INCOME PREDICTION BIAS IN THE GIG ECONOMY

Technical Report

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Abstract

Gig economy employment (e.g., driving for Uber or delivering food for Just Eat) has increased dramatically in the past decade. A defining characteristic of working in the gig economy is that gig income is variable across weeks and months, which makes it impossible to predict in exact terms. This represents a challenge for individuals who work in the gig economy, because an accurate estimate of future income is a foundational component of a household’s budget, and household budgets guide responsible financial decision-making. In this research, we introduce and test the hypothesis that gig workers display an *income prediction bias* in which they *over*-predict their gig income. We find support for this hypothesis across participant samples drawn from three different types of gigs: rideshare driving, online human intelligence tasks, and food delivery. We also find evidence that the bias occurs in part because gig workers overpredict the number of hours they will be able to work, although their expected hourly wage is quite accurate. Finally, we show that the income prediction bias can be reduced by prompting gig workers to base their income predictions on relevant past experience. Taken together, these findings help gig workers, gig firms, and policy-makers understand if and why gig workers overpredict their gig income, and how income predictions can be made more accurate.

Keywords**:** Income prediction bias; gig economy; planning fallacy; consumer financial decision making.

[*] This report has been prepared by the authors for the Think Forward Initiative.

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1. Introduction

Gig economy employment is defined as temporary, freelance work. Emblematic examples include driving for apps like Uber, delivering food through apps like Door Dash, and participating in research on platforms like Amazon Mechanical Turk. The speed and magnitude of the recent shift toward this type of employment has been remarkable. From 2005 to 2015 the number of Americans “gigging”, increased by nearly 50%, and 94% of net employment growth in the U.S. economy occurred in gig economy work arrangements (Katz and Kruger, 2016).

An important and previously unstudied aspect of working in the gig economy is that gig income is highly variable, which makes it difficult to predict. This represents a challenge for individuals who work in the gig economy because an accurate estimate of future income is important for financial planning, and financial planning aids wealth-accumulation, financial security, psychological well-being, and a vital social life. In four longitudinal studies, we measure gig workers’ predicted and actual weekly income to test the hypothesis that gig economy workers display an *income prediction bias* in which they *over*-predict their gig income. In Study 4, we also test two interventions designed to improve prediction accuracy by drawing workers’ attention to either relevant past experience or possible atypical outcomes when they predict their income.

The remainder of this report will unfold as follows: In Section 2, we draw from research on the psychology of misprediction to develop our income prediction bias hypothesis, and discuss ways in which the bias may be reduced. In Sections 3 and 4, we describe our studies and present our results. In Section 5, we discuss the implications of our work for theory and practice.

2. Hypotheses Development

2.1 Is there an Income Prediction Bias?

It is currently an open question as to whether gig workers systematically mispredict their gig income, and there are reasons to believe that their predictions may actually be reasonably accurate. For example, gig workers may engage in “income targeting” and simply work for as long as it takes to hit their target (Camerer et al., 1997). Notably, this type of behaviour is said to be encouraged by some gig economy intermediaries who gamify their apps to keep people working on their platform for longer periods of time (Scheiber, 2017). It may also be the case that the motivation to make optimistic predictions in the context of income is far less than, for example, in the context of expenses (Peetz and Buehler, 2009), because losses (expenses) hurt more than gains (income) feel good (Kahneman and Tversky, 1979a). Finally, there is at least one study in the labour economics literature showing that undergraduate students’ post-graduation salary expectations are generally accurate when compared to their self-reported salaries four years after graduation (Webbink and Hartog, 2004). Taken together, these findings suggest that income prediction accuracy may be the norm.

However, an honest evaluation of this evidence requires acknowledgement of three countervailing points. First, there is some controversy around the existence of income targeting (Farber, 2005; Ottenginer, 1999), and it has been shown that income targeting among Uber drivers, if it exists, dissipates quickly as drivers gain experience (Sheldon, 2017). Second, there is work suggesting that optimistic financial predictions are prevalent even in the absence of a motivational goal (Howard et al., 2021). Finally, the results in the labour economics literature are mixed: whereas Webbink and Hartog (2004) found undergraduate students’ salary expectations to be accurate across several (non-gig) professions, others have found them to be wildly optimistic (Betts, 1996; Jerrim, 2015; Smith and Powell, 1990).

In addition to the ambiguity of the evidence suggesting that income predictions may be accurate, there is also considerable evidence suggesting that predictions tend to be optimistic, even in the face of contradictory information. For example, research on expense prediction bias has shown that expense predictions are optimistic (e.g., Peetz and Buehler, 2012; Ulkumen et al., 2008), even when consumers know how much they spent in the recent past (Howard et al., 2021; Peetz and Buehler, 2009). Similarly, research on the planning fallacy has demonstrated that people tend to make optimistic predictions regarding project completion times, even when they are equipped with the knowledge that similar projects have taken longer than planned in the past (Buehler, Griffin, and Ross, 1994). Therefore, based on the logic that an optimistic income prediction means earning more money rather than less, we hypothesize that:

> **H1:** Gig economy workers display an *income prediction bias* in which they *over*-predict their gig income.

2.2 How Can Income Prediction Accuracy Be Improved?

Several streams of research support the proposition that when people try to predict future outcomes, they do not consider the full distribution of possible outcomes. For example, prediction biases across phenomena as diverse as expense prediction, project planning, prosocial behavior, voting, and relationship endurance have all been attributed in part to instantiations of "base-rate neglect", in which available information about possible outcomes is discounted or ignored (Buehler, Griffin, and Ross 1994; Dunning, Griffin, Milojkovic, and Ross 1990; Epley and Dunning 2000; Peetz and Buehler 2009; Vallone, Griffin, Lin, and Ross 1990). Two solutions to this problem that have successfully improved prediction accuracy in other domains are: 1) explicitly prompting people to take an "outside view", and base their predictions on relevant past behaviour, and 2) prompting people to consider atypical outcomes when formulating their prediction. One goal of this research is to systematically compare the effectiveness of these interventions in the context of income prediction.

2.2.1 Intervention One: Taking an Outside View

The "planning fallacy" refers to the phenomenon that people tend to under-predict their project completion times, even when they are equipped with the knowledge that similar projects take longer than planned in the past. One explanation for the planning fallacy is that when people make predictions they tend to adopt an "inside view", in which they focus on optimistic plan-based scenarios. These scenarios are inherently optimistic because it is virtually impossible for the human mind to conjure up every possible future outcome, especially those that represent an impediment to success. Accordingly, it has been proposed and demonstrated that the planning fallacy can be reduced by prompting people to adopt an "outside view", in which their predictions are based on relevant past experience (Buehler, Griffin, and Ross, 1994; Buehler, Griffin, and Peetz, 2010; Kahneman and Tversky, 1979b).

In this research we propose that the income prediction bias can also be reduced by taking an outside view. If H1 is correct and income predictions are optimistic, then prompting gig workers to base their income predictions on past experience that includes both high and low earnings should make predictions more realistic by providing people with a highly relevant cognitive anchor. Formally, we hypothesize that:

> **H2:** Prompting gig workers to base their predicted income on relevant past income reduces the income prediction bias.

2.2.2 Intervention Two: Considering Atypical Outcomes

Expense prediction bias is the phenomenon that consumers tend to drastically under-predict their future spending (e.g., Ulkumen et al. 2008). This bias has the potential to be highly problematic because an accurate estimation of one's future spending is required to make responsible decisions about how much money one should spend, save, or borrow in the interim. One reason this bias occurs is that expense predictions are based on highly typical expenses like groceries and rent, and they do not account for less typical expenses like car repairs or emergencies (Sussman and Alter 2012). Accordingly, it has been shown that the expense prediction bias can be neutralized by prompting consumers to consider reasons why their expenses will be different than usual, because this helps bring atypical expenses to mind (Howard et al. 2021).

In this research, we test the possibility that this "atypical intervention" can also improve income prediction accuracy. Specifically, we test the possibility that income prediction accuracy can be improved by prompting gig workers to consider reasons why their schedule might be different than usual. The logic underlying this possibility is that in the context of optimistic income predictions, "different than usual", could represent reasons why a person will work less than they think, and therefore earn less than they would otherwise predict. Concrete examples of this include getting sick, needing to care for a sick child or parent, dealing with an unexpected car repair, taking time off for social obligations like weddings and funerals, and so on. We therefore hypothesize that:

> **H3:** Prompting gig workers to consider reasons why their schedule will be different than usual reduces the income prediction bias.

3. Studies 1–3

The first goal of Studies 1–3 was to test H1 with samples drawn from different types of gig work. The second goal was to test the feasibility of different participant recruitment channels. These studies utilized the same design, so we present them here as a set.

Method

Participants and Procedure. Participants were recruited to take part in a two-stage survey about working in the gig economy. The first survey was completed immediately, and it asked participants to predict their gig income and hours for the next week. The second survey was sent to participants one week later, and it asked them to log into their gig's app and report their gig income and hours for the past week. This two-stage design allowed us to measure participants' prediction accuracy for their gig income and hours. It also let us measure the accuracy of participants' expected hourly wage (predicted income ÷ predicted hours), as compared to their actual hour wage (actual income ÷ actual hours).

Participants in Study 1 were US and Canadian residents who drive for Uber. Participants were recruited through r/uberdrivers, a reddit.com community that Uber drivers use to communicate with each other. We posted this study organically (i.e., as fellow reddit user, not as a paid advertiser), and with the permission of the community's moderators. The post invited drivers to participate in a two-stage survey about working in the gig economy in exchange for $2.50 of reddit gold, a virtual currency that can be used to access premium features on the website. Seventy-one participants completed the first survey (M_{age} = 35.0, 11.3% female) and thirty-eight (53.5%) completed the second (M_{age} = 36.6, 13.2% female). Across Studies 1–3, the predictions of participants who completed both surveys did not differ significantly from those who only completed the first survey (p's > .15). Because our focal hypothesis concerns prediction accuracy, all analyses reported below were performed using data from participants who completed both surveys.

Participants in Study 2 were US residents who perform human intelligence tasks on Amazon Mechanical Turk (AMT) in exchange for piecemeal wages. Two-hundred AMT workers completed the first survey in exchange for $0.50 (41.5% female, M_{age} = 34.7), and one hundred and twenty-nine (64.5%) completed the second survey for an additional $2.50 (40.3% female, M_{age} = 34.9).

Participants in Study 3 were US and Canadian residents who gig for food delivery apps like GrubHub and DoorDash. Participants were recruited through paid advertisements placed in reddit.com communities that app-based food delivery drivers use to share information with one another (e.g., r/grubhubdrivers). Our ads invited drivers to participate in a two-stage survey about working in the gig economy in exchange for a $10 Amazon.com gift certificate. Eighty-five participants completed the first survey (M_{age} = 30.4, 24.7% female) and forty-seven participants completed the second survey (M_{age} = 29.9, 23.4% female).

Results

The results of Studies 1–3 are presented in Figures 1–3. The Uber drivers in Study 1 overpredicted their gig income by 18.2% (Mean Difference = $63.90, 95% CI = [-.89, 128.69], $t(37)$ = 2.00, p = .053). They also over-predicted the number of hours they would work at their gig by 31.2% (Mean difference = 5.72, 95% CI = [3.34, 8.10], $t(37)$ = 4.87,

$p < .001$). However, their expected hourly wage was quite accurate as compared to the hourly wage they ended up earning (Mean difference = -\$.50, 95% CI = [-3.11, 2.11], $t(37) = -.39$, $p = .70$).

This pattern of results was replicated among the AMT workers in Study 2 and food delivery app drivers in Study 3. The AMT workers overpredicted their gig income by 11.6% (Mean difference = \$13.05, 95% CI = [1.01, 1.23], $t(128) = 2.14$, $p = .034$) and their gig hours by 18.6% (Mean difference = 4.00, 95% CI = [2.33, 5.72], $t(128) = 4.70$, $p < .001$), but their expected hourly wage was fairly accurate (Mean difference = –\$0.55, 95% CI = [-1.18, .08], $t(128) = -1.72$, $p = .088$). The food delivery app drivers overpredicted their gig income by 19.9% (Mean difference = \$63.52, 95% CI = [13.64, 113.40], $t(46) = 2.56$, $p = .014$) and their gig hours by 21.2% (Mean difference = 4.08, 95% CI = [1.69, 6.48], $t(46) = 3.43$, $p = .001$), but their expected hourly wage did not differ significantly from their actual hourly wage (Mean difference = -\$.52. 95% CI = [-2.32, 1.27], $t(45) = -.58$, $p = .56$).

Figure 1: Results of Study 1 (Uber Drivers, n = 38)

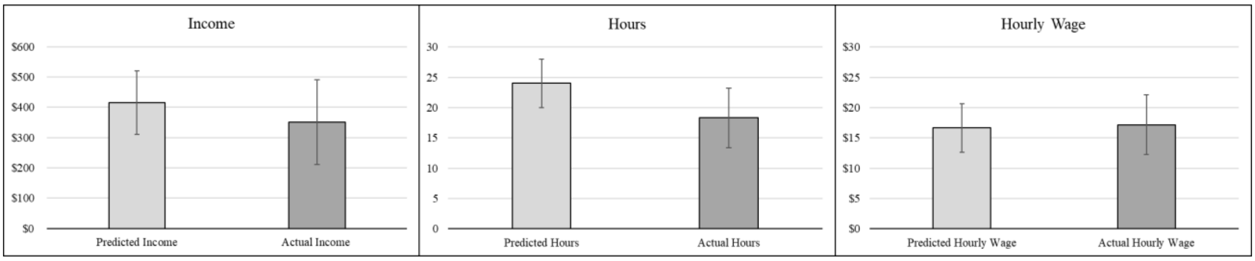


Figure 2: Results of Study 2 (AMT workers, n = 129)

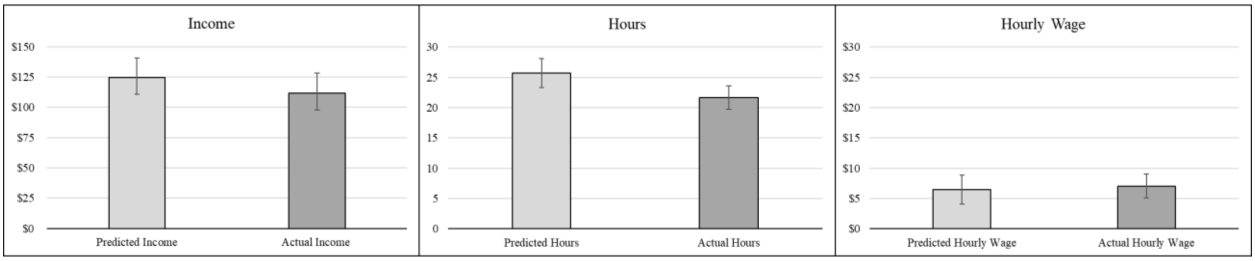
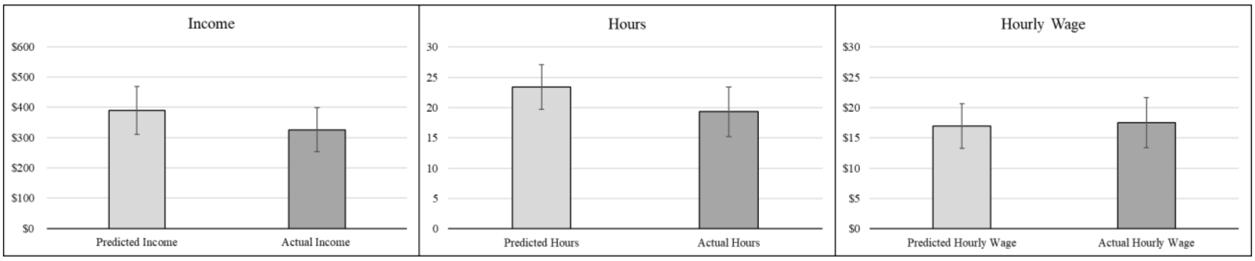


Figure 3: Results of Study 3 (Food Delivery App Drivers, n = 47)



Taken together, the results of Studies 1–3 support our hypothesis that workers in the gig economy display an income prediction bias in which they overpredict their future gig income (H1). These studies also indicate that gig workers overestimate the number of hours they will work, but that their expected hourly wage is relatively accurate.

A second contribution of Studies 1–3 is that they help illuminate the feasibility of recruiting participants for this type of research through three different channels: 1) organic reddit posts, 2) AMT HITs, and 3) paid reddit.com advertisements. Our organic reddit post was cost effective, but recruitment was slow (the study had to be posted two weeks in a row to net 38 participants). Recruiting through AMT was convenient, but weekly income from AMT is remarkably low. This introduces the possibility that interventions designed to increase prediction accuracy by decreasing predictions may fail on platforms such as Mechanical Turk due to a floor effect, even if those interventions would be successful in other gig contexts where income is higher. Recruiting through paid reddit advertisements is relatively expensive (we paid each participant with a $10 Amazon gift certificate, and we paid reddit approximately $1.00 per click through on our ad), but it is both quick and convenient. Therefore, we chose to run our intervention study using this method of recruitment.

4. Study 4: Improving Prediction Accuracy

The first goal of Study 4 was to replicate Studies 1–3, and better understand heterogeneity in prediction accuracy. For example, are more experienced drivers more accurate predictors? Do people with a higher propensity to plan (Lynch et al. 2010) have a better idea of how much they will earn? These are a sample of the questions we address in the control condition of this study.

The second goal of Study 4 was to test interventions designed to increase income prediction accuracy by making predictions less optimistic. Specifically, we tested an “outside view” intervention that has been shown to reduce prediction biases in other domains by prompting people to consider relevant past behavior when predicting future outcomes (e.g., Buehler, Griffin, and Ross 1994). We also tested an “atypical” intervention that has been shown to improve expense prediction accuracy by prompting predictors to consider reasons why the future might be different than usual (Howard et al. 2021).This study was preregistered on aspredicted.org (https://aspredicted.org/blind.php?x=nu8j4c).

Participant Recruitment

Study 4 was conducted with gig economy workers in the US who deliver food through apps like Grub Hub, Skip the Dishes, and UberEats. We recruited these individuals by placing advertisements on reddit.com communities that delivery drivers for these apps use to communicate with each other (e.g. r/grubhubdrivers). The advertisements offered participants “$10 for 10 minutes + chance to win $250” in exchange for completing a survey about driving for food delivery apps. After drivers clicked-through to the study they were provided with the following details: “We are conducting a short survey about working for food delivery apps, and you are invited to participate. Participation takes about 10 minutes in total: 7 minutes to complete today's survey, and 3 minutes to complete a quick follow-up survey that we will email to you one week from today. When you complete the follow-up survey you will automatically receive a $10 Amazon.com gift card, and we will enter you into a draw with four grand prize gift cards worth $250 each. If you would like to participate, please continue to the consent form on the next page!”

Eleven hundred and five drivers completed the first survey. Six hundred and sixty-two of these drivers (59.9%) completed the second survey and passed the data quality measures described below. Table 1 compares drivers who completed both surveys and passed the data quality measures to those who did not. Drivers in the first group did not differ significantly from those in the second group in terms of any variable that is observable for both groups (i.e., any variable measured in the first survey). Additionally, the percentage of drivers who completed both surveys and passed the data quality measures did not differ across the three conditions in this study ($\chi_{(2)}$ = 3.39, p = .18).

Table 1: Driver Characteristics in Study 4

Variable	Drivers who completed both surveys	Drivers who did not complete both surveys	Significance test
N	662	443	N/A
Predicted income	M = \$312.67, SD = 238.83	M = \$330.78, SD = 293.90	$t(1103) = 1.13, p = .26$
Typical income	M = \$317.86, SD = 269.80	M = \$348.73, SD = 376.18	$t(1103) = 1.59, p = .11$
Lowest income	M = \$151.29, SD = 166.19	M = \$156.21, SD = 170.23	$t(1103) = .48, p = .63$
Highest income	M = \$447.12, SD = 305.48	M = \$448.64, SD = 342.46	$t(1103) = .08, p = .94$
Predicted hours	$M = 21.65, SD = 15.02$	$M = 22.23, SD = 15.89$	$t(1103) = .62, p = .54$
Typical hours	$M = 20.80, SD = 14.20$	$M = 21.68, SD = 15.15$	$t(1103) = .98, p = .33$
Lowest hours	$M = 9.60, SD = 11.05$	$M = 10.37, SD = 10.76$	$t(1103) = 1.15, p = .25$
Highest hours	$M = 28.49, SD = 17.38$	$M = 29.32, SD = 18.33$	$t(1103) = .76, p = .45$
Gig experience	$M = 3.89, SD = 1.81$	$M = 3.71, SD = 1.84$	$t(1103) = 1.66, p = .10$
% female	35.00%	38.70%	$\chi_{(1)} = 1.54, p = .22$
Age	$M = 30.03, SD = 9.21$	$M = 30.23, SD = 10.23$	$t(1103) = .34, p = .73$
% of total income from gig	M = 6.13, SD = 3.59	M = 5.99, SD = 3.60	$t(1103) = .64, p = .53$
Short-term financial propensity to plan	$M = 4.65, SD = 1.04$	$M = 4.58, SD = 1.05$	$t(1103) = 1.20, p = .23$

Experiment Design

After providing informed consent, all participants were asked to indicate which food delivery apps they currently work for (Select all that apply: Foodora, Skip the Dishes, Uber Eats, DoorDash, Grubhub, Other). Participants were then randomly assigned to predict their gig income for the next week in one of three conditions:

Control Condition. The prediction instructions in the control condition were "Please take some time to estimate the total amount of money you will earn working for food delivery apps in the next week. (Page break.) How much money do you estimate you will earn (in total) working for food delivery apps in the next week?"[2]

Outside-view Intervention Condition. The prediction instructions in the outside-view intervention condition were: "Please take some time to estimate the **total** amount of money you have earned working for food delivery apps over the **past four weeks**. How much money do you estimate you have earned (in total) working for food delivery apps over the **past four weeks**? (Page break). Over the past 4 weeks you estimate you have earned $XX **per week** working for food delivery apps. Based on that experience, how much money do you estimate you will earn working for food delivery apps in the **next week**?" The value of $XX was the participant's answer to the preceding question divided by 4. So, for example, if a participant reported earning a total of $600 over the past four weeks, their prediction instructions read "Over the past 4 weeks you estimate you have earned $150 **per week** working for food delivery apps. Based on that experience, how much money do you estimate you will earn working for food delivery apps in the **next week**?"

Atypical Intervention Condition. The prediction instructions in the atypical intervention condition were "Please take some time to consider reasons why the number of hours you work for food delivery apps in the next week might

[2] Specific dates (e.g., Monday, November 16th to Sunday, November 22nd) were shown in parentheses after the words "next week" in all conditions.

be *different* than usual. Please list 2 reasons why the number of hours you work for food delivery apps in the next week might be *different* than usual. (Page break.) Keeping in mind your answer to the previous question, how much money do you estimate you will earn (in total) working for food delivery apps in the next week?"

After predicting their income for the next week, all participants completed each of the following measures:

Predicted hours: "How many hours do you estimate you will work for food delivery apps in the next week?" We collected this measure for two reasons: 1) we wanted to determine if gig workers overpredict their future income in part because they overpredict the number of hours they will be able to work, and 2) we wanted to measure the accuracy of workers' expected hourly wage, which we calculated as predicted income divided by predicted hours. Data from five participants whose expected hourly wage exceeded the sample mean ($15.77) by more than three standard deviations (9.61) was excluded from our analyses.

Past income: "To answer the following questions, please think about your experience working for food delivery apps over the **past 8 weeks**. (Line break.) Over the past 8 weeks, how much money did you earn from food delivery apps in a **typical** week? (Line break.) Over the past 8 weeks, how much money did you earn from food delivery apps in your **lowest** income week? (Line break.) Over the past 8 weeks, how much money did you earn from food delivery apps in your **highest** income week?" The typical income question was always presented first, and the order of the lowest and highest income questions was randomized. We presented participants with these questions so we could examine the relationship between predicted income and past income.

Past hours: Participants answered the same questions about the number of hours they worked for food delivery apps over the past 8 weeks as they did for income.

Percentage of total income from gig: "In the following question, "total income" refers to your income from delivering food **plus** your income from all other jobs that you worked. (Line break.) Over the past 8 weeks, what percentage of your total income did you earn from delivering food? (0-10%, 11-20%, 21-30%, … , 91-100%)." This measure was collected so we could examine its correlation with prediction accuracy in the control condition.

Gig experience: "How long have you been working for food delivery apps? (Less than one month, 1-3 months, 4-6 months, 7-9 months, 10-12 months, 1-2 years, 3-4 years, 5-6 years, more than 6 years)." This measure was collected so we could examine its association with prediction accuracy in the control condition.

Short-term financial propensity to plan: This six-item scale developed by Lynch et al. (2010) was included so we could examine its association with prediction accuracy in the control condition. At the end of the scale we embedded an attention check that instructed participants to "Please select strongly disagree for this statement." As per our preregistration, data from participants who failed this attention check (n = 70) was excluded from analysis.

After completing the short-term financial propensity to plan scale, participants in the control and outside-view conditions were asked to list 2 reasons why the number of hours they work for food delivery apps in the next week might be *different* than usual, just as participants in the atypical intervention had. We did this so that we could use gibberish responses (e.g., "asdofiauos") to this question as a preregistered data quality measure that applied equally to all three conditions. Only five participants provided such an answer. Participants then reported standard demographic information, and whether or not they had experienced any technical difficulties with the survey. The first survey concluded with the following instructions: "Thank you for taking the time to complete today's survey! We will email you the follow-up survey at 9am EST on [date piped in here], and it will be accessible until 11:59pm EST that day. Once you have completed the follow-up survey you will automatically receive your $10 Amazon.com gift card and be entered into the draw to win one of four grand prize gift cards worth $250 each. (Line break.) Please enter your email address below. (Page break.) Note: The best way to ensure that you complete the follow-up survey on time, receive your gift card, and get entered into the grand prize draw, is to set a reminder in your phone right now to look for the follow-up survey in your inbox between 9am and 11:59pm EST on [date piped in here]."

The second survey began by asking "Which food delivery apps did you work for in the past week? (Select all that apply: Foodora, Skip the Dishes, Uber Eats, DoorDash, Grubhub, Other)". All participants then completed the following measures:

Actual income earned and Actual hours worked: "The following questions ask about your overall experience working for food delivery apps this **past week**. To answer these questions as accurately as possible please consult each food delivery app that you worked for this past week. (Line break.) How much money did you earn (in total) working for food delivery apps this past week? (Line break.) How many hours did you work (in total) for food delivery apps this past week?" These measures were collected so we could examine the accuracy with which drivers predicted their income and hours.

Results

Control Condition Results. Supporting H1, delivery drivers in the control condition overpredicted their weekly income by $62.38 (23.2%), as revealed by a paired-samples t-test ($M_{\text{predictedincome}}$ = $331.66, $SD_{\text{predictedincome}}$ = 238.15; $M_{\text{actualincome}}$ = $269.28, $SD_{\text{actualincome}}$ = 238.30; $t(209) = 5.76$, $p < .001$, $d = .40$). They also predicted they would work 6.16 more hours than they ended up working ($M_{\text{predictedhours}} = 22.03$, $SD_{\text{predictedhours}} = 14.32$; $M_{\text{actualhours}} = 15.87$, $SD_{\text{actualhours}} = 12.87$; $t(209) = 8.37$, $p < .001$, $d = .58$). However, expected hourly wage and actual hourly wage were fairly similar ($M_{\text{predictedwage}}$ = $15.91, $SD_{\text{predictedwage}} = 7.03$; $M_{\text{actualwage}}$ = $16.81, $SD_{\text{actualwage}} = 8.67$; $t(209) = -1.64$, $p = .10$). These findings replicate the results of Studies 1–3.

To examine the relationship between past, predicted, and actual gig income and hours, as well as the individual differences we measured, we began by generating the correlation matrix presented in Table 2. All three measure of past income and hours are strongly associated with predicted income and hours, and predicted income and hours are strongly associated with actual income and hours. Propensity to plan is associated with higher predicted income and hours as well as higher actual income and hours, but not with prediction accuracy. Gig experience is positively correlated with typical hours worked per week, as well as with highest past income and hours. Percentage of total income from gig work is associated with higher income and hours, and also with stronger prediction bias. Women display a stronger working hours prediction bias than men. A pair of independent samples t-tests revealed this was because women and men predicted they would work the same number of hours (*Mean diff* = .37, SE = 2.07, $t(208) = .18$, $p = .86$), but women were unable to work as many hours as men throughout the week (*Mean diff* = -3.20, SE = 1.84, $t(208) = -1.73$, $p = .084$). Age is positive correlated with income, hours, and propensity to plan, but not with prediction accuracy.

Next, we conducted a set of paired-samples t-tests comparing predicted future income to lowest past income, highest past income, and typical past income. Predicted future income was significantly higher than lowest past income (*Mean diff* = $174.98, $SD = 166.39$, $t(209) = 15.24$, $p < .001$, $d = 1.06$), significantly lower than highest past income (*Mean diff* = -\$129.31, *SD* = 158.42, $t(209) = -11.83$, $p < .001$, $d = .82$), but not significant different than typical past income (*Mean diff* = \$-5.72, *SD* = 197.80, $t(209) = -.42$, $p = .68$). Similarly, predicted hours were significantly higher than lowest past hours (*Mean diff* = 11.89, *SD* = 10.44, $t(209) = 16.51$, $p < .001$, $d = 1.14$), significantly lower than highest past hours (*Mean diff* = -7.38, *SD* = 9.38, $t(209) = -11.40$, $p < .001$, $d = .78$), but relatively close to typical past hours (*Mean diff* = .39, *SD* = 7.08, $t(209) = .80$, $p = .43$).

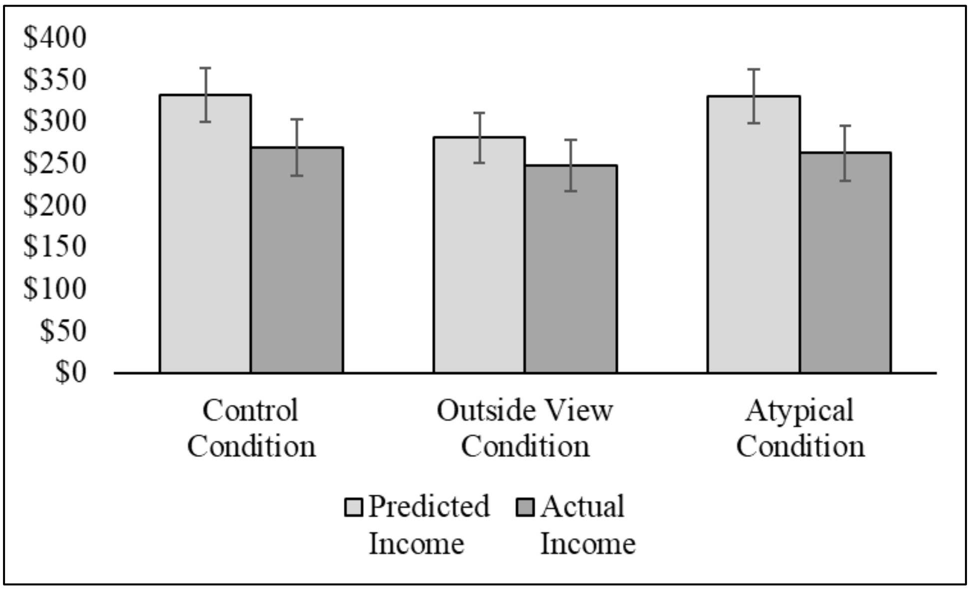
Table 2: Study 4 Control Condition Correlation Matrix

Variable Category	Variable	*M*	*SD*	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
Income	(1) Typical Past Income	$337.38	276.95	-																
	(2) Lowest Past Income	$156.67	164.32	$.59^{**}$	-															
	(3) Highest Past Income	$460.97	313.80	$.73^{**}$	$.70^{**}$	-														
	(4) Predicted Future Income	$331.66	238.15	$.72^{**}$	$.72^{**}$	$.87^{**}$	-													
	(5) Actual Income Earned	$269.28	238.30	$.57^{**}$	$.60^{**}$	$.75^{**}$	$.78^{**}$	-												
	(6) Income Prediction Bias	$62.38	156.84	$.22^{**}$	$.18^{**}$	$.19^{**}$	$.33^{**}$	$-.33^{**}$	-											
Hours	(7) Typical Past Hours	21.64	14.12	$.68^{**}$	$.56^{**}$	$.65^{**}$	$.67^{**}$	$.53^{**}$	$.21^{**}$	-										
	(8) Lowest Past Hours	10.14	10.89	$.42^{**}$	$.72^{**}$	$.51^{**}$	$.55^{**}$	$.49^{**}$	.09	$.67^{**}$	-									
	(9) Highest Past Hours	29.41	18.32	$.51^{**}$	$.48^{**}$	$.67^{**}$	$.65^{**}$	$.52^{**}$	$.19^{**}$	$.86^{**}$	$.58^{**}$	-								
	(10) Predicted Future Hours	22.03	14.32	$.58^{**}$	$.57^{**}$	$.66^{**}$	$.76^{**}$	$.60^{**}$	$.24^{**}$	$.88^{**}$	$.69^{**}$	$.86^{**}$	-							
	(11) Actual Hours Worked	15.87	12.87	$.47^{**}$	$.53^{**}$	$.63^{**}$	$.67^{**}$	$.86^{**}$	$-.29^{**}$	$.64^{**}$	$.61^{**}$	$.63^{**}$	$.70^{**}$	-						
	(12) Hours Prediction Bias	6.16	10.65	$.22^{**}$	.12	.13	$.21^{**}$	$-.24^{**}$	$.68^{**}$	$.40^{**}$	$.19^{**}$	$.39^{**}$	$.50^{**}$	$-.27^{**}$	-					
Individual Differences	(13) Propensity to Plan	4.55	1.10	$.16^{*}$	.12	$.14^{*}$	$.19^{**}$	$.16^{*}$	.05	$.21^{**}$	$.14^{*}$	$.19^{**}$	$.20^{**}$	$.21^{**}$	.02	-				
	(14) Gig Experience	3.94	1.88	.09	.09	$.22^{**}$	.08	.06	.04	$.14^{*}$	.13	$.20^{**}$	.13	.08	.08	.08	-			
	(15) % of total income from gig	6.10	10.65	$.37^{**}$	$.45^{**}$	$.38^{**}$	$.47^{**}$	$.37^{**}$	$.15^{*}$	$.46^{**}$	$.47^{**}$	$.43^{**}$	$.50^{**}$	$.41^{**}$	$.18^{**}$	$.18^{**}$	.10	-		
	(16) Sex (female = 1, male = 0)	35.70%	N/A	-.12	-.10	$-.18^{**}$	$-.16^{*}$	$-.20^{**}$	.06	.00	-.04	-.06	.01	-.12	$.16^{*}$	.13	-.01	-.05	-	
	(17) Age	29.25	8.93	$.24^{**}$	$.24^{**}$	$.31^{**}$	$.27^{**}$	$.25^{**}$	.03	$.28^{**}$	$.29^{**}$	$.27^{**}$	$.31^{**}$	$.24^{**}$	$.14^{*}$	.11	$.17^{*}$	.02	.05	-

*Correlation is significant at the 0.05 level (2-tailed). **Correlation is significant at the 0.01 level (2-tailed).

Intervention Effectiveness. To test the effect of the interventions on income prediction accuracy, we conducted a 3 (condition: control vs. outside view vs. atypical) × 2 (income: predicted vs. actual) mixed-model ANOVA with condition as a between-subjects variables and income as a within-subject variable. The model revealed no main effect of condition ($F(1, 659) = 1.75$, $p = .17$, $\eta_p^2 = .005$), a significant main effect of income ($F(1, 659) = 74.32$, $p < .001$, $\eta_p^2 = .101$), and a significant condition by income interaction ($F(1, 659) = 3.02$, $p = .050$, $\eta_p^2 = .009$). Planned contrasts confirmed that predicted income was significantly lower in the outside view condition (*M* = \$280.83, *SD* = 239.22) than in the control condition (*M* = \$331.66, *SD* = 238.15, $t(659) = 2.26$, $p = .024$, $d = .21$) or atypical condition (*M* = \$330.13, *SD* = 236.35, $t(659) = 2.20$, $p = .028$, $d = .21$), and that predicted income in the control and atypical conditions did not differ significantly ($t(659) = .07$, $p = .95$, $d = .01$). Planned contrasts also confirmed that actual income earned in the outside view condition (*M* = \$247.76, *SD* = 255.15) did not differ significantly from actual income earned in the control condition (*M* = \$269.28, *SD* = 238.30, $t(659) = .94$, $p = .35$, $d = .09$) or in the atypical condition (*M* = \$262.74, *SD* = 235.44, $t(659) = .65$, $p = .52$, $d = .06$), nor did actual income earned in the control and atypical conditions differ significantly ($t(659) = .28$, $p = .78$, $d = .03$). Drivers in the control condition overpredicted their income by \$62.38 or 23.2% ($t(209) = 5.76$, $p < .001$, $d = .40$), drivers in the atypical condition overpredicted their income by \$67.39 or 25.7% ($t(210) = 3.20$, $p < .001$, $d = .40$), and the magnitude of the bias did not differ between the control and atypical conditions ($t(419) = .32$, $p = .75$, $d = .03$). However, drivers in the outside view condition overpredicted their income by only \$33.07 or 13.4% ($t(240) = 3.20$, $p = .002$, $d = .21$), which represented a higher degree of prediction accuracy than in the control condition ($t(449) = -1.95$, $p = .051$, $d = .21$) or atypical condition ($t(450) = -2.22$, $p = .027$, $d = .21$). More concretely, the outside view intervention reduced the size of the income prediction bias by \$29.31 or 53.0% versus control.

Figure 4: Mean Predicted vs. Actual Income In Each Condition of Study 4



5. Conclusion and Discussion

Across four studies with 875 participants we find consistent support for our hypothesis that gig economy workers display an *income prediction bias* in which they *over*-predict their gig income (H1). We also find that this bias in reduced by prompting people to base their predictions on their past income (H2), but it is not affected by prompting people to consider reasons why their work schedule might be different than usual (H3). One reason why the atypical intervention failed in the context of income prediction despite its success in the context of expense prediction could be that income can be negatively or positively skewed, so that “different than usual” (i.e., different than the mode of the distribution) can mean higher or lower income. In contrast, expenses are almost always positively skewed, so in that context “different than usual” consistently means higher than usual, which corrects the tendency to *under*-predict expenses.

Our findings have two clear implications for practitioners such as financial advisors and policy-makers: 1) gig workers over-predict their gig income, and 2) taking an outside view improves prediction accuracy. In other words, practitioners who want to help gig economy workers improve their financial planning – and gig economy workers who want to accomplish this for themselves – should be aware that income overprediction is common in the gig economy, but using past income to predict future income can help overcome this bias. A third result with implications for practice is that income prediction bias is associated with over-predicting the number of hours one will be able to work rather than over-predicting one’s hourly wage. In other words, gig workers do not appear to be misled about how much they will earn from their gig when they work; rather, they seem to mislead themselves about how many hours they will be able to work. This finding is also important for theory because it suggests that optimism in the context of income prediction applies to how hard one will be able to work, but not necessarily how well one can perform their job. A second finding with implications for theory is that income predictions closely resemble perceived typical income, yet predicted income falls well short of reality. This suggests that income predictions may be based on an optimistic perception of past earnings, rather than optimistic plans or goals for the future.

The limitations of this research suggest important directions for future research. Our studies measure prediction accuracy over one week. Future research should measure weekly prediction accuracy over several weeks to determine if income over-prediction is a stable individual difference, or if prediction accuracy can be learned over time. Relatedly, we have not yet examined monthly prediction accuracy, and it is important for future studies to do so. Future research can also test different interventions, such as “unpacking” predictions (e.g., Kruger and Evans 2004). In the context of income, this could involve asking gig workers to create a detailed schedule of when they will be able to gig. Finally, it is important for future research to determine the downstream impact of improving income prediction accuracy. For example, does improving income prediction accuracy help people save more money and improve their financial well-being?

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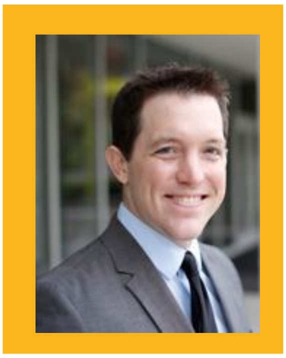

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