Referee Report - Pedro Pires (2024)

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

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1 Summary

This paper examines how gig workers mispredict their earnings due to behavioral biases and, in particular, biased memory, supported by a flexible work environment. Using novel survey data of 454 delivery and ride-share gig workers in the U.S., Pires provides evidence that these workers significantly overestimate both their predicted and recalled weekly earnings, while they underestimate their expenses and overestimate hours worked. The author concludes that agents hold incorrect beliefs about pay and labor supply. He argues these findings are consistent with "selective recall", where individuals tend to remember more positive experiences, leading to biased memory. Under this hypothesis, new information would not necessarily lead to more accurate beliefs (asymmetric and non-bayesian updating), and incorrect views persist over time.

In this regard, this paper builds on the behavioral economics literature on biased beliefs such as overconfidence. Hence, the author proposes "motivated beliefs" ((Bénabou and Tirole, 2002; Bénabou and Tirole, 2016) as the main mechanism behind the consistent overestimation of earnings. Agents would hold incorrect beliefs because of hedonic utility or as a motivational tool, developed and maintained by selective recall. That is why we can also link this paper with other works relating mistaken beliefs to the functioning of memory (Eil and Rao, 2011; Godker et al., 2022; Moebius et al., 2022; Sial et al., 2022). Moreover, this is one of the first studies to apply these concepts to the labor market ((Hoffman and Burks, 2020; Huffman et al., 2022), emphasizing the importance of flexible hours in generating mistaken beliefs.

Indeed, one of the propositions of this paper is that these biases might be due to the flexibility characteristic of gig jobs. Flexible hours would create a noisy work environment, adding challenges for workers to understand key job outcomes and influence their labor supply choices. Thus, this work contributes to both literature on flexible jobs (Camerer et al., 1997; Crawford and Meng, 2011; Farber, 2015; Fehr and Goette, 2007; Thakral and Tô, 2021) and the gig economy (Angrist et al. 2017; Bernhard et al., 2022; Cook et al., 2021; Hall et al., 2021; Koustas, 2018) by introducing behavioral biases to understand how labor supply decisions are made.

In the second half of the paper, Pires presents a behavioral labor supply model, taking into account the overestimation of earnings in gig jobs to predict agents' labor market decisions. Thus, this study relates to labor economics by challenging standard economic assumptions about rational labor supply, joining a growing literature on how the lack of information prevents agents from making optimal labor supply decisions. The novelty of this paper is that instead of exploring beliefs about outside job options (Jäger et al., 2022; Bandiera et al., 2022; Cortes et al., 2022), it focuses on the workers' beliefs about their jobs.

Even though the findings could be discussed, as detailed in the next sections, they have significant implications for labor market policy, platform design, and worker decision-making in the gig economy. It raises concerns about information asymmetry and transparency in platform work, while it calls for an updating of labor supply models, integrating behavioral biases to better predict decision-making in flexible labor markets.

Overall, we believe this paper makes a fair contribution to the intersection of behavioral economics and labor market research by highlighting how biased beliefs shape gig workers' labor supply decisions. With the suggested improvements this paper could be a candidate for publication in a economics or behavioral science journal, while its findings have important implications for both academic research and policy interventions.

2 Major Comments

To begin with, this study does not rely on actual data for expenses; instead, the paper estimates gig workers' expected expenses to calculate their actual expected net hourly and weekly pay. Thus, the cost estimation relies on several external sources and includes variable costs only: fuel, maintenance and repair, depreciation, and taxes. However, the author never explores alternative cost assumptions. If we understand the challenges of getting information on actual expenses at the individual level, the absence of any sensitivity analysis on those estimates might be a significant limitation of the paper, in our opinion. This means that potential variations in fuel prices, maintenance costs, or depreciation across different markets and driving conditions are not fully accounted for. On the one hand, this would not be an issue if expenses were higher than estimated. That is why the author tried to be conservative with the cost assumptions (e.g. removing fixed costs and insurance), implying that using real costs would reinforce the paper's findings that workers overestimate their net pay. On the other hand, the paper does not mention alternative cost assumptions or cost-savings behavior under which expense measures might have overestimated, partially weakening findings. The study uses AAA's Your Driving Costs 2022 guide for maintenance and repair expenses, Hyman et al. (2020) found that gig workers delay maintenance and minimize repairs to cut costs. Moreover, the study assumes average gas prices but does not account for cost-cutting driving behaviors. Furthermore, the study assumes all drivers own their vehicles and pay full costs, but some share cars or use rentals efficiently, driving depreciation, maintenance, and fixed costs down. Indeed, the paper ignores the behavioral responses of experienced gig workers who might learn to optimize expenses over time. As a result, we believe that a robust sensitivity analysis would help determine whether the core findings hold under different cost scenarios (high and low), in the absence of actual data to compare with. Finally, note that if the previous factors might weaken the findings, it would probably be only partially. Indeed, most workers likely face some unavoidable costs, so we have reasons to think the key conclusion—that workers overestimate net pay—is still likely true, just to a lesser degree.

Secondly, we believe the survey design, particularly in how it collects earnings forecasts, may unintentionally serve as a commitment device that influences workers' future labor supply decisions. Rather than purely reflecting workers' true expectations about future earnings, their self-reported predictions could function as goal-setting mechanisms that shape their subsequent behavior. Thus, instead of giving an accurate estimate of their future weekly pay, respondents might use the monetary bonus for accuracy as a motivational tool to push themselves to work harder. This is even more plausible when considering the relatively small size of the bonus; workers would probably derive more utility from the additional earnings they might receive than from their realistic pay plus the 5$ bonus. As a result, it could lead some workers to strategically set high predictions as a way to motivate themselves to increase effort, even if it means being less accurate. This other explanation aligns with the mere-measurement effect (Morwitz & Fitzsimons, 2004), where simply asking individuals about their future behavior can influence their actual actions. When gig workers predict next week's earnings in the survey, they may not just be giving their best estimate of future pay but rather setting a psychological target for themselves. It can function as a self-imposed goal that encourages them to work more hours to meet their expectations. Hence, if workers deliberately set high expectations to commit to working more, then the overestimation of earnings might not be entirely due to cognitive bias, such as selective recalls or motivated beliefs. Even though it does not contradict the findings of the papers, it is a potential complementary explanation for overestimation that might be worth studying. To test this hypothesis, we could observe whether workers who predict higher earnings work more hours to match their forecast. If no such relationship exists, then the predictions are likely genuine misperceptions rather than commitment strategies.

Lastly, the author dismisses the explanation that some of the overestimation might be the result of social desirability bias. First, he argues that accuracy is incentivized with a monetary bonus, which raises the cost of inflating beliefs. Secondly, he finds that working hours are significantly overestimated, while such bias would require workers to state working less (implying higher hourly pay and productivity). We believe these arguments are not sufficient for this paper to refute or not to test this hypothesis. Indeed, the accuracy bonus is only 5 $, even if it increases the cost of inflating beliefs, it might not be enough to match the utility received from being positively perceived thanks to higher earnings. Furthermore, in the context of self-reported work hours, this bias can manifest as individuals overestimating the amount of time they spend working to align with societal expectations that value hard work (Jacobs, 1998). If this is the case, the finding that workers overestimate their net pay may be partly driven by bias in reported work hours, and the paper should introduce self-presentation as another factor for overestimation.

3 Minor Comments

We have spotted two typographical errors that must be corrected before the paper can be published. The first one is a computation mistake on page 11 in the second paragraph "2.4 Sample Selection and Descriptive Statistics". We know the study ended up with 454 baseline survey responses, 210 midline survey responses, and 202 endline survey responses. However, it is stated that "these numbers imply a response rate of 46

The author recognizes that the sample is not perfectly representative of the population of gig workers in the US, and is prone to a self-selection bias. Indeed, the sample was self-selected via social media ads, gig worker groups, and newsletters, which may introduce bias. Hence, more engaged or literate gig workers are more likely to participate and the sample may under-represent casual gig workers. When comparing summary statistics to previous surveys on the gig economy (Parrott and Reich, 2020; Pew Research Center, 2021; Doordash, 2021), the sample appears to be "younger, more white and more educated" and working more hours than the median gig workers. As mentioned, the author is not concerned with this issue since "previous research has found that education is negatively correlated with behavioral biases (Stango and Zinman, 2020)." Moreover, mistakes are widespread across a wide range of demographic and other characteristics. Nevertheless, we believe the quality of the paper could be improved by comparing those numbers with administrative or large-scale data on American gig workers, by implementing weighting adjustments for underrepresented demographics (with an Inverse Probability Weighting), or by post-stratification. Even though the paper already provides a series of robustness checks, we think this would provide additional credibility to the findings.

Finally, Appendix Table A6 shows that workers in financial need tend to overestimate their weekly pay, but the paper does not expand on why being financially constrained is associated with stronger biases, even though they should be more motivated to assess pay correctly given their situation. We suggest providing additional behavioral explanations for this phenomenon, such as optimism and selection biases, or mental accounting errors, as it would improve the quality of the study.

4 References

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