**Supplementary Information: Income Prediction Bias in the Gig Economy**

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**Study 1 Supplementary Analysis and Results**

**Exploratory t-tests comparing predicted and average past income**

As per our preregistration, we conducted exploratory t-tests comparing predicted weekly income at the start of the study to three measures of average weekly income over the preceding eight weeks. The first measure of average weekly income is *recalled average income*, which was measured as follows: “On average, how much were your earnings per week driving for KABU over the past 8 weeks?” After excluding data from one participant who recalled earning an average of $8,000 per week, predicted weekly income in survey one (M = $451.90, SD = 479.36) was significantly lower than recalled average weekly income over the past eight weeks (M = $644.14, SD = 660.59), as revealed by a paired-samples t-test (*t*(41) = 2.02, *p* = .050, *d* = 0.31). This indicates that participants’ income predictions were not optimistic in at least one sense: they did not predict they would earn more in the next week than they *remembered* earning, on average, over the past eight weeks.

 The second and third measures of average weekly income were mean and median weekly income over the past eight weeks, which we were able to calculate for each driver using data provided by the app. In other words, these are objective measures of average weekly income, not what participants remembered earning. A pair of paired-samples t-tests revealed that predicted weekly income at the start of the study (M=$451.90, SD=479.36) was significantly higher than mean income over the past eight weeks (M=342.42, SD=384.33; *t*(41)=3.36, *p*=.002, *d*=.52), and significantly higher than median income over the past eight weeks (M=$313.23, SD=383.96; *t*(41)=4.16, *p*<.001, *d*=.64). This indicates that participants’ income predictions were optimistic in the sense that they predicted they would earn more in the next week than they actually earned, on average, over the past eight weeks.

**Exploratory regressions for IPB scores and past income summary statistics**

As the following tables illustrate, when regressing each income prediction bias score onto the mean and standard deviation (SD) of pre-study earnings, the association between each bias score and SD remains significant while controlling for mean pre-study earnings. This is consistent with the assertion that variable income is harder to predict than stable income.

**Week One Bias Score Regression Results for Study 1**



**Week Two Bias Score Regression Results for Study 1**



**Month One Bias Score Regression Results for Study 1**



**Month Two Bias Score Regression Results for Study 1**



**Study 2 & 3 Participant Recruitment Details**

To recruit participants for studies 2 and 3 we placed the paid advertisement pictured below in the following subreddits that food delivery app drivers use to communicate with each other: r/grubhubdrivers; r/ubereats; r/doordashdrivers; r/skipthedishes; r/couriersofreddit.



**Study 2 Supplementary Analysis and Results**

**Method**

This study was conducted in August of 2020. Participants were recruited through reddit advertisements to take part in a two-stage survey about working for food delivery apps. The first survey was completed immediately. The second survey was sent to participants one week later, and it asked them to log into the relevant apps and report their gig income and hours. There was no randomization in either survey; all participants completed the same measures in the same order, as detailed below.

The first survey included the following items, in the following order:

*Welcome.* “Welcome to our study about working in the gig economy. Completing this study takes about 10 minutes in total: 7-8 minutes to complete today's survey, and 2-3 minutes to complete a follow-up survey that we will email to you one week from today. When you complete the follow-up survey next week you will automatically receive a **$10** Amazon gift card. You will also be entered into a draw with two grand prize gift certificates worth **$250** each. The winners of the draw will be notified and paid on August 15th, 2020. If you would like to participate, please continue to the consent form on the next page.”

*Consent form*. Omitted until publication to maintain author anonymity during the review process.

*Apps.* “Which food delivery apps do you currently work for? Please select all that apply. (Foodora, Skip the Dishes, Uber Eats, DoorDash, Grubhub, Other, I do not currently work for a food delivery).” We collected this measure to determine how many different apps the average driver in our sample works for.

*Income prediction*. “Please take some time to estimate the total amount of money you will earn from delivering food inthe next week (i.e., the next 7 days). (Page break.) How much money do you estimate you will earn (in total) from delivering food in the next week?” We collected this measure so we could determine if there is an income prediction bias in this sample by comparing predicted income to actual income earned during the week of the study (which was measured in survey two).

*Predicted hours.* “How many hours do you estimate you will work delivering food in the next week?” We collected this measure so we could determine if there is an hours prediction bias in this sample by comparing predicted hours to actual hours worked during the week of the study (which was measured in survey two).

*Predicted hourly wage.* “How much money **per hour** do you estimate you will earn from delivering food in the next week?” We collected this measure so we could determine if there is an hourly wage prediction bias in this sample by comparing predicted hourly wage to actual hourly wage earned during the week of the study (which was measured in survey two).

“To answer the following questions, please think about your experience delivering food over the **past 8 weeks**.”

*Perceived average income*. “On average, how much were your **total earnings per week** from delivering food?” We included this measure to test the hypothesis that income predictions are based on what people perceive to be their average past behavior.

*Average hours.* “On average, how many **hours per week**did you work delivering food?” We included this measure to test the hypothesis that predicted hours are based on what participants perceive to be their average past hours.

*Average hourly wage.* “On average, how much money did you earn **per hour**delivering food?” We included this measure to test the hypothesis that predicted hourly wage is based on what participants perceive to be their average hourly wage.

*% of total income earned 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. Over the **past eight weeks**, what percentage of your total income did you earn from delivering food (0-10% = 1, 11-20% = 2, … , 91-100% = 10)?” We collected this measure to determine if it is correlated with income prediction accuracy.

*Experience.* “How long have you been working for food delivery apps (Less than one month = 1, 1-3 months = 2, 4-6 months = 3, 7-9 months = 4, 10-12 months = 5, 1-2 years = 6, 3-4 years = 7, 5-6 years = 8, more than 6 years = 9)?” We collected this measure to determine if gig experience is correlated with income prediction accuracy.

*Expense prediction.* “Please take some time to estimate your **total spending** for the next week (i.e., the next 7 days). By **total spending** we mean everything you will spend money on. (Page break.) Please enter your total estimated spending for the next week.” We collected this measure to compare predicted spending to actual spending during the week of the study (as measured in survey two) and determine if there is an expense prediction bias in this sample (Howard et al. 2022).

*Demographics.* We collected standard demographic information, including participants’ age and gender.

 The second survey in this study included the following items, in the following order:

*Apps.* “Which food delivery apps did you work for this **past week**(i.e., **the past 7 days**)? Please select all that apply. (Foodora, Skip the Dishes, Uber Eats, DoorDash, Grubhub, Other, I do not currently work for a food delivery).” We included this measure here so that participants would consider all relevant gig income sources when reporting their income for the past week.

*Reported income*. “Which food delivery apps did you work for this **past week**(i.e., **the past 7 days**)? Please select all that apply. (Line break.) How much money did you earn (in total) from delivering food this **past week**?” We collected this measure so we could determine if there is an income prediction bias in this sample by comparing predicted income to actual income earned during the week of the study.

*Reported hours.* “How many hours did you work (in total) delivering food this **past week**?” We collected this measure so we could determine if there is an hours prediction bias in this sample by comparing predicted hours to actual hours worked during the week of the study. Measuring reported hours also allows us to calculate participants’ hourly wage during the week of the study (reported income divided by reported hours), which we can then compare to their predicted hourly wage at the start of the study.

*Satisfaction*. “Please take a moment to recall how much money you *expected*to earn from delivering food at the beginning of this **past week.** (Line break.) How satisfied are you with the amount of money you earned from delivering food this **past week** *relative to how much you expected to earn* (Not at all satisfied = 1; Extremely satisfied)?” We collected this measure to determine if income prediction bias is negatively correlated with satisfaction.

*Primary vs Secondary Job.* “Is delivering food currently your primary job (i.e., the job from which you earn most of your income) or secondary job (i.e., a job from which you earn "extra" income) (Delivering food is currently my primary job = 1; Delivering food is currently my secondary job = 2)?” We collected this measure to determine if both full-time and part-time gig workers overpredict their income.

 *Time 2* *% of total income earned 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.) In the **past week** (i.e., **the past 7 days**), what percentage of your total income did you earn from delivering food? (0-10% = 1, 11-20% = 2, … , 91-100% = 10).” We collected this measure to see if it differs from participants’ responses to the corresponding question in survey one, which asked “Over the **past eight weeks**, what percentage of your total income did you earn from delivering food (0-10% = 1, 11-20% = 2, … , 91-100% = 10)?” If these two measures do not differ, then the income prediction bias cannot be easily explained by gig workers allocating their time to another job.

*Expense recall.* “Please take some time to estimate your**total spending** for the **past week** (i.e., **the past 7 days**). By total spending we mean everything that you spent money on this past week. (Line break.) Please enter your total estimated spending for the **past** **week**.” We collected this measure to compare predicted spending to actual spending during the week of the study and determine if there is an expense prediction bias in this sample (Howard et al. 2022).

**Results**

*Apps.* The mean number of apps participants reported working for was 1.62 (SD = 0.82).

*Income prediction bias.* Same analysis and results as in the main text.

*Hours prediction bias.* Same analysis and results as in the main text.

*Hourly wage prediction bias.* Same analysis and results as in the main text.

*Perceived average income*. Predicted income (M = $382.13, SD = 269.53) and perceived average income (M = $360. 82, SD = 236. 15) were strongly correlated (r(45) = .93, *p* < .001) and did not differ significantly (*t*(46) = 1.49, *p* = .14, *d* = .22). This suggests that income predictions may be based on perceived average income, in the same way that expense predictions are based on typical spending.

*Average hours.* Predicted hours (M = 23.00, SD = 12.62) and perceived average hours (M = 22.00, SD = 11.91) were strongly correlated (r(45) = .90, *p* < .001) and did not differ significantly (*t*(46) = 1.27, *p* = .21, *d* = .19). This suggests that predicted hours may be based on perceived average hours, which indicates that some time predictions may be based at least in part on relevant past experience (cf. Buehler, Griffin, and Peetz 2010).

*Average hourly wage.* Predicted hourly wage (M = $17.02, SD = 5.23) and perceived average hourly wage (M = 16.57, SD = 5.10) were strongly correlated (r(45) = .94, *p* < .001) and did not differ significantly (*t*(46) = 1.71, *p* = .10, *d* = .25).

*% of total income from gig*. As reported in the main text, the percentage of total income participants generally earned from food delivery (M = 5.70, SD = 3.71) was positively correlated with predicted income (r(45) = .47, *p* < .001) and reported income (r(45) = .50, *p* < .001), but not with income prediction bias scores (r(45) = .02, *p* = .91). (This variable was also not significantly correlated with percentage bias scores; r(45) = -.19, *p* = .20.) This indicates that this variable is not associated with the ability to accurately predict gig income. Additionally, the percentage of total income participants earned from food delivery during the week of the study (as reported in the second survey; M = 5.96, SD = 3.85) did not differ significantly from the percentage of total income they generally earned from food delivery (*t*(46) = -0.65, *p* = .52, *d* = - 0.09). Thus, the income prediction bias in this sample cannot be easily explained by people earning less at their gig because they chose to work elsewhere.

*Experience.* Same analysis and results as in the main text.

*Expense prediction bias.* Expense prediction bias was calculated at predicted spending at time one minus reported spending at time two. Data from one participant whose bias score ($2,650) exceeded the initial mean ($28.89) by more than five standard deviations (466.59) was excluded from this analysis. On average, participants underpredicted their spending by $28.09 (SD = 257.99) for the week. However, the difference between predicted spending (M = $313.80, SD = 231.58) and reported spending (M = $341.89, SD = 333.30) did not reach statistical significance (*t*(45) = -0.74, *p* = .46, *d* = -.11). This could be for one of several reasons. One possibility is simply that this analysis is underpowered; in their work on expense predictions bias Howard et al. (2022) include approximately 100 participants (or more) in each condition. Another possibility is that thinking about income before predicting expenses attenuates the expense prediction bias (i.e., the tendency to *under*predict future *spending*), because income prediction triggers thoughts of what earnings might be spent on. Examining these possibilities is a fruitful direction for future research.

*Satisfaction*. Satisfaction (M = 3.98, SD = 1.61) was not correlated with predicted income (r(45) = .18, *p* = .22), reported income (r(45) = .19, *p* = .19), or income prediction bias scores (r(45) = .01, *p* = .94). We interpret this as being inconsistent with a motivational account of the bias, because if the bias were driven by a strong desire to maximize earnings, it stands to reason that failure to achieve that goal would lead to dissatisfaction.

*Primary vs Secondary Job.* Same analysis and results as in the main text.

**Study 3 Supplementary Analysis and Results**

**Demographics**

 This study was conducted from November 2020 to March 2021. We received 1,319 responses to the first survey in this study. Two-hundred and forty of these responses came from a duplicate email address and/or the same IP address, latitude, and longitude; forty-nine came from inactive drivers (i.e., individuals who do not represent our population of interest); and thirty-five came from people who reported technical difficulties with the survey.[[1]](#footnote-1) We excluded these responses from our final sample because we think it is sensible to do so, but we note here that these exclusions were not preregistered because we did not anticipate these issues in advance of the study. (Indeed, we did not experience these issues when conducting study 2, which utilized the same method of recruitment.) Of the 995 unique, active drivers who did not experience technical difficulties while completing the first survey, 600 also completed the second survey and passed the preregistered data quality measures described below. The table below compares the 600 drivers who completed both surveys and passed the data quality measures to the 395 drivers who only completed the first survey and/or failed the data quality measures. Across the variables that are observable for both groups (i.e., the variables measured in the first survey), they differ significantly in only one regard: the final sample has more gig experience.

**Driver Characteristics in Study 3**



**Robustness Test**

 In the main text, we excluded data from four participants in study 3 whose expected hourly wage exceeded the sample mean by more than three standard deviations. Here, we present the results of a non-parametric median analysis that includes those outliers. The omnibus test with income prediction bias scores as the dependent variable and condition as the independent variable was significant (test statistic = 9.19, *p* = .010). The distribution of bias scores in the outside view condition was significantly different than in the control condition (Medianoutside\_view = $25.00; Mediancontrol = $50.00; test statistic = 6.17, *p* = .013) and in the atypical condition (Medianoutside\_view = $25.00; Medianatypical = $65.00; test statistic = 8.95, *p* = .003). Follow-up analyses indicates that the median prediction in the outside view condition was significantly lower than in the control condition (Medianoutside\_view = $200; Mediancontrol = $300; test statistic = 6.88, *p* = .009) and in the atypical condition (Medianoutside\_view = $200; Medianatypical = $300; test statistic = 7.77, *p* = .005), but that median income earned did not differ significantly between the three conditions (Medianoutside\_view = $174.00; Mediancontrol = $200.00; Medianatypical = $208.50; test statistic = 2.20, *p* = .33). Thus, the results of this non-parametric analysis with no outlier exclusions reinforce the results of the parametric analysis in the main text.

**Exploratory Measures and Results**

 *Gig satisfaction.* “In the survey you completed last week we asked you to estimate how much money you would earn working for food delivery apps from [Survey 1 completion date] to [one week after Survey 1 completion date]. Please enter your estimate in the space below, as best as you can remember. (Page break.) How satisfied are you with the amount of money you earned working for food delivery apps this **past week** *relative to how much you expected to earn*? (1 = Not at all satisfied; 7 = Extremely satisfied).” We collected this measure to determine if income overprediction is associated with lower gig satisfaction, which would be of concern to firms who employ gig workers.

 We performed a series of exploratory analyses examining the relationship between prediction accuracy and gig satisfaction. Collapsing across the three conditions, gig satisfaction (*M* = 4.05, *SD* = 1.89) was negatively correlated with income prediction bias scores (*r*(594) = -.34, *p* < .001), indicating that the more a person overpredicts their income the less satisfied they are with their gig. However, gig satisfaction did not differ significantly between conditions, as revealed by a one-way ANOVA (*F*(2, 593) = 0.85, *p* = .43). Taken together, these two outcomes appear contradictory: higher bias is associated with lower satisfaction, but decreasing bias (in the outside view condition) does not improve satisfaction. To explore why, we next conducted a 3 (condition: control vs. outside view vs. atypical) × 2 (income prediction: the amount people predicted at the start of the study vs. the amount people recalled predicting when asked one week later) mixed-model ANOVA with condition as a between-subjects variable and income prediction as a within-subject variable. The ANOVA revealed a significant main effect of income prediction (*F*(1, 593) = 10.34, *p* = .001, ηp2 = .017), a non-significant main effect of condition (*F*(2, 593) = 2.10, *p* = .12, ηp2 = .007), and a significant income prediction by condition interaction (*F*(2, 593) = 5.66, *p* = .004, ηp2 = .019). Contrast analysis confirmed that although actual income predictions at the start of the study were lower in the outside view condition than in the control and atypical conditions (as above), the amount people *remembered* predicting when they were asked one week later (during survey two) did not differ between the three conditions (*M*control = $298.53, *SE*control = 16.74; *M*outside view = $285.07, *SE*outside view = 15.43; *M*atypical = $312.54, *SE*atypical = 16.52; *F*(2, 593) = 0.74, *p* = .48, ηp2 = .002). The net result of this is that participants in the outside view condition accurately remembered their income predictions one week later (Mean difference = -$6.85, SE = 8.28, *p* = .41, ηp2 = .001), but participants in the control condition recalled an income prediction that was significantly lower than the one they had actually made (Mean difference = -$31.31, SE = 8.99, *p* < .001, ηp2 = .020), as did participants in the atypical condition (Mean difference = -$24.12, SE = 8.87, *p* = .007, ηp2 = .012).

*Percentage of total income earned from gig during the study:* “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.) In the **past week**, what percentage of your total income did you earn from delivering food? (0-10%, 11-20%, 21-30%, … , 91-100%).” We collected this measure to determine whether prompting people to make lower (and therefore more accurate) income predictions leads them to reallocate their time to other income generating activities. Knowing this is important for gig economy firms because it might be the case that intervening to help their employees make more accurate predictions causes people to work fewer hours for the firm.

The percentage of total income participants reported earning from food delivery apps during the week of the study did not differ significantly between conditions, as revealed by a one-way ANOVA (*M*control = 6.01, *SD* = 3.81; *M*outside view = 5.59, *SD*outside view = 3.84; *M*atypical = 6.08, *SD*atypical = 3.87; *F*(2, 593) = 0.99, *p* = .37, ηp2 = .003). This suggests that gig economy firms can help their workers make lower and therefore more accurate income predictions without fear of a mass exodus of people who choose to reallocate their time to other income generating activities.

**Supplemental Study 1 (S1)**

 This exploratory study was conducted in April of 2017. Participants were recruited from the Uber driver subreddit on reddit.com to take part in a two-stage survey about working for Uber. The first survey was completed immediately, and it asked participants to predict their Uber income, hours, and hourly wage for the next week, as well as their total expenses. Participants were also asked to recall each of these variables for the past week. In this study, prediction task order was randomized so that people either made their income predictions then their expense prediction, or their expense prediction then their income predictions. The order of prediction and recall was also randomized, so that participants either made all their predictions for the next week before recalling the past week, or vice versa. As shown below, prediction task order does not meaningfully affect prediction accuracy. The second survey was sent to participants one week later, and it asked them to report their Uber income, hours, and hourly wage for the past week, as well as their total expenses.

**Method**

Participants were US and Canadian residents who drive for Uber. They 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 a 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 in reddit gold, a virtual currency that can be used to access premium features on the website. Forty-two people completed the first survey (*M*age = 33.8, 4.8% female) and twenty-seven (64.3%) completed the second (*M*age = 35.5, 7.4% female). The first survey in this study included the following items:

 *Consent form*. Omitted until publication to maintain author anonymity during the review process.

 *Income prediction*. “Please take some time to estimate how much money you will earn driving for Uber inthe **next week** (i.e., the next 7 days). (Line break.) Please enter your estimate of how much money you will earn driving for Uber in the **next week**.” We collected this measure so we could compare predicted income at the start of the week to actual income earned during the week, and determine if there is an income prediction bias.

 *Hours prediction*. “How many **hours** do you estimate you will drive for Uber in the **next week**?” We collected this measure so we could compare predicted hours at the start of the week to actual hours worked during the week, and determine if there is an hours prediction bias.

 *Hourly wage prediction.* In this study we explicitly asked participants to predict their hourly wage as follows: “How much money **per hour** do you estimate you will earn driving for Uber in the **next week**?” This measure was collected so we could compare predicted hourly wage at the start of the week to actual hourly wage earned during the week, and determine if there is an hourly wage prediction bias.

 *Perceived typicality of predicted income.* “How *different* or *similar*do you think your **Uber earnings** will be for the **next week**, relative to a typical week (Very different = 1; Very similar = 7)?” We measured perceived typicality of predicted income to determine if it is correlated with predicted income, because perceived typicality of future *expenses* is a correlate of predicted *spending* (Howard et al. 2022).

*Income prediction confidence*. “How sure or confident are you that your estimate of your **Uber earnings** for **next week** is accurate (Very unsure = 1; Very sure = 7)?” We measured income prediction confidence because past research suggests it may play a role in optimistic expense predictions (Ülkümen, Thomas, and Morwitz 2008; but see also Howard et al. 2022). Thus, we wanted to if it is correlated with predicted income.

 *Expense prediction*. “Please take some time to estimate your**total expenses** for the **next week**(i.e., the next 7 days). Your estimate should account for all the expenses you will incur except monthly expenses like rent that happen to be due in the next week. (Line break.) Please enter your total estimated expenses for the **next week**.” We collected this measure so we could compare predicted expenses at the start of the week to actual expenses incurred during the week of the study, then determine if there is an expense prediction bias in this sample (Howard et al. 2022). However, we were unable to obtain reliable expense measures. (In the comment box at the end of each survey, several participants expressed confusion over which expenses they were supposed to predicted and recall. We asked for total expenses, but given the context, some people assumed we only wanted Uber expenses.) Therefore, we describe each expense variable below so that readers are aware of the study flow and logic, but we do not discuss these variables further.

 *Perceived typicality of predicted expenses.* “How different or similar do you think your **total expenses** will be for the **next week**, relative to a typical week (Very different = 1; Very similar = 7)?” We measured this variable to determine if it is correlated with predicted expenses (Howard et al. 2022).

 *Expense prediction confidence*. “How sure or confident are you that your estimate of your **total expenses** for **next week** is accurate (Very unsure = 1; Very sure = 7)?” We measured this variable to determine if it is correlated with predicted expenses (e.g., Ülkümen, Thomas, and Morwitz 2008).

 *Recalled income*. “*Without consulting your Uber payment statement*, please take some time to estimate how much money you earned driving for Uber inthe **past week** (i.e., the past 7 days). (Line break.) Please enter your estimate of how much money you earned driving for Uber in the **past week**.” We measured recalled income so we could compare it to actual income earned (as reported by the app), and determine if income recall is accurate.

 *Recalled hours.* “*Without consulting your Uber payment statement*, please answer the following questions about the **past week** (i.e., the past 7 days). (Line break.) How many **hours** do you estimate you drove for Uber in the **past week**?” We measured recalled hours so we could compare it to actual hours worked (as reported by the app), and determine if recalled hours is accurate.

 *Recalled hourly wage*. “How much money **per hour** do you estimate you earned driving for Uber in the **past week**?” We measured recalled hourly wage so we could compare it to actual hourly wage (as reported by the app), and determine if recalled hourly wage is accurate.

 *Actual income*. “Now, *please do consult your Uber payment statement* and answer the following questions forthe **past week** (i.e., the past 7 days). (Line break.) How much money did you actually earn driving for Uber inthe **past week**?” This was measured so we could determine if recalled income is accurate.

 *Actual hours.* “How many hours did you actually drive for Uber inthe **past week**?” This was measured so we could determine if recalled hours is accurate. We also computed actual hourly wage (actual income divided by actual hours) so we could determine if recalled hourly wage is accurate.

 *Perceived typicality of past income*. “How different or similar do you think your **Uber earnings**were for the **past week**, relative to a typical week (Very different = 1; Very similar = 7)?” We measured this variable to determine if perceived typicality of past income is lower than perceived typicality of predicted income, which would parallel the relationship between perceived typicality of predicted *expenses* and predicted *spending* (Howard et al. 2022).

 *Income recall confidence.* “How sure or confident are you that your estimate of your **Uber earnings** for the **past week** is accurate (Very unsure = 1; Very sure = 7)?” We measured this variable to see if it would be different than income prediction confidence.

 *Expense recall.* “Please take some time to estimate your**total expense** for the **past week**(i.e., the last 7 days). Your estimate should account for all the expenses you incurred except monthly expenses like rent that happened to be due in the past week. (Line break.) Please enter your total estimated expenses for the **past** **week**.” We measured this variable to see if it differs from predicted spending.

 *Perceived typicality of recalled expenses.* “How different or similar do you think your **total expenses** were for the **past week**, relative to a typical week (Very different = 1; Very similar = 7)?” We measured this variable to determine if it differs from perceived typicality of predicted expenses.

 *Expense recall confidence.* “How sure or confident are you that your estimate of your **total expenses** for the **past week** is accurate (Very unsure = 1; Very sure = 7)?” We measured this variable to determine if it differs from expense prediction confidence.

*Financial slack*. “Using the scale below, please indicate how much spare money you expect to have in the next week (Very little spare money = 1; A lot of spare money = 11).” We included this measure from Berman et al. (2016) to determine if it is correlated with predicted income.

 *Motivation.* “In general, saving money is very important to me (Strongly disagree = 1; Strongly agree = 9). (Line break.) In general, making money is very important to me (Strongly disagree = 1; Strongly agree = 9).” We adapted these measures from Peetz and Buehler (2009) to determine if motivation to save and/or earn is correlated with predicted income, reported income, or income prediction bias.

*Debt and Fico.* “The following questions ask about debt and credit. Please report as accurately as possible and remember that **all of the information you provide will be kept 100% confidential**. (Line break.) Please enter the approximate amount (in dollars) that you currently owe in debt for each of the following categories: Car loans, Credit cards, Money owed to family and friends, Payday loans (free response text boxes were provided for each category, and they were automatically summed so participants could their total debt). (Line break.) How would you describe your credit score? Excellent (FICO score 750 and above) = 5, Above average (FICO score 700-749) = 4, Average (FICO score 650-699) = 3, Below average (FICO score 600-649) = 2, Poor (FICO score 599 and below) = 1, I don’t know = 0.” We collected these measures to determine if they are correlated with predicted income, which would indicate that income predictions may be motivated by the need or desire to paydown debt or improve one’s credit score.

*Financial security.* “Having **financial security** means having the resources to support your standard of living now and in the foreseeable future. (Line break.) How would you describe your level of **financial security** (Extremely low = 1; Adequate = 5; Extremely high = 9)?” We collected this measure to determine if it is correlated with predicted income, which would indicate that income predictions may be motivated by the need or desire to reduce financial insecurity.

*Uber driving*. “What kind of driving do you primarily do for Uber? (Select all that Apply: UberPool, UberX, UberXL, UberSelect, UberBlack, I don’t drive for Uber.)” We measured this variable to determine which Uber service participants were driving for.

*Experience.* “How long have you been driving for Uber (Less than one month = 1, 1-3 months = 2, 3-6 months = 3, 6-12 months = 4, Longer than one year = 5)?” We collected this measure to determine if gig experience is correlated with income prediction accuracy.

*Average income*. “On average, how much **money per week** do you earn driving for Uber?” We included this measure to test the hypothesis that income predictions are based on what people perceive to be their average past behavior.

*Average hours.* “On average, how many **hours per week** do you drive for Uber?” We included this measure to test the hypothesis that predicted hours are based on what participants perceive to be their average past hours.

*% of total income earned from Uber.* “What proportion of your total annual income do you earn working for Uber (0-10% = 1, 11-20% = 2, … , 91-100% = 10)?” We collected this measure to determine if it is correlated with income prediction accuracy.

*Monthly income prediction.* “Previous questions in this survey have asked about your weekly income and expenses. We would now like to ask you a few brief questions about your **monthly** income and expenses. (Line break.) Please take some time to estimate how much money you will earn driving for Uber inthe **next month** (i.e., the next 4 weeks). (Line break.) Please enter your estimate of how much money you will earn driving for Uber in the **next month**.” We collected this measure to determine if monthly income predictions are (approximately) equal to weekly income predictions × 4.

*Monthly expense prediction*. Please take some time to estimate your**total expenses** forthe **next month**(i.e., the next 4 weeks). Your estimate should account for all the expenses you will incur in the next month. (Line break.) Please enter your total estimated expenses for the **next month**.” We collected this measure to determine what proportion of total expenses participants expected to cover through Uber driving.

*Demographics*. Standard demographic questions including gender and age.

The second survey in this study included the following items, in the following order:

*Time 2 income recall.* “*Without consulting your Uber payment statement*, please take some time to estimate how much money you earned driving for Uber inthe **past week** (i.e., the past 7 days). (Line break.) Please enter your estimate of how much money you earned driving for Uber in the **past week.**”

*Time 2 hours recall.* “How many **hours** do you estimate you drove for Uber in the **past week**?”

*Time 2 hourly wage recall*. “How much money **per hour** do you estimate you earned driving for Uber in the **past week**?”

*Time 2 actual income*. “Now, *please do consult your Uber payment statement* and answer the following questions forthe **past week** (i.e., the past 7 days). (Line break.) How much money did you actually earn driving for Uber inthe **past week**?”

*Time 2 actual hours*. “How many hours did you actually drive for Uber inthe **past week**?”

*Time 2 perceived typicality of past income*. “How different or similar do you think your **Uber earnings** were for the **past week**, relative to a typical week (Very different = 1; Very similar = 7)?”

*Time 2 income recall confidence*. “How sure or confident are you that your estimate of your **Uber earnings** for the **past week** is accurate (Very unsure = 1; Very sure = 7)?”

*Time 2 expense recall*. “Please take some time to estimate your**total expenses** forthe **past week**(i.e., the last 7 days). Your estimate should account for all the expenses you incurred except monthly expenses like rent that happened to be due in the past week. (Line break.) Please enter your total estimated expenses for the **past** **week**.”

*Time 2 perceived typicality of recalled expenses.* “How different or similar do you think your**total expenses** were for the **past week**, relative to a typical week (Very different = 1; Very similar = 7)?”

*Time 2 expense recall confidence.* “How sure or confident are you that your estimate of your**total expenses** for the **past week** is accurate (Very unsure = 1; Very sure = 7)?”

*Time 2 income prediction*. “Please take some time to estimate how much money you will earn driving for Uber inthe **next week** (i.e., the next 7 days). (Line break.) Please enter your estimate of how much money you will earn driving for Uber in the **next** **week**.”

*Time 2 hours prediction*. “How many **hours** do you estimate you will drive for Uber in the **next week**?”

*Time 2 hourly wage prediction.* “How much money **per hour** do you estimate you will earn driving for Uber in the **next** **week**?”

*Time 2 perceived typicality of predicted income*. “How different or *similar*do you think your **Uber earnings** will be for the **next week**, relative to a typical week (Very different = 1; Very similar = 7)?”

*Time 2 income prediction confidence*. “How sure or confident are you that your estimate of your **Uber earnings** for **next week** is accurate (Very unsure = 1; Very sure = 7)?”

*Time 2 expense prediction*. “Please take some time to estimate your**total expenses** forthe **next week**(i.e., the next 7 days). Your estimate should account for all the expenses you will incur except monthly expenses like rent that happen to be due in the next week. (Line break.) Please enter your total estimated expenses for the **next week**.”

*Time 2 expense prediction typicality.* “How different or similar do you think your **total expenses** will be for the **next week**, relative to a typical week (Very different = 1; Very similar = 7)?”

*Time 2 expense prediction confidence*. “How sure or confident are you that your estimate of your **total expenses** for **next week** is accurate (Very unsure = 1; Very sure = 7)?”

*Financial well-being.* Five items: “1) Because of my financial situation, I feel like I will never have the things I want in life (Does not describe me at all = 5; Describes me completely = 1), 2) I am just getting by financially (Does not describe me at all = 5; Describes me completely = 1), 3) I am concerned that the money I have or will save won't last (Does not describe me at all = 5; Describes me completely = 1), (Page break), 4) I have money leftover at the end of the month (Never = 1; Always = 5), 5) My finances control my life (Never = 5; Always = 1).” Items 1—3 were preface by “how well do the following statements describe you or your financial situation?” and items 4 and 5 were prefaced by “How often do the following statements apply to you?” These items were averaged to form a single measure (Cronbach’s alpha = .77) that represents a short-form version of the Consumer Financial Protection Bureau well-being scale (<https://files.consumerfinance.gov/f/201512_cfpb_financial-well-being-user-guide-scale.pdf>). We included this measure to determine if it is correlated with predicted income, which would indicate that income predictions may be motivated by a need or desire to improve one’s financial situation.

 *Financial habits*. We averaged the follow four items to create a financial habits index variable: “1) I often borrow money (Strongly disagree = 1; Strongly agree = 9), 2) I often spend more money than I thought I would (Strongly disagree = 1; Strongly agree = 9), 3) I am good at saving money (Strongly disagree = 9; Strongly agree = 1), and 4) I often come close to running out of money (Strongly disagree = 1; Strongly agree = 9).” Cronbach’s alpha = .81. We included this measure to determine if it is correlated with predicted income, which would indicate that income predictions may be motivated by a need or desire to improve one’s financial situation.

 *Short-term financial propensity to plan*. Six item scale from Lynch et al. (2010): “For the following six questions on this page please respond by selecting a value of 1 to 6, where **1 represents total disagreement**with the statement and **6 represents total agreement**with the statement. Please use the numbers in the middle if you fall between the extremes. (Line break.) I set financial goals for the next few days for what I want to achieve with my money; I decide beforehand how my money will be used in the next few days; I actively consider the steps I need to take to stick to my budget in the next few days; I consult my budget to see how much money I have left for the next few days; I like to look to my budget for the next few days in order to get a better view of my spending in the future; It makes me feel better to have my finances planned out for the next few days (Never = 1; Always = 6).” Cronbach’s alpha = .81. We included this measure to determine if it is correlated with income prediction accuracy, which would indicate that planners are more accurate predictors than non-planners.

 *Socioeconomic status*. **Think of this ladder as representing where people stand in the United States.**(Line Break.)At the **top**of this ladder are the people who are the best off – those who have the most money, the most education, and the most respected jobs. At the **bottom**are the people who are the worst off – those who have the least money, the least education, and the least respected jobs or no jobs. The higher up a person is on this ladder, the closer they are to the people at the very top; the lower they are, the closer they are to the people at the very bottom. (Line break.) **Where would you place yourself on this ladder?** Using the scale below, please indicate where you think you stand at this time in your life, relative to other people in the United States (Bottom of the ladder = 1; Top of the ladder = 10).” We included this measure to determine if it is correlated with predicted income, which would indicate that income predictions may be motivated by a need or desire to improve one’s financial situation.

 *Available resources*. “Imagine that you have to pay an unexpected bill immediately. For example, suppose that you have to pay an expensive medical bill that is not covered by insurance. Considering all possible resources available to you (including savings, borrowing, etc.), what is the maximum dollar amount that you could come up with on short notice? Please enter the amount below (free response text box).” We included this measure from Howard et al. (2022) to determine if it is correlated with predicted income, which would indicate that income predictions may be motivated by a need or desire to improve one’s financial situation.

**Results**

*Income prediction bias*. As noted above, the order of prediction tasks was randomized in this study. To determine if prediction task order affects income prediction bias, we performed a repeated measures ANOVA with order as a between-subjects factor and income (predicted vs reported) as a within-subjects factor. The ANOVA revealed a main effect of income (*F*(1, 23) = 13.85, *p* = .001, partial eta squared = .376), such that predicted income (M = $303.76, CI95% = [223.31, 384.21]) was significantly higher than actual income earned during the study (M = $187.20, CI95% = [116.91, 257.49]). The main effect of order was not significant (*F*(3, 23) = 0.99, *p* = .42, partial eta squared = .11), nor was the order by income interaction (*F*(3, 23) = 0.04, *p* = .99, partial eta squared = .005).

*Hours prediction bias.* To determine if prediction task order affects the hours prediction bias, we performed the same repeated measures ANOVA as above but with hours (predicted vs reported) as the within-subjects factor. The ANOVA revealed a significant main effect of hours (*F*(1, 23) = 21.43, *p* < .001, partial eta squared = .482), such that predicted hours (M = 21.35, CI95% = [17.10, 25.60]) were significantly higher than reported hours (M = 14.55, CI95% = [9.38, 19.72]). The main effect of order was not significant (*F*(3, 23) = 1.28, *p* = .30, partial eta squared = .143), nor was the order by income interaction (*F*(3, 23) = 0.28, *p* = .84, partial eta squared = .035).

*Hourly wage prediction bias.* To determine if prediction task order affects the hourly wage prediction bias, we performed the same repeated measures ANOVA as above but with hourly wage (predicted vs reported) as the within-subjects factor. The ANOVA revealed a non-significant main effect of hourly wage (MPredicted = $15.09, CI95% = [12.63, 17.56]; MActual = $14.12, CI95% = [10.95, 17.28]; *F*(1, 21) = 0.35, *p* = .56, partial eta squared = .016), a non-significant main effect of order (*F*(3, 21) = 1.37, *p* = .28, partial eta squared = .164), and a non-significant order by income interaction (*F*(3, 21) = 0.18, *p* = .91, partial eta squared = .025).

*Perceived typicality of predicted income.* Perceived typicality of predicted income (M = 5.26, SD = 1.53) was positively correlated with predicted income (r(25) = .47, *p* = .013), indicating that higher predicted income is perceived to be more typical than lower predicted income. Perceived typicality of predicted *expenses* is *negatively* correlated with predicted spending (Howard et al. 2022), so this null result may indicate a way in which income and expense prediction differ psychologically.

*Income prediction confidence.* Income prediction confidence (M = 5.15, SD = 1.17) was not significantly correlated with predicted income (r(25) = .18, *p* = .38). Prediction confidence is correlated with predicted spending (Howard et al. 2022; Ülkümen, Thomas, and Morwitz 2008), so this null result may indicate another way in which income and expense prediction differ psychologically.

*Recalled income.* Recalled income did not significantly differ from actual income (as reported by the app) at time one (Mrecall = $297.74, SD = 171.45; Mactual = 293.12, SD = 174.08; *t*(26) = 1.25, *p* = .22, *d* = .24) or time two (Mrecall = $224.80, SD = 171.71; Mactual = 198.98, SD = 163.65; *t*(26) = 1.62, *p* = .12, *d* = .31). This is important because it suggests participants in our studies that require income recall from memory are able to recall income with relative accuracy. Indeed, the results here show that if anything, people are somewhat prone to over-recalling their income, which would make our measures of income prediction bias conservative in the studies that rely on income recall. We note here that the tendency to recall the past in slightly optimistic terms is also consistent with past research (e.g., Buehler, Griffin, and Peetz 2010).

*Recalled hours.* Recalled hours were significantly higher than actual hours (as reported by the app) at time one (Mrecall = 19.70, SD = 10.91; Mactual = 17.79, SD = 10.62; *t*(26) = 2.31, *p* = .029, *d* = .44), but not at time two (Mrecall = 15.37, SD = 10.84; Mactual = 15.07, SD = 12.07; *t*(26) = 0.63, *p* = .54, *d* = .12). The inconsistency here may be because the Uber app does not record the time drivers spend waiting for rides, but when recalling hours worked Uber drivers may include this time in their estimate. To the extent that this is also true in our other studies, that makes our measurement of the hours prediction bias conservative, because higher recall means a lower bias.

*Recalled hourly wage.* Recalled hourly wage did not significantly differ from actual hourly wage (calculated as actual income divided by actual hours) at time one (Mrecall = 15.92, SD = 5.95; Mactual = 17.47, SD = 6.84; *t*(25) = -1.89, *p* = .070, *d* = -.37) or time two (Mrecall = 14.82, SD = 5.70; Mactual = 14.73, SD = 6.67; *t*(24) = 0.63, *p* = .95, *d* = .01).

*Perceived typicality of past income.* At time one, perceived typicality of *predicted* income (M = 5.26, SD = 1.53) was significantly higher than perceived typicality of *past* income (M = 4.33, SD = 1.66), as revealed by a paired-samples t-test (*t*(26) = 3.12, *p* = .004, *d* = .60). This echoes the relationship between perceived typicality and *expenses* documented by Howard et al. (2022). However, perceived typicality of predicted and past income at time two did not differ significantly (MT2\_predict = 4.67, SD = 1.86; MT2\_past = 4.15, SD = 2.21; *t*(26) = 1.57, *p* = .13, *d* = .30). This is notable, because Howard et al. (2022) show that consumers persistently believe their future expenses will be more typical than their past expenses week after week. Here, though, it seems as if that may not be the case for perceived typicality of income.

*Income recall confidence.* Income recall confidence (M = 5.96, SD = 0.98) was significantly higher than income prediction confidence (M = 5.15, SD = 1.17) at time one, as revealed by a paired-samples t-test (*t*(26) = 3.11, *p* = .004, *d* = .60). However, the two variables did not differ significantly at time two (MT2\_predict = 5.44, SD = 1.05; MT2\_past = 5.81, SD = 1.27; *t*(26) = 1.44, *p* = .16, *d* = .28).

*Financial slack.* Financial slack (M = 4.11, SD = 2.76) is not significantly correlated with predicted income (r(25) = -.01, *p* = .95). This is consistent with the argument that subjective and objective financial predictions are psychologically distinct (e.g., de la Rosa and Tully 2022).

*Motivation.* Motivation to save (M = 7.48, SD = 1.72) was not significantly correlated with predicted income (r(25) = .23, *p* = .24), reported income (r(25) = .20, *p* = .31), or income prediction bias (r(25) = .25, *p* = .20). Motivation to earn (M = 8.07, SD = 1.14) was significantly correlated with predicted income(r(25) = .43, *p* = .026), but not with reported income (r(25) = .12, *p* = .56) or income prediction bias (r(25) = .08, *p* = .68).

*Debt and Fico.* Total debt displayed strong positive skew (skew = 1.41) and was therefore LN transformed for analysis. This variable (M = $4,362.50, CI95% = [1,178.39, 16,148.78]) was not significantly correlated with predicted income (r(24) = -.02, *p* = .91), reported income (r(25) = -.24, *p* = .24), or income prediction bias (r(24) = .07, *p* = .75). FICO score (M = 2.70, SD = 1.61) was also not significantly correlated with predicted income (r(25) = -.16, *p* = .41), reported income (r(25) = -.13, *p* = .51), or income prediction bias (r(25) = -.08, *p* = .71). This suggest that motivation to reduce debt or improve credit score may not be primary drivers of predicted income, nor of actual income earned or the income prediction bias.

*Financial security.* Financial security (M = 4.22, SD = 2.69) was not significantly correlated with predicted income (r(25) = -.04, *p* = .83), reported income (r(25) = -.07, *p* = .72), or income prediction bias (r(25) = .02, *p* = .94). This suggest that motivation to reduce financial insecurity may not be a primary driver of predicted income, nor of actual income earned or the income prediction bias.

*Uber driving.* 14.8% of participants drove for UberPool, 100% drove for UberX, 3.7% drove for UberXL, 11.1% drove for UberSelect, and 0% drove for UberBlack.

*Experience.* Uber experience (M = 3.56, SD = 1.34) was not significantly correlated with predicted income (r(25) = .01 *p* = .95), reported income (r(25) = -.06, *p* = .78), or income prediction bias (r(25) = .08, *p* = .69). (Note: gig experience is also not significantly correlated with income prediction bias when bias is calculated as a percentage, r(23) = .20, *p* = .34.) This suggests that the ability to accurately predict Uber income does not improve with experience.

*Average income.* Average weekly income was strongly correlated with predicted income (r(25) = .80 *p* < .001) and actual income (r(25) = .85, *p* < .001), but it was not significantly correlated with income prediction bias (r(25) = .29, *p* = .14). Average weekly income (M = $278.11, SD = 170.61) did not differ significantly from predicted weekly income (M = $318.70, SD = 187.50), as revealed by a paired-samples t-test (*t*(26) = 1.86, *p* = .075, *d* = .36). However, average weekly income was significantly higher than actual income earned during the target week of the study (M = $198.98, SD = 163.65; *t*(26) = 2.99, *p* = .006, *d* =.58). These findings are suggest that financial predictions are based on what people perceive to be average, and that recalled average income may be based on an overly optimistic estimate.

*Average hours.* Average weekly hours was strongly correlated with predicted hours (r(25) = .77 *p* < .001) and actual hours (r(25) = .67, *p* < .001), but not with the hours prediction bias (r(25) = -.02, *p* = .94). Average weekly hours (M = 19.59, SD = 11.33) did not differ significantly from predicted hours (M = 21.52, SD = 10.38), as revealed by a paired-samples t-test (*t*(26) = 1.35, *p* = .19, *d* = .26). However, average weekly hours was significantly higher than actual hours worked during the target week of the study (M = 15.07, SD = 12.07; *t*(26) = 2.47, *p* = .021, *d* = .47). This pattern of results is consistent with the possibility that the number of hours people predict they will work in the future is based on the average number of hours they recall having worked in the past, and that the average number of hours people recall having worked in the past is perhaps an overly optimistic estimate.

*% of total income earned from Uber.* This variable (M = 4.48, SD = 3.72) was positively correlated with predicted income (r(25) = .42, *p* = .028), but not with actual income earned (r(25) = .21, *p* = .30) or income prediction bias (r(25) = .32, *p* = .11).

*Monthly income prediction.* To compare weekly and monthly income predictions we multiplied weekly income predictions by four and performed a paired-samples t-test. The two variables did not differ significantly (Mean difference = $28.52, SD = 391.49; *t*(26) = 0.38, *p* = .71, *d* = .07).

*Time 2 income prediction*. Income predictions at time one (M = $318.70, SD = 187.50) and time two (M = $265.74, SD = 203.60) were strongly correlated (r(25) = .80, *p* < .001), but they did differ significantly (*t*(26) = 2.21, *p* = .036, *d* = .43). Thus, participants appear to have updated their predictions between time one and two. However, time two prediction was significantly higher than actual income earned during the week of the study (M = $198.98, SD = 163.65; *t*(26) = 2.65, *p* = .013, *d* = .51), indicating that participants still expected to earn more in the future than they had in past. This suggests participants may not have updated their predictions sufficiently.

*Time 2 hours prediction.* Predicted hours at time one (M = 21.52, SD = 10.38) and time two (M = 17.59, SD = 11.64) were strongly correlated (r(25) = .83, *p* < .001), but they did differ significantly (*t*(26) = 3.12, *p* = .004 *d* = .60). However, predicted hours at time two did not differ significantly from actual hours worked during the week of the study (M = 15.07, SD = 12.07; *t*(26) = 1.85, *p* = .077, *d* = .36). Taken together with the preceding result, this indicates that people may be more likely to update their predicted hours than their predicted income.

*Time 2 hourly wage prediction.* Hourly wage predictions at time two (M = $15.39, SD = 5.09) did not differ significantly from hourly wage predictions at time one (M = $15.22, SD = 5.10; *t*(24) = -0.26, *p* = .80, *d* = -.05), nor did they differ significantly from actual hourly wage earned during the week of the study (M = $14.73, SD = 6.67; *t*(24) = 0.50. *p* = .62, *d* = .10).

*Time 2 perceived typicality of predicted income.* Perceived typicality of predicted income at time two (M = 4.67, SD = 1.86) was not significantly correlated with time two income prediction (r(25) = .04, *p* = .85). Additionally, perceived typicality of future income did not change significantly from time one to time two (*t*(26) = 1.65, *p* = .11, *d* = .32).

*Time 2 income prediction confidence.* Income prediction confidence at time two (M = 5.44, SD = 1.05) was not significantly correlated with time two income predictions (r(25) = -.05, *p* = .80). Prediction confidence is correlated with predicted *spending* (Howard et al. 2022; Ülkümen, Thomas, and Morwitz 2008), so this null result may indicate another way in which income and expense prediction differ psychologically. Additionally, prediction confidence did not change significantly from time one to time two (*t*(26) = 1.02, *p* = .32, *d* = .20), which provides evidence that participants did not update their beliefs about their ability to accurately predict the future between weeks one and two of the study.

*Financial well-being.* Financial well-being (M = 2.66, SD = 0.81) was not significantly correlated with time one income predictions (r(25) = -.02, *p* = .92) or time two income predictions (r(25) = .19, *p* = .34). This suggests that motivation to improve one’s financial well-being may not be a primary driver of income predictions.

 *Financial habits*. The financial habits index variable (M = 5.09, SD = 2.09) was not significantly correlated with predicted income at time one (r(25) = .11, *p* = .57) or time two (r(25) = -.08, *p* = .70). This suggests that motivation to improve one’s financial situation may not be a primary driver of income predictions.

 *Short-term financial propensity to plan*. Short-term financial propensity to plan (M = 4.13, SD = 1.03) was not significantly correlated with predicted income (r(25) = .21, *p* = .29), reported income (r(25) = .13, *p* = .52), or income prediction bias scores (r(25) = .13, *p* = .52).

 *Socioeconomic status*. Socioeconomic status (M = 4.74, SD = 1.91) was not significantly correlated with predicted income (r(25) = .08, *p* = .70), actual income earned during the week of the study (r(25) = .10, *p* = .63), or income prediction bias scores (r(25) = -.01, *p* = .96). The relationship between SES and predictions suggests that motivation to improve one’s financial situation may not be a primary driver of income predictions.

 *Available resources*. Available resources displayed strong positive skew (skew = 1.79) and was therefore LN transformed. This variable (M = $597.83, CI95% = [169.85, 2104.43]) was not significantly correlated with predicted income (r(25) = .04, *p* = .86), reported income (r(25) = -.13, *p* = .51), or income prediction bias scores (r(25) = .20, *p* = .32). The null relationship between available resources and predictions suggests that motivation to improve one’s financial situation may not be a primary driver of income predictions.

1. Participants indicated whether or not they experienced technical difficulties by answering ‘yes’ or ‘no’ to the question “Did you experience any technical difficulties while completing this study?”, which we included at the end of the first survey. On the next page of the study, participants who responded ‘yes’ were asked to “Please use the space below to let us know what technical difficulties you encountered” in a free response text box. The most common reason provided was a server error. [↑](#footnote-ref-1)