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Income Prediction Bias in the Gig Economy

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Abstract: Accurately predicting income is an important part of the consumer budgeting process. However, the rise of the gig economy means that an increasing number of consumers have variable income, which may make prediction more difficult. This research tests the hypothesis that consumers with variable income display an income prediction bias in which they over-predict their future earnings. This hypothesis is supported in five longitudinal studies conducted with participants from three paradigmatic gigs: rideshare driving, online human intelligence tasks, and food delivery. The authors also show that (a) people overpredict how many hours they will work at their gig, but not the amount they will earn per hour, (b) the bias is not associated with individual differences such as how long a person has worked at their gig, and (c) the magnitude of the bias is reduced by prompting people to consider relevant past experience when predicting their future income, but not by prompting them to consider atypical outcomes. In addition to documenting and debiasing a previously unidentified prediction error with broad implications for consumer financial decision making, these findings contribute to the debate regarding the costs and benefits of gig economy employment, and how to make gig work more equitable.

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INCOME PREDICTION BIAS IN THE GIG ECONOMY

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ABSTRACT

Accurately predicting income is an important part of the consumer budgeting process. However, the rise of the gig economy means that an increasing number of consumers have variable income, which may make prediction more difficult. This research tests the hypothesis that consumers with variable income display an *income prediction bias* in which they *over*-predict their future earnings. This hypothesis is supported in five longitudinal studies conducted with participants from three paradigmatic gigs: rideshare driving, online human intelligence tasks, and food delivery. The authors also show that (a) people overpredict how many hours they will work at their gig, but not the amount they will earn per hour, (b) the bias is not associated with individual differences such as how long a person has worked at their gig, and (c) the magnitude of the bias is reduced by prompting people to consider relevant past experience when predicting their future income, but not by prompting them to consider atypical outcomes. In addition to documenting and debiasing a previously unidentified prediction error with broad implications for consumer financial decision making, these findings contribute to the debate regarding the costs and benefits of gig economy employment, and how to make gig work more equitable.

Keywords: income prediction bias; budgeting; consumer financial decision making; forecasting; planning fallacy; gig economy

Budgeting is a common and consequential consumer behavior (Fernbach, Kan, and Lynch 2015; Lukas and Howard 2023; Lynch et al. 2010; Soman and Cheema 2002; Thaler 1999; Ülkümen, Thomas, and Morwitz 2008; Zhang et al. 2022). The primary reason people budget is to ensure they do not overspend their income (Zhang et al. 2022). Thus, a successful budget requires an accurate income prediction for the relevant time period, usually the next week or month (Heath and Soll 1996; Lukas and Howard 2023; Peetz et al. 2016; Zhang et al. 2022). Given the influence of budgets on spending (Lukas and Howard 2023), budgets based on inaccurate income predictions can lead to suboptimal spending decisions (Heath and Soll 1996). There are costs for both underprediction and overprediction, but the latter may be especially pernicious: if consumers budget based on an income prediction that is higher than what they end up earning, they may spend more than they can afford and have to deplete their savings or incur debt to make up the difference.

Despite the importance of income prediction accuracy to consumer budgeting and financial decision making, it is currently an open question as to whether consumers' income predictions are reasonably accurate. In the present research, we test the hypothesis that consumers who face variable income display an *income prediction bias* in which they tend to *over*-predict their future earnings. We also examine why this bias occurs, for whom it is most pronounced, and how it can be reduced.

One motivation for undertaking this work is that an increasing number of consumers face variable income flows, largely due to the rise of the so-called 'gig economy'. Gig economy employment refers to temporary, freelance, or on-demand work (Hershfield, Shu, and Benartzi 2020; Ludwig et al. 2022). Paradigmatic examples include driving for ride-hailing apps like Uber and delivering food for apps like DoorDash, but gig work can also take place offline, such as when caterers or musicians work on an as-needed basis. One defining characteristic of gig work is that the time commitment and associated income are inherently variable (Chen and Sheldon 2015; Hall and Krueger 2018; Katz and Krueger 2019), and therefore uncertain and potentially hard to predict.

The speed with which the gig economy has grown in recent years is remarkable. From 2005 to 2015 the number of Americans working in the type of 'alternative work arrangements' that correspond to our definition of gig employment increased by as much as 48% (Katz and Kruger 2019). Approximately one-third of the US labor market now works in the gig economy (McFeely and Pendell 2018), and gig income in the US totals over $1.3 trillion annually (Ozimek 2021). In the European Union, the number of gig workers (28.3 million) is now greater than the number of manufacturing workers (28 million) (Chee 2022). Globally, more than 1.1 billion people are engaged in gig work (Zgola 2021). The sheer volume of consumers facing variable income in today's economy indicates it is important to understand whether there is an income prediction bias, and if so, how it can be reduced.

Across five longitudinal studies conducted with consumers who work in the gig economy we find consistent support for the hypothesis that people who face variable income overpredict their future earnings. We also find: (a) people overpredict the number of hours they will work at their gig, but not the amount they will earn per hour, (b) the bias is not associated with individual differences such as how long a person has worked at their gig, and (c) the bias is reduced when people consider relevant past experience while predicting their future income, but not when they consider atypical outcomes. Taken together, these findings contribute to the consumer behavior literature by documenting and debiasing a previously unidentified prediction error with broad implications for consumer budgeting and financial decision making. More generally, these findings contribute to the current social debate regarding the costs and benefits of gig economy employment, and how to make gig work more equitable.

The rest of this article unfolds as follows. First, we situate our work in relation to relevant research on consumer budgeting and financial decision making. Second, we develop our hypotheses regarding the income prediction bias and how it can be reduced. Third, we test our hypotheses in five longitudinal studies conducted with consumers who work in the gig economy. Finally, we conclude by discussing the theoretical and practical implications of our work.

BACKGROUND

Budgeting is commonly conceptualized as a two-stage process in which consumers 1) allocate their income to different budget categories, and 2) track their spending in each category against their budget (Choe and Kan 2021; Heath and Soll 1996; Lukas and Howard 2023; Sussman and Alter 2012; Thaler 1999). However, when income is variable, an additional, prior stage is required in which consumers must first predict how much they will earn before allocating that income to different budget categories. Indeed, we speculate that the classic two-stage budgeting model introduced by Heath and Soll (1996) does not include an initial income prediction stage simply because far fewer consumers faced income variability at that time than do today (Katz and Kruger 2019).

Given that the two-stage model of budgeting has predominated for nearly three decades, it is perhaps unsurprising that a great deal of research has focused on income allocation and spending (Arkes and Blumer 1985; Heath 1995; Heath and Soll 1996; Henderson and Peterson 1992; Shefrin and Thaler 1988; Soman and Cheema 2004; Thaler 1999), and that relatively little research has focused on income prediction accuracy. There has been work investigating *subjective* predictions related to consumers' income, such as predicted financial slack (Berman et al. 2016; Zauberman and Lynch 2005) and the feeling of "having enough" (De La Rosa and Tully 2022). However, to the best of our knowledge, there has not yet been a systematic examination of consumers' *objective* income prediction accuracy for common budgeting time periods, which is to say, the difference between their predicted income for the next week or month and the amount they actually end up earning. In the following section, we discuss the arguments for and against the existence of an income prediction bias.

IS THERE AN INCOME PREDICTION BIAS?

The question of whether there is an income prediction bias is not a simple one to answer based on prior research and theory. On the one hand, there are reasons to believe that consumers' income predictions may be quite accurate. For example, people may engage in "income targeting" and simply work for as long as it takes to hit their target (Allon, Cohen, and Sinchaisri 2023; Camerer et al. 1997; Thakral and Tô 2021). Notably, this type of behavior is encouraged by some gig economy firms who gamify their apps to keep people working on their platform for longer periods of time (Allon, Cohen, and Sinchaisri 2023; Scheiber 2017). In addition, a defining feature of the high-tech gig economy is the provision of immediate and exact feedback on income, with apps showing users their cumulative income on an hour-by-hour or even minute-by-minute basis. This may reduce or eliminate any tendency toward an optimistic bias in income prediction, because immediate feedback is often posited to improve the calibration of people's judgment and decision-making (Kahneman 2011). Finally, people who work in the gig economy can be prone to an "inertia" effect in which the longer they spend on shift the more likely they are to keep working (Allon, Cohen, and Sinchaisri 2023). If people are unaware of this tendency when they predict their income, it could actually lead to income *under*prediction, given that longer shifts lead to higher earnings (Hall and Krueger 2018).

On the other hand, there are reasons to believe that income predictions will be optimistic, by which we mean *predicted* income for the next week or month will be greater than the *actual* amount earned during the relevant time period. For example, research has shown that consumers' financial predictions are optimistic in domains that are ostensibly related to income, such as expenses and savings (Howard et al. 2022; Koehler, White, and John 2011; Peetz and Buehler 2009; Sussman and Alter 2012; Ülkümen, Thomas, and Morwitz 2008). Similarly, research has shown that individuals' time predictions are subject to a "planning fallacy" in which they optimistically predict their task completion times, even when they are equipped with the knowledge that similar tasks have taken longer than planned in the past (Buehler, Griffin, and Ross 1994). This is relevant to income prediction in the gig economy, which requires predicting how many hours one will work. Given the correspondence between income prediction and these other areas of judgment in which optimism biases are well-established, we hypothesize that:

> **H1:** On average, consumers with variable income display an *income prediction bias* in which they *over*-predict their future income.

THE NATURE OF THE BIAS

If an income prediction bias does exist, it is almost certainly multiply determined, just as each of the optimism biases discussed in the preceding section are. In the present research, we examine two possible sources of an income prediction bias: 1) whether people overpredict the number of hours they will work, and 2) whether they overpredict the hourly wage they will earn. We discuss each of these possibilities in turn.

Predicting hours. Research on (mis)prediction provides ample evidence that individuals fail to consider the full distribution of possible outcomes when making predictions (see Buehler, Griffin, and Peetz 2010 for a review; see also Howard et al. 2022). For instance, when predicting task completion times, people do not think of life events that might interfere with their ability to complete the task as planned. Rather, they focus solely on the plan itself, and what steps it will take to complete the task successfully (Buehler, Griffin, and Ross 1994; Kahneman and Tversky 1977). In the context of income prediction, this suggests that people may fail to consider life events that could interfere with them working as much as they plan to. For example, when predicting their future income, an Uber driver might not consider the possibility that their car needs repairs next week, which would prevent them from working as much as they anticipated. This possibility leads to the expectation that people overpredict their income in part because they overpredict the number of hours they will work.

Predicting hourly wage. People tend to be overconfident in their abilities (West and Stanovich 1997), and overconfidence is one driver of optimistic financial predictions (Piehlmaier 2022; Odean 2002; Ülkümen, Thomas, and Morwitz 2008). If predicted hourly wage is at least partially a function of perceived ability, it stands to reason that people might overpredict their total income because they overpredict their hourly wage. Continuing the Uber driver example above, it is possible that this person overpredicts their gig income in part because they are overconfident in their ability to earn a higher-than-average hourly wage, perhaps by completing more trips than usual, or by earning higher tips than usual. A second psychological process that could lead to hourly wage overprediction is a generalized optimism bias in which people over-optimistically forecast almost everything (Sharot 2011). Therefore, if an income prediction bias is driven primarily by overconfidence or general optimism, we would expect people to overpredict their future hourly wage. However, we believe this is likely *not* the case, for the following reasons.

First, research on the planning fallacy shows that although people tend to miss deadlines because they fail to account for life events that interrupt their plans for success, they are pretty good at predicting “time on task” (Buehler, Griffin, and Ross 1994), which is to say, they have an accurate sense of how much they can accomplish with each hour of work they do. Translated to the context of income prediction, this suggests that hourly wage estimates may not differ much from reality.

Second, most people have a reservation wage beneath which they will not work, and reservation wages are closely tied to expected wages (Brown and Taylor 2013). In other words, most people will just stop working if they are not earning as much as they thought they would. Additionally, labor market competition limits how high wages can rise, because when wages go up, as in the case of ‘surge pricing’ for Uber drivers, more workers enter the market and quickly drive the price back down (Hall and Krueger 2018). In tandem, the ‘floor’ set by reservation wages and the ‘ceiling’ set by labor market competition imply that hourly wages do not vary much on a within-subject basis (see Hall and Krueger 2018 for empirical evidence of this). Therefore, assuming that relatively stable outcomes are easier to predict than more variable outcomes, it should be the case that hourly wage predictions are reasonably accurate.

Taken together, the observations we make regarding expected hours and hourly wages lead to the following hypothesis regarding the nature of the income prediction bias:

> **H2**: People overpredict how many hours they will work at their gig, but not how much money they will earn per hour.

IMPROVING PREDICTION ACCURACY

Several streams of research support the proposition that when people make predictions they focus narrowly on expected or typical outcomes and do not appropriately consider lessons from the past (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 reduced prediction biases in related domains are: 1) prompting people to include their past experiences in their predictions, (Buehler, Griffin, and Ross 1994; Flyvbjerg, Holm, and Buhl 2005), and 2) prompting people to consider atypical outcomes when formulating their predictions (Howard et al. 2022). One goal of the present research is to compare the effectiveness of these interventions in the context of income prediction.

Intervention One: Taking an Outside View

Our first intervention is derived from work on the planning fallacy. As discussed above, the "planning fallacy" refers to the phenomenon that people tend to underestimate their task completion times, even when they know similar tasks took 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 plan-based scenarios that do not consider all the ways that such plans can go wrong. 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; Flyvbjerg, Holm, and Buhl 2005; Kahneman and Tversky 1977).

In the present research, we propose that income prediction bias may also be reduced by taking an outside view. If, like time predictions, income predictions are biased due to plans that neglect possible obstacles to working as much and as successfully as expected, then prompting people to base their income predictions on past outcomes that reflect these obstacles should reduce the bias. We reasoned that one way to accomplish this is to have people consider their average past earnings while predicting their future earnings, because average earnings accounts for both good and bad weeks at work. Following this logic, we test the hypothesis that:

> **H3:** Prompting people to base their income predictions on their average past earnings reduces the income prediction bias.

Intervention Two: Considering Atypical Outcomes

Our second intervention is derived from work on expense misprediction. When consumers predict their future spending, their predictions are based on highly typical expenses such as groceries and rent, but not atypical expenses such as car repairs or home improvements (Sussman and Alter 2012). This leads to an expense prediction bias in which people underpredict their future spending, because in any given week or month most consumers will face at least some atypical expenses (Howard et al. 2022). Consistent with this analysis, the expense prediction bias can be neutralized by prompting people to consider reasons why their expenses will be different than usual, because this helps people bring atypical expenses to mind and incorporate them into their predictions (Howard et al. 2022).

In the present research we test the possibility that this type of “atypical” intervention can also reduce income prediction bias. Specifically, we test whether income prediction bias can be decreased by prompting people to consider reasons why their future work schedule might be different from a typical week. The logic underlying this intervention is that, in the context of income overprediction, deviations from a typical work schedule are asymmetric: most “surprises” capture reasons why a person might work *less* than usual. For example, when a gig worker needs to stay home to care for a sick child or parent, they will work fewer hours and income will go down. In contrast, there are relatively few surprises that lead a gig worker to have more time to work than usual. Thus, accounting for atypical experiences may reduce the tendency to over-predict future income, which led us to test the hypothesis that:

> **H4:** Prompting people to consider reasons why their work schedule will be different than usual reduces the income prediction bias.

OVERVIEW OF STUDIES

We test our hypotheses in a series of five longitudinal studies conducted with consumers who work in the gig economy. In study 1, we partner with a boutique ride-hailing app to conduct a field study that examines income prediction accuracy over a period of two months (H1). In studies 2—4, we conduct a series of diary studies that replicate study 1 and extend it by also examining whether people overpredict their gig hours and/or hourly wage (H2). These diary studies also demonstrate how researchers can effectively recruit participants who work in the gig economy. In study 5, we replicate studies 1—4 and extend them by also testing the two debiasing interventions (outside view and atypical influence) discussed above (H3 and H4), and exploring treatment effect heterogeneity. Studies 1 and 5 were preregistered on aspredicted.org (links below). Verbatim study materials are provided in each study description and the web appendix, and the data, syntax, and output files for all studies are available on the Open Science Framework (OSF):

https://osf.io/69xwq/?view_only=b10b86b610ad41c08bcc10b7caca0d16

STUDY 1: THE APP STUDY

The primary purpose of this study was to examine the magnitude, prevalence, and persistence of the income prediction bias on both a weekly and monthly basis. To accomplish this, we conducted a preregistered, longitudinal field study with KABU, a ride-hailing start-up in a major North American city that operates as a local competitor to apps like Uber and Lyft.

We also used this study to conduct several exploratory analyses of theoretical interest. First, we examined the relationship between income prediction bias and relevant gig experience (i.e., how long a person has worked at their gig), because experience may help people learn to make more accurate predictions over time. Second, we examined the relationship between income prediction bias and the proportion of total income a person earns from a gig, where total income refers to the amount of money earned across all jobs that a person holds. We did this based on the logic that people who earn a larger (vs smaller) share of their total income from a specific gig may be more motivated to maximize their earnings from that gig, and motivated reasoning has been connected to optimism in related domains such as expense and time predictions (Buehler, Griffin, and MacDonald 1997; Peetz and Buehler 2009).

Finally, we used this study to test two of our core assumptions. First, if variable income makes it more difficult to accurately predict future earnings—as we suggest in the introduction of this article—we should find that the standard deviation (SD) of an individual's past earnings is positively correlated with income prediction bias, such that a larger SD (i.e., higher variability) is associated with a larger bias. Second, the logic underlying the outside view intervention discussed earlier (and which we test in study 5) assumes that the true mean of past earnings is a strong predictor of future earnings, because mean past income is highly relevant experience that accounts for both good and bad weeks at work. In this study, we are able to test this assumption by comparing individuals' mean income over the eight weeks preceding the study to the income they earn during the study. This study was preregistered on aspredicted.org: https://aspredicted.org/B7M_4DH

Method

We recruited KABU drivers for this study through the direct messenger system used by the app. We offered drivers $25 in exchange for completing two surveys. The first survey was completed immediately, and the second survey was completed one month later. At the time of the study, KABU had 88 active drivers, all of whom were sent our recruitment message. Forty-nine drivers participated in the first survey, and thirty-nine of those who participated in the first survey also participated in the second. The drivers who participated in at least one survey did not differ significantly from the drivers who did not participate in either survey in terms of gender (95% of participants were male and 100% of non-participants were male; $\chi_{(1)}$ = 1.73, p = .19, ϕ = 0.15), age ($M_{participants}$ = 42.57, $SD_{participants}$ = 11.04, $M_{non\text{-}participants}$ = 43.74, $SD_{non\text{-}participants}$ = 7.90, t(75) = -0.52, p = .61, d = 0.12), or number of days since downloading the app ($M_{participants}$ = 445.20, $SD_{participants}$ = 132.50, $M_{non\text{-}participants}$ = 446.60, $SD_{non\text{-}participants}$ = 123.30, t(86) = -0.05, p = .96, d = .01).

In the first survey, we started by asking participants to predict their gig income for the next week. Specifically, we asked them:

> Please take some time to estimate the total amount of money you will earn driving for KABU in the next **week**.

How much money do you estimate you will earn (in total) driving for KABU in the next **week**? [Free response text box.]

Then, on the next page, we asked them:

How many hours in total do you estimate you will drive for KABU in the next **week**? [Free response text box.]

We then had participants complete the same prediction measures for the next month. After participants completed the prediction measures, we had them estimate their average weekly income and hours over the past eight weeks. The results for these exploratory measures are reported in the web appendix. We then asked:

In the following question, "total income" refers to the income you earned driving for KABU **plus** the income you earned from all other jobs that you worked.

Over the **past eight weeks**, what percentage of your total income did you earn driving for KABU? (0-10%, 11-20%, 21-30%, … , 91-100%)

Following the logic laid out in the study introduction, we collected this measure to explore the possibility that people who earn a relatively large share of their total income from their gig are more motivated to earn and hence more prone to overpredict, as compared to those who earn a relatively small share.

Finally, we asked participants "How long have you been driving for KABU?" (Less than one month; 1 to 3 months; 4 to 6 months; 7 to 9 months; 10 to 12 months; more than 12 months.) We collected this measure so we could explore the relationship between income overprediction and gig experience.

As noted above, the second survey in this study was sent to participants one month after the first. It included the same weekly and monthly prediction measures as the first survey so we could determine whether prediction accuracy improves over time. One month after the second survey was fielded, KABU provided us with each driver's actual earnings over the course of the study so we could measure income prediction bias, which we define as predicted income minus actual income. Additionally, KABU provided us with each driver's weekly earnings for the eight weeks preceding the first survey so we could perform the assumption checks detailed in the study introduction.

As per our preregistration, our intention was to compare participants' predicted income and hours to the amount of money they ended up earning and the number of hours they ended up working, as recorded by the app. However, at the conclusion of the study, KABU was only able to provide us with each driver's earnings, and not the amount of time they worked. Therefore, our analysis in this study focuses on income prediction bias (H1) and the exploratory questions outlined above, and we return to the question of whether people can accurately predict their gig hours and hourly wage (H2) in studies 2—5.

Results

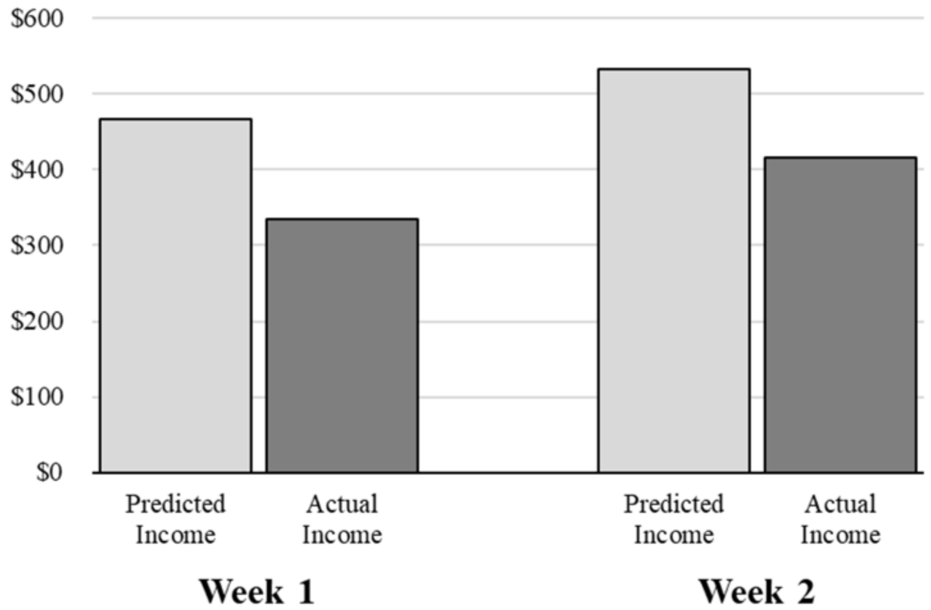
In the analyses that follow we use the term 'Week 2' (or 'week two') as shorthand for 'the first week of the second month of the study', because that is when participants made their second weekly income prediction.

Weekly income prediction bias. Figure 1 illustrates the results of our weekly income prediction bias analysis. Supporting H1, participants overpredicted their income for week one by an average of \$132.07 or 28.3%, as revealed by a paired-samples t-test ($M_{\text{predicted\_income}}$ = \$466.94, SD = 468.71; $M_{\text{actual\_income}}$ = \$334.87, SD = 403.56; $t(48) = 4.01$, $p < .001$, $d = .57$).

Moreover, the bias was prevalent: 75.5% of participants overpredicted to at least some extent, and 53.1% of participants over-predicted by $100 or more. One month later, participants also over-predicted their income for week two, by an average of $118.36 or 22.2% ($M_{predicted_income}$ = $533.59, SD = 540.57; M_{actual_income} = $415.23, SD = 480.54; $t(38) = 2.25$, $p = .030$, $d = .36$). This time, 69.2% of participants overpredicted to at least some extent, and 46.2% overpredicted by $100 or more. Among the thirty-nine participants who completed the weekly prediction measures in both surveys, prediction accuracy did not significantly improve over time ($t(38) = 0.23$, $p = .82$, $d = .04$). In sum, these results indicate that the magnitude of the income prediction bias for weekly earnings is large enough to be economically meaningful for many consumers, and that the weekly bias is both prevalent and persistent.

FIGURE 1

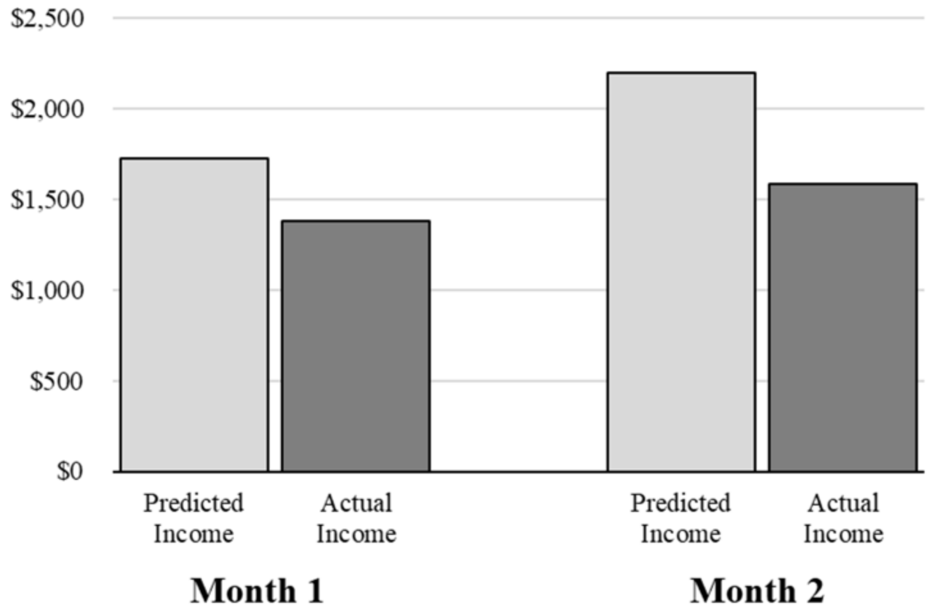
MEAN PREDICTED AND ACTUAL INCOME IN WEEKS 1 AND 2 OF STUDY 1



Monthly income prediction bias. Figure 2 illustrates the results of our monthly income prediction bias analysis. Supporting H1, participants overpredicted their income for month one by an average of \$347.43 or 20.1% ($M_{\text{predicted\_income}}$ = \$1724.52, SD = 1828.31; $M_{\text{actual\_income}}$ = \$1377.09, SD = 1722.71; $t(47) = 2.96$, $p = .005$, $d = .43$). The bias was once again prevalent: 66.7% of participants overpredicted to at least some extent, and 54.2% of participants overpredicted by \$300 or more. One month later, participants again over-predicted their income for month two, by an average of \$610.57 or 27.8% ($M_{\text{predicted\_income}}$ = \$2197.37, SD = 2139.27; $M_{\text{actual\_income}}$ = \$1586.80, SD = 1892.31; $t(37) = 3.18$, $p = .003$, $d = .52$). This time, 81.6% of participants overpredicted to at least some extent, and 60.5% over-predicted by more than \$300. Among the thirty-eight participants who completed the monthly prediction measures in both surveys, prediction accuracy deteriorated somewhat over time ($t(37) = -.2.03$, $p = .050$, $d = -.33$). Echoing the weekly results above, these findings indicate that the magnitude of the income prediction bias for monthly earnings is large enough to be economically meaningful for many consumers, and that the monthly bias is also prevalent and persistent.

FIGURE 2

MEAN PREDICTED AND ACTUAL INCOME IN MONTHS 1 AND 2 OF STUDY 1



Individual differences. To explore if income prediction bias is associated with gig experience or the percentage of total income a person earns from their gig, we produced the correlation matrix in Table 1. First, it can be seen that experience is not significantly correlated with predicted income, actual income earned, or income prediction bias for any of the four time periods we collected these measures.[1] This suggests that learning about gig income over time does not improve income prediction accuracy. Second, percentage of total income earned from the app is (unsurprisingly) correlated with predicted income and actual income earned, but it is not significantly correlated with income prediction accuracy.[2] One interpretation of this result is that the bias is not driven by motivated reasoning, such that a

[1] To be consistent with our other income prediction bias analyses the correlations in this matrix were calculated using raw bias scores (i.e., predicted income – actual income earned). Using percentage bias scores (i.e., [predicted income – actual income earned]/actual income earned]) produces the following correlations between experience and bias scores: Week 1: $r(32) = .11$, $p = .55$; Month 1: $r(34) = .09$, $p = .60$; Week 2: $r(28) = -.24$, $p = .20$; Month 2: $r(30) = .06$, $p = .75$.

[2] Using percentage bias scores produces the following correlations between % of total gig income and bias scores: Week 1: $r(32) = .22$, $p = .22$; Month 1: $r(34) = 0.22$, $p = .20$; Week 2: $r(28) = -.12$, $p = .53$; Month 2: $r(30) = -.04$, $p = .81$.

stronger (vs weaker) motivation to earn leads to higher predicted income but not higher actual income (cf. Peetz and Buehler 2009).

TABLE 1

STUDY 1 CORRELATION MATRIX

Variable Category	Variable	*M*	*SD*	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Individual Differences	(1) Gig Experience	5.39[a]	1.32	-													
	(2) % of total income from gig	4.15[b]	3.49	.20	-												
Week 1	(3) Predicted income	$466.94	468.71	.03	.69**	-											
	(4) Earned income	$334.86	403.56	-.02	.64**	.87**	-										
	(5) Income Prediction Bias	$132.07	230.76	.09	.28	.51**	.02	-									
Month 1	(6) Predicted income	$1,724.52	1828.31	.02	.71**	.97**	.86**	.44**	-								
	(7) Earned income	$1,370.32	1705.33	-.03	.69**	.88**	.95**	.12	.90**	-							
	(8) Income Prediction Bias	$347.43	814.28	.12	.15	.26	-.09	.70**	.35*	-.10	-						
Week 2	(9) Predicted income	$533.59	540.57	-.18	.71**	.90**	.82**	.40*	.90**	.88**	.19	-					
	(10) Earned income	$354.26	457.85	-.06	.65**	.84**	.89**	.16	.83**	.95**	-.15	.80**	-				
	(11) Income Prediction Bias	$118.36	328.19	.13	.27	.26	.03	.47**	.25	.05	.47**	.48**	-.15	-			
Month 2	(12) Predicted income	$2,197.37	2139.27	-.19	.71**	.93**	.81**	.48**	.93**	.88**	.27	.98**	.81**	.42**	-		
	(13) Earned income	$1,357.13	1791.29	-.07	.67**	.88**	.91**	.19	.86**	.95**	-.12	.82**	.98**	-.09	.83**	-	
	(14) Income Prediction Bias	$610.57	1183.87	.15	.23	.28	-.03	.62**	.29	.04	.59**	.46**	-.10	.90**	.47**	-.09	-

NOTES.— *$p < 0.05$. **$p < 0.01$. [a] Corresponds to approximately one year of experience. [b] Corresponds to earning 30% to 40% of total income from the gig.

Assumption Check #1: Income variability and prediction bias. To explore the relationship between income variability and prediction accuracy, we began by calculating the standard deviation of each participant's weekly gig income over the eight weeks prior to the study. We then calculated the Pearson correlation coefficient for this variable and each income prediction bias score measured during the study. Supporting our assumption that past income variability makes future earnings harder to predict accurately, standard deviation was positively correlated with income prediction bias scores for all prediction time periods within the study (Week 1: $r(47) = .40$, $p = .004$; Month 1: $r(46) = .29$, $p = .047$; Week 2: $r(37) = .36$, $p = .025$; Month 2: $r(36) = .46$, $p = .004$). In other words, higher income variability was associated with a higher degree of income overprediction. A robustness test described in the web appendix shows that this finding holds when controlling for mean weekly income over the eight weeks preceding the study, to control for income magnitude effects.

Assumption Check #2: Actual income earned vs mean past income. The argument underlying the outside view intervention that we test in study 5 assumes that mean past income is a strong predictor of future earnings, because mean past income accounts for both good and bad weeks at work. To test this assumption, we conducted an exploratory analysis to compare the amount of money participants earned in week one of the study to their mean weekly earnings over the eight weeks prior to the study. The assumption was supported: actual income earned during week one of the study (M = \$334.86, SD = 403.56) was not significantly different than mean weekly income over the eight weeks prior to the study (M = \$351.08, SD = 380.23), as revealed by a paired-samples t-test ($t(48) = 0.58$, $p = .56$, $d = 0.08$). Moreover, these two variables were very strongly correlated ($r(47) = .88$, $p < .001$).

Discussion

Study 1 yields several meaningful insights. First, we find initial support for our hypothesis that consumers who face variable income display an income prediction bias in which they overpredict their future earnings (H1). We also find that the magnitude of the bias in this study is large enough to be economically meaningful for many consumers, and that the bias is both prevalent and persistent. Second, we present preliminary evidence that income prediction bias is not significantly associated with relevant gig experience or the percentage of total income a person earns from their gig. One way to interpret these findings is that (a) learning about gig income over time does not improve income prediction accuracy, and (b) the bias is not driven by one specific form of motivated reasoning such that a stronger motivation to earn leads to higher *predicted* income but not higher *actual* income (cf. Peetz and Buehler 2009). Finally, we show that greater income variability is associated with greater overprediction, and that mean past income is a (very) strong predictor of future income.

One strength of study 1 is that working with an app provides us with very accurate longitudinal measurement of participants' earnings. The limitations are that we sample from a single type of gig work, both our sample and the population we draw from are relatively small, and participants' gig hours and hourly wage are unobservable, which means we cannot test H2. Thus, our goals for studies 2—4 include: (a) replicating study 1 with samples drawn from different gig populations, (b) testing the feasibility of different participant recruitment channels that may ultimately yield larger samples of gig workers, and (c) extending study 1 by measuring participants' gig hours and hourly wage so that we can test H2.

STUDIES 2—4: THE DIARY STUDIES

Studies 2—4 used a similar design and analysis framework, so we present them here as a set.

Method

Participants were recruited to take part in a two-stage survey about working in the gig economy. The first survey was completed immediately after participants clicked through an online post or advertisement, and it asked them 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 the relevant employment 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, as well as for their expected hourly wage (predicted income divided by predicted hours), as compared to their actual hourly wage (actual income divided by actual hours).[3] We also measured several exploratory variables in each of these diary studies. We summarize the most pertinent results regarding these variables in the general discussion, and we provide full details for them in the web appendix.

Study 2 participants were US residents who perform human intelligence tasks on Amazon Mechanical Turk (AMT). Two hundred and one AMT workers completed the first survey in exchange for $0.50 (41.3% female, M_{age} = 34.7). One hundred and thirty-nine of them (69.2%) completed the second survey (41.0% female, M_{age} = 35.3) and passed the pair of attention checks described in the web appendix. Compensation for completing the second survey was $2.50.

Study 3 participants 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 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).

Study 4 participants were US and Canadian residents who deliver food for apps such as DoorDash, UberEats, and GrubHub. 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; see web appendix for full list).

[3] We asked participants to explicitly predict and recall their hourly wage in study 3, and we found that these explicit measures did not differ significantly from the implied hourly wage measures we calculated using weekly earnings divided by hours.

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 and a chance to win $250. Eighty-five participants completed the first survey (M_{age} = 30.4, 24.7% female) and forty-seven (55.3%) completed the second survey (M_{age} = 29.9, 23.4% female).

Across studies 2—4, the predictions of participants who completed both surveys did not differ significantly from those who only completed the first survey (p's > .22). Because our focal hypothesis concerns prediction accuracy, all analyses were performed using data from participants who completed both surveys. Predicted and reported income in study 2 displayed very strong positive skewness (predicted income skewness = 1.87; reported income skewness = 2.73), because most AMT workers have fairly modest weekly earnings (Median = $120.38), but a few earn hundreds of dollars per week (99^{th} percentile = $817.00). To address this, we excluded data from four extreme outliers whose predicted and/or reported income for the week of the study differed from their self-reported average weekly income by more than 100%, and we LN-transformed predicted and reported income for inferential analysis. We then exponentiated the descriptive results into dollar amounts so they can be easily compared to the results of our other studies.

Results

The results of studies 2—4 are presented in Figures 3—5. The AMT workers in study 2 overpredicted their gig income by 11.1% ($M_{predicted\_income}$ = $124.35, 95% CI = [110.30, 140.19]; M_{actual_income} = $111.89, 95% CI = [97.88, 127.89]; $t(134) = 2.12$, $p = .036$, $d = .18$). They also overpredicted the number of hours they would work at their gig by 18.9% ($M_{predicted\_hours}$ = 26.50, 95% CI = [24.10, 28.90]; M_{actual_hours} = 22.29, 95% CI = [20.30, 24.28]; $t(134) = 5.10$, $p < .001$, $d = .44$). However, their expected hourly wage was relatively accurate, as compared to the hourly wage they ended up earning ($M_{predicted\_hourly\_wage}$ = \$6.39, 95% CI = [5.71, 7.06]; $M_{actual\_hourly\_wage}$ = \$6.94, 95% CI = [6.24, 7.64]; $t(134) = -1.82$, $p = .072$, $d = -.16$).

This pattern of results was replicated among the Uber drivers in study 3 and the food delivery app drivers in study 4. The Uber drivers overpredicted their gig income by 60.2% ($M_{predicted\_income}$ = \$318.70, 95% CI = [244.53, 392.88]; M_{actual_income} = \$198.98, 95% CI = [134.25, 263.72]; $t(26) = 4.32$, $p < .001$, $d = .83$) and their gig hours by 42.8% ($M_{predicted\_hours}$ = 21.52, 95% CI = [17.41, 25.62]; M_{actual_hours} = 15.07, 95% CI = [10.29, 19.85]; $t(26) = 4.89$, $p < .001$, $d = .94$), but their expected hourly wage was relatively accurate ($M_{predicted\_hourly\_wage}$ = \$15.52, 95% CI = [13.26, 17.79]; $M_{actual\_hourly\_wage}$ = 14.73, 95% CI = [11.97, 17.48]; $t(26) = 0.56$, $p = .58$, $d = .11$). The food delivery app drivers overpredicted their gig income by 19.9% ($M_{predicted\_income}$ = \$382.13, 95% CI = [302.99, 461.26]; M_{actual_income} = \$318.61, 95% CI = [246.13, 391.09]; $t(46) = 2.56$, $p = .014$, $d = .37$) and their gig hours by 21.6% ($M_{predicted\_hours}$ = 23.00, 95% CI = [19.29, 26.71]; M_{actual_hours} = 18.92, 95% CI = [14.80, 23.03]; $t(46) = 3.43$, $p = .001$, $d = .50$), but their expected hourly wage was similar to their actual hourly wage ($M_{predicted\_hourly\_wage}$ = \$16.98, 95% CI = [15.41, 18.55]; $M_{actual\_hourly\_wage}$ = \$17.50, 95% CI = [15.53, 19.46]; $t(45) = -.58$, $p = .56$, $d = -.09$).

FIGURE 3

STUDY 2 RESULTS (AMT WORKERS)

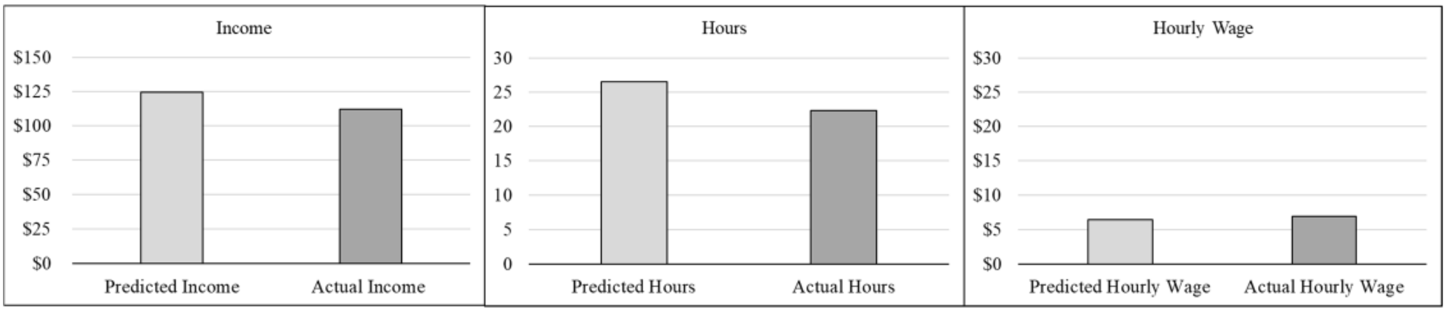


FIGURE 4

STUDY 3 RESULTS (UBER DRIVERS)

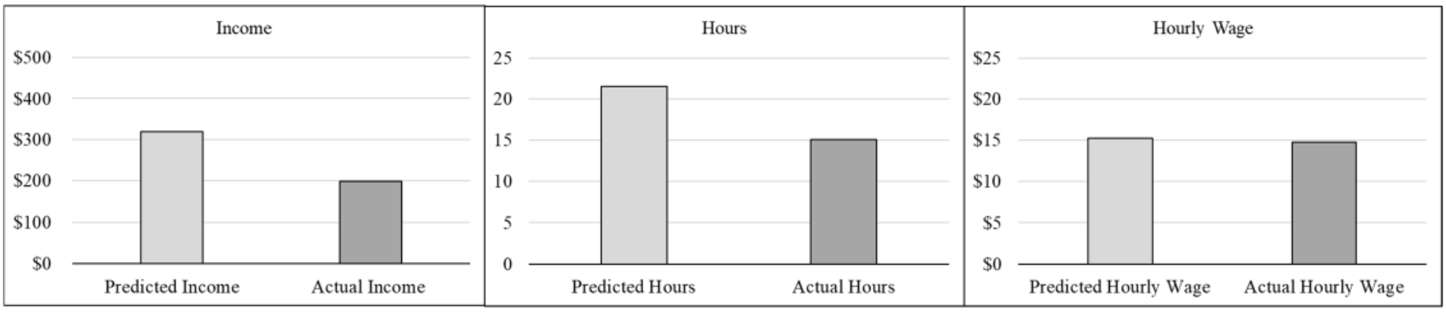
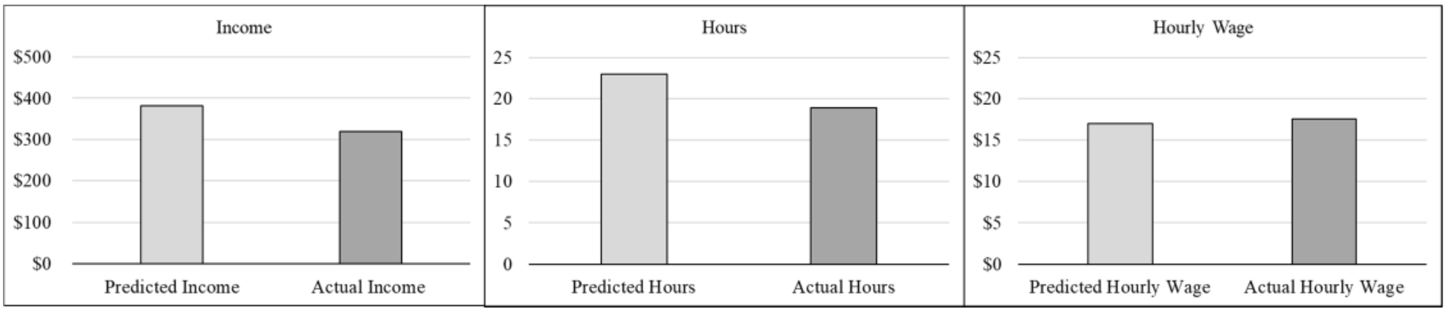


FIGURE 5

STUDY 4 RESULTS (FOOD DELIVERY APP DRIVERS)



Discussion

Studies 2—4 provide further support for H1, and initial support for H2. These studies also help illuminate the feasibility of recruiting participants for this type of research through three different channels: 1) AMT HITs, 2), organic reddit posts and 3) paid advertisements on reddit.com. Recruiting through AMT was convenient, but income from AMT is generally quite low. This introduces the possibility that interventions designed to increase prediction accuracy by decreasing predictions may fail on AMT due to a floor effect, even if those interventions would be successful in other gig contexts where income is higher. Our organic reddit post was cost effective, but recruitment was slow. (It took approximately 24 hours to net 27 participants). 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 study 5 using this method of recruitment.

STUDY 5: DEBIASING PREDICTIONS

The first goal of study 5 was to test the efficacy of the outside view and atypical interventions (H3 and H4). The second goal was to further explore the relationship between income prediction bias and individual differences such as gig experience, and to examine treatment effect heterogeneity by determining if variables like gig experience moderate the effect of our interventions on income prediction accuracy. This study was preregistered on aspredicted.org: https://aspredicted.org/blind.php?x=nu8j4c

Method

Study 5 was conducted with consumers in the US who deliver food through apps like DoorDash, UberEats, and GrubHub. As in study 4, we recruited participants by placing advertisements in reddit.com communities that app-based food delivery drivers use to share information with one another (e.g., r/grubhubdrivers; see web appendix for full list). 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."

We received 1,319 responses to the first survey. 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.[4] 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 4, 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. Table 2 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.

[4] 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.

TABLE 2

DRIVER CHARATERISTICS IN STUDY 5

Variable	Drivers who completed both surveys	Drivers who did not complete both surveys	Significance test
N	600	395	N/A
Predicted income	*M* = \$317.73, *SD* = 245.97	*M* = \$322.12, *SD* = 279.49	*t* (993) = -0.26, *p* = .79
Typical income	*M* = \$318.97, *SD* = 269.63	*M* = \$338.40, *SD* = 354.95	*t* (993) = -0.98, *p* = .33
Lowest income	*M* = \$153.79, *SD* = 170.38	*M* = \$153.90, *SD* = 166.13	*t* (993) = -0.01, *p* = .99
Highest income	*M* = \$450.88, *SD* = 307.76	*M* = \$437.08, *SD* = 326.57	*t* (993) = 0.68, *p* = .50
Predicted hours	*M* = 21.80, *SD* = 15.05	*M* = 22.61, *SD* = 16.05	*t* (993) = -0.81, *p* = .42
Typical hours	*M* = 20.87, *SD* = 14.06	*M* = 21.65, *SD* = 14.91	*t* (993) = -0.83, *p* = .41
Lowest hours	*M* = 9.69, *SD* = 11.22	*M* = 10.47, *SD* = 10.87	*t* (993) = -1.09, *p* = .28
Highest hours	*M* = 28.62, *SD* = 17.34	*M* = 29.48, *SD* = 18.14	*t* (993) = -0.75, *p* = .46
Gig experience	*M* = 3.91, *SD* = 1.79	*M* = 3.65, *SD* = 1.82	*t* (993) = 2.24, *p* = .025
% female	38.50%	34.70%	$\chi_{(1)}$ = 1.49, *p* = .22
Age	*M* = 29.89, *SD* = 9.20	*M* = 29.77, *SD* = 9.67	*t* (990) = 0.20, *p* = .85
% of total income from gig	*M* = 6.15, SD = 3.60	*M* = 5.96, SD = 3.60	*t* (993) = 0.81, *p* = .42
Short-term financial propensity to plan	*M* = 4.66, *SD* = 1.04	*M* = 4.58, *SD* = 1.06	*t* (993) = 1.11, *p* = .27

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. Participants in the control condition were asked, “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?” (Specific dates—e.g., Monday, November 16th to Sunday, November 22nd—were shown in parentheses after the words “next week” in all conditions.)

Outside View Intervention Condition. Participants in the outside view condition were asked to "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 $1,400 over the past four weeks, their prediction instructions read "Over the past 4 weeks you estimate you have earned $350 **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**?" We hypothesized that prompting people to base their predictions on this kind of relevant past experience would improve their prediction accuracy (H3), because average past income accounts for both good and bad weeks at work with relatively high and low earnings. Thus, our expectation was that the outside view intervention would lead to lower income predictions versus control, and therefore reduce the income prediction bias.

Atypical Intervention Condition. Participants in the atypical condition were asked to "Please take some time to consider reasons why the number of hours you work for food delivery apps in the next week might 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?" We hypothesized this 'atypical' intervention would improve prediction accuracy (H4) based on the assumption that deviations from a typical work schedule will usually capture reasons why a person might work less than usual. If so, this should lead to lower income predictions (versus control), and therefore reduce the bias.

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 so we could test H2 as in studies 2—4. Data from four participants whose expected hourly wage exceeded the sample mean (M = $15.70) by more than three standard deviations (SD = 9.54) were excluded from all analyses, because they represent highly implausible wages in this context that likely stem from typos (e.g., typing $1,500 instead of $150). This exclusion criterion was not preregistered, so as a robustness test, we present a non-parametric analysis in the web appendix that shows the difference between the median income prediction bias in each condition is unaffected by the inclusion of these outliers.

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 explore the relationship between predicted income and recalled past income.

Past hours: Participants answered the same questions about the number of hours they worked for food delivery apps over the past eight 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 relationship with prediction accuracy, and test whether it moderates the effect of our interventions on income prediction bias.

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 relationship with prediction accuracy, and test whether it moderates the effect of our interventions on income prediction bias.

Short-term financial propensity to plan: This six-item scale developed by Lynch et al. (2010) was included so we could examine its relationship with prediction accuracy, and test whether it moderates the effect of our interventions on income prediction bias. 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, participants who failed this attention check (n = 62) were excluded from the final sample.

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 condition had. We did this so that we could use gibberish responses to this question (e.g., numbers rather than words) as a preregistered data quality measure that applied equally to all three conditions. As per our preregistration, participants who provided such a response (n = 4) were excluded from the final sample. Finally, participants reported standard demographic information, and whether or not they had experienced any technical difficulties with the survey.

The second survey, sent one week after the first, 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.

Finally, participants completed a pair of exploratory measures related to gig satisfaction and earnings that we present in the web appendix.

Results

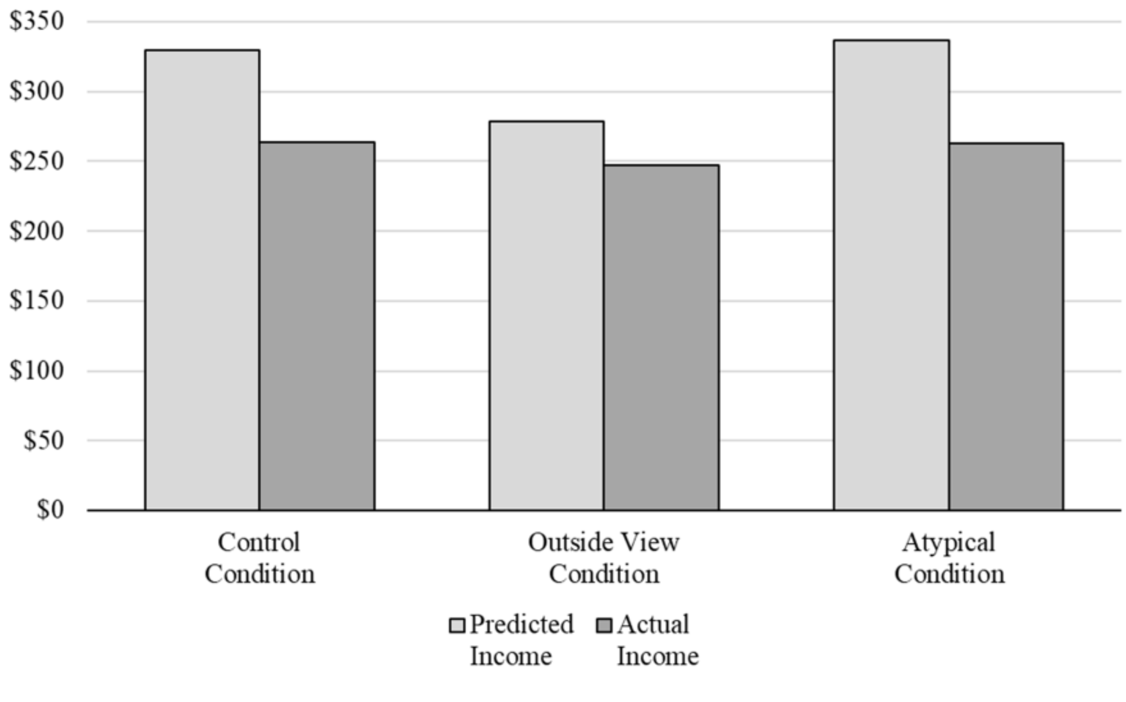
Intervention Effectiveness. Figure 6 plots mean predicted income versus mean actual income in each condition of study 5. To test the effect of the interventions on income prediction accuracy, we conducted a preregistered 3 (condition: control vs. outside view vs. atypical) × 2 (income: predicted vs. actual) mixed-model ANOVA with condition as a between-subjects variable and income as a within-subject variable. The model revealed a significant main effect of income ($F(1, 593) = 71.10$, $p < .001$, $\eta_p^2 = .107$), a non-significant main effect of condition ($F(2, 593) = 1.80$, $p = .17$, $\eta_p^2 = .006$), and a significant condition by income interaction ($F(2, 593) = 4.07$, $p = .018$, $\eta_p^2 = .014$). Supporting H1, participants in the control condition overpredicted their income by $66.42 or 25.2% ($F(1, 593) = 30.18$, $p < .001$, $\eta_p^2 = .048$).[5] Supporting H3, participants in the outside view condition only overpredicted their income by $30.83 or 12.5% ($F(1, 593) = 7.65$, $p = .006$, $\eta_p^2 = .013$), which represents a higher degree of prediction accuracy than in the control condition ($t(403) = 2.20$, $p = .029$, $d = .22$). More concretely, the outside view intervention reduced the size of the income prediction bias by $35.59 or 53.6% versus control. H4 was not supported. Participants in the atypical condition overpredicted their income by $74.07 or 28.2% ($F(1, 593) = 38.53$, $p < .001$, $\eta_p^2 = .061$), and the magnitude of the bias did not differ between the control and atypical conditions ($t(375) = 0.45$, $p = .65$, $d = .05$). Planned contrasts confirmed that predicted income was significantly lower in the outside view condition (M = $278.22, SD = 233.82) than in the control condition (M = $329.83, SD = 230.28, $t(403) = 2.23$, $p = .026$, $d = .22$) and atypical condition (M = $336.66, SD = 236.39, $t(408) = 2.51$, $p = .012$, $d = .25$), and that predicted

[5] H2 was also supported in the control condition of study 5: participants overpredicted the number of hours they would work at their gig by 42.2% ($M_{predicted\_hours}$ = 22.14, SD = 14.37; M_{actual_hours} = 15.57, SD = 12.36; $t(185) = 8.48$, $p < .001$, $d = .62$), but their expected hourly wage was relatively accurate, as compared to the hourly wage they ended up earning ($M_{predicted\_hourly\_wage}$ = $15.77, SD = 7.06; $M_{actual\_hourly\_wage}$ = $16.48, SD = 8.84; $t(185) = -1.19$, $p = .24$, $d = -.09$).

income in the control and atypical conditions did not differ significantly ($t(375) = 0.28$, $p = .77$, $d = .03$). Planned contrasts also confirmed that actual income earned in the outside view condition (M = \$247.39, SD = 252.01) did not differ significantly from actual income earned in the control condition (M = \$263.41, SD = 225.63, $t(403) = 0.67$, $p = .50$, $d = .07$) or in the atypical condition (M = \$262.60, SD = 227.78, $t(408) = 0.64$, $p = .52$, $d = .06$), nor did actual income earned in the control and atypical conditions differ significantly ($t(375) = 0.04$, $p = .97$, $d = .00$). Thus, importantly, the outside view intervention reduced income prediction bias by producing lower income predictions without significantly lowering actual income earned.

FIGURE 6

MEAN PREDICTED AND ACTUAL INCOME IN EACH CONDITION OF STUDY 5



Individual differences. To explore the relationship between income prediction bias and the individual differences we measured, we began by creating the correlation matrix in Table

3 using only data from participants in the control condition. The only individual difference variable significantly correlated with income prediction bias is percentage of total income earned from the gig, but the size of the correlation ($r(184) = .15$) is small. Echoing the results of study 1, this suggests that if motivation to earn is higher for people who earn a relatively large (vs small) proportion of their total income from their gig, then motivated reasoning is only a minor determinant of the bias. The low correlations overall suggest that prediction accuracy does not improve with gig experience or propensity to plan. This latter finding may be because a focus on plans does not improve prediction accuracy if plans neglect potential barriers to success (Buehler, Griffin, and Ross 1994).

TABLE 3

STUDY 5 CONTROL CONDITION CORRELATION MATRIX

Variable Category	**Variable**	***M***	***SD***	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**	**(13)**	**(14)**	**(15)**
	(1) Typical Past Income	$330.04	258.15	-														
	(2) Lowest Past Income	$157.91	165.06	.66**	-													
Income	(3) Highest Past Income	$460.01	308.95	.76**	.72**	-												
	(4) Predicted Future Income	$329.83	230.28	.74**	.75**	.86**	-											
	(5) Actual Income Earned	$263.41	225.63	.57**	.65**	.73**	.76**	-										
	(6) Income Prediction Bias	$66.42	157.51	.27**	.16*	.21**	.37**	-.32**	-									
	(7) Typical Past Hours	21.39	13.59	.61**	.59**	.67**	.68**	.53**	.23**	-								
	(8) Lowest Past Hours	10.23	11.07	.49**	.72**	.53**	.59**	.54**	.09	.74**	-							
Hours	(9) Highest Past Hours	29.64	18.32	.54**	.48**	.65**	.62**	.50**	.20**	.92**	.62**	-						
	(10) Predicted Future Hours	22.14	14.37	.61**	.56**	.64**	.74**	.58**	.25**	.92**	.71**	.86**	-					
	(11) Actual Hours Worked	15.57	12.36	.48**	.57**	.61**	.64**	.85**	-.28**	.67**	.67**	.62**	.70**	-				
	(12) Hours Prediction Bias	6.57	10.56	.27**	.09	.16*	.25**	-.21**	.66**	.46**	.18*	.45**	.54**	-.22**	-			
Individual Differences	(13) Propensity to Plan	4.54	1.11	.20**	.15*	.17*	.24**	.22**	.02	.25**	.18*	.21**	.23**	.26**	.01	-		
	(14) Gig Experience	3.96	1.85	.16*	.09	.24**	.11	.10	.02	.20**	.13	.23**	.15*	.12	.07	.10	-	
	(15) % of total income from gig	6.12	3.67	.40**	.43**	.36**	.45**	.35**	.15*	.48**	.47**	.42**	.49**	.41**	.19*	.20**	.11	-

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

Treatment effect heterogeneity. To determine if the individual differences we measured in study 5 moderate the effect of the outside view intervention on bias scores, we next performed a set of pre-registered regression analyses in which we regressed bias scores onto a condition dummy variable (control = 0, outside view = 1), an individual difference variable, and a condition × individual difference interaction term. So, in our first regression we regressed bias scores onto condition, propensity to plan, and a condition × propensity to plan interaction term, in our second regression we replaced propensity to plan with gig experience, and in our third regression we replaced gig experience with percentage of total income earned from the gig. (Individual difference variables were mean centered.) As seen in Table 4, these regressions revealed that none of the individual differences we measured moderated the effect of the outside view intervention on bias scores versus control (p's > .46). This is a potentially important finding for consumers and practitioners because it suggests that the outside view intervention may work equally well for a broad cross-section of consumers, including those who have high propensity to plan and those who do not, those with lots of gig experience and those with very little, and those who work at their gig full-time as well as those who work part-time. The same set of regressions using atypical = 1 (instead of outside view = 1) also did not yield any significant interactions (p's > .11). Thus, in summary, the effectiveness of the interventions did not vary significantly across the individual differences that we measured in this study.

TABLE 4

STUDY 5 REGRESSION RESULTS

	(1)	(2)	(3)
Condition (control = 0, outside view = 1)	-36.04*	-35.55*	-35.01*
	(16.350)	(16.254)	(16.156)
Individual difference	3.43	2.03	6.36
	(10.758)	(6.474)	(3.245)
Interaction	-3.383	-3.23	-3.141
	(15.238)	(8.933)	(4.469)
Adjusted R-Squared	0.012	0.012	0.024
	(1)	(2)	(3)
Condition (control = 0, atypical = 1)	3.92	4.18	2.93
	(8.459)	(8.395)	(8.284)
Individual difference	3.43	2.03	6.36*
	(10.833)	(6.474)	(3.221)
Interaction	-5.95	7.23	2.55
	(8.173)	(4.716)	(2.293)
Adjusted R-Squared	0.002	0.016	0.042

NOTES.— *Coefficient is significant at the 0.05 level (2-tailed). The individual difference in each model is (1) short-term financial propensity to plan, (2) gig experience, and (3) percentage of total income earned from the gig. Standard errors in parentheses.

Discussion

The results of study 5 provide support for H1, H2, and H3, but not H4. Given the success of the atypical intervention in the context of improving expense predictions (Howard et al., 2022), its failure to improve income predictions suggests that the psychology of income prediction may be different than the psychology of expense prediction. We also find that three individual differences of theoretical interest are, at most, weakly correlated with bias scores, and they do not moderate the effect of our interventions on the bias. We expand on the implications of these findings in the General Discussion.

GENERAL DISCUSSION

Across five longitudinal studies conducted with consumers who work in three different types of gig, we find consistent support for the hypothesis that people who face variable income display an income prediction bias in which they overpredict their future earnings. Moreover, we find that the bias is sizeable, persistent, and prevalent. We also find: (a) people overpredict the number of hours they will work at their gig, but not the amount they will earn per hour, (b) the bias is not meaningfully correlated with theoretically relevant individual differences like gig experience, percentage of total income earned from a gig, or short-term financial propensity to plan, and (c) the bias can be reduced by prompting people to consider relevant past experience when predicting their future income, but not by prompting them to consider atypical outcomes.

One practical recommendation that we can offer based on our findings is that consumers can make more accurate income predictions by basing their predictions on their average earnings in the recent past. We can also suggest that consumers do not try to improve their income prediction accuracy by considering atypical outcomes, even though that approach helps people improve their expense prediction accuracy (Howard et al. 2022). We next discuss the broader implications of our work, and directions for future research.

The Psychology of Income versus Expenses

Our findings indicate that the psychology of income prediction may be different than the psychology of expense prediction in important ways. First, we find that considering atypical outcomes does nothing to reduce income prediction bias, but past research has shown the same strategy virtually eliminates expense prediction bias (Howard et al. 2022). Relatedly, we provide evidence in the web appendix that perceived typicality of future income (which we measured as an exploratory variable in studies 2 and 3) may be positively correlated with income predictions. In contrast, Howard et al. (2022) show that perceived typicality of future *expenses* is *negatively* correlated with predicted spending. Taken together, these findings indicate that income and expense prediction may differ substantially in terms of their relationship to perceived typicality of future outcomes.

Second, we provide suggestive evidence that income prediction bias may not be driven by motivated reasoning, which has been connected to expense misprediction (Peetz and Buehler 2009; Ülkümen, Thomas, and Morwitz 2008). To start, if the bias were primarily caused by motivated reasoning, it should be more strongly associated with the importance of gig income (as measured by the percentage of total income earned from a gig) than we observe. Additionally, as we detail in the web appendix, we find in studies 2 and 3 that income prediction bias is not associated with motivation to earn or save. We also observe across studies 2—4 that predicted income does not differ significantly from perceived average income (see web appendix for analysis and results). This is inconsistent with a motivational explanation for income overprediction because if income overprediction were driven by motivation to improve one's financial well-being, we would expect people to make income predictions that are higher than their (perceived) average earnings. In aggregate, these results suggest that income and expense prediction may be distinct in that the latter is more easily explained by motivational cognitive processes than the former.

Finally, our exploratory analysis in the web appendix also suggests that income prediction bias is not associated with prediction confidence. However, past research has found that prediction confidence is associated with expense prediction bias (Ülkümen, Thomas, and Morwitz 2008; but see also Howard et al. 2022). Thus, the psychology of income and expense prediction may also differ in terms of the role that confidence plays in producing optimistic predictions.

In light of these findings regarding typicality, motivation, and confidence, one fruitful avenue for future research is to directly compare the psychology of income and expense prediction and establish the nature of these differences. In the same way that money can occupy a different psychological space than time (Leclerc, Schmitt, and Dubé 1995; Mogilner and Aaker 2009; Soman 2001), our findings introduce the possibility that different types of money—namely income and expenses—can also occupy different psychological spaces.

Budgeting Theory

When income is stable—for example, when a person earns a salary that pays the same amount on the first of each month—budgeting does not necessarily require an income prediction, because future income is known with a high degree of certainty. When income is variable, as it is for the 1.1 billion people who currently work in the gig economy (Zgola 2021), consumers must try to predict their future income before they can allocate it to different budget categories for spending. Given the rapidly increasing number of people who face variable income (Katz and Krueger 2019), one implication of our theorizing is that the way budgeting is conceptualized needs to be expanded to include income prediction as an antecedent of budget setting.

An expanded three-stage model of budgeting, in which consumers predict income, allocate it to different budget categories, then track their spending against their budget, offers several exciting directions for future research. For example, does income prediction bias lead people to allocate too much money to spending and hence drive debt? Anecdotal evidence regarding consumer debt levels suggests it might, but more research is required to confirm this. Relatedly, consumers often make financial predictions on the fly when considering individual purchases (Peetz et al. 2016). It is thus worth investigating if optimistic income predictions cause people to overspend on these purchases. In general, we believe that examining the potential downstream consequences of income prediction bias for consumers' budgeting and spending decisions can make important contributions to the consumer behavior literature.

Generalizability

Our theorizing leads to a clear proposition regarding the generalizability of the income prediction bias: where there is sufficient variability, there will be overprediction. Thus, we expect that this phenomenon generalizes beyond the three gig contexts which we study here. Other relevant examples include salespeople with variable commissions, service sector employees like waiters and bartenders whose income is earned largely through variable tips, and even salaried employees whose income can be partially variable in terms of bonuses and other financial rewards. Indeed, we expect that even faculty members who sometimes engage in outside consulting work may overpredict their earnings from that variable stream of income (before reading this article, but of course not after).

Our proposition that variability leads to income overprediction gives rise to specific, testable hypotheses concerning the underlying structure of income prediction bias in different contexts. As an example, consider a bartender who works the same 40-hour schedule each week but whose tips are highly variable, so that some nights he earns $10/hour and other nights he earns $50/hour. Our theorizing suggests that, in contrast to the gig contexts we study, this person will display an income prediction bias because he overpredicts his hourly wage but *not* the number of hours he will work. This possibility means that future research on income prediction bias need not be confined to "merely" establishing the generalizability of the phenomenon, it can also meaningfully test and expanded theory related to the underlying cause(s) of the bias.

Potential Moderators and Boundary Conditions

If variability is a necessary condition for overprediction, then an important direction for future research is to establish what constitutes *sufficient* variability. Doing so will not only identify a boundary condition of income prediction bias, it will also advance understanding of misprediction more generally.

In the present research, we examine the relationship between income prediction bias and three individual differences: gig experience, percentage of total income earned from a gig, and short-term financial propensity to plan. In theory, each of these variables could be directly related to the bias, and/or moderate the effect of interventions designed to reduce the bias. We do not find compelling evidence of this, but we encourage future research in a similar vein. For example, it is reasonable to hypothesize that individual differences like conscientiousness and cognitive reflection may be negatively correlated with the bias, and therefore act as boundary conditions on the bias and interventions designed to reduce it.

Future research should also test other interventions designed to reduce the income prediction bias. For example, does the unpacking intervention derived from support theory (Kruger and Evans 2004; Tversky and Koehler 1994), in which predictions are explicitly "unpacked" into their constituent parts (e.g., hours to be worked each day) improve income prediction accuracy? Does incentivizing prediction accuracy reduce the tendency to overpredict? Answering these questions has the potential to improve consumer financial decision making by reducing the bias, and inform theories of why the bias the occurs.

Societal Implications

There are benefits to working in the gig economy. Chief among them, consumers who engage in gig work have a much higher degree of flexibility in their work schedule than those with more traditional jobs. However, our findings suggest that this flexibility comes with a previously hidden cost: income that is difficult to predict accurately. Whether this cost outweighs the corresponding benefits remains to be seen, but if income overprediction leads to overspending, as seems likely, it may be the case that flexible work arrangements end up being financial disadvantageous for many people.

Our work also contributes to the debate regarding wage transparency in the gig economy. Some gig intermediaries have been accused of overstating how much money their (potential) workers can earn (Griswold 2014). This type of explicit deception is clearly unacceptable and should be stopped. However, our work indicates that even when people know exactly how much money they will earn on an hourly basis, they still overpredict their total income because they overpredict how many hours they will work. This suggests that merely increasing wage transparency in the gig economy is not sufficient to give people an accurate view of their potential earnings.

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