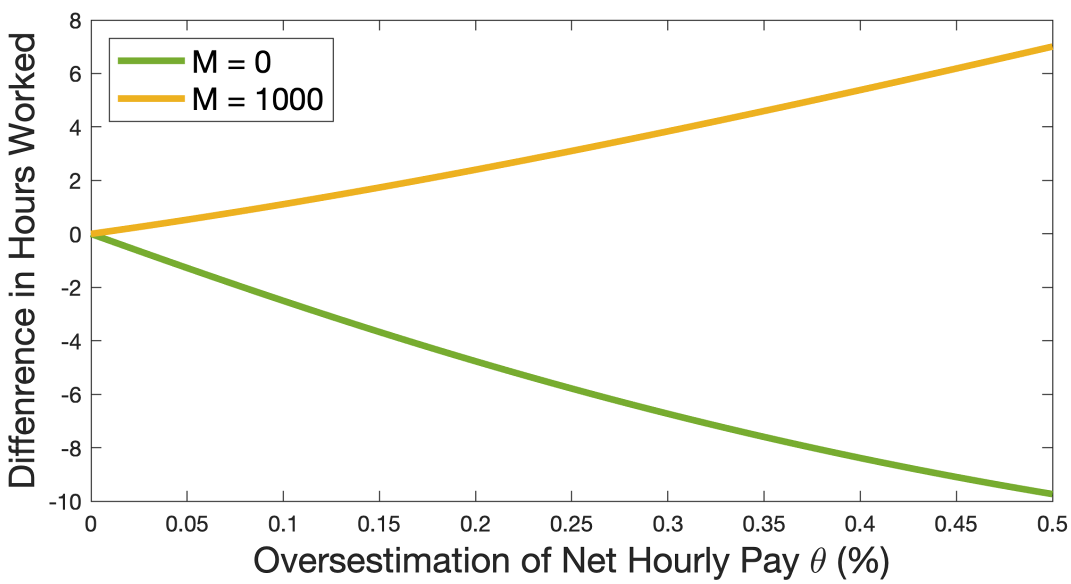


Notes: We plot the average of different measures of net weekly pay. The *Implied Net Weekly Pay (Recall)* is the product of the recall of three variables: gross hourly pay, weekly hours and one minus the expenses share. We pool recalls of the week and the month before the baseline survey. The next three variables replace one element of the implied net weekly pay recall with its correct equivalent. *Hourly Pay (Actual)* is found by replacing the recall for the actual gross hourly pay, while keeping the recalls for weekly hours and expenses. *Weekly Hours (Actual)* and *Expected Expenses (Actual)* are constructed in an analogous manner. Actual job outcomes refer to the same time period as the recalls and are obtained using both information from screenshots from gig platform apps and a calculation of expected expenses by car category and car age group. We plot the average actual expected net weekly pay as a red line on the y-axis.

Figure 6: Solving behavioral labor supply model while varying overestimation parameter θ



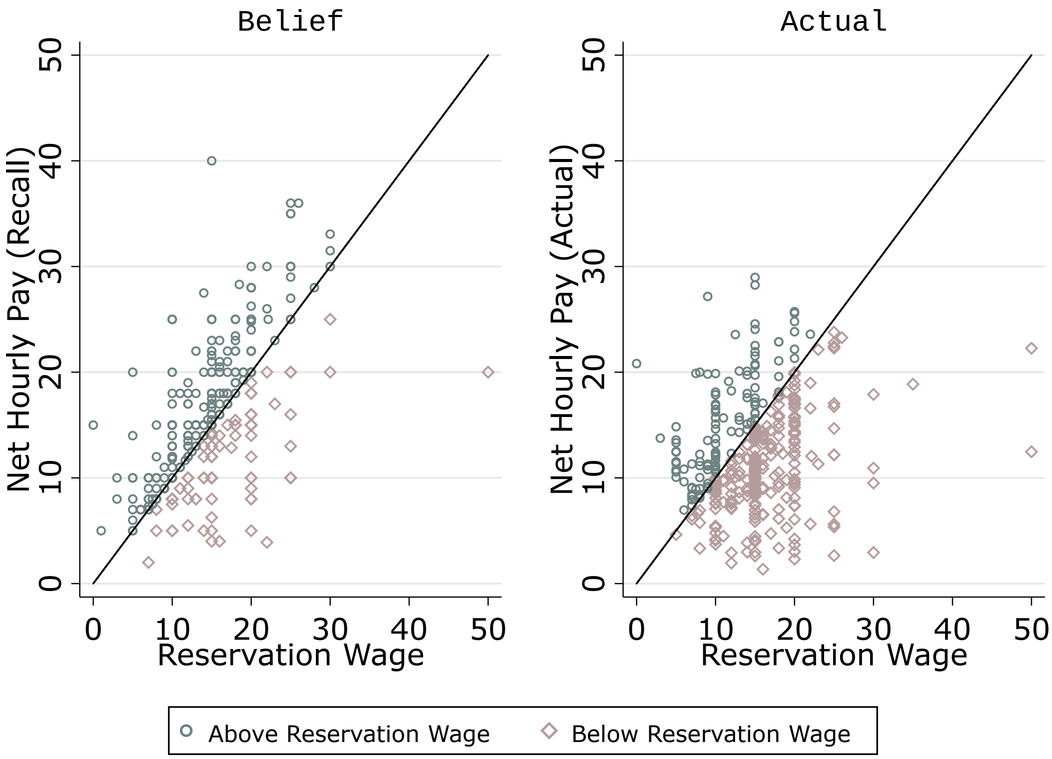
(A) Under-smoothing of labor supply and job choice



(B) Errors in total labor supply

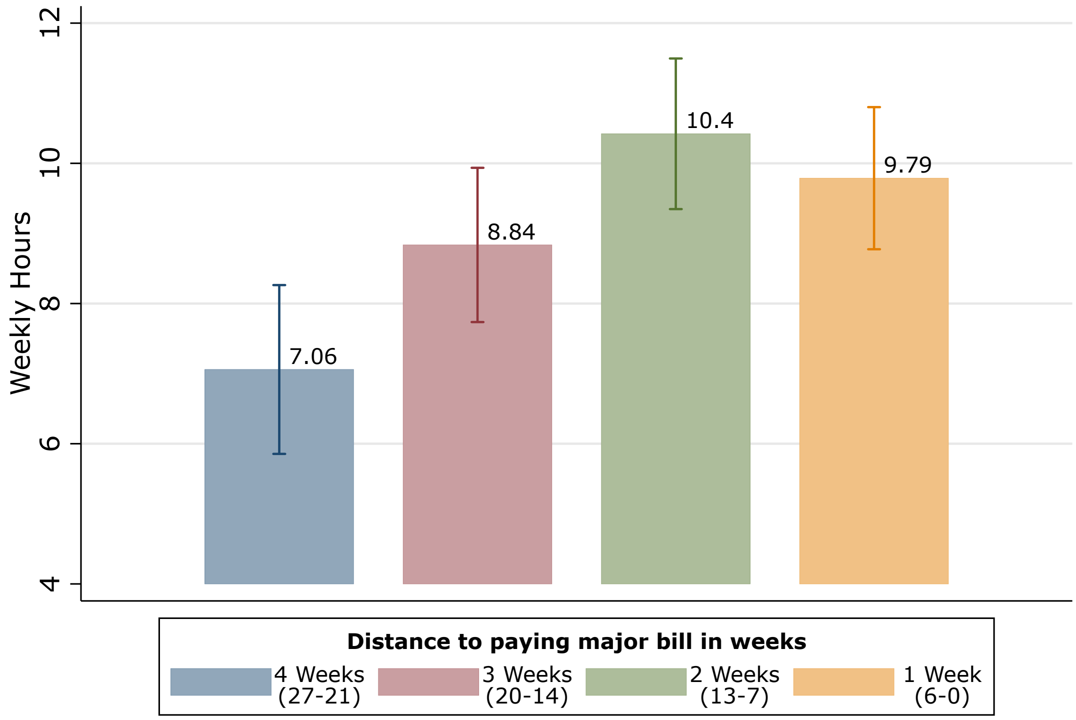
Notes: We numerically solve the model described in Section 5.1 for different values of the overestimation parameter θ, holding all other parameters fixed. In Panel (A), we plot the labor supply in each period as a function of θ. The worker in Panel (A) chooses the non-gig job for $\theta < 0.125$. In Panel (B), we plot the difference in total labor supply across both periods between a worker with the θ shown in the x-axis and one with $\theta = 0$. We plot two separate lines, one for non-labor income $M = 1000$ and one for $M = 0$. We assume that the consumption utility function is $u(c) = 0.85 \cdot c^{0.8}$, the cost of effort function is $c(h) = h^{1.2}$, the continuation value of savings function is $V(s) = 0.02 \cdot s$ and the gig hourly net pay is $w_G = 12$. In Panel (A), we assume that the net hourly pay at the outside job is $w_O = 13.5$, that the shift parameter in the Stone-Gehry utility function is equal to $\bar{c} = 0$, and that $M = 0$. In Panel (B), we assume that $w_O = 0$ and $\bar{c} = 800$.

Figure 7: Relationship of belief and actual net hourly pay with reservation wages



Notes: In each graph, we relate a measure of net hourly pay with workers' stated reservation wage. The reservation wage is the answer to the question: "What is the lowest hourly pay after taxes and expenses that would accept and keep working for [gig company]?" Each chart includes a 45 degree line. Points above this line represent workers for whom the net hourly pay measure is above the reservation wage, with the opposite being true for points below this line. Plotted on the y-axis on the left chart is a recall of net hourly pay, which pools the week and the month before the baseline survey. Plotted on the y-axis on the right chart is the actual expected net hourly pay, referring to the same time period as the recalls and obtained using a calculation of expected expenses and information from screenshots from gig platform apps.

Figure 8: Relationship between due date of major bills and labor supply



Notes: We use information on self-reported days of the month where each worker has to pay major bills (Appendix Figure A9) to measure the average amount of work hours relative to when a bill is due, in 7 day intervals. For each interval, we calculate the total amount of hours worked. In this calculation, we assume work hours are spread evenly across the week. We use the minimum of the distance to a bill if a worker reports two dates for paying major bills. Actual work hours data is derived from screenshots from the gig platform app and includes information of job performance for the 4 previous weeks before the baseline survey.

Appendix A: Additional Tables and Figures

Table A1: Selective attrition on midline survey

Answered Midline survey?		**No**			**Yes**		
	N	Mean	SD	N	Mean	SD	**Diff.**
Age 18-34	244	0.46	0.50	210	0.38	0.49	-0.083*
Age 35-54	244	0.43	0.50	210	0.52	0.50	0.098**
White	244	0.75	0.44	210	0.70	0.46	-0.041
Male	244	0.43	0.50	210	0.39	0.49	-0.040
College Degree	244	0.36	0.48	210	0.41	0.49	0.054
HHold Income 0−40k	244	0.59	0.49	210	0.49	0.50	-0.104**
No Household Budget	244	0.24	0.43	210	0.19	0.39	-0.056
Struggling Financially	244	0.47	0.50	210	0.38	0.49	-0.086*
Experience Delivery (12+ mo.)	244	0.52	0.50	210	0.63	0.48	0.109**
Experience Rideshare (12+ mo.)	244	0.21	0.41	210	0.26	0.44	0.049
Gig Pay is Essential	244	0.84	0.37	210	0.83	0.37	-0.003
Employed Full-Time Prior to Gig	244	0.38	0.49	210	0.35	0.48	-0.029
Employed Part-Time Prior to Gig	244	0.18	0.39	210	0.23	0.42	0.048
Unemployed Prior to Gig	244	0.10	0.30	210	0.10	0.30	-0.002
Has Other Gig Job	244	0.36	0.48	210	0.35	0.48	-0.008
Has Non-Gig Job	244	0.17	0.37	210	0.18	0.38	0.008
Hourly Pay	210	17.57	7.40	190	18.33	7.64	0.761
Hourly Net Pay	193	12.19	5.32	167	12.61	5.20	0.424
Weekly Hours	213	17.87	16.19	191	16.90	13.12	-0.975
Weekly Pay	240	271.04	227.91	205	299.60	274.24	28.559
Hourly Pay (Recall)	236	18.61	6.34	200	19.14	6.14	0.523
Net Hourly Pay (Recall)	219	15.48	6.04	193	15.43	6.61	-0.044
Weekly Pay (Recall)	236	362.15	240.15	203	385.23	292.92	23.074
Weekly Hours (Recall)	238	22.58	14.00	202	22.82	13.21	0.239

Notes: We present the number of observations, the mean and standard deviation of observable characteristics for the group of individuals who either did not (*No*) or did (*Yes*) reply to the midline survey. The data in these table is collected in our baseline survey. *Struggling Financially* is defined as receiving calls from collectors, contemplating bankruptcy, or struggling to pay the bills. The four final rows present pooled recalls of job outcomes for the previous week and the previous month. The four rows before that show actual job outcomes, collected from screenshots of gig economy apps that workers submit. The last column shows the difference in means between the two groups for each variable. Stars are used to denote the statistical significance of this difference (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$).

Table A2: Selective attrition on endline survey

Answered Endline survey?	**No**			**Yes**			
	N	Mean	SD	N	Mean	SD	**Diff.**
Age 18-34	218	0.42	0.50	190	0.42	0.50	-0.001
Age 35-54	218	0.44	0.50	190	0.51	0.50	0.065
White	218	0.70	0.46	190	0.73	0.45	0.024
Male	218	0.39	0.49	190	0.43	0.50	0.046
College Degree	218	0.36	0.48	190	0.40	0.49	0.038
HHold Income 0−40k	218	0.57	0.50	190	0.48	0.50	-0.085*
No Household Budget	218	0.22	0.41	190	0.22	0.41	0.000
Struggling Financially	218	0.43	0.50	190	0.41	0.49	-0.021
Experience Delivery (12+ mo.)	218	0.56	0.50	190	0.61	0.49	0.055
Experience Rideshare (12+ mo.)	218	0.27	0.44	190	0.22	0.42	-0.045
Gig Pay is Essential	218	0.83	0.37	190	0.82	0.38	-0.014
Employed Full-Time Prior to Gig	218	0.33	0.47	190	0.41	0.49	0.080*
Employed Part-Time Prior to Gig	218	0.18	0.38	190	0.23	0.42	0.047
Unemployed Prior to Gig	218	0.11	0.31	190	0.09	0.29	-0.016
Has Other Gig Job	218	0.35	0.48	190	0.34	0.48	-0.011
Has Non-Gig Job	218	0.13	0.34	190	0.22	0.41	0.087**
Hourly Pay	194	17.48	7.87	168	18.47	7.12	0.987
Hourly Net Pay	175	12.30	5.55	151	12.47	4.84	0.175
Weekly Hours	192	18.27	16.87	173	16.62	12.81	-1.657
Weekly Pay	216	279.26	251.44	184	282.62	238.69	3.364
Hourly Pay (Recall)	207	18.87	6.46	184	19.06	6.20	0.183
Net Hourly Pay (Recall)	194	15.74	6.49	178	15.48	5.98	-0.251
Weekly Pay (Recall)	208	369.80	256.66	185	376.68	273.98	6.881
Weekly Hours (Recall)	208	22.63	14.29	187	22.71	13.13	0.081

Notes: We present the number of observations, the mean and standard deviation of observable characteristics for the group of individuals who either did not (*No*) or did (*Yes*) reply to the endline survey. The data in these table is collected in our baseline survey. *Struggling Financially* is defined as receiving calls from collectors, contemplating bankruptcy, or struggling to pay the bills. The four final rows present pooled recalls of job outcomes for the previous week and the previous month. The four rows before that show actual job outcomes, collected from screenshots of gig economy apps that workers submit. The last column shows the difference in means between the two groups for each variable. Stars are used to denote the statistical significance of this difference (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$).

Table A3: Comparing our sample with other studies and the United States gig market

	Mean of: Worked for Company		
	Sample (percent)	US (Millions)	US (Sample)
DoorDash	64.76	2.00	2.00
Postmates	5.29	0.10	0.15
Grubhub	16.96	0.45	0.53
Uber Eats	35.02	0.80	1.09
Instacart	32.16	0.60	1.03
Uber	16.08	1.50	0.50
Lyft	10.79	1.00	0.34

(A) Company distribution

	Summary Stats Across Studies			
	Sample	Pew (2021)	Parrott-Reich (2020)	Doordash (2021)
Hourly Pay	17.94		23.23	25.00
10+ Hours	0.61	0.37		0.10
20+ Hours	0.34		0.56	
Age 18-34	0.42		0.37	
Age 35-54	0.47		0.53	
White	0.73	0.51	0.45	0.62
Male	0.42	0.44	0.83	0.53
Has Another Job	0.50	0.69	0.59	0.54
College Degree	0.38	0.22		

(B) Sample comparison

Notes: In Panel (A), we show how the distribution of companies in our sample compares to the distribution of gig workers for each gig company in the United States. The data from our sample is the answer to the question: "For which gig companies did you work in the past 3 months?". We obtain information on contracting for gig companies in the United States from multiple sources referring to 2020 or 2021. We use market share information and our own calculations to reach these figures. In the third column of Panel (A), we normalize the values from the first column so that the number of workers working for DoorDash in our sample matches the number of DoorDash workers in the United States (2 million). Comparing these numbers with the second column says whether other companies in our sample are over or underrepresented relative to DoorDash. In Panel (B), we compare mean characteristics in our sample to previous studies of the gig economy. Parrott and Reich (2020) survey both Uber and Lyft drivers in Seattle, Doordash (2021) is a corporate DoorDash survey and Pew (2021) is a study from Pew Research Center of all gig work on online platforms in the United States. In Doordash (2021), hourly pay is based only on time spent actively on gigs. In addition, zero work hour weeks are included in their calculations. For all studies besides ours and Pew (2021), *White* excludes Hispanic white. We define binary variables for 10+ and 20+ hours of work that equal 1 if an individual works at least that amount on average. The statistics presented here for other studies are partially derived from the author's calculations.

Table A4: Correlation of overestimation in forecasts and recalls across job outcomes

	Overestimation (Forecast - Actual)		
	Weekly Pay	Weekly Hours	Hourly Pay
Weekly Pay	1.00		
Weekly Hours	0.65***	1.00	
Hourly Pay	0.04	-0.31***	1.00

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(A) Forecast

	Overestimation (Recall - Actual)				
	Weekly Pay	Net Weekly Pay	Weekly Hours	Hourly Pay	Net Hourly Pay
Weekly Pay	1.00				
Net Weekly Pay	0.77***	1.00			
Weekly Hours	0.54***	0.42***	1.00		
Hourly Pay	0.29***	0.16***	-0.14**	1.00	
Net Hourly Pay	0.16***	0.13**	-0.18***	0.70***	1.00

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(B) Recall

Notes: We present the correlation matrix of overestimation of forecasts – Panel (A) – or recalls – Panel (B) – of job outcomes. Overestimation may be negative and is measured as the recall or forecast belief minus the actual job outcome for the same time period. Recall variables pool recalls of the week and the month before the baseline survey. Forecast variables refer to the first full week (starting on a Monday) following the baseline survey. We use an estimate of expected expenses to calculate net weekly pay and net hourly pay. Stars are used to denote statistical significance (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$).

Table A5: Overestimation of job outcome by recall period

	Overestimation (Recall - Actual)				
	Weekly Pay	Net Weekly Pay	Weekly Hours	Hourly Pay	Net Hourly Pay
Last Week	66.8***	71.5***	3.33***	0.81	2.97***
	(13.0)	(13.2)	(0.95)	(0.62)	(0.60)
Last Month	99.4***	102.1***	7.05***	0.64	2.35***
	(8.96)	(9.15)	(0.69)	(0.45)	(0.45)
Observations	439	400	397	393	345

Notes: Robust standard errors in parentheses. Stars are used to denote the statistical significance of each coefficient (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$). The regressions include no constant term. Overestimation of each outcome may be negative is defined as the recall belief minus the actual job outcome for the same time period. *Last Week* (*Last Month*) is a binary variable equal to 1 if the worker was asked to recall the last week (last month) in the baseline survey. We use an estimate of expected expenses to calculate net weekly pay and net hourly pay.

Table A6: Heterogeneity analysis for overestimation of recalls of job outcomes

	Overestimation (Belief - Actual)				
	(1)	(2)	(3)	(4)	(5)
	Weekly Pay	Net Weekly Pay	Weekly Hours	Hourly Pay	Net Hourly Pay
Certain of Beliefs	22.5	18.5	2.68*	0.85	1.59*
	(19.9)	(19.9)	(1.48)	(0.95)	(0.93)
Excluded Group	70.2***	76.8***	3.55***	0.0021	1.26
	(18.2)	(18.0)	(1.34)	(0.86)	(0.84)
Observations	439	400	397	393	345

(A) Certainty of beliefs

	Overestimation (Belief - Actual)				
	(1)	(2)	(3)	(4)	(5)
	Weekly Pay	Net Weekly Pay	Weekly Hours	Hourly Pay	Net Hourly Pay
Full-Time Driver	-2.32	33.1*	-11.8***	2.56**	2.26**
	(17.7)	(17.7)	(1.49)	(0.99)	(0.98)
Excluded Group	89.4***	84.3***	7.48***	0.30	2.22***
	(8.44)	(8.61)	(0.57)	(0.39)	(0.39)
Observations	439	400	397	393	345

(B) Full-time workers

	Overestimation (Belief - Actual)				
	(1)	(2)	(3)	(4)	(5)
	Weekly Pay	Net Weekly Pay	Weekly Hours	Hourly Pay	Net Hourly Pay
No Household Budget	30.7*	19.4	4.18***	0.22	-0.14
	(17.9)	(18.0)	(1.35)	(0.88)	(0.86)
Struggling Financially	9.00	-1.81	1.93*	-0.28	-1.06
	(15.2)	(15.5)	(1.15)	(0.75)	(0.74)
Pay is Essential	61.9***	54.9**	2.71*	0.27	1.19
	(20.8)	(21.2)	(1.57)	(1.03)	(1.02)
Excluded Group	25.9	42.1**	1.69	0.55	2.06**
	(19.5)	(19.9)	(1.48)	(0.97)	(0.96)
Observations	439	400	397	393	345

(C) Financial need

Table A6: Heterogeneity analysis for overestimation of recalls of job outcomes (cont.)

	Overestimation (Belief - Actual)				
	(1)	(2)	(3)	(4)	(5)
	Weekly Pay	Net Weekly Pay	Weekly Hours	Hourly Pay	Net Hourly Pay
Age 18-34	4.91	-26.1	-0.043	2.26*	0.33
	(27.4)	(27.6)	(2.09)	(1.35)	(1.31)
Age 35-54	24.3	21.6	2.40	1.86	0.18
	(26.8)	(26.9)	(2.04)	(1.32)	(1.29)
White	3.22	7.75	-0.62	-0.80	-0.69
	(17.4)	(17.5)	(1.32)	(0.86)	(0.86)
Male	12.3	25.4	1.06	-0.68	0.74
	(16.1)	(16.3)	(1.20)	(0.77)	(0.77)
College Degree	-10.5	-10.3	-0.74	0.25	0.42
	(15.4)	(15.7)	(1.18)	(0.75)	(0.76)
HHold Income $0-$40k	10.4	13.4	2.08*	0.055	0.54
	(15.5)	(15.8)	(1.18)	(0.76)	(0.76)
Excluded Group	66.2**	73.5**	3.76	-0.40	2.08
	(32.6)	(32.8)	(2.49)	(1.61)	(1.58)
Observations	439	400	397	393	345

(D) Demographics

	Overestimation (Belief - Actual)				
	(1)	(2)	(3)	(4)	(5)
	Weekly Pay	Net Weekly Pay	Weekly Hours	Hourly Pay	Net Hourly Pay
Was Employed Full-Time	48.6***	61.8***	3.26**	0.54	0.53
	(17.5)	(17.9)	(1.34)	(0.86)	(0.86)
Was Employed Part-Time	-6.72	-1.17	1.31	-1.50	-0.86
	(20.6)	(20.7)	(1.58)	(1.02)	(1.00)
Was Self-Employed	54.6*	61.5*	2.03	-2.06	-1.42
	(32.9)	(32.5)	(2.62)	(1.64)	(1.64)
Has Other Gig Job	8.03	12.2	1.14	0.82	0.61
	(15.7)	(16.0)	(1.21)	(0.77)	(0.77)
Has Non-Gig Job	-43.4**	-50.7**	-2.32	-0.50	-0.65
	(20.3)	(20.4)	(1.53)	(0.99)	(0.98)
Excluded Group	74.1***	70.9***	4.20***	0.72	2.54***
	(13.1)	(13.2)	(1.00)	(0.65)	(0.64)
Observations	439	400	397	393	345

(E) Labor market

Notes: We regress overestimation of job outcome for recalls against worker characteristics. Robust standard errors in parentheses. Stars are used to denote the statistical significance of each coefficient (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$). Overestimation of each outcome may be negative and is defined as the recall belief minus the actual job outcome for the same time period. We pool recalls of the week and the month before the baseline survey. *Certain of Beliefs* is a binary variable equal to 1 if a worker is totally or somewhat certain about their recalls. *Full-Time Worker* is equal to 1 if a gig worker, on average, works for at least 30 hours a week and is 0 otherwise. *Struggling Financially* is a binary variable equal to 1 if a worker reports either to struggle to pay the bills, get calls from collectors or is considering bankruptcy. *Gig Pay is Essential* is a binary variable equal to 1 if gig income is used primarily for purchasing essential goods such as food and housing. On Panel (E), we define binary variables relating to employment previous to working for the gig company (prefixed by "*Was*") and other employment currently (prefixed by "*Has*").

Table A7: Correlation of gig work experience with overestimation of job outcomes

	Overestimation (Belief - Actual)				
	(1)	(2)	(3)	(4)	(5)
	Weekly Pay	Net Weekly Pay	Weekly Hours	Hourly Pay	Net Hourly Pay
Experience Delivery (6-12 mo.)	17.1	-16.2	0.19	2.64**	0.10
	(23.6)	(24.6)	(1.86)	(1.17)	(1.16)
Experience Delivery (12+ mo.)	72.5***	53.5***	2.71**	3.19***	2.26***
	(16.9)	(17.2)	(1.31)	(0.83)	(0.83)
Experience Rideshare (6-12 mo.)	-15.3	34.0	1.77	-0.18	0.61
	(30.6)	(31.1)	(2.49)	(1.60)	(1.58)
Experience Rideshare (12+ mo.)	9.32	-0.96	0.31	-0.76	-0.0060
	(17.8)	(17.9)	(1.37)	(0.87)	(0.87)
Excluded Group	43.2***	61.3***	3.98***	-1.36*	1.21*
	(14.8)	(15.0)	(1.14)	(0.72)	(0.71)
Observations	439	400	397	393	345

Notes: We regress overestimation of weekly pay on binary variables for experience in ride share and delivery gig work. The excluded group has less than 6 months of experience in both ride share and delivery. Robust standard errors in parentheses. Stars are used to denote the statistical significance of each coefficient (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$). Overestimation of each outcome is defined as the recall belief minus the actual job outcome for the same time period. We pool recalls of the week and the month before the baseline survey.

Table A8: Robustness checks for over-recalling of job outcomes

	Overestimation (Belief - Actual)				
	(1)	(2)	(3)	(4)	(5)
	Weekly Pay	Net Weekly Pay	Weekly Hours	Hourly Pay	Net Hourly Pay
One Company	-27.2*	-16.3	-0.96	-1.58**	-1.23*
	(14.8)	(15.1)	(1.13)	(0.72)	(0.71)
Excluded Group	102.1***	100.0***	6.23***	1.48***	3.17***
	(10.3)	(10.5)	(0.79)	(0.51)	(0.50)
Observations	439	400	397	393	345

(A) Number of companies

	Overestimation (Belief - Actual)				
	(1)	(2)	(3)	(4)	(5)
	Weekly Pay	Net Weekly Pay	Weekly Hours	Hourly Pay	Net Hourly Pay
Belief is a Round Number	68.2***	22.3	5.21***	0.91	0.65
	(16.1)	(15.5)	(1.25)	(0.72)	(0.70)
Excluded Group	43.0***	83.6***	2.06*	0.26	2.54***
	(13.5)	(9.59)	(1.06)	(0.52)	(0.48)
Observations	432	400	392	387	337

(B) Rounding up

Notes: We regress overestimation of job outcomes recalls against covariables. Robust standard errors in parentheses. Stars are used to denote the statistical significance of each coefficient (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$). Overestimation of each outcome can be negative and is defined as the recall belief minus the actual job outcomes for the same time period. We pool recalls of the week and the month before the baseline survey. *One Company* is a binary variable equal to 1 if a worker has only worked for one gig company in the past 3 months. *Belief is a Round Number* is equal to 1 if a worker's recall belief is a multiple of 5 (for weekly hours,hourly wage and net hourly wage) or a multiple of 50 (for gross and net weekly pay) and 0 otherwise.

Table A9: Predictions from motivated beliefs theory: selective recall and updating (other)

	Recall Belief					
	Weekly Hours			**Hourly Pay**		
	(1)	(2)	(3)	(4)	(5)	(6)
Maximum	0.38***	0.34***	0.13	0.22***	0.20***	0.081
	(0.081)	(0.081)	(0.15)	(0.056)	(0.056)	(0.092)
Minimum	0.22**	0.22**		0.18***	0.18***	
	(0.10)	(0.10)		(0.067)	(0.068)	
Mean			0.47***			0.33***
			(0.18)			(0.11)
Observations	293	293	293	289	289	289
Demographic Controls		✓			✓	
p-value(Max=Min)	0.37	0.49		0.76	0.86	

(A) Selective Recall

	Belief$_t$			
	Weekly Hours		**Hourly Pay**	
	(1)	(2)	(3)	(4)
Belief$_{t-1}$	0.66***	0.62***	0.79***	0.79***
	(0.064)	(0.072)	(0.090)	(0.097)
1{Actual$_t$ $\geq$ Belief$_{t-1}$}	10.8***	10.2**	8.55***	9.46***
	(2.11)	(3.90)	(1.84)	(3.17)
1{Actual$_t$ $<$ Belief$_{t-1}$}	-2.25	-2.28	2.49	3.45
	(1.80)	(3.72)	(2.01)	(3.30)
Observations	149	149	140	140
Demographic Controls		✓		✓
p-value(Above=Below)	0.014	0.29	0.0033	0.045

(B) Belief Updating

Notes: Robust standard errors in parentheses. Stars are used to denote the statistical significance of each coefficient (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$). Our set of demographic controls consists of binary variables for male, white, age between 18-34, age between 35-54, at least a college degree and household income below $40,000/year. Outcome variables in Panel (A) are recalls referring to the month before the baseline survey. Panel (A) shows regressions of recalls of job outcomes on functions of the 4 previous weeks of the actual job outcome. We define the minimum, the maximum and the mean for this set of four weeks. We present the p-value for a test of whether the coefficients for the maximum and the minimum variables are the same. In Panel (B), only participants that replied to our midline survey are included. $Belief_t$ is the recall of a job outcome of the first full week (starting on a Monday) after the baseline survey. $Belief_{t-1}$ is the pooled recall for each job outcome for the week or the month before the baseline survey. $Actual_t$ refers to the actual job outcome (obtained from a screenshot submitted from the gig platform app) of the first full week after the baseline survey. Each column shows the result of the regression of $Belief_t$ on $Belief_{t-1}$ and two binary variables: a variable equal to 1 if $Actual_t$ is above or equal to $Belief_{t-1}$, and a variable equal to 1 if $Actual_t$ is below $Belief_{t-1}$. There is no constant term in the regressions in Panel (B). We present the p-value for a test of whether the coefficients for the two indicator variables are the same.

Table A10: Predictions from motivated beliefs theory: variance of outcomes (other)

	Overestimation (Belief - Actual)			
	Weekly Hours		Hourly Pay	
	(1)	(2)	(3)	(4)
Last 4 Weeks (Actual)				
Coefficient of Variation (CV)	0.072**	0.077***	0.10***	0.10***
	(0.028)	(0.029)	(0.029)	(0.030)
Constant	4.03***	1.23	-1.47**	-1.91
	(1.36)	(3.67)	(0.72)	(2.32)
Observations	201	201	202	202
Demographic Controls		✓		✓
Average CV (SD/Mean)	0.41	0.41	0.19	0.19

Notes: Robust standard errors in parentheses. Stars are used to denote the statistical significance of each coefficient (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$). Overestimation of a job outcome may be negative and is defined as the recall belief minus the actual job outcomes for the same time period. We show regressions of the overestimation of a job outcome against the coefficient of variation for the 4 previous weeks of that outcome. The coefficient of variation is the standard deviation over the mean. We normalize this variable so that a 1 unit increase is equal to an increase of 1 percentage point. We present the average coefficient of variation underneath each column. Our set of demographic controls consists of binary variables for male, white, age between 18-34, age between 35-54, at least a college degree and household income below $40,000/year.

Table A11: Predictions from motivated beliefs theory: selective recall (forecasts)

	Forecast Belief								
	Weekly Pay			Weekly Hours			Hourly Pay		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Last 4 Weeks									
Maximum	0.65***	0.63***	0.48***	0.42***	0.38***	0.27	0.17**	0.16**	0.0068
	(0.076)	(0.079)	(0.16)	(0.11)	(0.11)	(0.20)	(0.067)	(0.067)	(0.12)
Minimum	0.22**	0.23**		0.099	0.13		0.22***	0.23***	
	(0.10)	(0.11)		(0.14)	(0.14)		(0.079)	(0.080)	
Mean			0.37**			0.26			0.39***
			(0.19)			(0.23)			(0.13)
Observations	262	262	262	235	235	235	229	229	229
Control Variables		✓			✓			✓	
p-value(Max=Min)	0.015	0.023		0.17	0.29		0.73	0.62	

Notes: Robust standard errors in parentheses. Stars are used to denote the statistical significance of each coefficient (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$). Forecast beliefs refer to the week after the baseline survey. Our set of demographic controls consists of binary variables for male, white, age between 18-34, age between 35-54, at least a college degree and household income below $40,000/year. We shows regressions of forecast of job outcomes on functions of the 4 previous weeks of the same job outcome. We define the minimum, the maximum and the mean for this set of four weeks. We present the p-value for a test of whether the coefficients for the maximum and the minimum variables are the same.

Table A12: Relationship of net hourly pay with reservation wage (means)

	Net Hourly Pay	
Mean	Belief	Actual
Panel A: Full Sample		
Reservation Wage (w_R)	14.91	14.91
Net Hourly Pay (w)	15.46	12.38
$w - w_R$	.55	-2.53
Panel B: Outside Option Less Likely to be Gig		
Reservation Wage (w_R)	14.15	14.15
Net Hourly Pay (w)	14.84	12.3
$w - w_R$	.69	-1.85
Panel C: Reservation Wage is Overestimated		
Reservation Wage (w_R)	14.91	13.24
Net Hourly Pay (w)	15.46	12.38
$w - w_R$	.55	-.85
Panel D: Wage at Other or Previous Jobs		
Wage in Other Jobs (w_R)	17.76	17.76
Net Hourly Pay (w)	15.46	12.38
$w - w_R$	-2.30	-5.38
Panel E: Maximum Weekly Net Hourly Pay		
Reservation Wage (w_R)	14.91	14.91
Net Hourly Pay (w)	15.46	14.3
$w - w_R$	.55	-.61

Notes: Belief w is the pooled net hourly pay recall of the week and the month before the baseline survey. Actual w is the actual expected net hourly pay referring to the same period. Reservation wage proxy w_R is the answer to the following question: "What is the lowest acceptable hourly pay after taxes and expenses that would accept to keep working for [gig company]?". In the first two rows of each panel, we calculate the mean of w_R and w. In the final row of each panel, we calculate the difference between w and w_R. Panel A is our full sample and base measure. In Panel B, we include only workers that did not do gigs before their current gig job and that do not work for other gig companies. In Panel C, we assume w_R is measured with half as much error as w by gig workers. In Panel D, we use the worker's gross hourly wages in either a previous job or in another current job. This measure is elicited in 5-dollar bins, for which we take the midpoint. In Panel E, we assume the actual w is the maximum weekly average of the net hourly pay in the past 4 weeks.

Figure A1: Baseline survey: Recall of job outcomes

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We will now ask you questions about your pay and amount of work you do for **DoorDash**.

Please answer to the best of your ability. Your answers will be aggregated with those of other participants to create insights about working for online gig platforms.

Think about the **last month** you worked for DoorDash.

Please answer the following questions considering **only DoorDash**, and do not use commas in your numerical answers.

Consider tips, bonuses, promotions and platform fees when thinking about your pay.

How many hours do you work per week?

[ ] hours per week

How much do you get paid **per hour** on average, **before expenses and taxes**?

$ [ ] /hour

How much do you get paid **per week**, **before expenses and taxes**?

$ [ ] /week

Out of your total pay **before expenses and taxes**, what percentage comes from bonuses and tips?

[ ] %

For this question, consider only the time in which you are either picking up deliveries or passengers or bringing them to their destination.

How much do you get paid **per hour actively working on gigs** on average, **before expenses and taxes**?

$ [ ] /hour

How much do you spend on **gas** per week?

$ [ ] /week

How much do you spend on **expenses and taxes** per week?

$ [ ] /week

How much do you get paid **per hour** on average, **after expenses and taxes**?

$ [ ] /hour

Figure A2: Baseline survey: Forecast of job outcomes

Berkeley
UNIVERSITY OF CALIFORNIA

We now ask you to estimate your weekly pay driving for DoorDash for the week starting on next Monday 12:01AM (Monday, October 10, 2022) and ending on the following Sunday at 11:59PM (Sunday, October 16, 2022)

As a reward for predicting accurately, you will receive a bonus. This reward is in addition to the $10 you receive by completing this survey.

For example, **if you make exactly the weekly earnings you predict, you will get an extra $5 Amazon gift card.** For each dollar you're off, the reward will go down, with larger reductions the further you are off.

If you're off by $100, you get an extra $3 Amazon gift card. And **if you're off by $160 or more, you get no bonus reward.**

This might sound complicated, but this system has been used in other research, and is specially designed so that you maximize your reward by stating your true beliefs.

We will email you in a few weeks with more details on your performance.

If you want to know more, select this option below.

I want more details

I do not want more details

Consider tips, bonuses, promotions and platform fees when thinking about your pay.

How much do you think your total weekly pay, **before expenses and taxes**, will be?

$ ______ /week

Keep considering the work you will do for DoorDash in **the week starting on next Monday 12:01AM (Monday, October 10, 2022) and ending on the following Sunday at 11:59PM (Sunday, October 16, 2022)**

You will not be paid for your accuracy in the following questions.

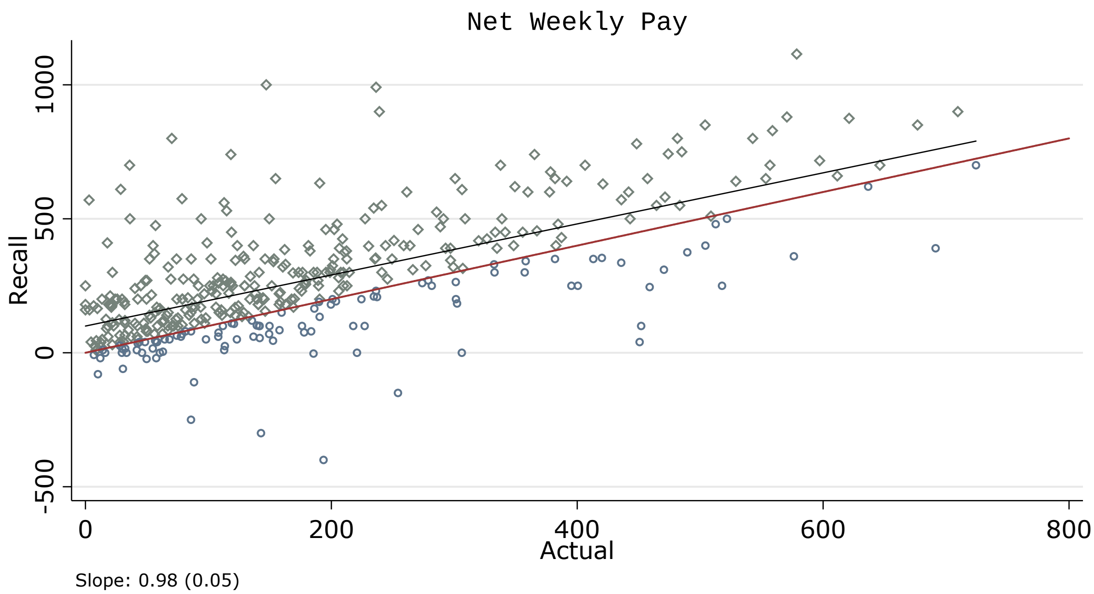
How much do you think your average pay per hour, **before expenses and taxes**, will be?

$ ______ /hour

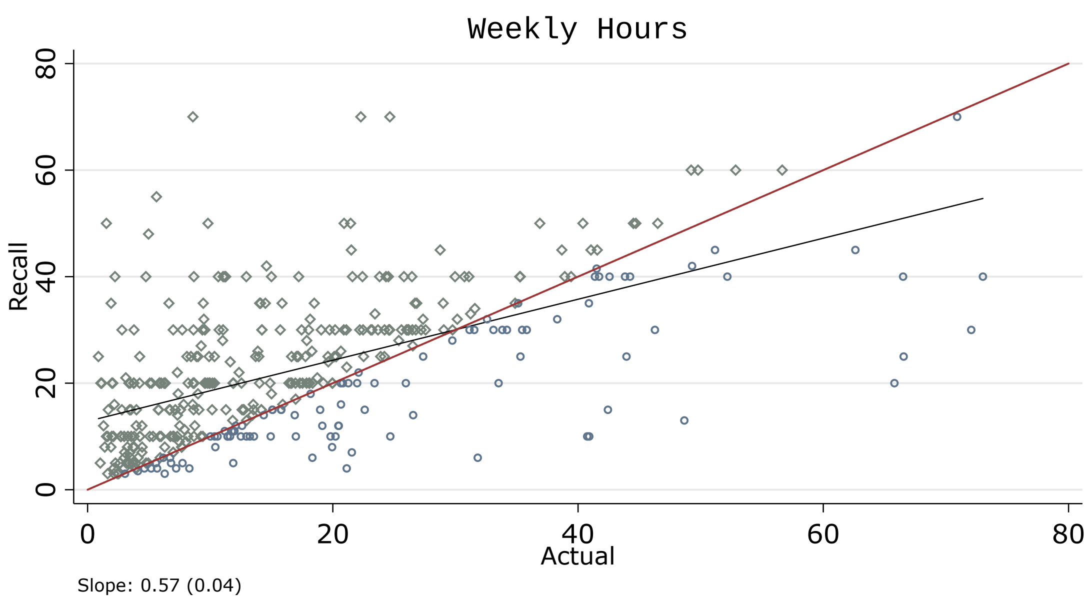
How many hours do you think you will work?

______ hours per week

Figure A3: Scatter plots relating recalls and actual job outcomes

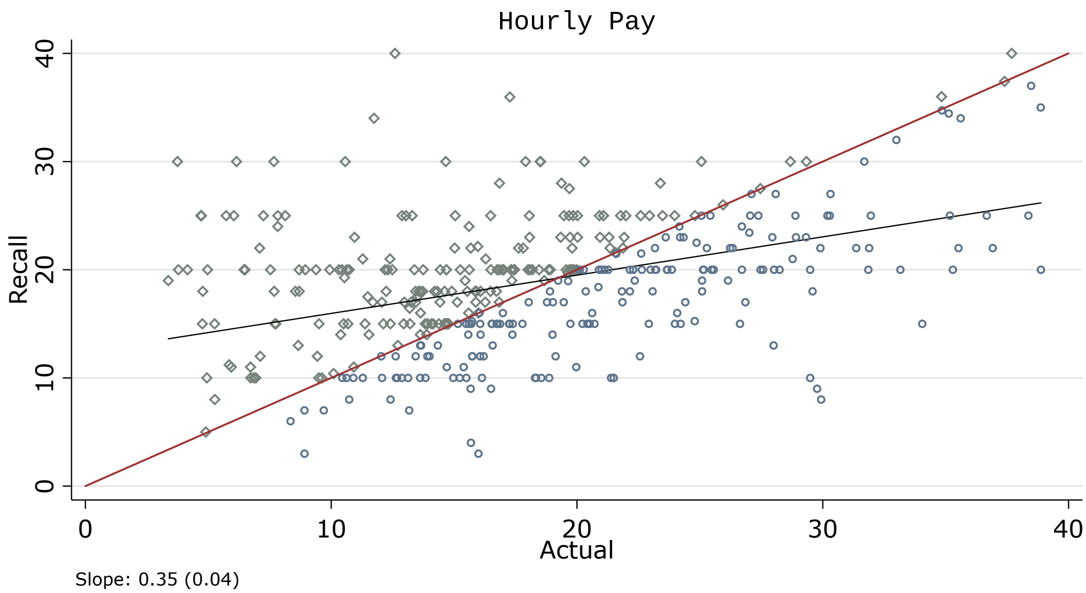


(A) Net Weekly Pay

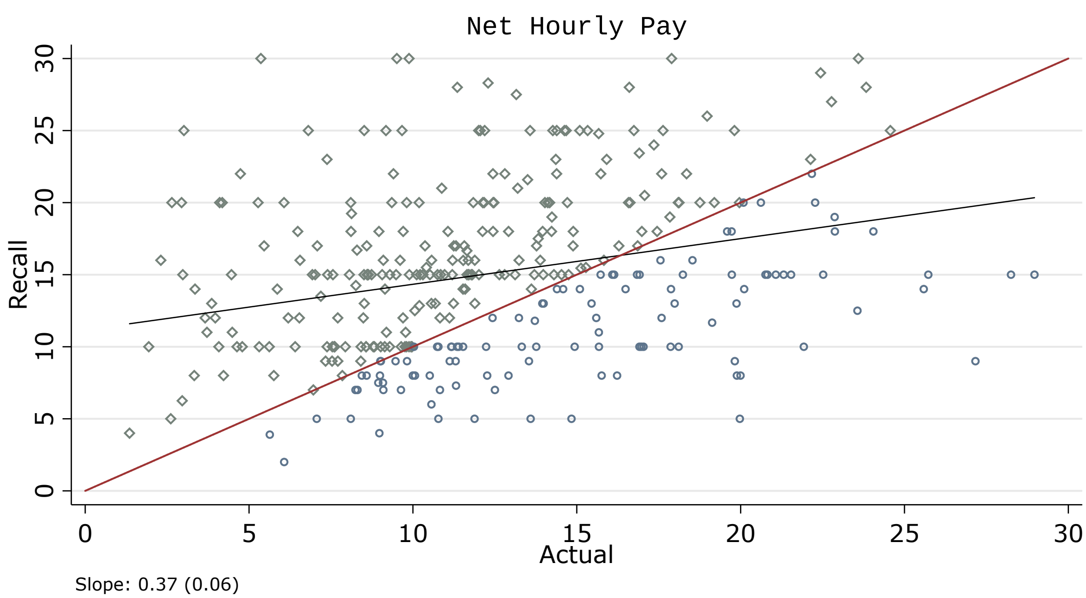


(B) Weekly Hours

Figure A3: Scatter plots relating recalls and actual job outcomes (cont.)



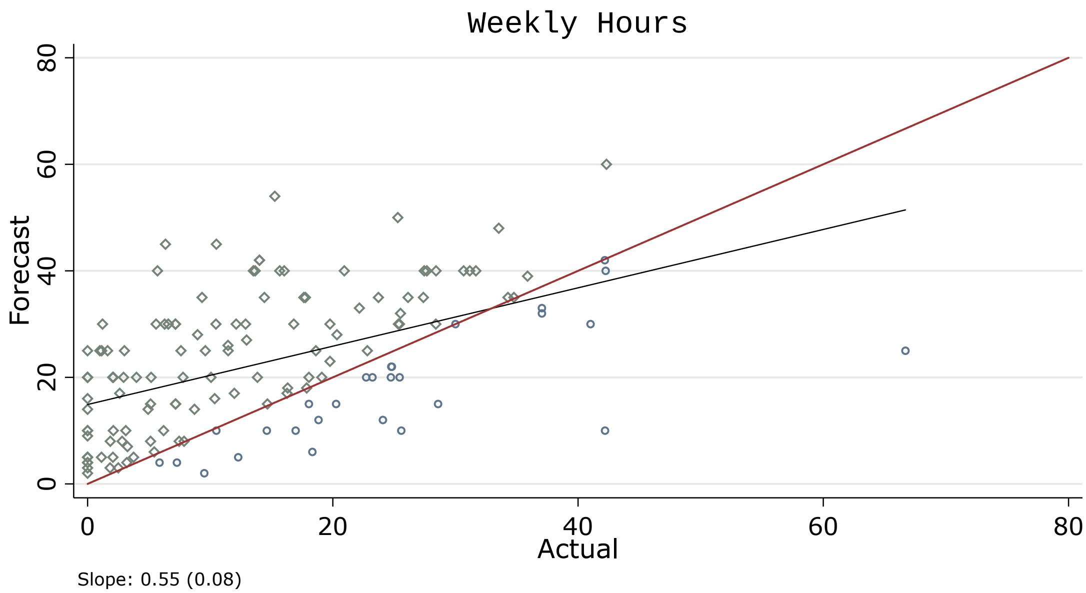
(C) Hourly Pay



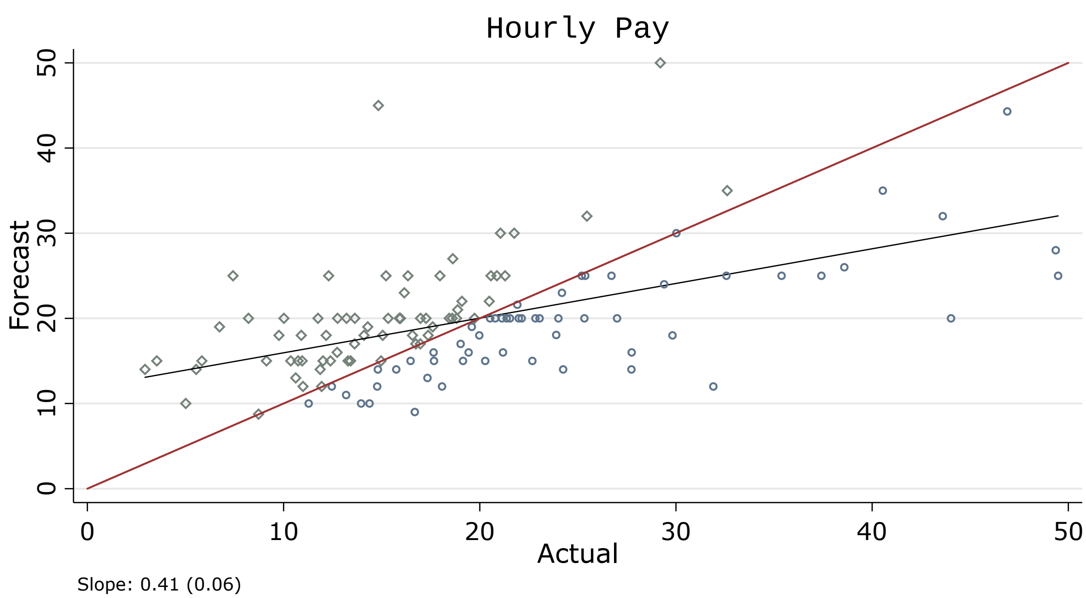
(D) Net Hourly Pay

Notes: In each graph, we draw a 45 degree line and the estimated slope of the regression of the belief on the actual the job outcome. Underneath each graph, we present the slope from the regression of the actual outcome versus its recall belief, with the associated standard error in parentheses. We exclude some outliers from each graph. Points above the 45 degree line indicate overestimation, whereas points below the 45 degree line indicate underestimation of the job outcome. We pool recalls of the week and the month before the baseline survey. The actual job outcomes pay refers to the same time period as the recalls and are obtained using information from screenshots from gig platform apps.

Figure A4: Scatter plots relating forecasts and actual job outcomes



(A) Weekly Hours



(B) Hourly Pay

Notes: In each graph, we draw a 45 degree line and the estimated slope of the regression of the belief on the actual the job outcome. Underneath each graph, we present the slope from the regression of the actual outcome versus its forecast belief, with the associated standard error in parentheses. We exclude some outliers from each graph. Points above the 45 degree line indicate overestimation, whereas points below the 45 degree line indicate underestimation of the job outcome. Forecast refer to the week following the baseline survey. The actual job outcomes pay refers to the same time period as the forecasts and are obtained using information from screenshots from gig platform apps.

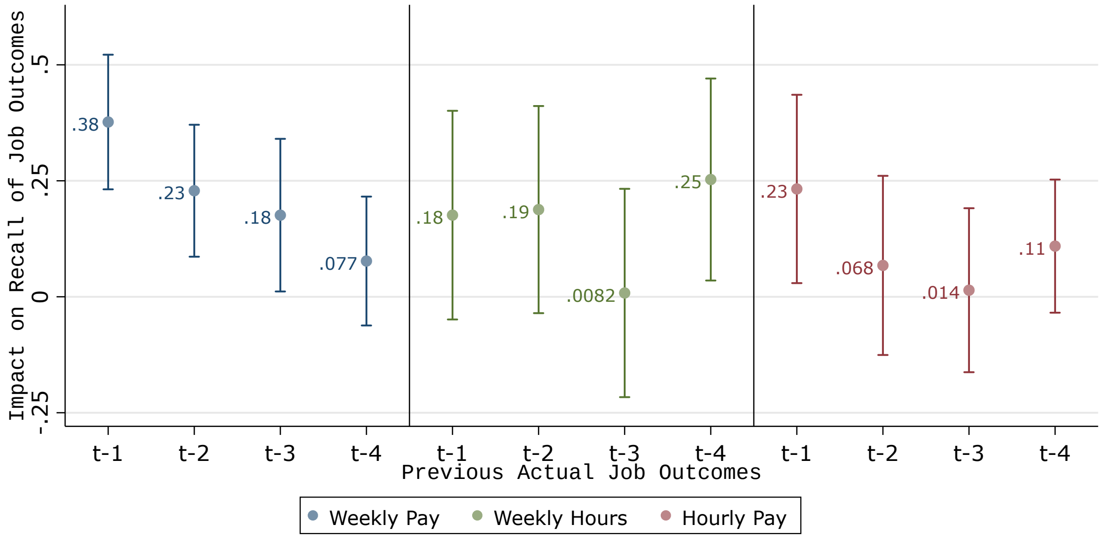
Figure A5: Relationship between forecast and recall overestimation of job outcomes

Notes: We draw the fitted line of the regression relating the forecast overestimation and the recall overestimation of job outcomes. The slope and its standard error are shown underneath. We exclude some outliers from this graph. We pool recalls of the week and the month before the baseline survey. The forecast refers to the first full week (starting on a Monday) following the baseline survey. Overestimation is measured as the recall or forecast minus the actual job outcome.

Figure A6: Relationship between forecast and recall beliefs

Notes: In each graph, we draw the fitted line of the regression relating the recall belief and the forecast belief of a job outcome. The slope and its standard error are shown underneath each plot. We exclude some outliers from each graph. We pool recalls of the week and the month before the baseline survey. The forecast refers to the first full week (starting on a Monday) following the baseline survey.

Figure A7: Estimated recall belief weights by recency of previous job outcomes



Notes: We plot the coefficients from regressions of recall beliefs for the past month on the last four weeks of actual realizations of the same outcome, ordered by recency, and a constant (omitted from the graph). Only recalls of the last month and workers who submitted four weeks of screenshots containing data on actual job performance are included. The notation for weeks on the x-axis ($t-1$, $t-2$, $t-3$, $t-4$) do not necessarily refer to four previous consecutive weeks, but only indicate the relative ordering of the four weeks.

Figure A8: Categories of costs considered in expenses calculation by gig workers

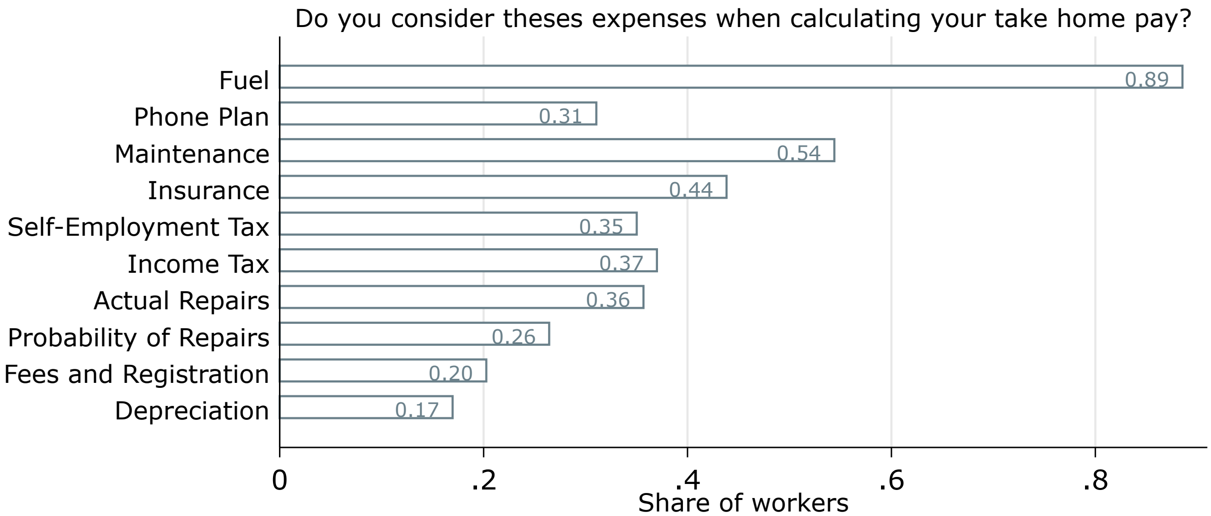
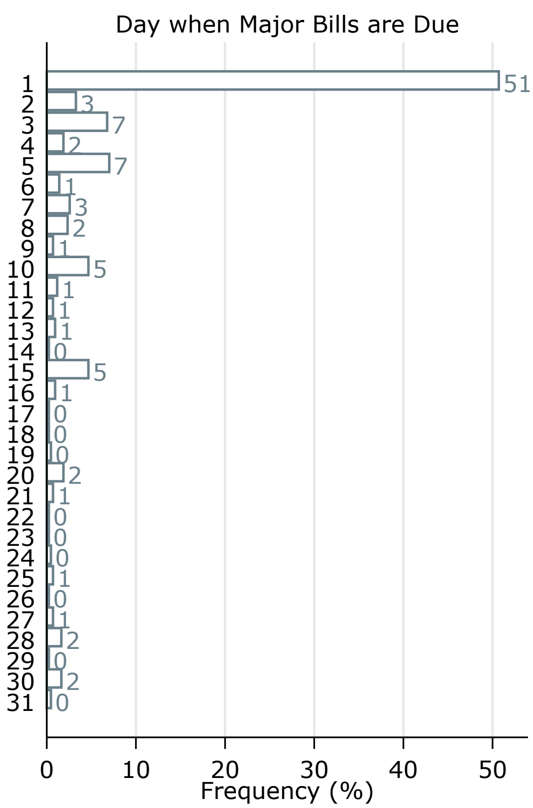
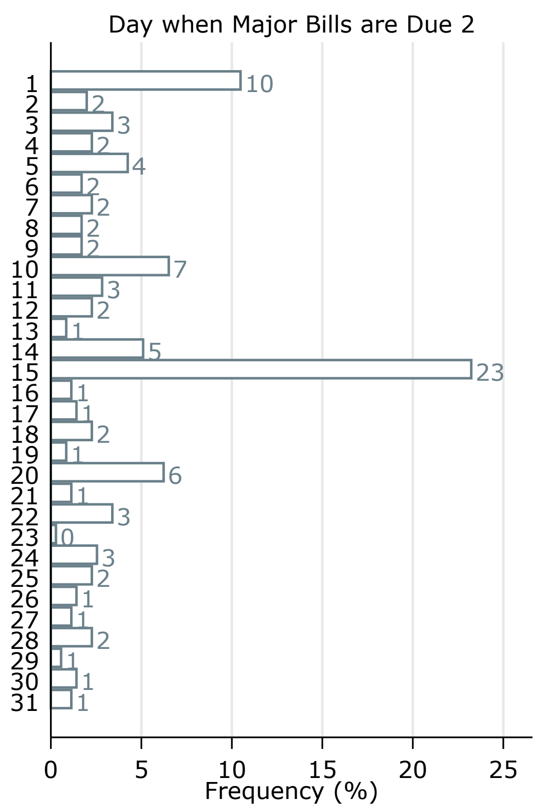


Figure A9: Days of the month where workers pay major bills





Appendix B: Details of Expenses Calculation

We now provide details of our calculations of expected expenses associated with gig work, which we use to estimate the actual expected net hourly and weekly pay. Only variable costs are considered: fuel, maintenance and repair, variable depreciation, self-employment taxes, and federal income taxes. We obtain estimates of operating costs from the AAA Your Driving Costs 2022 booklet. This guide has been published since 1950 and uses a proprietary methodology to calculate the costs of owning and operating a *new* car in the United States over five years.

This source has estimates of per mile operating costs for 9 different car categories: small sedan, medium sedan, subcompact SUV, compact SUV, medium SUV, midsize pickup, half-ton pickup truck, hybrid, and electric. We use expected maintenance and repair costs from this guide. We only use its estimates of fuel costs for hybrid and electric cars. For other categories, we average the AAA's gas price for the three months before the baseline survey. This is combined with information on fuel efficiency (miles per gallon) taken from the guide. Only the variable part of depreciation, resulting from driving additional miles, is considered. We calculate this cost by taking the increase, estimated in the guide, in total depreciation costs from driving 15,000 to 20,000 miles and dividing that by 5 thousand. In this way, we obtain an estimate of variable depreciation per mile for each car category.

To account for variation in costs with car age, we adjust the reported costs in the Your Driving Costs guide based on information from CarEdge. We use three car age groups: between 0 and 5 years, 6 and 10 years, and 10 years and above. We then calculate how (i) maintenance and repair costs and (ii) variable depreciation costs increase with car age. For each car category, we take an average of this variation for the top five car models.[22] On

[22]For each respective car category, these are: small sedan (Honda Civic, Hyundai Elantra, Nissan Sentra, Toyota Corolla, Volkswagen Jetta), medium sedan (Chevrolet Malibu, Honda Accord, Hyundai Sonata, Nissan Altima, Toyota Camry), subcompact SUV (Chevrolet Trax, Honda HR-V, Hyundai Kona, Jeep Compass, Subaru Crosstrek), compact SUV (Chevrolet Equinox, Ford Escape, Honda CR-V, Nissan Rogue, Toyota RAV4), medium SUV (Chevrolet Traverse, Ford Explorer, Subaru Outback, Jeep Grand Cherokee, Toyota Highlander), midsize pickup (Chevrolet Colorado, Ford Ranger, Honda Ridgeline, Jeep Gladiator, Toyota Tacoma), half-ton pickup truck (Chevrolet Silverado, Ford F-150, Nissan Titan, Ram 1500, Toyota

average across car categories, and relative to the costs for a car that is between 0 and 5 years old, depreciation costs are estimated to be 84% (43%) of the initial ones from years 6 to 10 (after year 10). According to our estimates, repair and maintenance costs for cars between 6 and 10 years old are, on average, 2.75 times higher than those for cars from 0 to 5 years old. This number is 3.76 for cars older than 10 years. We then multiply these factors by the estimates of depreciation and maintenance and repair from the AAA guide. Fuel expenses are assumed to be the same regardless of the age of the car.

We assume workers drive, on average, for 10 miles a hour. This allows us to turn per mile costs from the Your Driving Costs guide into per hour costs. We calculate self-employment taxes by first subtracting gross earnings per hour by the IRS mileage rate deduction ($.585/mile x 10 miles) and, following IRS procedure, multiplying the result by 0.925 and then by 15.3%.

Income taxes per hour are estimated by using the reported yearly household income, calculating how much of that income comes from gig work and then applying the standard deduction for 2022 for single filers. We assume gig workers work in half of the weeks of the year and make their average weekly earnings in each of these weeks. We divide the result by an estimate of total miles driven per year, still assuming that 10 miles are driven per hour. In our calculations, income taxes are, on average, 1% of total expected costs.

To determine how much of the driver's total pay is going to expected expenses, we subtract fuel, maintenance and repairs, depreciation, self-employment tax, and income taxes from their gross earnings per hour. Using this method, we calculate our post-expenses and taxes earnings per hour and convert it into a share of total gross pay. Appendix Table B1 provides an example of how this calculation is done, considering a driver of a 2022 Honda Accord who earns $20/hour and works 20 hours per week. Using this estimated expenses share, we calculate the actual expected net hourly and weekly pay. We do not calculate expected expenses for workers who rent a car to do gig work or who use a bike or scooter.

Tundra), hybrid vehicle (Ford Explorer, Honda CR-V, Hyundai Ioniq, Toyota Prius Liftback, Toyota RAV4) and electric car (BMW i3, Chevrolet Bolt, Hyundai Kona Electric, Nissan Leaf, Tesla Model 3)

Table B1: Example of expenses calculation

Category	Calculation	Value
Gross Earnings (1)		$20/hour
Fuel (2)		-$1.57/hour
Maintenance and Repair (3)		-$1.04/hour
Variable Depreciation (4)		-$0.52/hour
Pre-Tax Net Earnings (5)	(1) - (2) - (3) - (4)	$16.86/hour
Expenses Deductions (6)		- $5.85/hour
Self-Employment Tax (7)	[(1) - (6)]*0.925*15.3%	-$2.00/hour
Federal Income Tax (8)		-$0.19/hour
Post-Tax Net Earnings (9)	(5) - (7) - (8)	$14.66/hour
Share of Expenses (10)	[(1) - (9)] / (1)	26.6%

Notes: Example of calculation used to estimate the expected expenses share out of total pay. We consider a driver of a 2022 Honda Accord who makes $20/hour, works 20 hours a week and drives, on average, for 10 miles per hour. Our cost measures for maintenance, repair and variable depreciation are based on the AAA Your Driving Costs 2022 guide. Fuel costs are the average of gas prices from AAA in the three months before the baseline survey. We adjust for variation of maintenance, repair and depreciation costs over a car's lifespan by using information from CarEdge. We apply the IRS mileage rate deduction in 2022 ($.585/mile) to calculate self-employment taxes and we estimate federal income taxes by combining reported yearly household income, an estimate of gig income over the year and by applying the standard deduction for 2022.

Appendix C: Beliefs about Other Workers

One important aspect of optimistic beliefs is overplacement (Healy and Moore, 2007): the belief that one is more skilled relative to others than one actually is. To analyze this phenomenon in our setting, we ask, for a sub-sample, beliefs about job outcomes for other workers. In particular, for half of the individuals in the control group of the information treatment (or one quarter of the full sample), we elicit beliefs about job outcomes for the average worker for the same gig company in the baseline survey.[23] See Appendix Figure C1 for an example of the questions we ask.

Our first set of results are shown in Appendix Figure C2. We compare, divided by job outcome, the average (i) actual outcome, (ii) recall belief for oneself and (iii) recall belief for the average worker of the same gig company. We find that workers believe the average worker works longer hours and has a higher weekly pay. This effect is very large, and implies a belief of the average worker working full-time for the gig company, which is not correct for our sample. In addition, workers believe the average worker has a slightly higher gross hourly pay and a similar net hourly pay to themselves.

We then subtract each worker's belief for other workers from the recall belief about their own job performance. We next calculate leave-out means of the actual job outcomes. Then, we subtract each worker's actual job outcome by this leave-out mean. Finally, we compare these two differences to test for overplacement, which exists if workers believe their job outcome is higher relative to others than it actually is.

Results are shown in Appendix Table C1. We find no evidence of overplacement on hourly pay and find evidence of underplacement for weekly hours. Finally, we ask workers whether they believe other workers in the same gig company misunderstand their pay: 72% of workers believe it's likely others overestimate pay, versus 43% for others underestimating pay.

[23] These beliefs are elicited for everyone in the midline and endline surveys.

Figure C1: Questions on beliefs about the average gig worker

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For the next four questions, consider **the group of people who worked for DoorDash in the last month** and who will reply to this survey.

Please answer the following questions considering only the work they do for **DoorDash**, and do not use commas in your numerical answers.

Consider tips, bonuses, promotions and platform fees when thinking about pay.

How much do you think **this group** gets paid **per week**, **before expenses and taxes**?

$ [ ] /week

How much do you think **this group** gets paid **per hour** on average, **after expenses and taxes**?

$ [ ] /hour

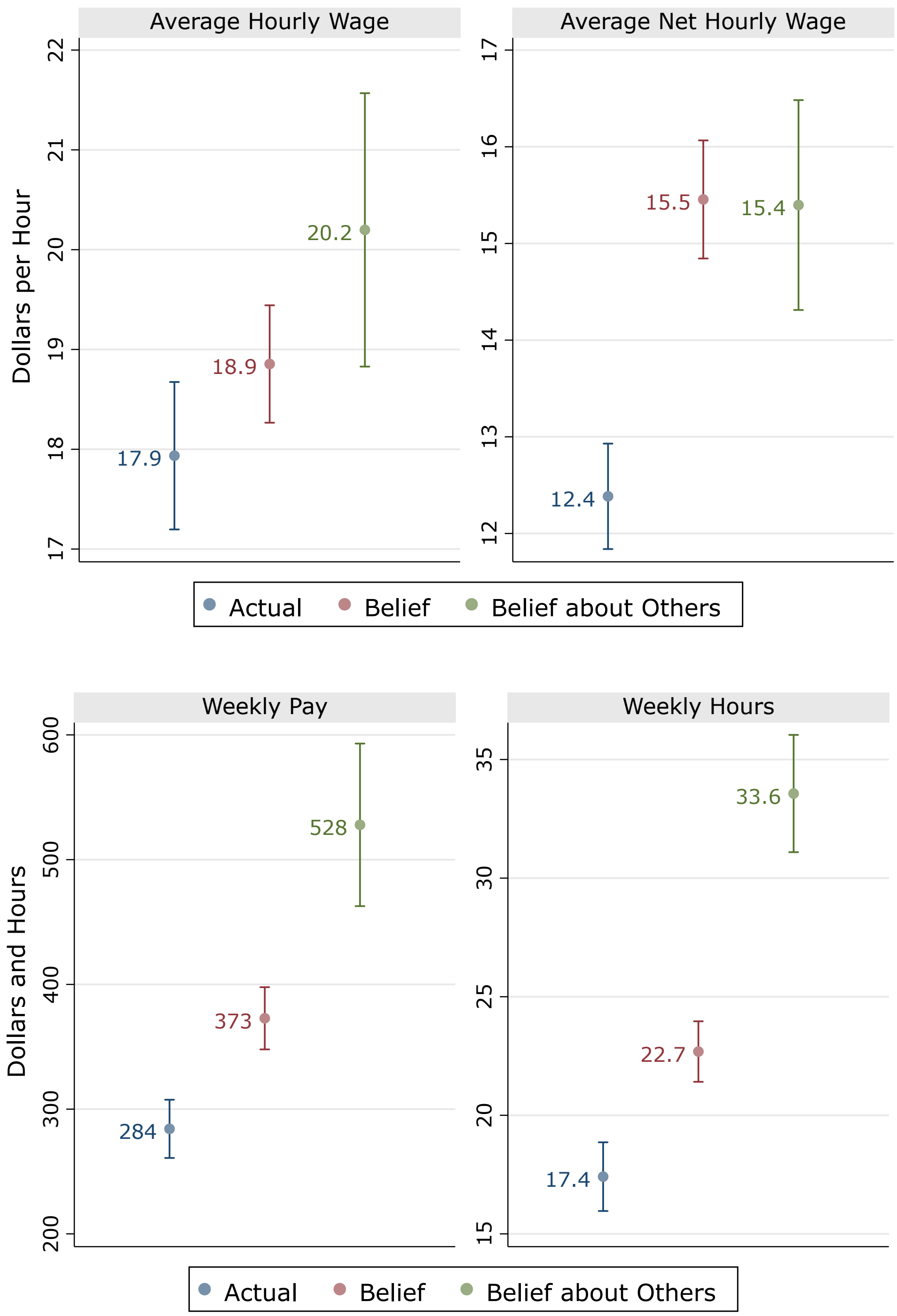
How many hours do you think **this group** works per week on average?

[ ] hours per week

How much do you think **this group** gets paid **per hour** on average, **before expenses and taxes**?

$ [ ] /hour

Figure C2: Comparison of actual job outcomes with self beliefs and beliefs about others



Notes: We plot the mean and the 95% confidence intervals of three measures pooled for the week and the month before the baseline survey: the actual job outcome, the recall belief of the job outcome for oneself and the belief of the job outcome for the average gig worker at the same company.

Table C1: Beliefs of job outcomes for self versus other workers

Pay Relative to Others (Belief)	**Summary Statistics** Mean	P25	Median	P75	Std. Dev.	N
Hourly Wage	-1.34	-4.75	0.00	2.00	7.07	108
Net Hourly Wage	0.21	-2.00	0.00	3.00	4.91	99
Weekly Pay	-184.91	-300.00	-150.00	0.00	289.76	110
Weekly Hours	-11.92	-20.00	-10.00	-3.00	14.89	113

(A) Belief

Pay Relative to Others (Belief - Actual)	**Summary Statistics** Mean	P25	Median	P75	Std. Dev.	N
Hourly Wage	-1.52	-7.23	-0.73	4.12	9.85	98
Net Hourly Wage	0.27	-2.72	0.95	4.47	6.47	77
Weekly Pay	-147.35	-292.57	-108.03	65.94	341.45	108
Weekly Hours	-9.47	-17.69	-9.43	-0.04	14.13	99

(B) Belief - Actual

Notes: We present summary statistics of variables comparing outcomes for oneself and for other workers. Recalls are pooled for the week and the month before the baseline survey. In Panel (A), we compare recall beliefs for oneself versus for the average worker. A negative value means that a workers believes the job outcomes for the average worker is higher than for themselves. On Panel (B), we do a double difference: we subtract the recall comparison of self and others from Panel (A) with the difference of actual job outcomes for oneself minus the leave-out mean of the same outcome for other workers.

Appendix D: Additional Robustness Checks

We now provide some robustness checks to how we measure the job performance of gig workers in our sample. Because gross weekly pay is salient and is reported to workers with bonuses, tips and fees included, we do not believe it is subject to credible concerns on this front. In contrast, measuring work hours is not as straightforward. We measure work hours as *online* hours, which is the total time a gig worker has the platform app turned on and is available for gigs. We believe his measure captures the nature of a standard job in which only part of the time is spent actively working.

Yet, gig workers may believe active hours, which includes only the time spent actively working on gigs, is the correct measure of labor supply. In this case, there will be a discrepancy between our definition and theirs. We will *underestimate* the overestimation of weekly hours but overstate the overestimation of hourly pay, as labor supply appears in the denominator of this variable.

To empirically access how much the definition of work hours matters, we provide a robustness check in Appendix Table D1. Our regressions include binary variables for behaviors that might lead to inaccurate measures of actual work hours, such (i) multi-tapping, or having more than one gig platform app active at the same time; (ii) being online on the app but with no intent to actually do gigs; (iii) not considering the time spent waiting for gigs as work or (iv) thinking commuting is work. We find that overestimation of recalls of job outcomes is robust to excluding gig workers who report doing any of these behaviors. In other words, our overestimation results are not the result of a mismatch between ours' and the gig workers' definition of work hours.

Our measure of actual expenses is based on expected costs calculated at the car category and age level. This measure is therefore less reliable than job outcomes derived directly from screenshots. We now detail a few ways in which we may be underestimating the expenses involved in gig work. First, our calculations ignore fixed costs such as insurance, registration fees, and non-variable depreciation (that is, depreciation not due to driving more miles).

This means we likely underestimate costs for drivers who buy cars primarily for doing gig work. In addition, we ignore state income taxes and assume drivers can deduct miles driven when calculating self-employment taxes. This deduction is known to reduce self-employment taxes. Yet, this deduction is not available to 47% of gig drivers in our sample, since they report not recording their miles.

Table D1: Robustness checks for overestimation considering definition of work hours

	Overestimation (Belief - Actual)				
	(1)	(2)	(3)	(4)	(5)
	Weekly Pay	Net Weekly Pay	Weekly Hours	Hourly Pay	Net Hourly Pay
Online but Not Working	28.8	23.6	3.97***	-0.24	-0.65
	(19.1)	(19.8)	(1.46)	(0.94)	(0.92)
Multiple Apps	56.5***	32.3*	1.31	3.20***	2.41***
	(16.1)	(16.6)	(1.26)	(0.79)	(0.78)
Considers Wait Not Work	-10.9	9.50	-0.15	0.076	0.65
	(16.2)	(16.6)	(1.24)	(0.79)	(0.78)
Considers Commute Work	-0.014	-5.23	-0.19	-0.12	0.64
	(15.8)	(16.3)	(1.21)	(0.77)	(0.76)
Excluded Group	70.6***	77.0***	4.79***	-0.17	1.51**
	(12.9)	(13.1)	(0.99)	(0.63)	(0.62)
Observations	439	400	397	393	345

Notes: We regress overestimation of job outcomes recalls against covariables. Robust standard errors in parentheses. Stars are used to denote the statistical significance of each coefficient (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$). Overestimation of each outcome can be negative and is defined as the recall belief minus the actual job outcomes for the same time period. We pool recalls of the week and the month before the baseline survey. *Online but Not Working* is a binary variable equal to 1 if a worker, either all the time or frequently, is online in the gig platform app with no intention of accepting gigs. *Multiple Apps* is a binary variable equal to 1 if a worker, either all the time or frequently, is online in more than one gig platform app at the same time. *Considers Wait Not Work* is equal to 1 if a worker considers little or none of the time spent waiting for rides as work hours and 0 otherwise. *Considers Commute Work* is equal to 1 if a worker considers all or most of the time spent commuting before and after a shift as work hours and 0 otherwise.

Appendix E: Details of the Information Treatment

We now detail our randomized information treatment. Our treatment is inspired by previous work aiming to change beliefs and behaviors through de-biasing interventions (Cullen and Perez-Truglia, 2022; Card et al., 2012; Bottan and Perez-Truglia, 2020). In the baseline survey, workers are randomly assigned to the treatment group with a 50% probability.[24] In that case, workers are required to manually input the weekly pay and weekly hours information from all screenshots they submit. This was done so we could provide feedback on their beliefs during the baseline survey. This also has the added effect of forcing them to face the information contained in the screenshots.

Then, on a single page, we explain the following: (i) how we calculate their gross hourly pay and its value; (ii) show how we calculate their expected expenses share, given their car; (iii) calculate their actual net hourly pay based on this information; (iv) compare the actual net hourly pay with their recall, informing them if they are under or overestimating it. We provide gig workers with an informative signal. Despite this, the signal is not fully accurate at the individual level due to noise in outcomes and in measuring expenses.

The next page informs them that gig workers in our sample often overestimate their job outcomes. We then provide them with a brief explanation of the concept of overconfidence. We find that 72% of gig workers say they plan to use in practice the information we provide, and that 81% say they agree partially or entirely with the information presented to them. Appendix Figure E1 shows an example of our information treatment. During the midline survey, we give the treatment group the same information pages presented at baseline. The purpose of this is to reinforce the information initially presented to them. Control group gig workers receive the same information, but only at the end of the endline survey.

If a worker does not use a car in his gig work, or if he rents a car to do gigs, we provide an alternative version of the information treatment, as we believe our measure of expected expenses would then be inadequate. In particular, we show these workers similar information,

[24] Appendix Table E1 shows a randomizing balancing test.

but concerning their gross weekly pay. This happens for less than 5% of our sample. This group is excluded from all results regarding the information treatment.

Estimation Strategy

Our treatment will have heterogeneous effects depending on which direction we correct gig workers' beliefs. In other words, treatment effects should differ based on whether we tell gig workers they overestimate (*Bad Signal*) or underestimate (*Good Signal*) their net hourly pay. As a result, we estimate treatment effects separately based on whether the initial overestimation of net hourly pay is positive or negative. Our main specification is:

$$y_{it} = \beta_0 + \beta_1 Over_i + \beta_2 Bad\,Signal_i + \beta_3 Good\,Signal_i + X_{i0}\Gamma + \varepsilon_{it} \tag{7}$$

where y_{it} are belief or labor market outcomes for individual i at period t. Period t a post-information treatment period. $Over_i = 1$ if initial overestimation of net hourly pay is positive and 0 if it is negative. Our two variables of interest here are $Bad\,Signal_i$ and $Good\,Signal_i$: $Bad\,Signal_i$ is equal to 1 if an individual is in the treatment group and $Over_i = 1$; $Good\,Signal_i$ if an individual is in the treated group and $Over_i = 0$. Finally, X_{i0} is the covariates matrix, composed of binary variables for male, white, age between 18-34, age between 35-54, at least a college degree and household income at most $40k/year. In addition, it includes the pre-treatment outcome y. The variable ε_{it} is the regression error. We use robust standard errors in all of our regressions.

In the above specification, the treatment effect is identified by comparing all workers who overestimate (underestimate) their net pay in the treatment group with all workers who overestimate (underestimate) it in the control group. By doing so, we ignore the magnitude of the mistakes gig workers make. In order to take that into account, we use the following alternative specification:

$$y_{it} = \beta_0 + \beta_1 Mis_i + \beta_2 Treat_i + \beta_3 Treat_i \cdot Mis_i + X_{i0}\Gamma + \varepsilon_{it} \tag{8}$$

where $Treat_i$ is the treatment binary variable, equal to 1 if an individual is in the treatment group, Mis_i is the initial overestimation (recall belief minus actual) in net hourly pay. In equation (8), β_2 identifies the intercept of the treatment effect, while β_3 identifies its slope: it measures how the treatment effect varies depending on the value of the initial overestimation of net hourly pay.

Effect on Beliefs

We now analyze the effects of our randomized information treatment on beliefs about gig job outcomes. After the information treatment, all of the beliefs we elicit about job outcomes are recalls and concern periods following the treatment. Thus, effects on beliefs are also dependent on how job market outcomes change as a result of our treatment. For instance, our treatment may affect a worker's choice of hours. As a result, actual hourly pay can change in ways that should alter beliefs about net hourly pay. Many settings for information treatments, in contrast, do not allow the subject to influence the actual outcome after knowing its value. The following results should be analyzed with this in mind.

After the information treatment, workers in the treatment group can review their incentivized forecast of weekly pay for the next week. We expect workers who are told they overestimate their net hourly pay to lower their forecast. This is because they might decide to work fewer hours in the future and can also lower their belief of their hourly pay. The opposite should happen for workers initially underestimating their pay.

Appendix Table E2 confirms this. In column (1), we regress the change in weekly pay forecast against the initial net hourly pay overestimation. On average, workers who review their pay forecast decrease it by \$10. In addition, a raise in initial overestimation by \$1/hour is associated with a decrease in the forecast of around \$1.6, which is significant at 10%. Using column (2), we test whether workers are more likely to review their forecasts when told they are making larger mistakes (in absolute value). It appears that this is the case.

In Appendix Table E3, we show the average overestimation of job outcomes at our midline and endline surveys, separately by the treatment and the control groups. Compared with the control group, the treatment group overestimates recall of job outcomes less after one week at the midline (one week recall) and after two to five months at the endline (one month recall). It is worth noting that our midline survey has a lower level of misestimation. We believe this is due to us (unlike in the baseline survey) requesting a recall of a specific week, explicitly stating the beginning and the end dates. Thus, it is likely that a share of workers looked at their actual job outcomes in that week and input them. We do not observe this pattern at the endline survey, where we elicit one month recalls.

We also examine how the information treatment affects beliefs when the initial level of overestimation is taken into account. Results are shown in Appendix Table E4 The first finding is that workers' recall beliefs for the expenses share rise when they initially underestimate net hourly pay (and the opposite when they overestimate). Our treatment does not seem to affect recall beliefs of net hourly pay in the expected way. This might partially be due to changes in behaviors (in response to our intervention) happening at the same time as our information provision. Alternatively, our information treatment might change beliefs immediately, but this effect may fade away over time.

On the middle two columns of both panels, we find some evidence that belief for the *average worker*'s net hourly pay does react in the expected way: increasing for those underestimating and decreasing for those told they are overestimating. This is however, not statistically significant. Possibly, beliefs about others are less affected by labor market decisions and are more easily changeable. Appendix Table E5 presents an alternative specification for measuring effects on beliefs. We use a continuous measure of net hourly pay overestimation. Our findings are similar.

Effects on Labor Market Outcomes

We discussed the main effects of our information treatment on job market outcomes in Section 5.2 and in Table 7. In Appendix Table E6, we estimate an alternative specification for our analysis of effects of labor supply and other jobs. In particular, we use a continuous measure of initial net hourly pay overestimation. Following the predictions of our model, we estimate effects on labor supply separately by financial need, using information on whether the worker's household is struggling financially.[25] We find similar effects to those reported in Table 7: labor supply is affected more by the information treatment when there is less financial need.

[25]Struggling financially is defined as reporting to be receiving calls from collectors, contemplating bankruptcy, or struggling to pay the bills.

Figure E1: Example of information treatment

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We now compare your perceptions of pay to the information in the screenshots you submitted.

Please read carefully, as you might find the following information valuable to your decision making.

Earlier in the survey, you said that you believe that your average pay per hour, *after* expenses and taxes, is $18. We will now try to estimate what is your actual post-expenses hourly pay.

According to information from the AAA Driving Costs brochure and our calculations, an average driver of a Midsize pickup from 2019 needs to **subtract around 29% of their earnings to account for expenses and taxes, *such as fuel, car maintenance and repair, depreciation, self-employment and income taxes.***

If you wish to see further details on how this number was reached, select this option below.

I want more details

I do not want more details

Consider the following example for a part-time driver for DoorDash who makes $20/hour, works 20 hours a week and drives, on average, for 10 miles per hour in a Midsize pickup from 2019.

We base this calculation on *expected costs* over a year, taken from the AAA Driving Costs brochure. For instance, mechanical problems are unpredictable but will occur at some point. Using *expected* costs takes into account this possibility and how likely it is to happen. We only include variable costs, and so we assume that a car was already available to do gigs.

If a car was bought expressively to do gigs, these expenses can be considerably higher.

Gross Earnings: $20/hour
Fuel: -$2.35/hour
Maintenance and Repair: -$0.99/hour
Depreciation (Drop in Resale Value): -$0.85/hour
Pre-Tax Net Earnings: $20/hour - $2.35/hour - $0.99/hour - $0.85/hour = $15.81/hour
Self-Employment Tax: -$2.00/hour
Federal Income Tax: -$0.19/hour
Post-Tax Net Earnings: $15.81 - $2.00-$0.19 = $13.62/hour
Share of Expenses: ($20-$13.62)/$20 = **28.8%**

The calculations are an approximation and will likely not perfectly describe anyone's condition. Click on the link below for more information and sources.

Figure E1: Example of information treatment (Cont.)

In the **screenshots you submitted for last week**, you worked approximately **9.2 hours** for DoorDash. Your total pay in this time were **$155.12**.

Assuming you were working for DoorDash the whole time you were online on the app, your **actual** average pay per hour, *before* expenses and taxes, is found by dividing your total pay by the time you worked during these weeks. This is equal to **$16.86 per hour**.

Using the expenses share of 28.8%, we can estimate that your **actual** average take home pay (or hourly pay *after* expenses and taxes) to be around **$12**.

This is 33% lower than your assessment ($18).

This might indicate that you are *overestimating your take home pay.*

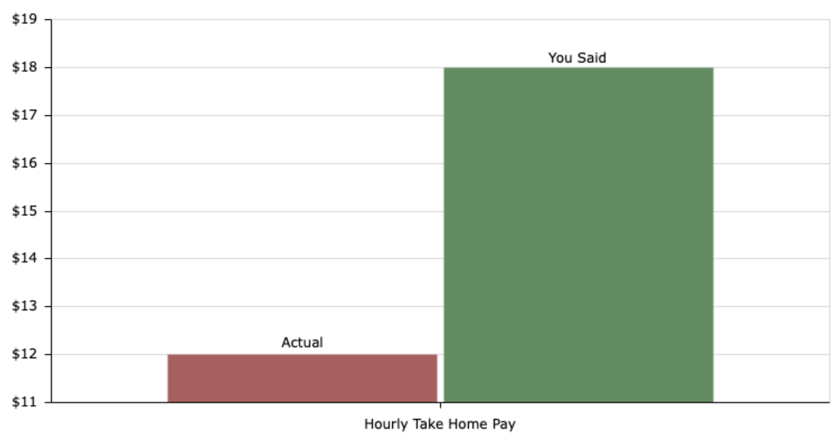

Figure E1: Example of information treatment (Cont.)

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We will now to share some of the preliminary results we have obtained from our study.

Following similar calculations as the ones we just presented, we found that previous respondents to our survey have, on average, **overestimated** their pay and **underestimated** their expenses.

According to our data, drivers, on average, overestimate their average hourly pay by **8.3%**, their average hourly pay after expenses by **23.8%** and their weekly pay by **23.9%.**

While this might seem weird, as it can imply that drivers do not always have a good understanding of how much money they make on gig economy jobs, **we believe they can be explained by the psychological concept of *overconfidence*.**

Overconfidence means that, in many situations, people have a tendency to be too optimistic and too certain about important aspects of their lives. For instance, three-quarters of US drivers consider themselves better-than-average drivers.

These concepts matter more in situations where understanding something is a hard task. In our view, that is exactly the case for calculating pay in gig economy jobs, as pay tends to vary a lot depending on time of day, expenses and market conditions each day.

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Recall that we asked you to predict your weekly pay driving for DoorDash for the week starting on next Monday 12:01AM (Monday, October 10, 2022) and ending on the following Sunday at 11:59PM (Sunday, October 16, 2022). As a reward for predicting accurately, you will receive a bonus.

Before, you predicted a total weekly pay equal to $ **before expenses and taxes**.

If you want to change your prediction, please write it down in the box below.

$ ______ /week

Table E1: Balancing table for randomized information treatment

Baseline Survey	**Full Sample**			**Control**		**Treatment**		
	N	Mean	SD	Mean	SD	Mean	SD	**Diff.**
Age 18-34	454	42.07	49.42	41.95	49.45	42.20	49.50	0.3
Age 35-54	454	47.14	49.97	48.73	50.09	45.41	49.90	-3.3
White	454	72.69	44.61	75.42	43.15	69.72	46.05	-5.7
Male	454	41.19	49.27	40.25	49.15	42.20	49.50	1.9
College Degree	454	38.55	48.72	41.10	49.31	35.78	48.05	-5.3
HHold Income 0−40k	454	54.19	49.88	54.66	49.89	53.67	49.98	-1.0
No Household Budget	454	21.59	41.19	18.22	38.68	25.23	43.53	7.0*
Struggling Financially	454	42.73	49.52	41.53	49.38	44.04	49.76	2.5
Gig Pay is Essential	454	83.48	37.18	83.47	37.22	83.49	37.22	0.0
Has Other Gig Job	454	35.68	47.96	36.44	48.23	34.86	47.76	-1.6
Has Non-Gig Job	454	17.18	37.76	17.80	38.33	16.51	37.22	-1.3
Employed Full-Time Prior to Gig	454	36.34	48.15	38.98	48.87	33.49	47.30	-5.5
Employed Part-Time Prior to Gig	454	20.26	40.24	18.64	39.03	22.02	41.53	3.4
Unemployed Prior to Gig	454	10.13	30.21	8.47	27.91	11.93	32.48	3.5
Experience Delivery (12+ mo.)	454	57.49	49.49	56.78	49.64	58.26	49.43	1.5
Experience Rideshare (12+ mo.)	454	23.57	42.49	23.31	42.37	23.85	42.72	0.5

(A) Covariates

Baseline Survey	**Full Sample**			**Control**		**Treatment**		
	N	Mean	SD	Mean	SD	Mean	SD	**Diff.**
Hourly Pay	400	17.94	7.52	18.36	7.24	17.47	7.80	-0.9
Hourly Net Pay	360	12.38	5.26	12.50	4.85	12.27	5.65	-0.2
Weekly Pay	445	284.20	250.44	261.02	217.48	308.76	279.61	47.7**
Weekly Hours	404	17.41	14.81	16.70	13.95	18.17	15.66	1.5
Expenses Share	408	32.19	5.19	32.42	5.17	31.95	5.21	-0.5
Hourly Pay (Recall)	436	18.85	6.25	18.98	6.31	18.72	6.19	-0.3
Net Hourly Pay (Recall)	412	15.46	6.31	15.73	6.21	15.15	6.42	-0.6
Weekly Pay (Recall)	439	372.82	265.80	371.20	259.91	374.57	272.62	3.4
Weekly Hours (Recall)	440	22.69	13.63	22.68	13.57	22.69	13.73	0.0
Hourly Pay (Forecast)	324	19.36	6.80	18.87	6.32	19.92	7.31	1.1
Weekly Pay (Forecast)	344	376.79	324.95	354.20	313.60	402.77	336.65	48.6
Weekly Hours (Forecast)	333	23.24	14.05	22.19	13.55	24.47	14.56	2.3

(B) Outcomes

Notes: Data in this table is collected in our baseline survey. We first show the full sample. We then divide it into the control and the treatment groups for our information treatment. The treatment group receives detailed information on whether they overestimate or underestimate their net hourly pay. The last column shows the difference in means between the control and the treatment groups for each variable. Stars are used to denote the statistical significance of this difference (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$).

Table E2: Effect of information treatment on reviewing incentivized forecast of weekly pay

	Reviews Weekly Pay Forecast	
	(1)	(2)
	Change in Forecast	Has Reviewed Forecast
Overestimation Net Hourly Pay	-1.60*	
	(0.83)	
Abs(Overestimation Net Hourly Pay)		0.014*
		(0.0075)
Constant	-10.9*	0.17***
	(6.06)	(0.057)
Observations	147	149

Notes: Robust standard errors in parentheses. Stars are used to denote the statistical significance of each coefficient (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$). Only individuals in the information treatment group are included in the regressions, as they were the only ones allowed to review their forecast of weekly pay for following full week. *Overestimation Net Hourly Pay* is the overestimation in net hourly pay, which is defined as the recall belief minus the actual net hourly pay. Recall of net hourly pay is pooled for the week and the month before the baseline survey, with the actual job outcomes referring to the same time period for each worker. *Abs(Overestimation Net Hourly Pay)* is the absolute value of the overestimation in net hourly pay. *Change in Pay Forecast* measures the within-individual difference in the weekly pay forecast before and after receiving the information treatment. *Has Reviewed Pay Forecast* is a binary variable equal to 1 if the individual has chosen to review their weekly pay forecast immediately after the information treatment.

Table E3: Effect of information treatment on overestimation of job outcomes

	Overestimation (Recall - Actual)			
	(1)	(2)	(3)	(4)
	Weekly Pay	Weekly Hours	Hourly Pay	Net Hourly Pay
Treatment	-4.66	0.21	0.35	2.21^{***}
	(13.4)	(0.91)	(0.84)	(0.67)
Control	17.0	1.62^{*}	2.12^{***}	2.39^{***}
	(12.2)	(0.83)	(0.74)	(0.64)
Observations	172	162	161	131

(A) Two Weeks After Treatment

	Overestimation (Recall - Actual)			
	(1)	(2)	(3)	(4)
	Weekly Pay	Weekly Hours	Hourly Pay	Net Hourly Pay
Treatment	43.7^{**}	3.64^{***}	-1.07	1.62^{**}
	(17.6)	(1.13)	(0.77)	(0.69)
Control	63.3^{***}	4.27^{***}	0.029	2.05^{***}
	(16.4)	(1.06)	(0.70)	(0.66)
Observations	159	152	147	126

(B) Two to Five Months After Treatment

Notes: Robust standard errors in parentheses. Stars are used to denote the statistical significance of each coefficient (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$). We regress the overestimation of recalls of job outcomes on two binary variables: one for the treatment group and one for the control group in the information treatment. We omit the constant term of these regressions. *Overestimation* is the recall belief minus the actual job outcome. Thus, positive (negative) overestimation implies overestimation (underestimation) of a job outcome. The recalls are for the last week in Panel (A) – measured in our midline survey – and for the last month in Panel (B), measured in our endline survey.

Table E4: Effect of information treatment on beliefs of job outcomes

	Belief Net Hourly Pay		Belief Other Net Hourly Pay		Belief Expenses Share	
	(1)	(2)	(3)	(4)	(5)	(6)
Good Signal	2.41	1.07	2.91	2.37	-9.40**	-9.76*
	(1.90)	(1.91)	(1.90)	(1.79)	(4.72)	(4.94)
Bad Signal	0.072	0.81	-1.31	-1.31	4.45	3.84
	(1.30)	(1.26)	(1.16)	(1.24)	(3.14)	(3.53)
Observations	136	136	141	141	145	145
Baseline Outcome		✓		✓		✓
Demographic Controls		✓		✓		✓
p-value(Treatment No Effect)	0.45	0.69	0.17	0.23	0.054	0.080

(A) Two Weeks After Treatment

	Belief Net Hourly Pay		Belief Other Net Hourly Pay		Belief Expenses Share	
	(1)	(2)	(3)	(4)	(5)	(6)
Good Signal	2.22	1.23	-0.68	-0.95	-2.05	0.74
	(1.72)	(1.58)	(1.37)	(1.33)	(4.11)	(4.53)
Bad Signal	1.23	1.85*	-0.77	-0.85	-4.57	-5.54**
	(1.20)	(1.06)	(0.82)	(0.88)	(2.83)	(2.73)
Observations	129	128	132	132	136	136
Baseline Outcome		✓		✓		✓
Demographic Controls		✓		✓		✓
p-value(Treatment No Effect)	0.26	0.17	0.57	0.49	0.24	0.13

(B) Two to Five Months After Treatment

Notes: Robust standard errors in parentheses. Stars are used to denote the statistical significance of each coefficient (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$). We estimate versions of $y_{it} = \beta_0 + \beta_1 Over_i + \beta_2 BadSignal_i + \beta_3 Good\ Signal_i + X_{i0}\Gamma + \varepsilon_{it}$, where y_{it} is the outcome variable for individual i at period t. $Over_i = 1$ if initial overestimation of net hourly pay is positive and 0 otherwise. Our two variables of interest here are $Bad\ Signal_i$ and $Good\ Signal_i$: $Bad\ Signal_i$ is equal to 1 if an individual is in the treatment group and $Over_i = 1$; $Good Signal_i$ if an individual is in the treated group and $Over_i = 0$. Individuals in the treatment group were told whether they misestimated their actual net hourly pay. X_{i0} is the covariates matrix. Our set of demographic controls consists of binary variables for male, white, age between 18-34, age between 35-54, at least a college degree and household income below $40,000/year, in addition to the outcome variable in the baseline survey. We test whether all treatment variables (*Good Signal* and *Bad Signal*) are jointly significant and provide a p-value for this test for each model. *Beliefs* dependent variables refer to the recall for net hourly pay (models (1) and (2)), the recall for expenses share (models (5) and (6)) and the belief of hourly net pay for the average worker in the same gig company (models (3) and (4)). The recalls are for the last week in Panel (A) – measured in our midline survey – and for the last month in Panel (B), measured in our endline survey.

Table E5: Effect of information treatment on beliefs of job outcomes (other specification)

	Belief Net Hourly Pay		Belief Other Net Hourly Pay		Belief Expenses Share	
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	1.53	0.59	0.70	0.53	-2.19	-2.51
	(1.13)	(1.08)	(1.13)	(1.13)	(3.03)	(3.28)
Treatment · Overestimation	-0.26*	0.0025	-0.24	-0.23	0.65	0.61
	(0.16)	(0.15)	(0.17)	(0.16)	(0.40)	(0.40)
Observations	136	136	141	141	145	145
Baseline Outcome		✓		✓		✓
Demographic Controls		✓		✓		✓
p-value(Treatment No Effect)	0.14	0.85	0.37	0.36	0.28	0.32

(A) Two Weeks After Treatment

	Belief Net Hourly Pay		Belief Other Net Hourly Pay		Belief Expenses Share	
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	1.97*	1.16	-0.75	-1.01	-4.78*	-3.96
	(1.08)	(0.99)	(0.82)	(0.82)	(2.57)	(2.57)
Treatment · Overestimation	-0.17	0.069	-0.019	0.019	0.22	-0.018
	(0.14)	(0.13)	(0.12)	(0.12)	(0.39)	(0.41)
Observations	129	128	132	132	136	136
Baseline Outcome		✓		✓		✓
Demographic Controls		✓		✓		✓
p-value(Treatment No Effect)	0.17	0.27	0.49	0.42	0.17	0.22

(B) Two to Five Months After Treatment

Notes: Robust standard errors in parentheses. Stars are used to denote the statistical significance of each coefficient (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$). We estimate equation (8) defined in Appendix E. We include in our regressions but do not report the constant term and *Overestimation*. *Overestimation* is defined as the recall belief of net hourly pay minus the actual net hourly pay, pooled for one week and one month before the baseline survey. *Treatment* is a binary variable equal to 1 if the worker was assigned to our information treatment at the baseline survey. Our set of demographic controls consists of binary variables for male, white, age between 18-34, age between 35-54, at least a college degree and household income below $40,000/year, in addition to the outcome variable in the baseline survey. We test whether all treatment variables (*Treat and Treat · Overestimation*) are jointly significant and provide a p-value for this test for each model. *Beliefs* dependent variables refer to the recall for net hourly pay (models (1) and (2)), the recall for expenses share (models (5) and (6)) and the belief of hourly net pay for the average worker in the same gig company (models (3) and (4)). The recalls are for the last week in Panel (A) – measured in our midline survey – and for the last month in Panel (B), measured in our endline survey.

Table E6: Effect of information treatment on labor market decisions (other specification)

	Other Jobs		Weekly Hours	
	(1)	(2)	(3)	(4)
Treatment	-0.12*	-0.11		
	(0.071)	(0.070)		
Treatment · Overestimation	0.022**	0.024**		
	(0.011)	(0.011)		
Treatment × Less Need			0.89	0.081
			(1.77)	(1.52)
Treatment × Need			0.77	-1.13
			(3.92)	(3.01)
Treatment · Overestimation × Need			-0.19	0.17
			(0.43)	(0.53)
Treatment · Overestimation × Less Need			-0.20	-0.36*
			(0.25)	(0.20)
Observations	168	168	162	153
Baseline Outcome		✓		✓
Demographic Controls		✓		✓
p-value(Treatment No Effect)	0.080	0.056	0.92	0.47

Notes: Robust standard errors in parentheses. Stars are used to denote the statistical significance of each coefficient (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$). We estimate equation (8) defined in Appendix E. We include in our regressions but do not report the constant term and *Overestimation*. *Overestimation* is defined as the recall belief of net hourly pay minus the actual net hourly pay, pooled for one week and one month before the baseline survey. *Treatment* is a binary variable equal to 1 if the worker was assigned to our information treatment at the baseline survey. Our set of demographic controls consists of binary variables for male, white, age between 18-34, age between 35-54, at least a college degree and household income below $40,000/year, in addition to the outcome variable in the baseline survey. We test whether all treatment variables are jointly significant and provide a p-value for this test for each model. *Need* (*Less Need*) is equal to 1 if the gig worker is in a household that is (not) struggling financially and 0 otherwise. *Struggling Financially* is defined as receiving calls from collectors, contemplating bankruptcy, or struggling to pay the bills. In addition, we add but do not a binary variable of *Need* to our model. The dependent variable for models (3) and (4) is the weekly hours worked for the main gig company for in the week following the baseline survey (including zeroes). *Other Jobs* is a binary variable equal to 1 if the worker has another gig or non gig job.