Workers' Preferences over Payment Schedules: Evidence from Ridesharing Drivers

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Abstract: This paper investigates the importance of quick remuneration for gig workers. To explore this question, I run a large-scale survey experiment with ridesharing drivers in Brazil. The main finding is that the median driver would be willing to forgo a third of their potential earnings to be paid on the same day of their rides, compared to the alternative of being paid a month later. Such a strong preference for quick pay seems to be associated with liquidity constraints, as drivers under heavier financial stress are more likely to prioritize same-day remuneration. I also document that priming drivers to think about their personal budget makes them more inclined to favor larger (instead of faster) payments, suggesting that pay-me-now can be a default choice for this population. These results advance the literature on job attributes by showing that payment timing is a relevant aspect of an occupation. This chapter also contributes to the gig work debate by emphasizing that digital platforms are best positioned to offer agile pay schemes, which help workers address liquidity shortages in the short run but might induce poverty traps over the long run. **JEL codes:** D91; J22; J24; J31; M52. **Keywords:** Labor Supply; Occupational Choice; Self-employment; Platform Work; Gig Economy; Liquidity Constraints.

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1. Introduction

People working by themselves are often paid less than their peers who have wage jobs, and are systematically overrepresented among the poorest workers in their local labor markets.[1] This statistical regularity has gained renewed attention with the recent increase of gig work in its modern form, in which labor services are mediated by digital platforms, which include ridesharing and delivery services.[2] For policymakers now facing the challenge of regulating these platforms, it is crucial to understand why people take up these activities despite the relatively low pay rates. One potential reason is that workers appreciate these jobs' extra autonomy and flexibility. However, it is still unclear if these non-monetary benefits are enough to compensate for the magnitude of the earnings penalty they suffer.

In this chapter, I propose and investigate another reason why gig work might be attractive: its rapid payment timing. In essence, gig workers are not only able to adjust their working hours as needed, but they are also paid relatively fast for their services. From the workers' perspective, quickly securing some income might be crucial, especially when consumption needs are pressing or there are few liquidity sources available other than one's own labor. Most forms of own-account work — including modern ridesharing and delivery activities — can offer this benefit, as their earnings can be cashed in by the workers faster than the 15 or 30-day intervals that are typical for employees.

If this hypothesis is true, we should expect that the workers taking up those occupations would indeed be willing to trade off larger earnings for faster payments. That is the motivation for the key empirical questions this chapter addresses. In practice, how much value do gig workers assign to quick remuneration? Who values this feature the most? Moreover, since this preference is potentially related to liquidity, how does the salience of one's financial conditions at home affect one's priorities when facing this trade-off?

The difficulty lies in the identification of this preference in a real-world setting. The workers that are paid shortly after their services (such as daily construction workers, hairdressers working on their own, street vendors, or ridesharing drivers) are in many ways different from those with longer payment terms (such as office workers with monthly paychecks or consultants paid after a long project). Without imposing further assumptions, it is difficult to isolate the marginal importance of the payment timing just from the distribution of workers and payment schemes.

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1. See Gindling and Newhouse (2014), Bandiera et al. (2022), Scarelli (2022), and Scarelli and Margolis (2023).

2. As discussed by Oyer (2020), International Labour Office (2021), and Garin et al. (2023).

This chapter addresses this challenge by exploring the setting of the ridesharing drivers using a survey experiment in the field. The choice to focus on ridesharing here has two advantages. First, this activity is of intrinsic interest to researchers and policymakers since it represents a new form of labor market engagement. Second, from a methodological perspective, this setting is particularly well-suited for the identification of preferences for quick payment, as it combines three advantages: (a) all workers perform a homogeneous, well-defined task, (b) the time to remuneration is a salient feature of the activity, and (c) payment rules can potentially be changed at the platform's discretion without affecting the fundamental nature of the job.

Leveraging this context, I run a discrete choice experiment with over 14,000 drivers who work with a major ridesharing platform in Brazil. The key outcome of interest is the drivers' reported preference when facing a hypothetical comparison between being paid their usual rate per kilometer always on the same day of their rides, or receiving a higher rate always 30 days after their rides. With the manipulation of the pair of rates they chose from, it is possible to identify an interval of forgone compensation that represents the relative importance of the rapid remuneration timing for each individual driver.

The main result from this elicitation protocol is that the median driver would rather be paid the same day than wait 30 days to receive a fare 1.48 times higher. This choice is equivalent to forgoing one-third of one's nominal earnings per unit of effort (0.48 out of 1.48) in exchange for the benefit of being paid faster. In other words, the median compensated willingness to pay (WTP) for same-day remuneration is at least 33%.

What may explain such high levels of WTP? The survey includes a randomized module just before the preference elicitation protocol to uncover some potential mechanisms behind this result. A third of the respondents are asked how they would cover some unexpected expense, another third is asked how they would use some unexpected income of the same magnitude, and the remaining group serves as a control. Such a design provides a large sample of textual descriptions, offering us a rich insight into the drivers' economic life, while exogenously inducing them to mentally retrieve their financial circumstances, a manipulation that identifies the effect of salient household budgets on payment timing preferences.

Taking stock of the results, a strong preference for fast payment (a) reflects a structural context of resource scarcity and liquidity constraints combined with (b) a modest degree of behavioral heuristics that favors quick pay as a default safe choice. The first point is supported by the finding that drivers living in the poorest households tend to have the highest levels of WTP. Text analysis techniques refine this result by highlighting the feedback interaction between resource scarcity and liquidity: the workers who would choose to receive more are the ones who already have precautionary reserves or could use their credit cards. At the same time, those who prioritize being paid faster tend to rely on family support when facing temporary shocks — or would need to work longer hours to make up for unexpected expenses.

For the second point, an analysis of the experimental treatment shows that the drivers randomly exposed to the budget questions take a few seconds longer to choose their preferred contract and end up assigning marginally lower importance to be paid faster (or, equivalently, higher importance to earn more) relative to the control group. While it would be plausible to expect people to react differently depending on the content of the hypothetical shock they discussed (unexpected expense or unexpected income), the results suggest that it is the introspective financial exercise in itself that affects the workers' reactions to the intertemporal trade-off in focus, since both treatment arms lead to a similar reduction of about 1.5 percentage point in the WTP for same-day remuneration. This effect is coherent with the hypothesis that fast payment is a default choice (as it is preferred more often in the unprimed group), while the later payment requires a more costly cognitive operation involving the management of deferred flows in the context of one's current conditions (which is kick-started by the forced information retrieval from the budget discussion).

The nature of the hypothetical, non-incentivized elicitation mechanism imposes an important limitation on these results. The preferences reported by the drivers will be meaningful proxies of real-life decisions to the extent that the subjects (a) can understand the proposed trade-off, (b) can anticipate what their decision would be, and (c) do not misrepresent their choices. Those assumptions are plausible in my experimental setting because ridesharing drivers are the experts when it comes to reasoning in terms of kilometer fares. Moreover, they can anticipate the actual consequences of the changes in payment rules proposed in the experiment better than the rest of the population, given that their income is a function of the earnings from their rides.

This chapter contributes to four strands of the economic literature. Firstly, it documents that workers can attach very high value to the simple job feature of being paid shortly after the task, extending the debate on job attributes. In this sense, the proposed measurement of the WTP for same-day remuneration is close in spirit to the elicitation of WTP for work flexibility (Mas and Pallais 2017; K.-M. Chen et al. 2020), for less commute time (Le Barbanchon, Rathelot, and Roulet 2021), for stability and earnings growth (Wiswall and Zafar 2018), and for fringe benefits (Eriksson and Kristensen 2014).

Secondly, this research also relates to the extensive literature on intertemporal problems, where subjective time discount rates are typically inferred from choices over when to receive arbitrary rewards, with variations in the structure of the posited discounting function (the range of methods and results have been reviewed by Frederick, Loewenstein, and O'Donoghue 2002; Chabris, Laibson, and Schuldt 2016; Ericson and Laibson 2019; Cohen et al. 2020; Imai, Rutter, and Camerer 2021; Matousek, Havranek, and Irsova 2021). However, the present chapter is interested in intertemporal trade-offs in the specific context of the labor market, in which the relevant choice refers to a recurring payment rule and the payoff is the counterpart of a labor service.

Within the literature on the timing of labor earnings, my findings contrast with the series of studies that manipulate the payment rule for farmers and informal workers in Kenya and Malawi (Brune and Kerwin 2019; Casaburi and Macchiavello 2019; Kramer and Kunst 2020; Brune, Chyn, and Kerwin 2021). Those experiments consistently find that workers prefer a single deferred payment over more frequent, smaller installments. In such a design, however, the choice for later payment is also a choice for a bulky payment, which explains the interpretation that the results reflect a demand for safe savings devices that allow the workers to purchase large indivisible goods. In the present chapter, the contracts differ in the *interval between the work task and the respective pay* (either $t+0$ or $t+30$). Since neither option allows the accumulation of earnings over multiple days, the results are uncontaminated by potential preferences for lump-sum amounts.

Thirdly, this chapter extends the adoption of quantitative analysis of free text in applied economic research, illustrating how this non-standard data can offer original insights and provide concrete interpretations for conceptual parameters. From a methodological perspective, the present application is closest to the discussion presented by Ferrario and Stantcheva (2022), who use word clouds and keyword analysis to study partisan differences in people's concerns regarding taxation in the United States. For an overview of other recent developments in the analysis of text in economics, see Gentzkow, Kelly, and Taddy (2019) and Ash and Hansen (2023).

Finally, my results complement the ongoing debate on the costs and benefits of platform work, one major case among the increasing menu of alternative work arrangements, as reviewed in Mas and Pallais (2020). While the literature points to flexibility as the primary benefit of the modern gig economy (see for instance Hall and Krueger 2018; M. K. Chen et al. 2019; Oyer 2020; The World Bank 2023; Callil and Picanço 2023), my chapter argues it is also a way to secure income faster, which is a precious feature if workers need (or expect they might need) to address short-term shocks. In this sense, my results are aligned with the findings from Koustas (2018, 2019), who documents that drivers in the United States tend to take up this activity following a period of falling income, decreasing assets, and increasing debt, on average. The rideshare earnings offset part of the lost income, but not all of it, analogous to a safety net.

The remainder of this chapter is organized as follows. Section 2 describes the operation of the ridesharing activities in Brazil, focusing on the rules that determine the drivers' payout. Section 3 describes the survey design, the preference elicitation method, and the experimental manipulation, and provides an overview of the sample. Section 4 reports descriptive results from my survey, including a profile of the ridesharing drivers and their work routine. The same section also presents a text analysis of the qualitative responses from the drivers. Section 5 reports the experimental results, investigates heterogeneity in the effects for those who drive as a primary or a secondary occupation, discusses the evidence on a potential mechanism, and performs robustness checks. Section 7 concludes with a discussion of the implications of the results and directions for further research.

2. Context

There were at least 1.3 million people actively working as ridesharing drivers in Brazil in the third quarter of 2022, according to the administrative records from the leading platforms (Callil and Picanço 2023). While this group remains a small slice of the total working population (99.3 million), it already represents about 1/4 of the contingent employed by the sectors of accommodation and food services nationwide (5.3 million), or 1/6 of the workers in the construction sector (7.4 million), as per the estimates from the national household survey for the same period (Instituto Brasileiro de Geografia e Estatística 2023).

In essence, ridesharing platforms are companies that use digital applications to intermediate the supply and demand of personal transportation services. When a client requests a ride on such platforms, the task is proposed to available drivers in that geographic area, who can accept it under the posted rates. In this chapter, we define ridesharing drivers as those who supply labor in the form of transportation services under this arrangement.

A crucial attribute of this job is a relatively low entry barrier. To join the pool of active drivers for the major ridesharing platforms in Brazil, one must have a smartphone, no criminal record, and a professional driver's license (which requires psychological tests conducted by the local transit authority). Even though most drivers use their own car to work, this is not a requirement — indeed, about 1 out of 4 rent their working vehicles, as I document in the next section. Renting is also an alternative adopted by drivers whose car does not comply with city-level standards for vehicles used in professional transportation.

At the time of the experiment, ridesharing workers in Brazil were in a gray area between regular employees and autonomous service providers from the perspective of labor regulation and social security coverage. They could access the public health system and were eligible for means-tested cash transfers and disability benefits, which are universal welfare policies. However, the social security system only grants contributing workers labor protection benefits (such as temporary work incapacity, maternity leave, and retirement pension). While any platform driver could pay social security contributions as individual own-account workers, this participation was not enforced, and coverage was effectively dependent on the driver's initiative (Center for Education and Research in Innovation 2021). Furthermore, drivers are not subject to the national minimum wage nor work hours restrictions that apply to employees.

From the driver's perspective, rides are priced based on a starting fare, a rate by minute, and a rate by kilometer, subject to a minimum total amount. The exact reference value for each component is specific to the region where the driver operates, as the companies adopt different remuneration rates according to local market conditions. The platforms offer temporary multipliers when demand is high to attract more drivers.

Despite this combination of factors, the bulk of the drivers' remuneration is typically determined by the base rate per kilometer (except for unusual circumstances, such as one-block rides). This is relevant for the purposes of this research, as we exploit the fact that the kilometer rate is a salient earnings component.

Importantly for my research design, the platform has extensive autonomy to set (and to change) the details of their compensation policy, including the base rates and the payment timing, in contrast to most work arrangements. At the time of the experiment, compensation was organized as follows: the passenger pays the platform at the end of a ride, the amount due to the drivers is added to their outstanding balance, and the accumulated value is deposited in the drivers' bank account once a week.

While all the major platforms adopted a similar policy on payment timing at the time of the survey, they were not constrained by technical reasons (a same-day deposit would be equally feasible), legal regulations (the payment standards from the labor code did not apply to ridesharing drivers), nor social norms (there was no longstanding tradition nor strong expectations that ridesharing drivers should be paid weekly). In fact, the leading companies have already introduced mechanisms that allow drivers to access their outstanding balance before the weekly deposit date, but these alternatives require the use of a payment card provided by the platform, which can be subject to transaction fees. There is no public information regarding the drivers' adoption of such payment devices.

3. Experimental design

The survey experiment was implemented with one of the leading ridesharing platforms in Brazil. On the afternoon of January 24, 2023, an invitation to participate was distributed to the mobile phones of all drivers registered with this company. A reminder was sent two days later, and the data collection was concluded on the 31st. Within this period, I documented the participation of

14,265 drivers, making it one of the largest surveys with platform workers to date.

The sample includes all individuals who agreed to participate and were assigned to a treatment or a control group. In practice, it means they answered at least the question regarding the subnational region where they usually work, which is the information required to perform the stratified randomization. The sample excludes (a) 35 cases flagged by the survey software as potentially repeated responses by the same individual and (b) 7 observations coming from the two strata with less than 20 observations. Unfortunately, it is not possible to report the precise response rate to the recruitment because the number of drivers registered with the company is confidential information. For a broad reference of magnitude, there were about 1.27 million active drivers in that period (Callil and Picanço 2023). This figure implies we collected data on about 1.1 percent of the universe. Section 4.1 provides further discussion on how the sample compares to the relevant reference groups in terms of demographics.

The design represents a field experiment in the sense that it targets the relevant subject pool in a real-world context, namely ridesharing drivers evaluating ridesharing contract bundles (Harrison and List 2004). The recruiting message was sent via the ridesharing application itself, and participants could participate in the survey while waiting for their next passenger.

However, the survey was conducted outside the ridesharing application, in a third-party software with a distinct visual identity, to emphasize that the company did not do the data collection. To minimize the risk that people would participate strategically, the recruiting message and the consent form stressed upfront that an academic economist was running the survey to study the drivers' routine and their personal experience with this activity.

3.1. Preference elicitation protocol

While the questionnaire covers a rich set of sociodemographic and work-related variables, the key innovation is the elicitation of the workers' preferences for payment timing. The core question reads as follows:

> For some drivers, it is important to be paid for their rides as soon as possible. Others prefer a higher value, even if it takes longer for it to be deposited.
>
> **If you could choose, which of those options would work best for you?**
>
> [ ] I'd prefer {*base rate b*} per km, always deposited on the same day of the ride.
> [ ] I'd prefer {*multiplier m* $\times$ *b*} per km, always deposited 30 days after the ride.

The bracketed values were calculated dynamically according to the geographical region of the driver, such that the baseline rate b for the same-day option matches the actual kilometer rate that the respondent is familiar with. The 30 days rate is calculated using a multiplier m to the baseline rate b (1.24 in the first question; 1.06 or 1.96 for the second question; and 1.03, 1.12, 1.48 or 2.92 for the third question, as detailed in figure 1). This strategy ensures that the relative monetary differences are the same at each step regardless of the city where the driver works, even though everybody sees values that are realistic within their own market.

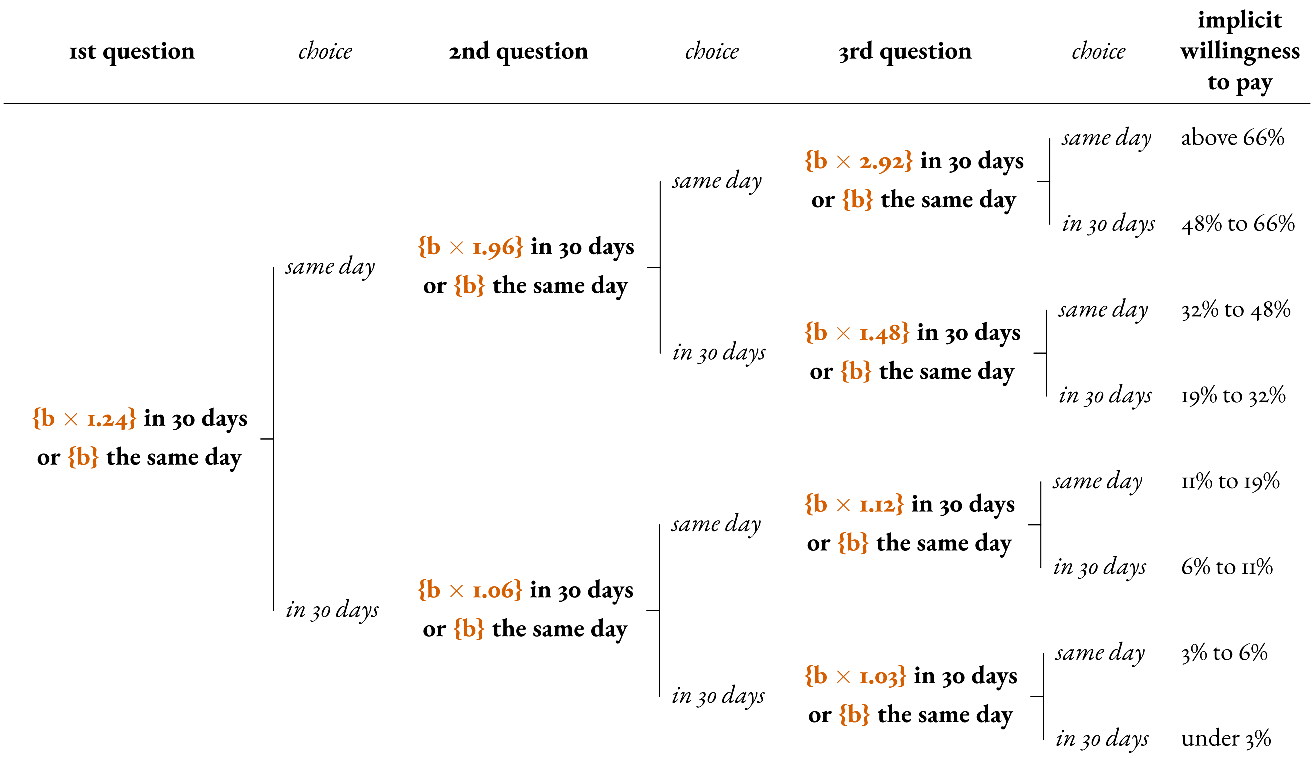


FIGURE 1 – Sequences of possible contract choices and the corresponding rates. The multipliers were set with the objective of balancing precision (having sufficiently narrow intervals, especially at the bottom of the distribution) and coverage (being able to capture preferences all over the potential distribution), with a minimal number of iterations (3 questions). To that end, the simple rule adopted was to double the marginal percent increase over the tree branches: 3, 6, 12, 24, 48, 96, and 192. The 30 days deferral was chosen to mimic the longest interval without payment that is typical for a wage worker in Brazil.

This measurement strategy (also called "titration", "unfolding brackets", "bisection", "double bounds", or "staircase method") has a long tradition in lab and field applications. It is internally consistent by design and requires only a brief sequence of pairwise choices, which are desirable properties for a mobile-based survey. In essence, the design identifies a range containing the individual indifference point by interactively increasing the value of the option that was not selected before. If the respondent chooses same-day payment, the follow-up question will propose a higher multiplier to the late remuneration; conversely, if they select the late payment, the follow-up question will show a smaller multiplier for this option. Since indifference was not an option, individuals were forced to devote sufficient attention to picking their preferred choice. The unfolding protocol is repeated three times, leading to eight indifference intervals.

The interpretation proposed in this chapter is that each choice provides boundaries for how much the individual values the fast payment option in terms of forgone earnings. In concrete terms, if I take the same-day contract in the first question, I am willing to forgo at least 0.24 out of every 1.24 of my potential earnings per kilometer to have the benefit of being paid faster. Equivalently, this choice implies a lower bound of about 19% for the willingness to pay for this feature — or, more precisely, the *compensated* WTP, as the discussion is about the pay rate per unit of effort, abstracting from possible changes in working intensity. Throughout this chapter, all mentions of WTP should be understood in these terms.

An alternative interpretation would be to frame the results in terms of pure time preference and to infer a subjective monthly discount rate of at least 24% from the aforementioned choice. This chapter favors the use of a WTP framework instead. First, the WTP is agnostic on the underlying links between utility and different choices over deferred payment, while a pure time preference framework requires some extra functional form assumptions. Second, WTP has a natural scale that goes from zero (not willing to renounce any earnings) to almost one (willing to forgo nearly all earnings), while discounting would range from 0 to positive infinity, imposing additional difficulties on the interpretation of the highest interval in the elicitation scale. More importantly, WTP is a more general concept than pure time preference in that it need not assume that the observed behavior is a consequence of a taste parameter. While heterogeneity in pure time discounting is likely to be a reason behind the choices I document, they are not required to be the only channel, and the measurement choice makes this point more transparent. Finally, reporting the results in terms of WTP puts them on the same scale usually adopted by other choice experiments manipulating job attributes. In practice, if one still favors the time discount perspective, the qualitative results would remain valid, but the magnitudes would require the appropriate conversion following the ancillary assumptions, for instance, using an exponential functional form and a monthly frequency.

One could worry that loss aversion would contaminate the results if the alternatives present values nominally inferior to the ongoing rates, as workers tend to respond strongly against the perception of earnings cuts. To avoid this concern, the choice structure always uses multipliers (of at least 1.03) on top of real-world rates.

Another concern is potential status quo bias if the alternatives include the current payment rule. This risk is not present in this design because the respondent is always choosing between two competing net gains relative to the status quo: either you have your usual rate b, but paid sooner than weekly, or you can have a nominal increase over b, but deferred for a longer time than the current rule.

Finally, note that the choices are designed to avoid, in all scenarios, the possibility of earnings accumulation over multiple working days. This is meant to block the possibility of payments in large chunks, which could confound the results since deferred lump sums are known to be valuable for workers as a commitment device and as savings instruments in themselves (Brune and Kerwin 2019; Casaburi and Macchiavello 2019; Brune, Chyn, and Kerwin 2021). In my design, the interest is solely on the time interval between work and payment; therefore, it is essential to eliminate the accumulation channel.

This chapter acknowledges that reported choices for hypothetical scenarios have limitations. To be clear, respondents received no remuneration to participate in the survey and were informed that their answers would not affect their contracts with the platforms. The critical question is whether voluntary, unincentivized participation could compromise the results. In a methodological discussion, Read (2005) stresses that incentives are not unconditionally necessary nor sufficient for valid results and notes that applied researchers should instead ponder what role a monetary payoff would play in a given elicitation design. In the present case, to recover unbiased results, we require that the subjects understand the alternatives, correctly anticipate their choice, and do not misrepresent their preferences. These assumptions are plausible in this setting because the experiment is close to the subjects' familiar working routine. In other words, I assume that adult drivers do not require extra incentives to understand how kilometers translate into income, can anticipate what consequences a change in the payment timing would have for their household budget, and do not have a systematic reason to distort their choices.

3.2. Experimental manipulation

To measure how the salience of one's financial conditions may affect one's preferences for rapid payment timing, the implementation of the survey splits the respondents into three groups, as shown in figure 2.

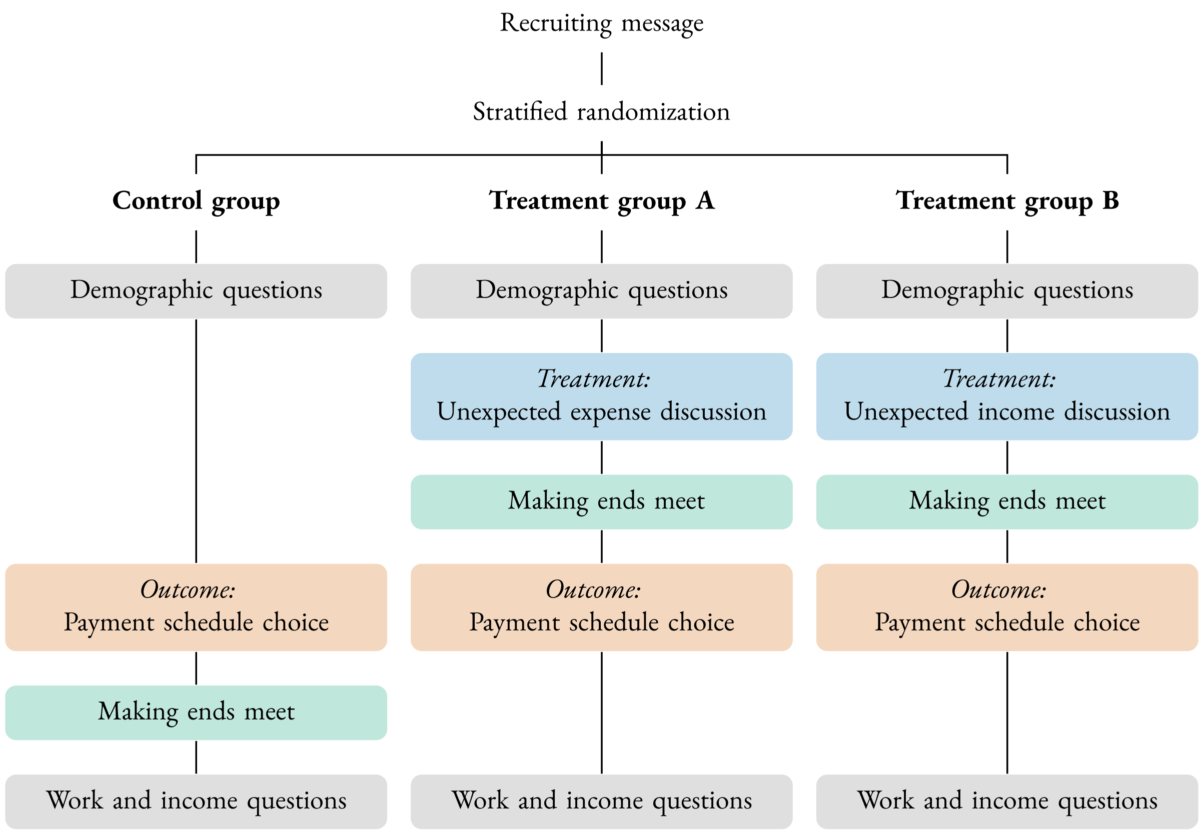


FIGURE 2 – Sequence of the survey blocks according to the assignment groups. The randomization was stratified by geographical region, with the regions defined as (a) the capital of the State and the surrounding cities or (b) the remaining cities in the State, for each State in the country.

A third of the respondents are taken as the reference group, in which case people are asked about their sociodemographic characteristics and then invited to choose their preferred contract, following the protocol described above. In treatment group A, respondents are exposed to an additional question block inviting them to discuss how they would deal with an unexpected expense in the amount of R$ 1,400 (or about US$ 560 under purchase power parity, slightly above the monthly minimum wage for a full-time job in Brazil). In treatment group B, they are asked how they would spend an unexpected gain of the same magnitude. In both cases, the extra questions take place just before the contract choice.

The objective is to exogenously induce people to an introspective exercise that retrieves the information necessary to react to the problem at hand. Treated individuals do not receive any new data, they are primed to become particularly aware of their circumstances. The critical assumption is that, after the exercise, the financial context examined by the respondent remains readily available in their minds.

In this context, two complementary problems (coping with unexpected expenses versus using unexpected income) were designed to pin down which part of the induced salience can explain any systematic difference observed in the reported choices. The treatment consists of the *unexpected expense* scenario:

> Imagine you received news of a domestic emergency (an urgent home repair, or a health treatment that cannot wait). Because of this, you will have to disburse R$ 1,400 more than expected this week.
>
> **What is the first word that comes to your mind?**
>
> **In practice, how would you cover this unexpected expense of R$ 1,400 right now?**

Or the following *unexpected income* scenario:

> Imagine you received news of a surprise payment (the result of a lottery or an unexpected refund, for example). Because of this, you will receive an extra deposit of R$ 1,400 this week.
>
> **What is the first word that comes to your mind?**
>
> **In practice, what would you do with this unexpected income of R$ 1,400 right now?**

Since typing demands more attention and cognitive effort than just clicking or swiping through questions, we can be confident that respondents were engaging with the problems, as also suggested by the time spent in the treatment module. Of all participants actively answering the questionnaire just before the treatment block, 96% typed at least a word in their responses (94% in the expenses arm, 98% in the income arm). Most participants took between 20 seconds and one minute to describe what they would do in the proposed scenario, with a median of 29 seconds in the case of an unexpected expense, and 35 seconds if they had to decide how to spend the surprise income. In both treatment arms, under 2% of the active respondents took less than 30 seconds to go through the whole treatment protocol (that is, vignette, the first word that comes to mind, and what would you do).

Another benefit of applying this treatment to a sample of ridesharing drivers is that they are familiar with smartphones, contributing to the very high compliance. Recurring spelling mistakes, systematic punctuation use, and the occasional emoticon in the responses also reflect a high level of engagement and minimize concerns with computer-generated responses.

4. Descriptive results

This section covers two complementary sets of descriptive results. First, I provide an overview of the sociodemographic characteristics of the ridesharing drivers in the sample, emphasizing that they are similar to the general working population in many dimensions. The sample description also discusses their work routine, their earnings, and the differences between those who drive as a primary or a secondary job.

Next, I characterize the distribution of WTP for same-day earnings among the participants, as measured in the main elicitation protocol. Two findings stand out: there is a wide dispersion of preferences, with at least 5 percent of workers in each possible WTP interval that we observe, but they are strongly overrepresented at higher buckets, with WTP of 32% or more. The analysis of associations between the WTP and other attributes, in particular their total household income per capita, supports the interpretation that such distribution is partially driven by structural material scarcity.

4.1. Who are the ridesharing drivers?

The ridesharing drivers in this study are predominantly young adults (52.4% are less than 38 years old), identify themselves as black or mixed-race (62.8%), and have no college degree (83.9%). In most cases, they live with another adult (57.6%) and at most one child (70.3%). Even though the subjects were sampled from the active drivers of a particular company, they are similar to the general population of platform drivers in the country, according to the observable demographics reported by other sources. The reference closest to the present study is Callil and Picanço (2023), who conducted telephone interviews with 1,518 drivers between August and November 2022. They report that 56% of them are under 39 years old, 62% are black or mixed race, and 81% have no college degree. They do not report statistics on household composition.[3]

What is more remarkable, the drivers in this study also reflect the general diversity of the urban, adult, working population in Brazil in terms of ethnicity, age, education, and household composition, as documented in table 1. While it would be excessive to claim that the participants of this study are representative workers in a broad sense, this tabulation shows that they are not a particularly eccentric group.

3. Other studies have used the combination of category ("own-account worker"), reported occupation ("driver"), and activity ("passenger transportation") to identify platform drivers in the National Household Survey (PNADC), notably Góes, Firmino, and Martins (2021) and Góes, Firmino, and Martins (2022). While useful as an initial approach, it is not the ideal proxy because it does distinguish platform drivers from taxi drivers. For this reason, I still use PNADC to characterize the adult urban workforce in Brazil, for which it remains the best source in this context, but I avoid using it for the purpose of studying the platform drivers in particular.

Table 1 – Characteristics of the drivers in the survey and corresponding summaries for urban adult workers in Brazil

	Ridesharing Drivers Survey						*National Household Survey (PNADC)*					
	All drivers		*Driver as main job*		*Driver as secondary job*		*Adult urban workforce*		*Adult urban own-account workers*		*Adult urban employees*	
	stat.	*s. e.*	*stat.*	*s. e.*	*stat.*	*s. e.*	*stat.*	*s. e.*	*stat.*	*s. e.*	*stat.*	*s. e.*
Gender (share in %)												
Male	93.2	(0.21)	92.7	(0.30)	93.9	(0.46)	54.8	(0.14)	63.2	(0.35)	52.6	(0.20)
Ethinicity (share in %)												
Black	13.4	(0.29)	13.1	(0.39)	14.0	(0.67)	11.3	(0.16)	10.7	(0.29)	11.8	(0.20)
Mixed-race	49.4	(0.42)	49.0	(0.57)	47.9	(0.96)	43.1	(0.27)	43.2	(0.45)	42.7	(0.31)
White	37.3	(0.41)	37.9	(0.55)	38.1	(0.94)	45.6	(0.30)	46.1	(0.49)	45.6	(0.33)
Age group (share in %)												
18 to 27 years old	14.1	(0.30)	15.0	(0.41)	12.1	(0.63)	23.1	(0.18)	14.4	(0.31)	24.2	(0.23)
28 to 37 years old	38.3	(0.41)	39.1	(0.55)	37.1	(0.93)	26.6	(0.21)	25.4	(0.39)	27.8	(0.26)
38 to 47 years old	31.5	(0.39)	29.9	(0.52)	35.1	(0.92)	24.5	(0.18)	24.9	(0.35)	25.1	(0.22)
48 to 57 years old	12.2	(0.28)	12.0	(0.37)	12.0	(0.63)	16.9	(0.15)	20.0	(0.30)	16.2	(0.18)
58 years old or more	4.0	(0.17)	4.0	(0.22)	3.7	(0.36)	8.9	(0.12)	15.2	(0.29)	6.7	(0.12)
Education (share in %)												
Primary education or less	11.1	(0.27)	10.9	(0.35)	8.3	(0.53)	24.1	(0.23)	32.7	(0.41)	21.0	(0.25)
Some high school	7.9	(0.23)	8.2	(0.31)	5.7	(0.45)	6.7	(0.11)	7.1	(0.21)	6.2	(0.12)
High school	44.1	(0.42)	44.7	(0.57)	43.1	(0.95)	38.1	(0.24)	36.2	(0.39)	38.2	(0.29)
Some college	20.7	(0.35)	21.4	(0.47)	20.5	(0.78)	7.3	(0.11)	5.3	(0.18)	8.0	(0.14)
College or above	16.2	(0.32)	14.8	(0.40)	22.5	(0.80)	23.8	(0.31)	18.7	(0.43)	26.7	(0.35)

Table 1 – Characteristics of the drivers in the survey and corresponding summaries for urban adult workers in Brazil *(continued)*

	Ridesharing Drivers Survey						*National Household Survey (PNADC)*					
	All drivers		*Driver as main job*		*Driver as secondary job*		*Adult urban workforce*		*Adult urban own-account workers*		*Adult urban employees*	
	stat.	*s. e.*	*stat.*	*s. e.*	*stat.*	*s. e.*	*stat.*	*s. e.*	*stat.*	*s. e.*	*stat.*	*s. e.*
Household composition												
N. of adults (age 18+)	2.4	(0.01)	2.4	(0.01)	2.4	(0.02)	2.5	(0.01)	2.4	(0.01)	2.5	(0.01)
N. of kids (age < 18)	1.0	(0.01)	1.0	(0.01)	1.0	(0.02)	0.8	(0.01)	0.8	(0.01)	0.8	(0.01)
Work routine												
Work hours per week	53.0	(0.24)	60.1	(0.26)	32.9	(0.39)	39.7	(0.05)	38.0	(0.13)	40.0	(0.05)
Monthly income (in R$)												
Average work income	2,267	(15)	2,501	(17)	1,597	(23)	2,805	(28)	2,293	(32)	2,743	(28)
Average household inc. per capita	1,381	(12)	1,333	(13)	1,517	(25)	2,084	(23)	1,987	(28)	2,143	(25)
How long in this job (share in %)												
Less than 3 months	12.2	(0.31)	10.3	(0.35)	16.6	(0.72)	10.9	(0.14)	8.6	(0.24)	12.3	(0.17)
3 to 6 months	10.0	(0.28)	9.3	(0.33)	12.2	(0.63)	6.5	(0.11)	4.6	(0.22)	7.5	(0.13)
6 months to 1 year	11.7	(0.30)	11.7	(0.37)	12.1	(0.63)	6.3	(0.11)	4.1	(0.17)	7.4	(0.14)
1 to 2 years	16.8	(0.35)	16.1	(0.42)	18.1	(0.74)	10.8	(0.14)	7.9	(0.23)	12.3	(0.17)
2 to 4 years	29.4	(0.42)	30.5	(0.52)	26.4	(0.85)	22.2	(0.17)	23.1	(0.34)	22.1	(0.20)
More than 4 years	19.8	(0.37)	22.1	(0.47)	14.7	(0.68)	43.4	(0.23)	51.7	(0.42)	38.5	(0.26)
Social indicators (share in %)												
Contributes to a pension system	43.0	(0.53)	31.2	(0.58)	76.1	(0.91)	67.4	(0.23)	33.5	(0.44)	79.8	(0.23)
Household inc. per cap. < USD 5.5/day	11.3	(0.32)	12.2	(0.39)	8.4	(0.56)	8.5	(0.15)	8.4	(0.23)	4.8	(0.11)

Table 1 – Characteristics of the drivers in the survey and corresponding summaries for urban adult workers in Brazil *(continued)*

	Ridesharing Drivers Survey						*National Household Survey (PNADC)*					
	All drivers		*Driver as main job*		*Driver as secondary job*		*Adult urban workforce*		*Adult urban own-account workers*		*Adult urban employees*	
	stat.	*s. e.*	*stat.*	*s. e.*	*stat.*	*s. e.*	*stat.*	*s. e.*	*stat.*	*s. e.*	*stat.*	*s. e.*
Country region (share in %)												
North	8.8	(0.24)	8.5	(0.32)	8.3	(0.53)	7.5	(0.13)	8.7	(0.22)	6.9	(0.14)
Northeast	20.0	(0.34)	20.3	(0.46)	19.3	(0.76)	21.4	(0.24)	23.1	(0.38)	19.7	(0.27)
Southeast	46.7	(0.42)	48.0	(0.57)	44.6	(0.96)	47.7	(0.34)	46.1	(0.51)	48.7	(0.40)
South	13.6	(0.29)	12.8	(0.38)	16.4	(0.71)	14.8	(0.20)	14.1	(0.29)	15.6	(0.24)
Central-West	10.9	(0.26)	10.4	(0.35)	11.4	(0.61)	8.6	(0.14)	7.9	(0.19)	9.1	(0.17)
Survey sample												
Number of observations	14,265		7,741		2,708		133,762		31,270		83,369	

Notes: [1] The drivers' survey was conducted by the author between the 24th and the 31st of January 2023 and its underlying population is all drivers working with a leading ridesharing company in Brazil. [2] The figures regarding to the general workforce are calculated using the microdata from Brazil's official labor survey, refer to the full year of 2022, and are weighted to be representative of the active population above 18 years old and living in urban areas. In particular, I use the data collected by PNADC's 5th interview with the sampled households, which records household income from all sources. [3] For all variables and all subpopulations, the statistics are calculated using the available responses required for that specific item, and therefore the number of observations may vary for different attributes. The sample size for all drivers represents to the number of unique individuals who participated in the survey, while the combined number primary job drivers and secondary job drivers refer to the respondents for whom there is sufficient information for this breakdown. [4] Monetary values from PNADC are reported in January 2023 equivalent terms. [5] Work-related statistics (such as *work income*, *work hours* and *how long in this job*) are specific to the occupation indicated in the column. [6] The *household income per capita* is composed of all income sources from all invidividuals in a given household. [7] Non-male drivers are composed by 6.7% of female drivers and 0.1% of respondents who do not identify neither as male nor female; PNADC has no comparable gender information.

The striking exception is that males represent 93.2% among the ridesharing drivers, in contrast to 54.8% in the urban workforce. However, such gender unbalance is typical for this industry, particularly in low- and middle-income countries. The International Labour Office reports that females make up, on average, 5% of the ridesharing drivers in Chile, Ghana, India, Indonesia, Kenya, Lebanon, Mexico, Morocco, and Ukraine (International Labour Office 2021). Looking at the base of Uber drivers in the United States, Cook et al. (2021) document a female share of 27.3%, with the caveat that the proportion of active female drivers at any given month is lower than that because women leave the job at a higher rate (76.5% of them are no longer active within six months, compared to 65.0% for men).

For completeness, table 8 in the appendix replicates the descriptive statistics from table 1 but keeps only men in both the drivers' sample and in the general workforce. In this case, after removing the women from the comparison, the share of workers with college decreases, while the average work hours and work income increase for all subgroups.

The drivers report an average net income from ridesharing of R$ 2,267 per month, after regular working expenses, which is equivalent to about US$ 900, adjusting for purchase power parity (see figure 3 for the distribution of monthly earnings from ridesharing). This average value represents 1.7 times the national minimum wage for a full-time formal employment position in Brazil. On the other hand, it is about 20% below the average monthly earnings reported by the general workforce in the same period (or 26% less, if we compare only male drivers with the male working population), as measured by the national household survey.

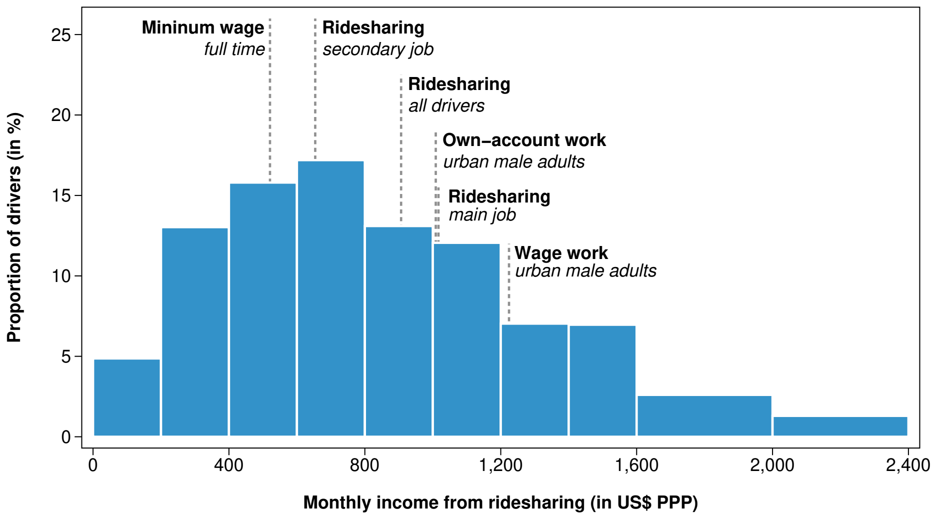


Figure 3 – Distribution of monthly earnings for the ridesharing activity and the average work earnings for selected reference groups. The dashed lines mark the average work earnings for the different reference groups. The underlying values can be found at table 8 in the appendix.

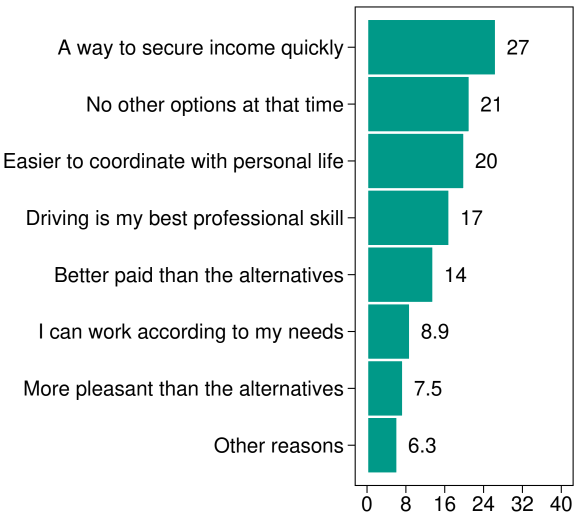
Going beyond the general average, it is possible to identify two very distinct profiles in this population: 3/4 of the drivers engage in ridesharing as their sole or main occupation (in the sense that it represents their main income source), while 1/4 use it as a supplementary activity. Primary job drivers report working an average of 6 days per week and 10 hours per day, with net earnings of R$ 2,500 per month (US$ 1,000 PPP). In contrast, secondary job drivers drive 4.4 days per week and 7.2 hours per day, with net earnings of nearly R$ 1,600 per month (US$ 640 PPP).

These figures imply that secondary job drivers are able to earn about 14% more per hour (US$ 4.2 vs. US$ 4.9 in PPP terms), suggesting that they are able to optimize their driving routine, choose more profitable periods, or to respond more strongly to changes in demand compared to main job drivers, who work more regularly.

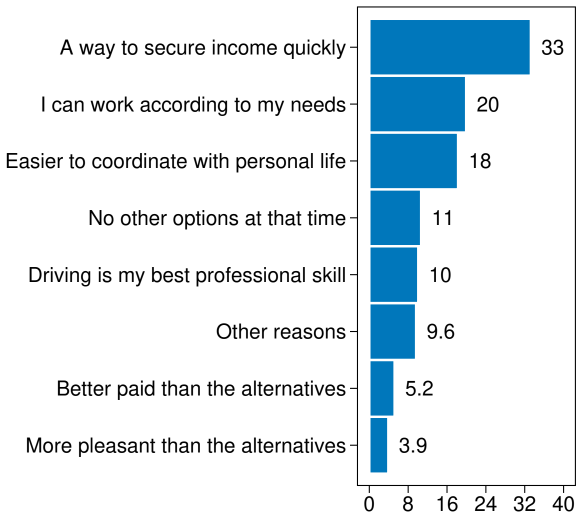
My data does not allow us to conclude if Brazilian ridesharing drivers follow some form of earnings targets, as proposed in the lively literature on the labor supply of taxi drivers (Camerer et al. 1997; Farber 2008; Crawford and Meng 2011; Thakral and Tô 2021). However, the behavior of primary job drivers appears to be consistent with a maximization of their total monthly earnings, instead of their hourly gains. Since most drivers in this group tend to work more than 8 hours per shift, we can conclude that they regularly find the marginal revenue from the 9th hour more valuable than going back home in a typical working day.

The polarization between those two types of drivers is also reflected in other dimensions, as primary job drivers are systematically younger, less educated, live in poorer households, and are less likely to contribute to a pension system. Yet, these two groups have a major feature in common: *both appreciate the fact that this activity offered them a way to secure some income quickly*. Indeed, this is the single most frequent reason mentioned by the respondents when asked about what motivated them to take up ridesharing, considering the other paid activities they could do, as detailed in figure 4.

This is an important result because it complements the usual argument that points to flexibility and autonomy as the major differential benefits from the ridesharing activity (see Hall and Krueger 2018; Oyer 2020; The World Bank 2023; Callil and Picanço 2023). It is unclear how the order of importance reported in similar surveys would be affected if they had included an explicit option about quick payments.



(a) Main job drivers



(b) Secondary job drivers

FIGURE 4 – Most important reasons for taking up ridesharing, by driver type. The questionnaire presented this set of alternatives in random order to the respondents to avoid sequence bias. The total share of responses may add to more than 100 percent, as people could choose more than one option.

The caveat about these results is that the wording "a way to secure income quickly" can potentially cover two distinct senses for "quick": (a) the low entry barrier that allows people to start working faster relative to the counterfactual of searching for a match with a company and (b) the short time between the work and the associated payment. Both are likely to be present, as discussed in Scarelli and Margolis (2023), but the distinction between them is substantive.

In the next section, we take this investigation a step further with the results from the WTP protocol, which have the double benefit of eliminating ambiguity (by isolating the value of the payment timing only) while being more precise regarding its importance (by measuring it in terms of forgone earnings).

4.2. How much do drivers value same-day remuneration?

The main finding from the preference elicitation protocol is that the possibility of quickly converting labor into cash is extremely valuable for ridesharing drivers. The median driver would rather be paid the same day than 1.48 times as much in 30 days, a choice that suggests a WTP of at least 32% (from foregoing 48 cents out of each 1.48 monetary units of payment). Almost 1 in every 4 drivers would take the same day pay against nearly 3 times as much for the 30-day delay, with an implied WTP of at least 66%. Taking the midpoint of each interval weighted by their mass, the mean WTP is close to 40%.

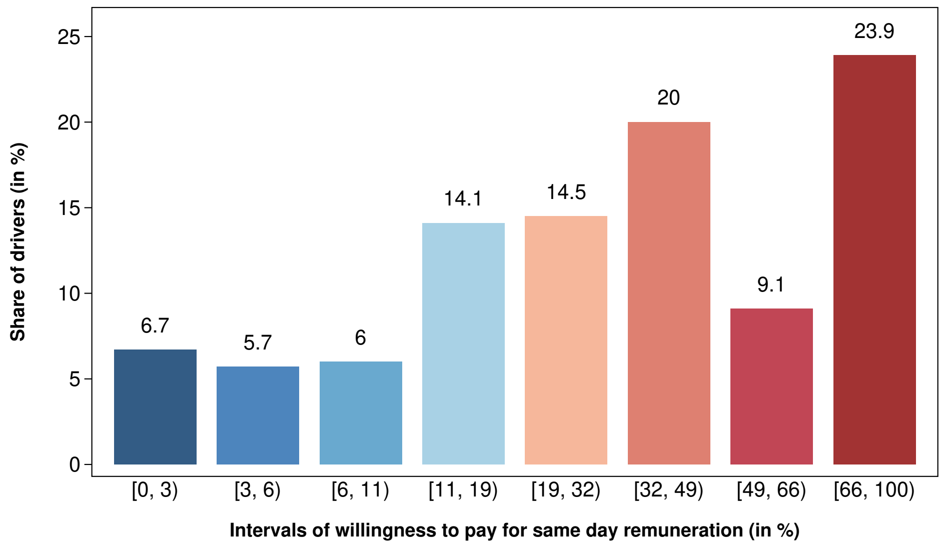


FIGURE 5 – Distribution of preferences for same-day remuneration

High inflation and high interest rates could be trivial reasons motivating people to avoid deferred payments. However, we can reject that these concerns rationalize the bulk of the behavior documented here, given the magnitude of the multipliers proposed for future payments. For reference, at the time of the data collection, headline inflation in Brazil was under 0.4 percent per month, and food inflation was under 1 percent per month (Ferreira et al. 2023). Similarly, the baseline interest rate in the financial system was around 1 percent per month. All in all, these reference rates mean that the present value of the later payment option in real terms should be adjusted by no more than a few percentage points and thus cannot explain any choice beyond the very first bucket at the bottom of the distribution.

Instead, these extreme preferences appear to partly reflect a context of structural resource scarcity and missing financial instruments, which makes one's labor a source of both domestic solvency *and* liquidity. This view is supported by the monotonic association between contract choices and poverty: the lower the total household income per capita, the more valuable the option to access one's earnings the same day, as summarized in figure 6.

A similar correlation emerges at the geographical level. There is a known gradient in the median regional income (and in other poverty indicators derived from the surveys of the national statistics office) going from the Northern (poorest) to the Southern (richest) regions of the country. Since I collect data from drivers in all regions, I can document that a similar gradient holds for the WTP for same-day remuneration but in the opposite direction, as depicted in figure 7. Under the mild assumption that the potential association between the outcome and the response rates is not region-specific, the results suggest that drivers in the poorest regions are the ones who favor quick payment the most.

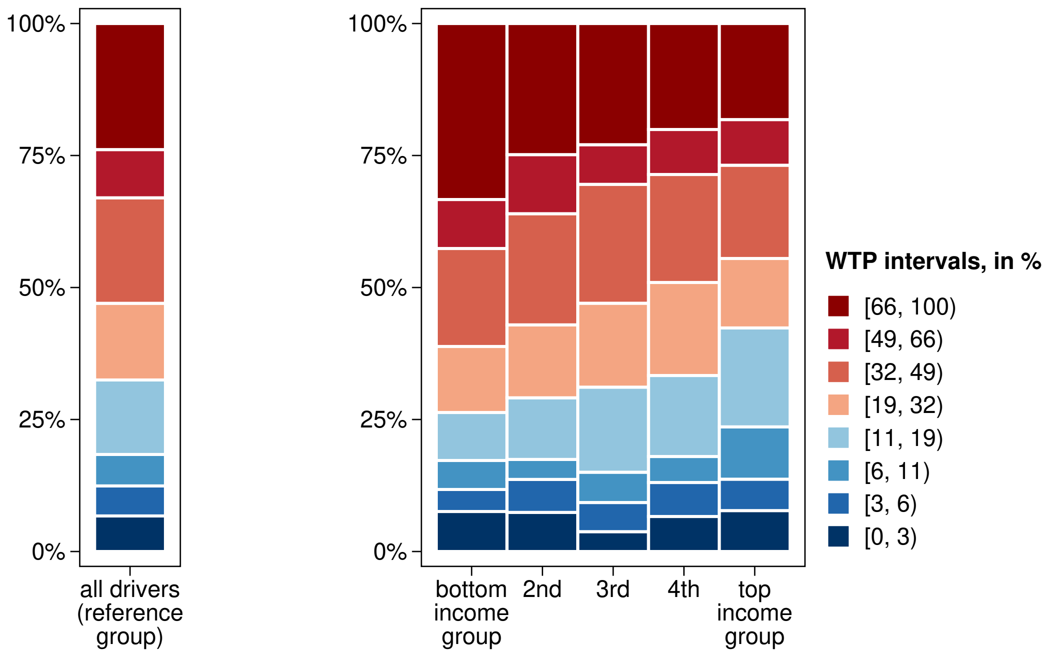
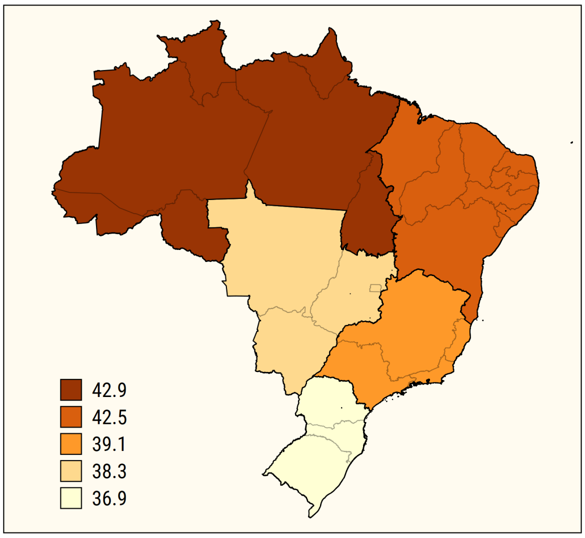
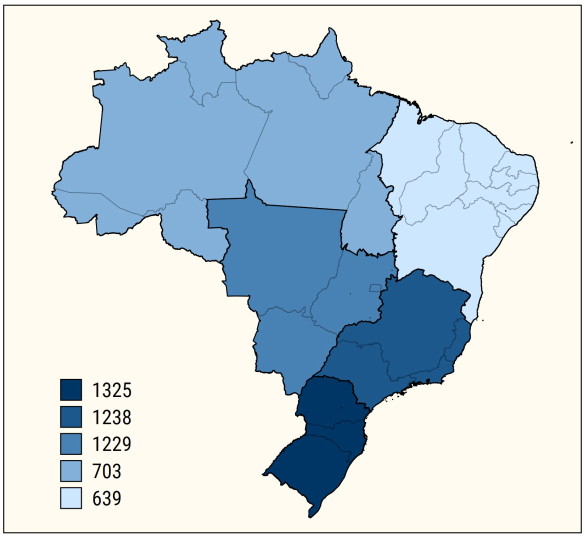


FIGURE 6 – Distribution of preferences for same-day remuneration by quintile of household income per capita



(a) Average WTP, as measured in the drivers survey



(b) Median household income per capita, as measured in the PNADc

FIGURE 7 – Payment preferences and median income level by macroregion

Compared to the valuation of other job amenities documented in the literature, the amount people are willing to give up for same-day remuneration is indeed at the high end, but it is not implausible. Manipulating the application process for a position in a call center in the United States, Mas and Pallais (2017) find that the applicants were willing to forgo 20% of their wages to avoid a schedule set by an employer on short notice, and 8% for the option to work from home. Using a panel of Danish respondents, Eriksson and Kristensen (2014) estimate a 13% WTP for high job flexibility, 8% for 5 days of training, and 7% for a large health package. With a sample of undergraduate students from the New York University (NYU), Wiswall and Zafar (2018) document that female students report a WTP of 4% for a percentage point lower chance of being fired, and a WTP of 7% for the option of working part-time. Looking at how much the workers in India are averse to accepting tasks that do not align with their own identity, Oh (2023) finds that 43% are willing to forgo at least 10 times their daily wage to avoid a type of work that is associated with other castes.

Part of the dislike of being paid later may also come from a concern that the company might fail to honor its payment commitments at some point, willingly or not. This factor is unlikely to play a large role in the results because most drivers already have a track record of many months working with this firm, which contributes to building trust in its payment capacity. As suggestive evidence of this, I find that those who have just started the activity tend to have the highest WTP, as depicted in figure 9. However, this result should be taken with a grain of salt, given that newcomers could plausibly be the most liquidity-constrained. In any case, there is little systematic association between seniority and WTP beyond the very first month of experience. Furthermore, according to Brazilian commercial law, the workers, service providers, and contractors have priority in the event of a business liquidation. Hence, the risk of non-payment due to the company quitting the market should not explain the magnitude of results I find, and much less so for a short 30-day interval.

There could also be some habit formation regarding payment rules, in the sense that people tend to lean towards the schemes they are already familiar with. If this is true in this setting, drivers who were previously wage employees (and, thus, subject to a form of deferred payment) could show less resistance to the 30-day interval relative to drivers who had other occupations. Yet, if we break down the preferred contract choices by the previous state, we find little difference between those coming wage-employment or self-employment. Instead, the major contrast in this dimension comes from those with or without any form of paid activity, with the inactive and the unemployed showing the highest willingness to pay for same-day remuneration, as per figure 9.

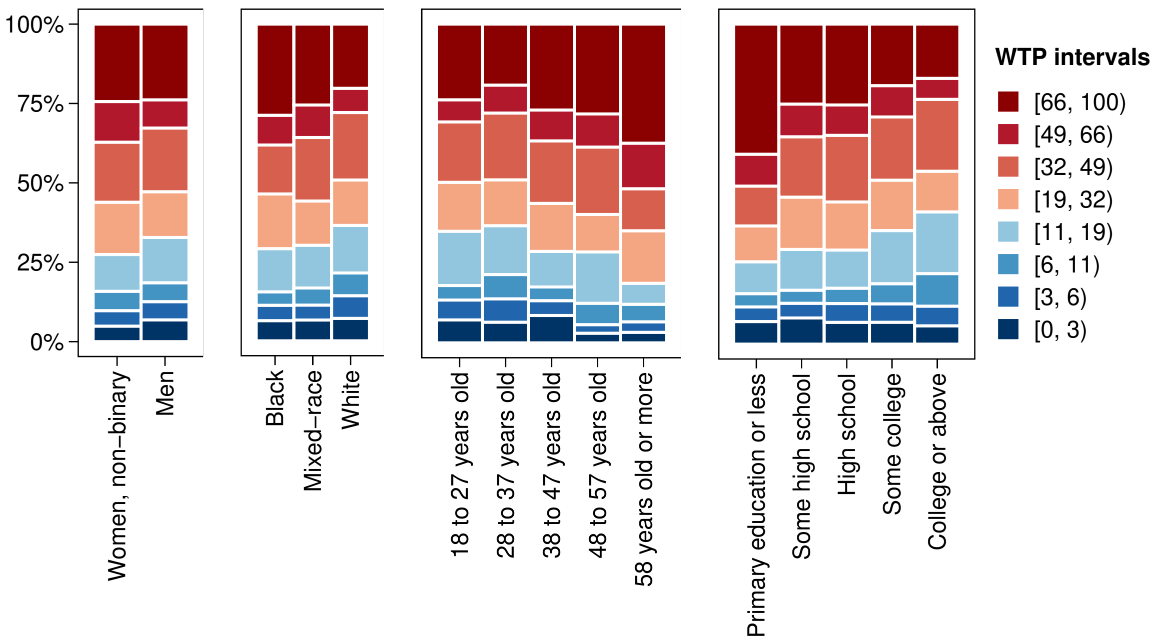


FIGURE 8 – Preferences for same-day remuneration by demographics

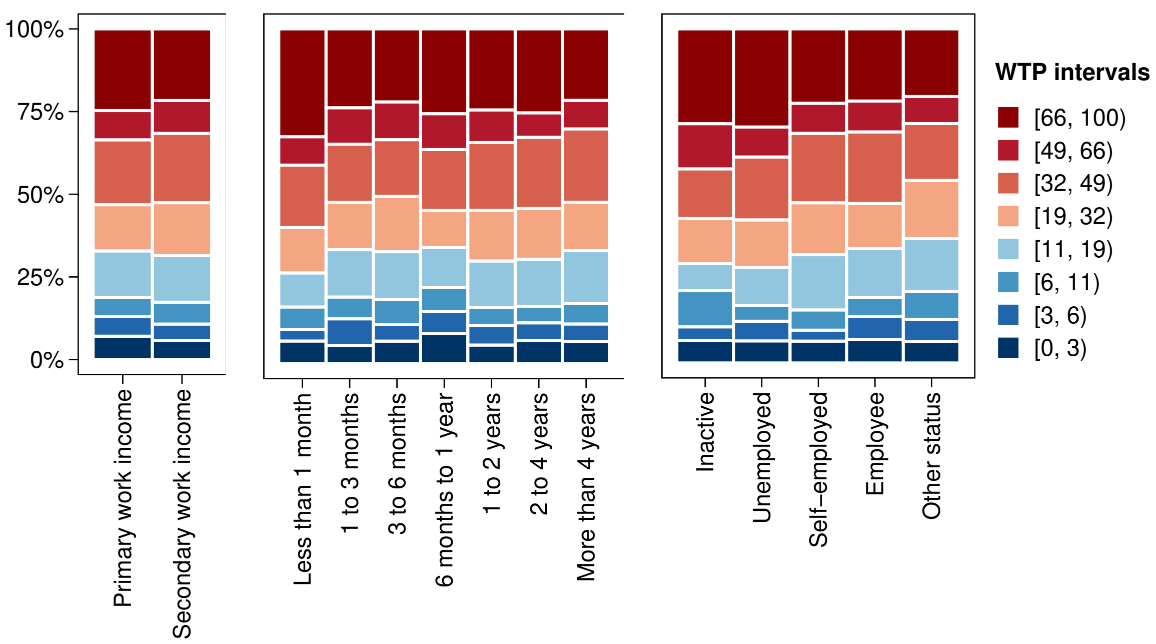


FIGURE 9 – Preferences for same-day remuneration by work profile

Having reviewed some alternative explanations for our findings, I argue that these results reflect primarily a condition of liquidity constraints from the workers' perspective. What is more, even if the choices reported by the Brazilian drivers imply a very high urgency for liquidity, they should not be taken as an anomaly from an exotic setting. To see this point, we may refer to the use of payday loans in the United States, a practice that shares many economic similarities with the patterns we find here despite taking place in a different context. These are short-term advances on a worker's future paycheck, typically over small amounts (80% of them being under US$ 300), with implicit interest rates between 400 and 1,000 percent per year (Stegman 2007), which would be equivalent to 14% to 22% in compounded monthly rates. The conditions for such loans are so extreme that 16 jurisdictions prohibit payday lending under variations of usury laws, but even formal limitations have only a modest effect on actual access to it, as 12% of the consumers in these jurisdictions have taken payday loans at least once in the past 5 years, often through online lenders (Harvey, Robb, and Peterson 2024). In total, 12 million American adults use payday loans annually, most frequently to cover recurring expenses, such as utilities, credit card bills, rent or mortgage payments, or food (the main reason for 69% of the first payday loans), followed by unexpected expenses, such as a car repair or emergency medical expense (16%) (The Pew Charitable Trusts 2012).

Also in the US context, McDevitt and Sojourner (2023) show that people are willing to pay high fees to access the funds from their paper checks faster. Given a choice between depositing a check (and waiting for it to clear through the banking system) and cashing it (for a fee), an extra day of check-clearing time makes the average account holder 65% more likely to cash it. They estimate that the average customer is willing to pay the equivalent of US$ 11.17 per day to get their cash faster, which implies an annualized discount rate of 11,054% for the average check, or 48% per month. In line with our results, they find that such willingness to pay for liquidity is higher among households with the lowest income.

Finally, we can ask what consequences such a strong preference for liquidity could have for the platforms that intermediate the services performed by these drivers. The magnitude of the results allows us to conclude that the companies are most likely saving money by offering payment intervals well under a month (that is, daily or weekly, depending on whether the drivers use the company-issued payment card). To see that, let us perform a simple counterfactual exercise taking at face value the preferences reported by the drivers. If a company were to implement the 30-day rule and pay each driver using the rate they would demand to make this change, the nominal payroll would increase by about 67%, assuming no differential responses in labor supply.[4]

While useful for illustrating the magnitude of these preferences in monetary terms, this is admittedly an extreme scenario. Some drivers at the high end of the WTP distribution would take the deferred payment at rates lower than their preferred ones if that was the only option on the table, a scenario that the elicitation does not cover. However, a large share of them would simply not drive if a short payment interval were not available. The best proxy for this group is the 24% who never took the deferred payment in the experiment. In any case, fast payment schemes seem to allow the platforms to attract more drivers than they would otherwise, which is a strategic need of this business given that a large pool of drivers leads to a lower waiting time for the passengers. This is possible because the returns the platforms would have by keeping the cash for longer (say, via traditional financial instruments) are much lower than the value the workers assign to getting it sooner.

5. Experimental results

This section presents the findings related to the experimental manipulation module. It starts by defining the working sample adopted in the different treatment effect estimations and discusses the randomization balance over the treatment arms.

After that, I apply text analysis to the open-ended responses provided by the drivers as part of their treatments. Since these techniques are not yet standard tools in Economics, I briefly discuss the decisions involved in the process of text cleaning before reporting the patterns of liquidity constraints that emerge from the keywords used by the individuals with the strongest payment urgency.

The core of this section is dedicated to analyzing the treatment effects. The main results suggest that both treatments (either a discussion about emergency expenses or the use of unexpected income) induce ridesharing drivers to decrease the importance they assign to immediate payment and increase the probability they choose a larger payment instead. The section concludes with a discussion of potential cognitive mechanisms behind such an effect.

5.1. Working sample and treatment randomization balance

Given the nature of the data collection, it is reasonable to expect a gradual attrition throughout the questionnaire. The drivers may receive an offer to pick up someone or may want to check an incoming message on their mobile phone, among many other reasons, leading them to drop out at some point. With that

4. This figure can be calculated using microdata at the individual level and is linked to the average willingness-to-pay of 40% reported above by the WTP definition: 0.4 = (1.67 - 1)/1.67.

in mind, the survey was designed to be concise, and achieved a relatively high completion rate. Of the 14,265 individuals who responded to the first question, about two-thirds finished it.

From the perspective of the treatment effect estimation, the main concern is that attrition affects the randomization balance between the different arms. As the first step to address this issue, figure 10 plots the number of respondents by treatment group throughout the survey. Participation is consistently very high in all arms over the initial demographic question. However, respondents were slightly more likely to quit after being asked about how they would address a financial emergency (the red line in the plot), while those facing a hypothetical scenario with a surprise income were less likely to drop out (in green), in comparison to the control group (in blue).

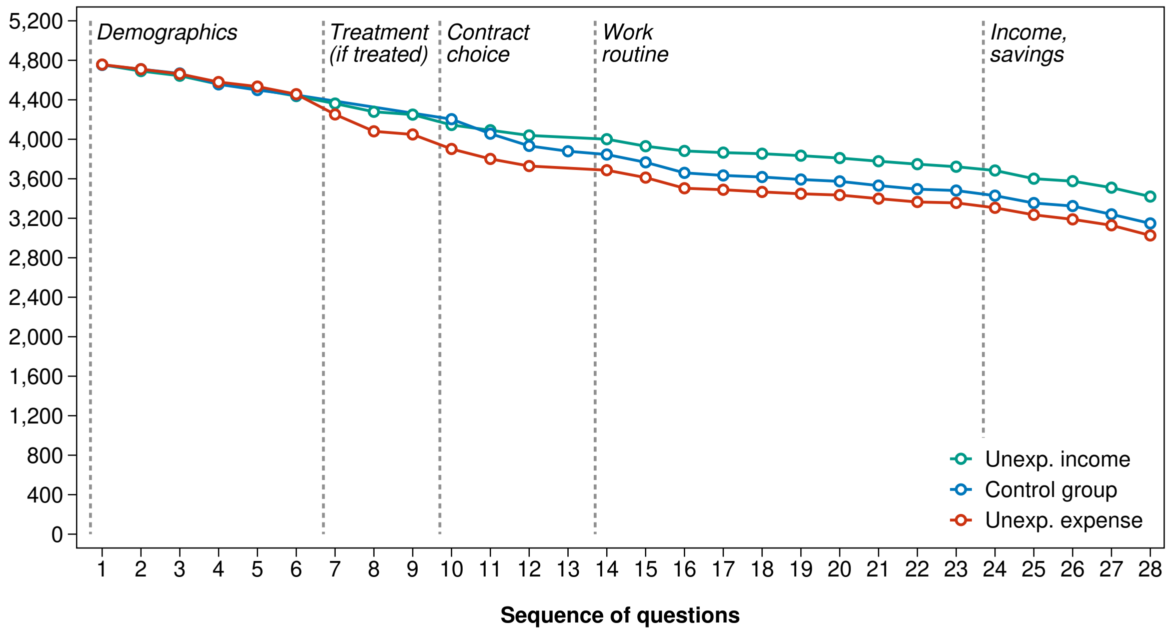


FIGURE 10 – Number of active respondents throughout the survey, by treatment condition. A respondent is considered to be active until the last question they answer. Dotted lines are used to signal a question that was not part of the questionnaire in that particular treatment arm.

To investigate if the differential response rates are affecting the sample composition, we look at the characteristics of the respondents. The statistical summaries presented in table 2 suggest that, while people in the expense treatment condition were marginally more likely to drop out, this attrition was not driven by a particular profile of respondents. Formally, we can reject that the set of attributes we observe are jointly significant to distinguish those who completed the survey within this treatment arm. However, that is not the case for the income treatment. The excess of responses recorded in this group is particularly linked with full-time drivers (and, by extension, those who were previously unemployed, work more hours, and do not contribute to social security).

Table 2 – Summary statistics and randomization balance

	Control group (n = 2,672)	*Treatment group A: unexpected expense (n = 2,597)*		*Treatment group B: unexpected income (n = 2,873)*	
	mean (1)	*mean (2)*	*p-value (1) = (2)*	*mean (3)*	*p-value (1) = (3)*
Gender and ethnicity					
Male	0.94	0.92	0.053	0.93	0.324
Ethinicity					
Black	0.12	0.12	0.836	0.14	0.253
Mixed-race	0.49	0.49	.	0.48	.
White	0.39	0.38	.	0.39	.
Age group					
18 to 27 years old	0.16	0.14	0.327	0.16	0.976
28 to 37 years old	0.39	0.40	.	0.39	.
38 to 47 years old	0.31	0.32	.	0.31	.
48 to 57 years old	0.11	0.11	.	0.11	.
58 years old or more	0.03	0.04	.	0.03	.
Education					
Primary education or less	0.09	0.09	0.833	0.09	0.869
Some high school	0.07	0.07	.	0.08	.
High school	0.45	0.44	.	0.43	.
Some college	0.21	0.22	.	0.22	.
College or above	0.18	0.18	.	0.17	.
Household composition					
N. of adults (age 18+)	2.38	2.40	0.606	2.36	0.366
N. of kids (age < 18)	1.03	1.04	0.908	1.04	0.818
Other jobs					
Driver only	0.62	0.62	0.652	0.67	0.001
Driver and employee	0.20	0.20	.	0.18	.
Driver and self-employed	0.18	0.17	.	0.15	.
Previous status					
Inactive	0.03	0.03	0.067	0.04	0.000
Unemployed	0.27	0.30	.	0.33	.
Self-employed	0.23	0.23	.	0.21	.
Employee	0.38	0.36	.	0.34	.
Other status	0.09	0.09	.	0.09	.
Income					
Income from this work	2,283	2,324	0.201	2,239	0.185
Total household income	4,022	4,096	0.285	3,756	0.001

Table 2 – Summary statistics and randomization balance *(continued)*

	Control group (n = 2,672)	*Treatment group A: unexpected expense (n = 2,597)*		*Treatment group B: unexpected income (n = 2,873)*	
	mean (1)	*mean (2)*	*p-value (1) = (2)*	*mean (3)*	*p-value (1) = (3)*
Work routine					
Work days per week	5.57	5.60	0.439	5.67	0.020
Work hours in a working day	9.21	9.07	0.024	9.26	0.428
How many apps	2.03	2.00	0.178	1.98	0.004
Vehicle ownership					
Rented from friend, family	0.11	0.12	0.460	0.13	0.256
Rented from agency	0.12	0.11	.	0.12	.
Own car, still paying	0.57	0.57	.	0.56	.
Own car, fully paid	0.19	0.20	.	0.19	.
How long in this job					
Less than 1 month	0.02	0.03	0.469	0.02	0.543
1 to 3 months	0.10	0.09	.	0.09	.
3 to 6 months	0.10	0.10	.	0.10	.
6 months to 1 year	0.12	0.11	.	0.13	.
1 to 2 years	0.16	0.15	.	0.17	.
2 to 4 years	0.30	0.29	.	0.30	.
More than 4 years	0.20	0.22	.	0.20	.
Share of work income usually saved					
Less than 10%	0.73	0.69	0.002	0.74	0.376
Between 10% and 25%	0.18	0.21	.	0.18	.
More than 25%	0.09	0.10	.	0.08	.
Social security					
Not currently contributing	0.52	0.52	0.686	0.57	0.002
Public system (as individual)	0.22	0.23	.	0.21	.
Public system (as employee)	0.16	0.16	.	0.15	.
Private system	0.03	0.02	.	0.02	.
Does not know	0.07	0.07	.	0.05	.
Country region					
North	0.08	0.08	0.986	0.08	0.998
Northeast	0.20	0.20	.	0.20	.
Southeast	0.47	0.47	.	0.47	.
South	0.13	0.13	.	0.14	.
Central-West	0.11	0.11	.	0.11	.
Mobile phone					
Android 8 or below	0.03	0.04	0.171	0.04	0.565
Android 9	0.05	0.05	.	0.05	.

Table 2 – Summary statistics and randomization balance *(continued)*

	Control group (n = 2,672)	*Treatment group A: unexpected expense (n = 2,597)*		*Treatment group B: unexpected income (n = 2,873)*	
	mean (1)	*mean (2)*	*p-value (1) = (2)*	*mean (3)*	*p-value (1) = (3)*
Android 10	0.18	0.17	.	0.16	.
Android 11	0.24	0.23	.	0.24	.
Android 12	0.27	0.28	.	0.28	.
Android 13	0.04	0.04	.	0.04	.
iPhone	0.19	0.19	.	0.19	.
Joint significance test					
p-value	.	0.122		0.000	

Notes: [1] The baseline sample is composed of the drivers with valid observations for all attributes displayed in the table. [2] For attributes represented as continuous or binary variables, the p-values refer to the statistical significance test of equality of means between the control group and each of the two treatment groups. It is calculated using an OLS regression of the variable on treatment indicators, with standard errors clustered at the sub-state geographical level, according to the experimental design stratification. [3] For attributes measured as factor variables, the p-value is calculated using a pairwise chi-squared test of independence between the control group and each of the two treatment groups. [4] The joint significance test reports the p-value associated with the F-test from a regression of the treatment indicator on all covariates displayed in the table.

Given the slight excess of primary-job drivers in one of the treatment groups, I favor the estimation techniques that use the available information about the drivers to mitigate the consequences of this imbalance. In practice, it means that the working sample needs to be restricted to the 8,142 individuals for whom we observe the full set of covariates that will serve as controls, which are the ones described in table 2.

5.2. Text analysis

This section serves two purposes. On the one hand, it documents how the respondents are reacting to the treatment questions. In this respect, the evidence suggests that the vast majority of the participants invested the necessary effort to provide meaningful answers when primed to do so. Since the differential exposure to this exercise is precisely the dimension manipulated by the experiment, this analysis opens the treatment black box and provides confidence that it is triggering a response.

On the other hand, by leveraging the information recovered through the open-ended questions, it is possible to investigate further the structural reasons behind the dispersion in preferences documented above. While descriptive in nature, the analysis of the words mentioned by the drivers provides a foundation for the analysis of the underlying determinants of the preferences for quick payment.

The quantitative methods adopted here require the transformation of text strings into high-dimensional count vectors (Ash and Hansen 2023). In essence, the idea is to build a matrix where lines represent individual responses and the columns represent the universe of terms that were mentioned in the sample.

In the present case, individual response is defined as the combination of their answers to both questions that make up the treatment (that is, *what is the first word that comes to mind?* and *what would you do?*). In total, 8,507 individuals typed at least one word in their answers, with over 7,000 unique raw words.

The cleaning consists of harmonizing these terms. As a first step, all characters are transformed to lowercase (for example, "App" to "app"), punctuation and diacritical marks are removed ("gratidão" to "gratidao"). Next, I split words that are unintentionally merged ("boahora" to "boa hora"), correct general misspellings ("poblema" to "problema"), and remove stopwords (frequently used ancillary terms that carry little information by themselves, such as demonstrative pronouns). Finally, I keep a single form for words that can be inflected in Portuguese, undoing number declension ("atrasadas" to "atrasada"), gender declension ("atrasada" to "atrasado") and verb conjugation ("adoraria" to "adorar"). The resulting 1,647 terms are translated to English, for presentation purposes, favoring expressions that are closest to the particular context of this survey.

After this cleaning protocol, we recover two distinct matrices, one for each alternative treatment. The first matrix comprises 1,017 unique terms used by 4,157 drivers when describing their reactions to the hypothetical financial emergency. The top 200 terms in this set are summarized in figure 11, in which size and color intensity are proportional to how often the drivers mention them.

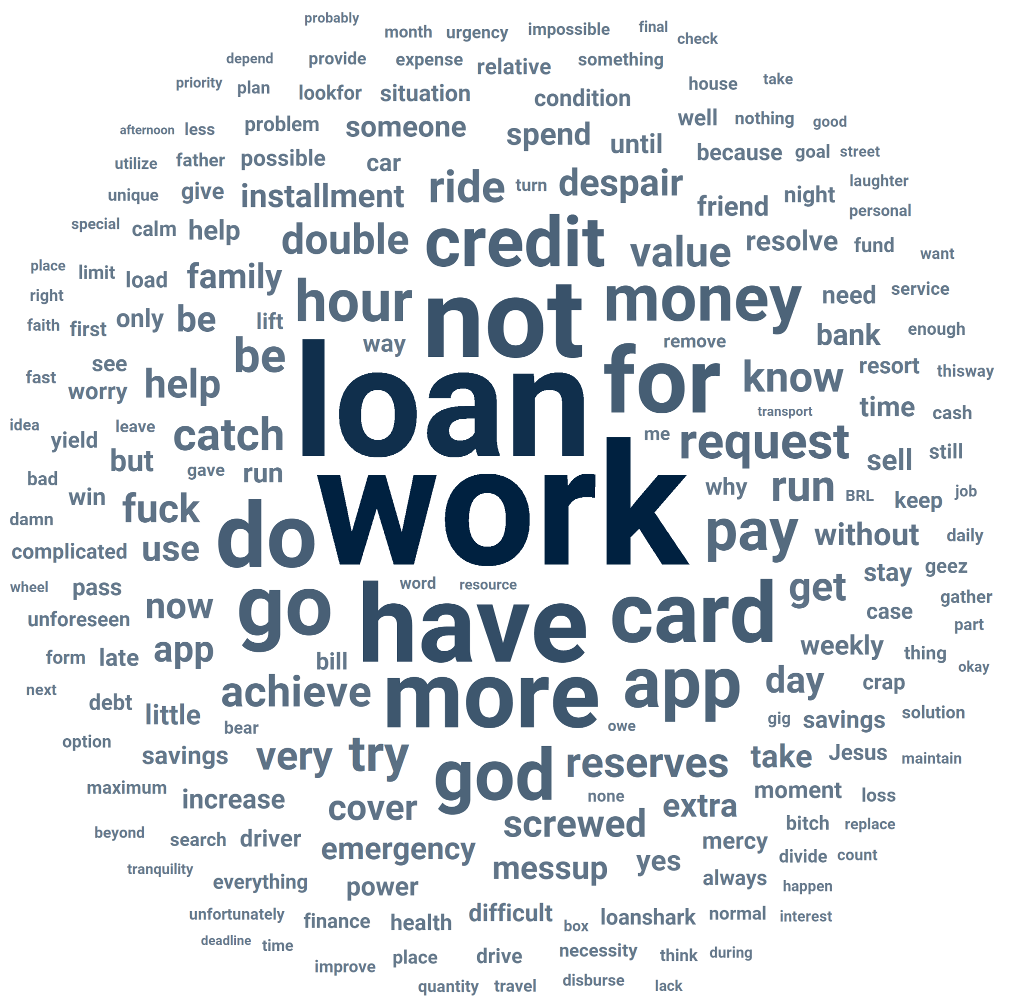


Figure 11 – Most frequent terms mentioned by drivers when discussing how they would cover an unexpected expense. The word cloud depicts the 200 most frequent terms used by the ridesharing drivers who were invited to consider a situation where they would need to disburse R$ 1,400 (US$ 560 PPP) more than expected that week. The size and color intensity are proportional to the incidence of the term. The same representation using the original terms in Portuguese is available in figure 15 in the appendix.

Two concepts stand out in this graphical representation of total frequency: "work" and "loan". This pattern suggests that (a) precautionary savings are often modest or missing among this population and (b) work intensity is a primary margin of adjustment in reaction to negative liquidity shocks. If that is the case, it means that the possibility to choose your hours and quickly cash them can serve as an insurance mechanism.

Taking their responses seriously, how much extra work do people have in mind? A simple extrapolation using the net earnings from section 4 implies that the average driver would need about 130 working hours to make up the R$ 1,400 proposed in the scenario (about 2 or 3 working weeks).

Looking at the mirror image of this problem, the second set of answers includes 1,244 unique terms used by 4,350 drivers to discuss what they would do with an unexpected cash windfall. The word cloud shown in figure 12 is dominated by a single term: "pay". In this context, the most common reaction appears to be guided by concerns with recurring household bills and outstanding debts.

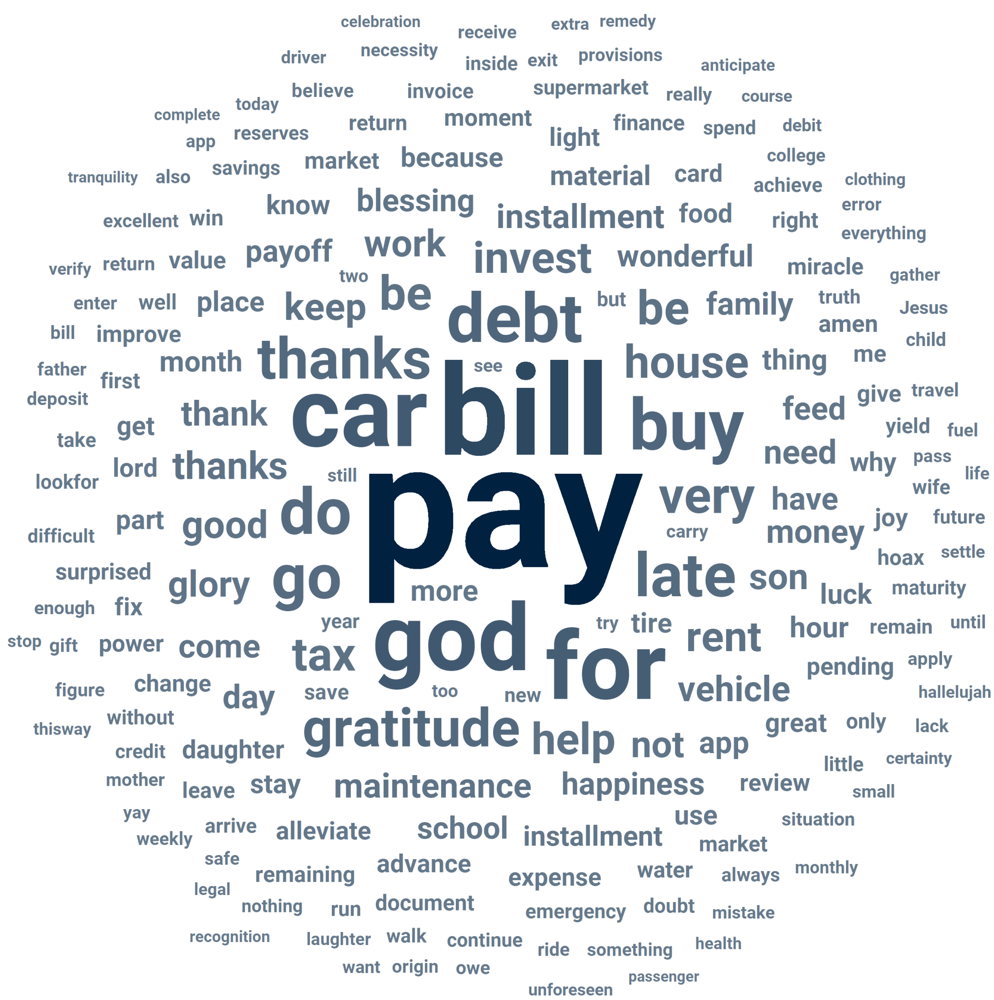


Figure 12 – Most frequent terms mentioned by drivers when discussing what they would do with an unexpected income. The word cloud depicts the 200 most frequent terms used by the ridesharing drivers who were invited to consider a situation where they would receive an unexpected deposit of R$ 1,400 (US$ 560 PPP) that week. The size and color intensity are proportional to the incidence of the term.

It is interesting to note that the religious terms are clearly present in both scenarios. In the first case, "God" comes to mind as a potential source of relief given the financial struggle, while religious terms show up associated with expressions of gratitude in the second group. Likewise, family members are mentioned in both circumstances, as the primary social network available during emergency situations and to share the windfall.

While word clouds are useful for highlighting the predominant topics, they must be complemented with other strategies that are better suited to uncovering the associations between the responses and other observable features. In particular, we want to study which terms are disproportionally adopted by individuals who also show a very strong preference for quick payment rules.

For simplicity, I divide the drivers into two groups: the top third of the distribution (those who claim to prefer same-day payment over 2 or 3 times larger rates) and the rest. The keyword analysis, in this case, is analogous to a chi-square test for a contingency table, in which we study whether a given term is statistically overrepresented in one of the groups. The higher the chi-square statistic, the stronger the evidence against the null hypothesis that a given term is equally likely to be used in both groups. If the term appears in excess among people with high WTP for same-day remuneration, the test statistic is positive (depicted by the red lines in the keyword plots), and it is negative otherwise (the blue lines in the plots).

The results show that the people who rely on family members and on their own labor to help them fix a financial emergency are more likely to prioritize fast payment, as summarized in figure 13. On the other end, drivers who already have credit cards and precautionary funds available are the ones favoring larger earnings.

Similarly, the terms describing potential uses of the unexpected income reflect a strong polarization between circumstances of pressing needs (drivers claiming they would spend their cash windfall procuring food for their household tend to have the strongest preferences for same-day payment) and precautionary behavior (drivers who would save the money for the future also favor contracts with larger, deferred payments), as shown in figure 14.

A critique to this type of analysis is that words lose much of their meaning outside a sentence. While this remains an important caveat in this chapter, the concern is partially mitigated by the constraints imposed by the text collection strategy. We have the benefit of recording responses that are not bounded by a small pool of close-ended alternatives, while being sufficiently tied to the context to give us confidence in their interpretation. For instance, if we had a random sample of twitter posts, it would be hard to interpret the excess of terms like "family", compared to our case where they appear in the reaction to a particular financial scenario.

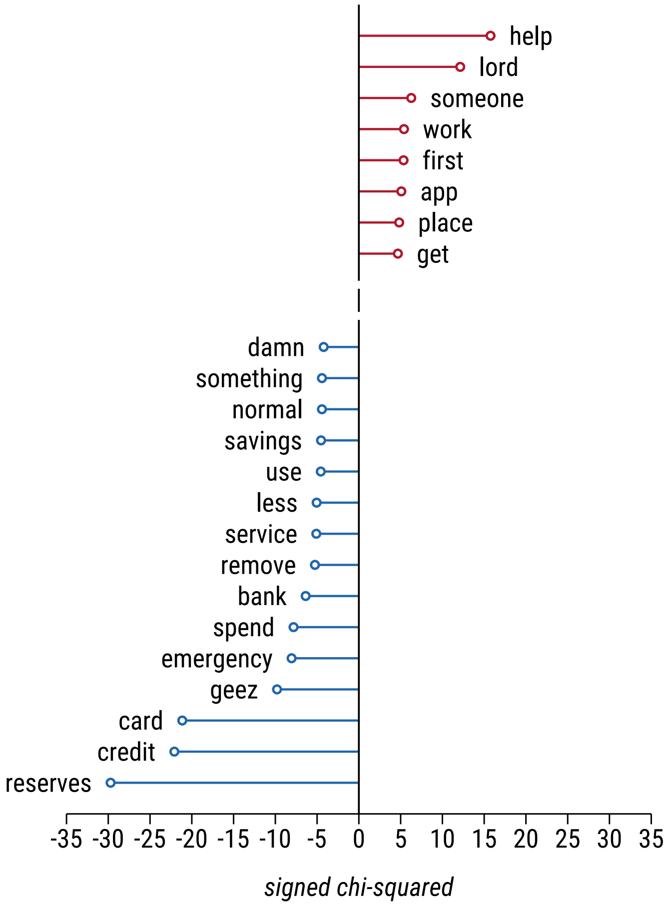


Figure 13 – Keywords from the *liquidity* discussion that distinguish the drivers with the strongest preference for same-day payment. The plot includes terms that were mentioned by more than 0.1% of the individuals and have a chi-squared statistic of at least 3.84, the critical value for 5% significance in a test with two groups. The break in the vertical axis is a reminder that all terms with a statistic in the interval [-3.84, 3.84] are omitted.

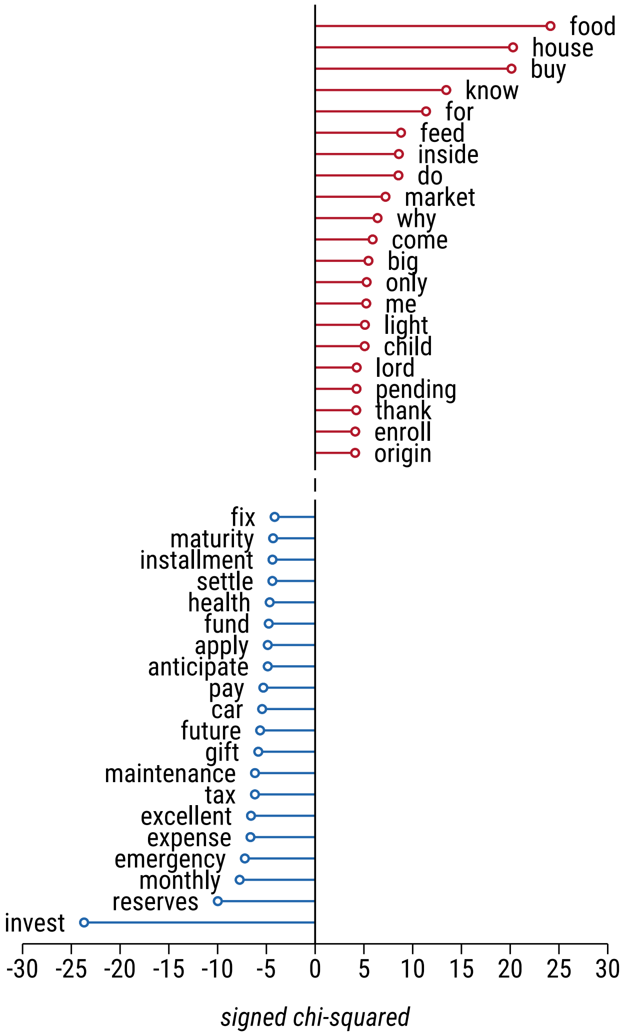


FIGURE 14 – Keywords from the *consumption* discussion that distinguish the drivers with the strongest preference for same-day payment. The plot includes terms that were mentioned by more than 0.1% of the individuals and have a chi-squared statistic of at least 3.84, the critical value for 5% significance in a test with two groups. The break in the vertical axis is a reminder that all terms with a statistic in the interval [-3.84, 3.84] are omitted.

5.3. Average treatment effects

This section investigates whether the salience of the workers' financial circumstances, as exogenously induced by the budget questions, changes how they perceive the importance of fast earnings.

In the baseline specification, the average treatment effects are estimated via ordinary least squares as:

$$Y_i = \alpha + \beta_{exp}\ \mathit{Expense\ Discussion}_i + \beta_{inc}\ \mathit{Income\ Discussion}_i + \gamma X_i + \varepsilon_i \tag{1}$$

where *Expense Discussion* and *Income Discussion* are indicators for random assignment to one of the treatment arms. The outcome Y_i is the relative value of the contract that pays faster, measured as the midpoint of the WTP interval recovered from the preference elicitation protocol. The estimation also controls for a set of sociodemographic and work-related covariates, X_i, which are described in table 2. The standard errors are clustered at the regional level adopted in the stratified randomization (defined as capital and non-capital areas, for each state).

The inclusion of other covariates in this estimation is justified by two reasons. First, the individual attributes we observe in the data can be structural determinants of the drivers' preferences for payment timing. In this case, they can be associated with some of the dispersion in choices, and including them as controls increases the precision of the estimates.

Second, at least one of the treatment arms is unbalanced relative to the reference group in terms of observable characteristics. If different profiles of drivers are reporting their preferences in each group, the differences in averages between treatment arms cannot be assigned to the treatment only. The introduction of the full set of covariates controls for such imbalance.

Before moving on to the results, it is useful to review what we might hope to learn from this design. A priori, the unexpected expense treatment could reinforce the perception of financial hardship and cause people to prioritize fast payment even more, especially those who already have a relatively high WTP. Alternatively, this treatment could push them to consider the long-term consequences of the trade-off more carefully, as a permanently higher income is a more effective way to cover that sort of hypothetical emergency in the future. Furthermore, if the results are driven by the specific content of the mental exercise (expenses imposing an extra burden, windfall alleviating constraints), the complementary arm with the unexpected income would flip the signs of the effect. Finally, if the effect of both treatments is simply to increase one's awareness, considering that the information recovered to answer the question sets is not too different, both treatments could lead to a similar effect, whose sign should be determined empirically.

The main experimental results are summarized in table 3. The first column reports the simple difference between the average WTP for treated and control drivers, using the midpoint of the WTP interval as the outcome. The second column reports the estimates from the regression described in equation (1), introducing the controls. Finally, the third column is an interval regression estimated using maximum likelihood, a specification that is more general because it formally incorporates the fact that the outcome is always observed between two boundaries.

Table 3 – Effects of budget salience on the WTP for same-day remuneration

	outcome: WTP midpoint		*outcome: WTP interval*
	Difference in Means	OLS	Interval Regression
	(1)	(2)	(3)
Treatment A:			
Unexpected expense discussion	-1.3	-1.7	-1.6
	(0.7)	(0.7)	(0.7)
Treatment B:			
Unexpected income discussion	-0.7	-1.6	-1.5
	(0.8)	(0.7)	(0.6)
Reference level:			
Control group mean	39.9	39.9	37.4
	(0.7)	(0.7)	(0.6)
Number of observations	8,142	8,142	8,142

Notes: The standard errors (reported in parenthesis under the point estimate) are clustered at the regional level. For the interval regression, the estimation results are bootstrapped over 500 replications. The controls in (2) and (3) include geographical area, gender, race, age, education, household composition, work experience, previous labor market status, number of apps, vehicle ownership, work days per week, work hours per day, extra jobs, looking for another job, work income from driving, total household income, savings, and pension contribution.

The main experimental result is that both the unexpected expenses and the unexpected income discussions led to a small decrease in the importance of same-day compensation, as reported in table 3. The preferred specifications (columns 2 and 3) suggest that the average WTP for same-day remuneration is at least 1.5 percentage points lower for treated drivers, relative to those in the reference group. Still looking at the specifications that include controls, we cannot reject that the effect is statistically the same in both treatments.

Notably, we also find that the effect is not homogeneous over the underlying distribution of preferences for payment timing. To investigate who is driving this result, I look at each threshold separately. Under the assumption that the ranking of preferences is stable, it is possible to stack the indifference intervals. That is, if 24% of the respondents have a WTP above 66%, and 9% have a WTP between 49% and 66%, then 33% have a WTP above 49%. This approach has the advantage of using the frontiers of the intervals as it was elicited, with no need for extra assumptions for their midpoints.

Using each possible threshold in turn, I study the level at which the effects take place, as reported at table 4. One pattern stands out: the treatments have small effects, if any, on the share of people with WTP above 6%, 11%, or 19%, but there is evidence that both treatments reduce the share of people choosing same-day remuneration against very large multipliers (1.5, 2 or 3 times) within 30 days.

Overall, drivers appear to be more likely to consider larger, deferred payments after mentally recovering their financial conditions. This result is consistent with the interpretation that the drivers in the control group are providing their first, intuitive answer to the contract choice — while treated subjects were judging the optimal balance between flexibility and long-term results with their financial context slightly more salient in their minds.

Table 4 – Average effects of budget salience on the probability of choosing a contract above a given threshold

	Linear Probability Model						
	Outcome: WTP > 3%	*Outcome: WTP > 6%*	*Outcome: WTP > 11%*	*Outcome: WTP > 19%*	*Outcome: WTP > 32%*	*Outcome: WTP > 49%*	*Outcome: WTP > 66%*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treatment A:							
Unexpected expense discussion	-1.9	-1.4	-0.8	-0.8	-2.2	-2.8	-2.5
	(0.7)	(0.8)	(1.0)	(1.6)	(1.3)	(1.0)	(0.9)
Treatment B:							
Unexpected income discussion	0.4	0.3	-0.1	-1.5	-2.6	-3.0	-2.2
	(0.6)	(0.9)	(1.2)	(1.4)	(1.4)	(1.0)	(1.0)
Reference level:							
Control group mean	93.3	87.6	81.6	67.5	53.0	33.0	23.9
	(0.5)	(0.7)	(0.9)	(1.1)	(1.1)	(1.0)	(1.0)
Number of observations	8,142	8,142	8,142	8,142	8,142	8,142	8,142

Notes: The standard errors (reported in parenthesis under the point estimate) are clustered at the regional level. The controls include geographical area, gender, race, age, education, household composition, work experience, previous labor market status, number of apps, vehicle ownership, work days per week, work hours per day, extra jobs, looking for another job, work income from driving, total household income, savings, and pension contribution.

5.4. Potential mechanisms

From the perspective of the behavioral literature, the intervention induces a costly cognitive process that combines memory and a mental accounting exercise (*what would you do if...*). The subjects' responses retrieve particular features of their household budgets and thus provide them with an implicit reference point for the subsequent question (Gennaioli and Shleifer 2010; Shleifer 2012; Bordalo, Gennaioli, and Shleifer 2020, 2022).

In the present case, how can we make sense of the effects introduced by the treatments? Since the magnitude and signs of the effects are similar, we should look at what the treatments have in common: both require a costly information retrieval that puts the trade-off into a more complex context. In my preferred interpretation, it is precisely this common feature of both treatments that drives the modest effect I find. Relative to the control group, treated individuals were primed to actively consider their financial conditions. Once they have this information active in their minds (due to the expenses *or* the income questions), they can project themselves in the future, ponder the alternatives more carefully, and become less likely to pick the safest (but more expensive) option. The exposure to the financial question, more than its exact formulation, seems to be behind the key mechanism.

Another piece of evidence that supports this interpretation is their response time, which is precisely recorded by the survey instrument. While it is not possible to claim that individuals in both treatment groups were thinking *harder* about the trade-off, they did think *longer* than individuals in the control group. This result is consistent with treated individuals perceiving the question as a harder one, or being more careful in their choices, given the richer set of information that was made salient to them. Table 5 reports how the response time differed between treatment arms. The specification follows the baseline equation (1) closely, including the controls, except that the outcome here is the number of seconds spent on each of the three questions that make up the elicitation protocol. On average, drivers exposed to the expense discussion took 5 more seconds to complete the whole protocol, and those in the income discussion treatment took 3 seconds longer, out of an average of about 90 seconds for the control group. In both cases, the increase is most clearly identified in the third question.

This pattern is informative because the third question should, by design, offer people a trade-off closer to their indifference point. While the average time falls from the first to the third question due to the increasing familiarity with the structure of the alternatives, it does not fall as much in the treatment groups, where a share of the drivers appears to be taking the time to contemplate contracts that pay them more.

Table 5 – Effect of budget salience on the time to choose a contract

	outcome: seconds on q1	*outcome: seconds on q2*	*outcome: seconds on q3*	*outcome: total seconds*
	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)
Treatment A:				
Unexpected expense discussion	2.5	1.1	1.1	5.0
	(0.9)	(0.4)	(0.3)	(1.5)
Treatment B:				
Unexpected income discussion	0.9	0.8	1.3	3.0
	(1.1)	(0.5)	(0.3)	(1.8)
Reference level:				
Control group mean	49.9	22.5	15.8	90.1
	(1.0)	(0.4)	(0.2)	(1.5)
Number of observations	8,142	8,142	8,142	8,142

Notes: Response times are winsorized at 1 percent. The standard errors (reported in parenthesis under the point estimate) are clustered at the regional level. Controls include geographical area, gender, race, age, education, household composition, work experience, previous labor market status, number of apps, vehicle ownership, work days per week, work hours per day, extra jobs, looking for another job, work income from driving, total household income, savings, and pension contribution.

As a caveat, I cannot rule out that the treatments led to a modest decrease in the reported WTP each for a different reason. For instance, the mental budget under a positive shock could trigger a perception of liquidity relief, while the negative shock could lead to a budget reconsideration and increase the attractivity of larger monetary amounts. However, if one of those were indeed the key mechanism, we should expect opposite effects for each arm, since the treatments intentionally mirror the other. For this reason, I maintain as my preferred explanation that the results were driven by what the questions have in common, and not by what makes them different.

6. Robustness analysis

The main threat to the identification of the experimental effects comes from the differential attrition rate observed between the treatment arms. Individuals exposed to the unexpected expenses question were more likely to quit the survey, while those exposed to the income question were more likely to finish it.

The baseline estimation addresses this concern by including a set of sociodemographic and work-related covariates as controls in the OLS equation. In this section, I adopt doubly robust techniques to provide further evidence that the results are not induced by eventual imbalances between treatment groups (Bang and Robins 2005; Tan 2010; Wooldridge 2010).

As summarized in table 6, the doubly robust estimates reinforce the finding that the increased salience of the household financial conditions induced by the expense and income questions led to a small marginal decrease in the average willingness to pay for same-day compensation. The point estimates for the doubly robust estimations are between -1.4 and -1.5 percentage points, qualitatively similar to the baseline results.

Table 6 – Doubly robust estimation of the effect of budget salience on the time to choose a contract

	outcome: WTP midpoint		*outcome: WTP interval*
	Difference in Means	Doubly Robust: IPW and Covariate Adj. via Regression	Doubly Robust: IPW and Covariate Adj. via Interval Regression
	(1)	(2)	(3)
Treatment A:			
Unexpected expense discussion	-1.3	-1.5	-1.5
	(0.7)	(0.7)	(0.7)
Treatment B:			
Unexpected income discussion	-0.7	-1.5	-1.4
	(0.7)	(0.7)	(0.7)
Reference level:			
Control group mean	39.9	40.2	38.9
	(0.7)	(0.6)	(0.7)
Number of observations	8,142	8,142	8,142

Notes: The standard errors (in parenthesis) are clustered at the regional level. In (2) and (3), the standard errors also account for the estimation of the inverse probability weights (IPWs): in (2), the errors are calculated analytically; in (3), the two steps are bootstrapped over 500 replications. The additional controls used in (2) and (3), both in the regression and the propensity estimation, are the same covariates adopted in the baseline estimation.

For reference, I keep the simple difference in means in the first column. As discussed in the baseline result section, the direct comparison between the average WTP in the control group and in the treatment groups underestimates the effect of the budget discussion, particularly in the arm that discusses the use of an extra income. More importantly, columns 2 and 3 adopt the full set of controls and weight the observations by the inverse probability of being observed in the group where they are. The most conservative estimation is in column 3, as the covariate adjustment and the IPW are applied with an interval regression estimation.

Table 7 – Doubly robust estimation of the effects of budget salience on the probability of choosing a contract above a given threshold

	Doubly Robust Method: Inverse Probability Weight and Covariate Adjustment via Regression						
	Outcome: WTP > 3%	*Outcome: WTP > 6%*	*Outcome: WTP > 11%*	*Outcome: WTP > 19%*	*Outcome: WTP > 32%*	*Outcome: WTP > 49%*	*Outcome: WTP > 66%*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treatment A:							
Unexpected expense discussion	-1.9	-1.3	-0.6	-0.4	-1.9	-2.7	-2.4
	(0.6)	(0.8)	(0.9)	(1.4)	(1.3)	(1.0)	(1.0)
Treatment B:							
Unexpected income discussion	0.5	0.4	0.0	-1.3	-2.4	-3.0	-2.2
	(0.6)	(0.9)	(1.2)	(1.3)	(1.3)	(1.0)	(1.0)
Reference level:							
Control group mean	93.4	87.8	82.0	68.0	53.3	33.6	24.2
	(0.4)	(0.7)	(0.8)	(1.0)	(1.1)	(0.9)	(0.9)
Number of observations	8,142	8,142	8,142	8,142	8,142	8,142	8,142

Notes: The standard errors (in parenthesis) are clustered at the regional level and account for the joint estimation of the inverse probability weights (IPWs). The additional controls, both in the regression and the propensity estimation, are the same covariates adopted in the baseline estimation.

Finally, table 7 reports the doubly robust estimates on the probability of assigning a value to the early payment option superior to each of the reference thresholds defined in the elicitation method. The same conclusion from the baseline estimation holds: the bulk of the effects come from a reduction in the share of drivers who would prefer same-day payment even against very high multipliers (that is, paying 2 or 3 times as much).

7. Concluding remarks

This chapter finds that ridesharing drivers tend to prioritize work contracts that pay faster over contracts that pay more. Such a preference is particularly strong among drivers from the poorest households, those who have little precautionary savings and no access to credit, and those who would spend their marginal dollar on food.

As a whole, this body of evidence supports the interpretation that scarcity and liquidity constraints can *by themselves* be part of the structural context that makes workers turn down offers that would pay them more. The workers who would benefit the most from higher earnings are the ones most likely to refuse them.

The simplest justification for this puzzling result is that choices that pay faster are valuable simply because they address the pressing needs of today. This chapter takes a step further and claims that the quick payment feature also compounds the benefit of flexibility in hours that is characteristic of the platform work context. If prompt payment provides a source of liquidity, prompt payment for the amount of work of one's choosing serves as insurance. This new perspective stresses how labor market arrangements can partly substitute for pure financial instruments if those are not fully available. When that happens, a work remuneration scheme is not only valued as the exchange between labor and money; it can also embed an exchange between labor and money *over time* (sooner rather than later) and *over states* (whenever is needed). Under these conditions, the same-day contract may be the most appealing alternative — even if it is an expensive one.

The conclusion that fast payment can be a safe, intuitive, automatic choice for many workers in this population is supported by the results of the experimental intervention. Simple questions about a hypothetical expense or windfall appear to remove the treated workers from the automatic setting and force them to pause and evaluate their financial conditions for a moment. The subsequent contract choices are then more reflexive, use some extra seconds of response time, and become marginally more likely to favor larger payments.

Importantly, the small magnitude of the experimental results also allows us to conclude that the very large WTP recorded for the control group is not a result of lack of attention or pure heuristics bias. Treated individuals spend significantly more time in the preference elicitation protocol and yet their average WTP reduces by no more than a few points. Whatever structural reasons explain the distribution of choices, they appear to be more relevant than the primed salience of financial circumstances.

Taking a broader perspective, the general question of the timing of the workers' paycheck has received much less attention in the labor economics literature than other job features. In this sense, this chapter claims that this dimension can be consequential and merits further research. In the context of developing countries, short payment timing is a relevant issue because it can contribute to the persistence of informal arrangements and self-employment. But workers in rich countries are not immune to similar tradeoffs. As platforms and other non-standard work arrangements become more common, payment schedules can become a more salient margin in the labor markets around the globe.

More concretely, as policymakers are actively moving to regulate platform work, this chapter invites them to consider that their relatively rapid payment is a feature appreciated by the people who have self-selected into this activity. Surprisingly, it is of primary importance for those driving full-time as well as for occasional drivers, two groups that are otherwise very different. In this sense, my implications complement the findings from Koustas (2018, 2019), who stresses how gig work can partly offset financial shocks.

The other side of this coin is that fast payment (combined with flexible labor supply) is likely one of the reasons why modern gig work can be popular while paying relatively little. The underlying risk is that it becomes a dead end: if this activity does not foster human or financial capital accumulation, people could be locked into a low-income equilibrium in which the low pay from gig work leaves them vulnerable to future shocks, which increases the insurance value of this kind of work, generating a negative feedback loop. The next step in this research agenda should be to assess if these activities lead to net welfare gains for the workers (by providing them with a viable option to mitigate shocks) or net welfare losses (by limiting their earnings in the long term).

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Appendix A. Additional figures and tables

FIGURE 15 – Most frequent terms mentioned by drivers when discussing how they would cover an unexpected expense (original terms in Portuguese). The word cloud depicts the 200 most frequent terms used by the ridesharing drivers who were invited to consider a situation where they would need to disburse R$ 1,400 (US$ 560 PPP) more than expected that week. The size and color intensity are proportional to the incidence of the term.

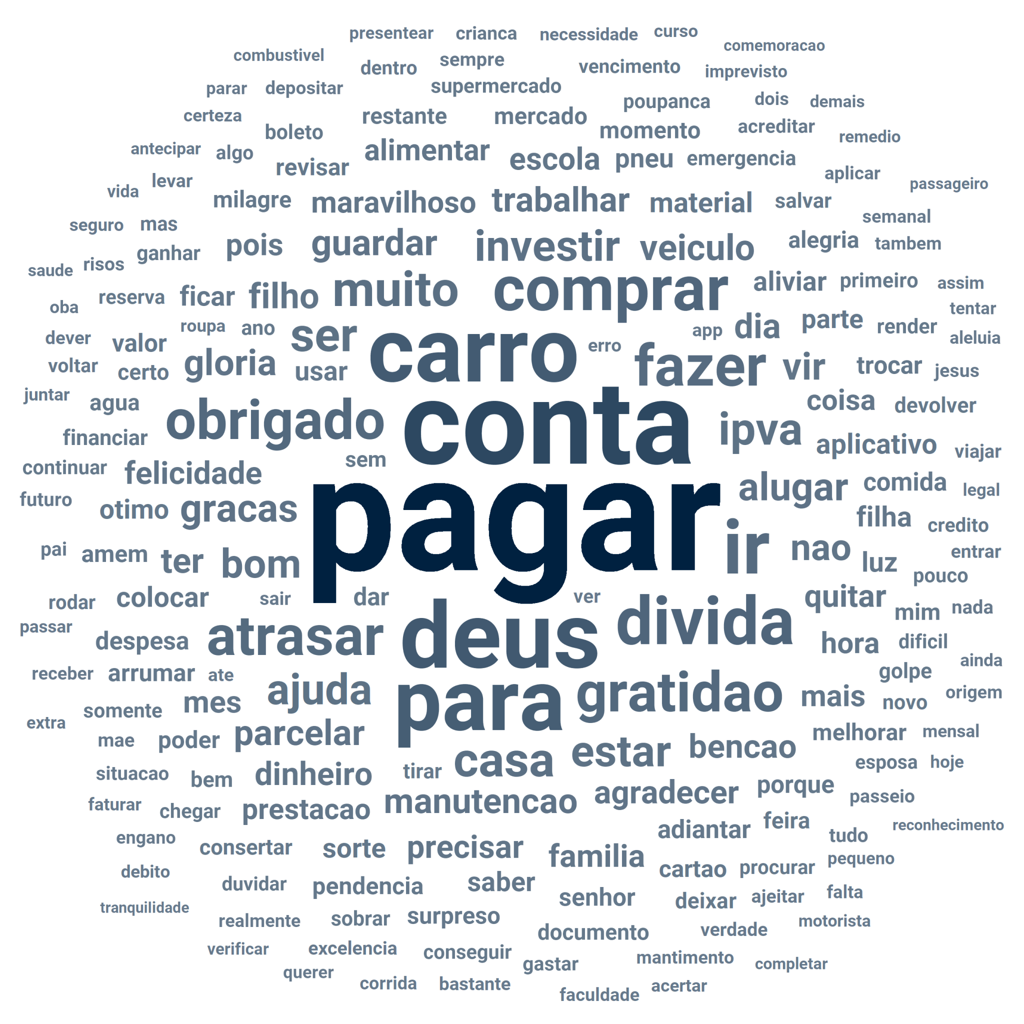

Figure 16 – Most frequent terms mentioned by drivers when discussing what they would do with an unexpected income (original terms in Portuguese). The word cloud depicts the 200 most frequent terms used by the ridesharing drivers who were invited to consider a situation where they would receive an unexpected deposit of R$ 1,400 (US$ 560 PPP) that week. The size and color intensity are proportional to the incidence of the term.

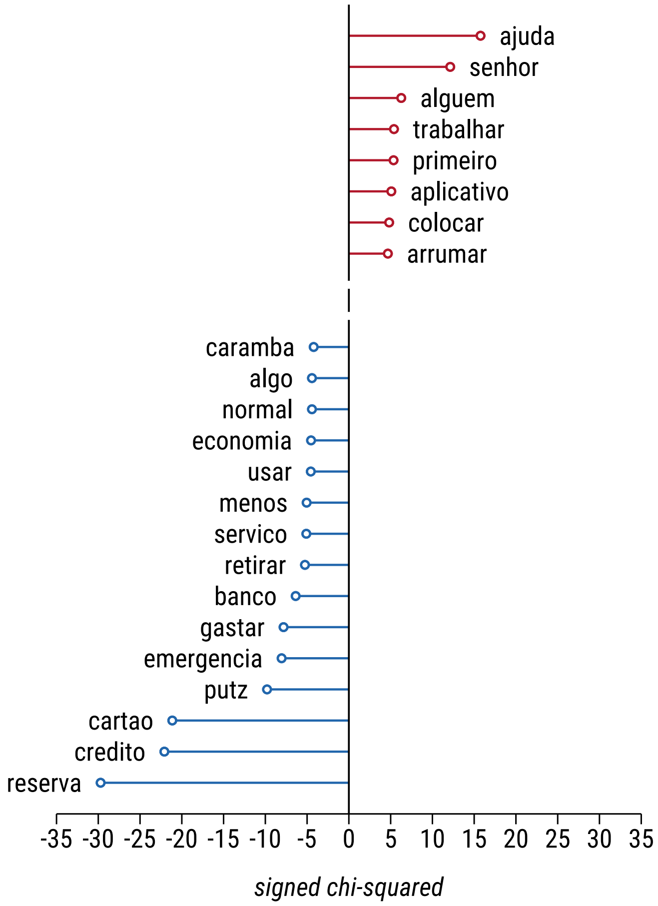

Figure 17 – Keywords from the *liquidity* discussion that distinguish the drivers with the strongest preference for same-day payment. The plot includes terms that were mentioned by more than 0.1% of the individuals and have a chi-squared statistic of at least 3.84, the critical value for 5% significance in a test with two groups. The break in the vertical axis is a reminder that all terms with a statistic in the interval [-3.84, 3.84] are omitted.

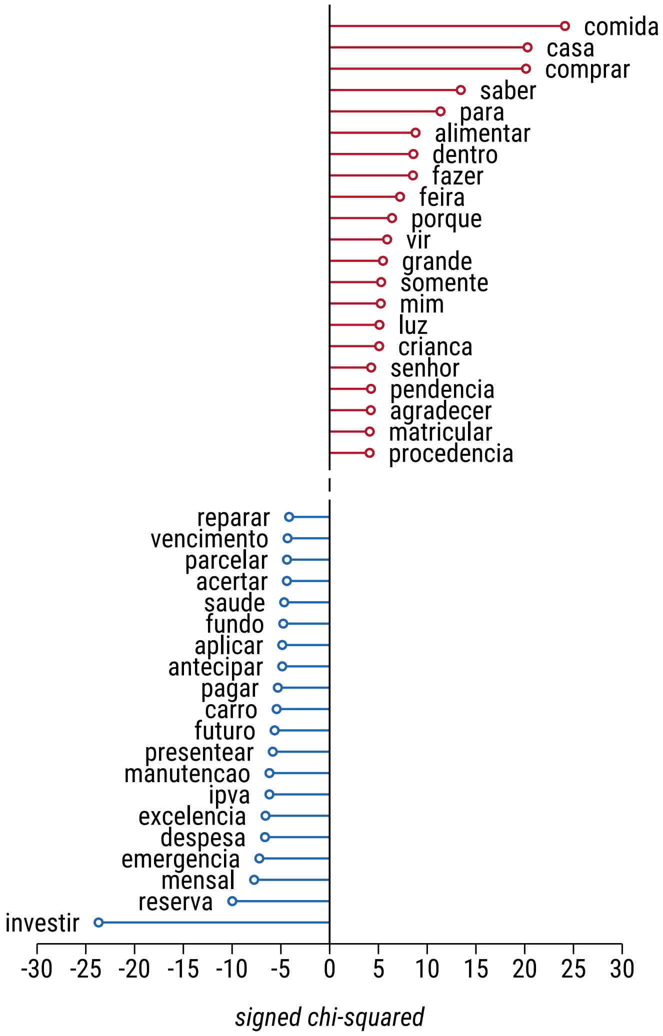

Figure 18 – Keywords from the *consumption* discussion that distinguish the drivers with the strongest preference for same-day payment.The plot includes terms that were mentioned by more than 0.1% of the individuals and have a chi-squared statistic of at least 3.84, the critical value for 5% significance in a test with two groups. The break in the vertical axis is a reminder that all terms with a statistic in the interval [-3.84, 3.84] are omitted.

Table 8 – Characteristics of the male ridesharing drivers in the survey and corresponding summaries for male urban adult workers

	Ridesharing Drivers Survey						*National Household Survey (PNADC)*					
	All drivers		*Driver as main job*		*Driver as secondary job*		*Male adult urban workforce*		*Male adult urban own-account workers*		*Male adult urban employees*	
	stat.	*s. e.*	*stat.*	*s. e.*	*stat.*	*s. e.*	*stat.*	*s. e.*	*stat.*	*s. e.*	*stat.*	*s. e.*
Ethinicity (share in %)												
Black	13.8	(0.30)	13.6	(0.41)	14.5	(0.70)	11.7	(0.20)	11.4	(0.38)	12.2	(0.24)
Mixed-race	49.6	(0.44)	49.2	(0.59)	48.1	(1.00)	44.0	(0.31)	44.6	(0.51)	43.9	(0.38)
White	36.6	(0.42)	37.2	(0.57)	37.3	(0.96)	44.2	(0.33)	44.0	(0.54)	43.9	(0.39)
Age group (share in %)												
18 to 27 years old	14.3	(0.31)	15.2	(0.42)	12.3	(0.65)	23.1	(0.23)	14.0	(0.37)	25.6	(0.30)
28 to 37 years old	38.2	(0.43)	39.0	(0.58)	37.2	(0.96)	26.3	(0.25)	24.1	(0.47)	28.3	(0.33)
38 to 47 years old	31.4	(0.41)	29.9	(0.54)	34.9	(0.95)	23.9	(0.22)	25.0	(0.43)	24.0	(0.28)
48 to 57 years old	12.1	(0.29)	11.8	(0.38)	12.0	(0.64)	16.8	(0.18)	20.7	(0.36)	15.2	(0.24)
58 years old or more	4.1	(0.17)	4.1	(0.23)	3.6	(0.37)	9.9	(0.15)	16.2	(0.35)	6.9	(0.15)
Education (share in %)												
Primary education or less	11.5	(0.28)	11.3	(0.37)	8.6	(0.56)	28.2	(0.28)	38.5	(0.50)	23.9	(0.32)
Some high school	8.1	(0.24)	8.5	(0.33)	5.8	(0.46)	7.6	(0.14)	7.7	(0.26)	7.2	(0.17)
High school	44.6	(0.44)	45.1	(0.59)	44.0	(0.99)	38.0	(0.29)	34.4	(0.48)	39.6	(0.37)
Some college	20.2	(0.36)	20.9	(0.48)	20.1	(0.80)	6.7	(0.14)	4.8	(0.21)	7.5	(0.18)
College or above	15.5	(0.32)	14.2	(0.41)	21.4	(0.82)	19.4	(0.32)	14.6	(0.46)	21.8	(0.39)
Household composition												
N. of adults (age 18+)	2.4	(0.01)	2.4	(0.01)	2.4	(0.02)	2.6	(0.01)	2.5	(0.01)	2.6	(0.01)
N. of kids (age < 18)	1.1	(0.01)	1.1	(0.01)	1.1	(0.02)	0.7	(0.01)	0.7	(0.01)	0.8	(0.01)

Table 8 – Characteristics of the male ridesharing drivers in the survey and corresponding summaries for male urban adult workers *(continued)*

	Ridesharing Drivers Survey						*National Household Survey (PNADC)*					
	All drivers		*Driver as main job*		*Driver as secondary job*		*Male adult urban workforce*		*Male adult urban own-account workers*		*Male adult urban employees*	
	stat.	*s. e.*	*stat.*	*s. e.*	*stat.*	*s. e.*	*stat.*	*s. e.*	*stat.*	*s. e.*	*stat.*	*s. e.*
Work routine												
Work hours per week	53.5	(0.25)	60.7	(0.27)	33.3	(0.40)	41.6	(0.06)	40.6	(0.14)	41.7	(0.06)
Monthly income (in R$)												
Average work income	2,305	(15)	2,542	(18)	1,635	(24)	3,128	(35)	2,522	(41)	3,061	(36)
Average household inc. per capita	1,384	(12)	1,335	(14)	1,520	(26)	2,106	(24)	1,922	(31)	2,149	(27)
How long in this job (share in %)												
Less than 3 months	11.8	(0.31)	9.9	(0.35)	16.0	(0.73)	10.6	(0.18)	8.6	(0.29)	12.1	(0.23)
3 to 6 months	9.7	(0.29)	8.9	(0.34)	12.2	(0.65)	6.0	(0.15)	4.1	(0.29)	7.3	(0.18)
6 months to 1 year	11.5	(0.31)	11.4	(0.38)	11.9	(0.64)	5.8	(0.13)	3.9	(0.20)	7.0	(0.17)
1 to 2 years	16.6	(0.36)	16.0	(0.43)	17.9	(0.76)	10.3	(0.17)	7.1	(0.26)	12.2	(0.23)
2 to 4 years	29.8	(0.44)	31.0	(0.55)	26.7	(0.88)	21.8	(0.22)	21.4	(0.40)	22.4	(0.28)
More than 4 years	20.5	(0.39)	22.8	(0.50)	15.3	(0.72)	45.5	(0.29)	54.9	(0.51)	39.0	(0.35)
Social indicators (share in %)												
Contributes to a pension system	43.4	(0.55)	31.5	(0.61)	76.3	(0.93)	66.9	(0.29)	32.7	(0.50)	81.6	(0.28)
Household inc. per cap. < USD 5.5/day	11.0	(0.33)	12.0	(0.40)	8.4	(0.57)	8.4	(0.16)	9.0	(0.29)	4.9	(0.14)
Country region (share in %)												
North	8.7	(0.25)	8.4	(0.33)	8.4	(0.55)	7.8	(0.15)	8.8	(0.25)	7.3	(0.17)
Northeast	20.5	(0.35)	20.7	(0.48)	19.6	(0.79)	21.6	(0.26)	23.0	(0.42)	20.0	(0.30)
Southeast	46.9	(0.44)	48.2	(0.59)	44.7	(0.99)	47.2	(0.36)	45.7	(0.57)	48.0	(0.46)

Table 8 – Characteristics of the male ridesharing drivers in the survey and corresponding summaries for male urban adult workers *(continued)*

	Ridesharing Drivers Survey						*National Household Survey (PNADC)*					
	All drivers		*Driver as main job*		*Driver as secondary job*		*Male adult urban workforce*		*Male adult urban own-account workers*		*Male adult urban employees*	
	stat.	*s. e.*	*stat.*	*s. e.*	*stat.*	*s. e.*	*stat.*	*s. e.*	*stat.*	*s. e.*	*stat.*	*s. e.*
South	13.2	(0.30)	12.4	(0.39)	15.8	(0.72)	14.7	(0.21)	14.5	(0.32)	15.3	(0.27)
Central-West	10.8	(0.27)	10.3	(0.36)	11.6	(0.64)	8.7	(0.15)	7.9	(0.22)	9.3	(0.20)
Survey sample												
Number of observations	13,108		7,155		2,538		71,858		19,630		42,453	

Notes: [1] The drivers' survey was conducted by the author between the 24th and the 31st of January 2023 and its underlying population is all drivers working with a leading ridesharing company in Brazil. [2] The figures regarding to the general workforce are calculated using the microdata from Brazil's official labor survey, refer to the full year of 2022, and are weighted to be representative of the active male population above 18 years old and living in urban areas. In particular, I use the data collected by PNADC's 5th interview with the sampled households, which records household income from all sources. [4] For all variables and all subpopulations, the statistics are calculated using the available responses required for that specific item, and therefore the number of observations may vary for different attributes. The sample size for all drivers represents to the number of unique individuals who participated in the survey, while the combined number primary job drivers and secondary job drivers refer to the respondents for whom there is sufficient information for this breakdown. [4] Monetary values from PNADC are reported in January 2023 equivalent terms. [5] Work-related statistics (such as *work income*, *work hours* and *how long in this job*) are specific to the occupation indicated in the column. [6] The *household income per capita* is composed of all income sources from all individuals in a given household.

Table 9 – Descriptive statistics when ridesharing is their main or secondary job

	All drivers		*Driver as main job*		*Driver as secondary job*	
	stat.	*s. e.*	*stat.*	*s. e.*	*stat.*	*s. e.*
Gender and ethnicity						
Male	93.2	(0.21)	92.7	(0.30)	93.9	(0.46)
Ethinicity						
Black	13.4	(0.29)	13.1	(0.39)	14.0	(0.67)
Mixed-race	49.4	(0.42)	49.0	(0.57)	47.9	(0.96)
White	37.3	(0.41)	37.9	(0.55)	38.1	(0.94)
Age group						
18 to 27 years old	14.1	(0.30)	15.0	(0.41)	12.1	(0.63)
28 to 37 years old	38.3	(0.4)	39.1	(0.6)	37.1	(0.9)
38 to 47 years old	31.5	(0.4)	29.9	(0.5)	35.1	(0.9)
48 to 57 years old	12.2	(0.28)	12.0	(0.37)	12.0	(0.63)
58 years old or more	4.0	(0.17)	4.0	(0.22)	3.7	(0.36)
Education						
Primary education or less	11.1	(0.27)	10.9	(0.35)	8.3	(0.53)
Some high school	7.9	(0.23)	8.2	(0.31)	5.7	(0.45)
High school	44.1	(0.42)	44.7	(0.57)	43.1	(0.95)
Some college	20.7	(0.35)	21.4	(0.47)	20.5	(0.78)
College or above	16.2	(0.32)	14.8	(0.40)	22.5	(0.80)
Household composition						
N. of adults (age 18+)	2.4	(0.01)	2.4	(0.01)	2.4	(0.02)
N. of kids (age < 18)	1.0	(0.01)	1.0	(0.01)	1.0	(0.02)
Work routine						
Work days per week	5.6	(0.01)	6.0	(0.01)	4.5	(0.03)
Work hours in a working day	9.2	(0.03)	9.9	(0.03)	7.2	(0.06)
Work hours per week	53.0	(0.24)	60.1	(0.26)	32.9	(0.39)
Income						
Average work income	2,267	(15)	2,501	(17)	1,597	(23)
Average household inc. per capita	1,381	(12)	1,333	(13)	1,517	(25)
Household inc. per cap. < USD 5.5/day	11.3	(0.32)	12.2	(0.39)	8.4	(0.56)
How long in this job						
Less than 3 months	12.2	(0.31)	10.3	(0.35)	16.6	(0.72)
3 to 6 months	10.0	(0.28)	9.3	(0.33)	12.2	(0.63)
6 months to 1 year	11.7	(0.30)	11.7	(0.37)	12.1	(0.63)
1 to 2 years	16.8	(0.35)	16.1	(0.42)	18.1	(0.74)
2 to 4 years	29.4	(0.42)	30.5	(0.52)	26.4	(0.85)
More than 4 years	19.8	(0.37)	22.1	(0.47)	14.7	(0.68)

Table 9 – Descriptive statistics when ridesharing is their main or secondary job *(continued)*

	All drivers		*Driver as main job*		*Driver as secondary job*	
	stat.	*s. e.*	*stat.*	*s. e.*	*stat.*	*s. e.*
Previous status						
Inactive	4.0	(0.18)	3.6	(0.21)	4.4	(0.40)
Unemployed	29.3	(0.43)	35.6	(0.55)	12.3	(0.63)
Self-employed	22.8	(0.39)	23.0	(0.48)	21.1	(0.79)
Employee	34.7	(0.45)	28.9	(0.52)	52.2	(0.96)
Other status	9.2	(0.27)	8.9	(0.32)	9.9	(0.57)
Other jobs						
Driver only	61.6	(0.48)	85.1	(0.42)		
Driver and employee	20.8	(0.40)	3.9	(0.23)	65.5	(0.95)
Driver and self-employed	17.6	(0.38)	11.0	(0.37)	34.5	(0.95)
Looking for a job						
Looking for a job	0.4	(0.00)	0.5	(0.01)	0.2	(0.01)
How many apps						
1 app	26.9	(0.42)	26.3	(0.50)	28.3	(0.87)
2 apps	50.9	(0.48)	50.8	(0.57)	51.1	(0.96)
3 apps	18.5	(0.37)	19.2	(0.45)	17.0	(0.72)
More than 3	3.7	(0.18)	3.8	(0.22)	3.6	(0.36)
Vehicle ownership						
Rented from friend, family	12.2	(0.31)	13.9	(0.39)	7.5	(0.51)
Rented from agency	11.9	(0.31)	13.7	(0.39)	6.9	(0.49)
Own car, still paying	56.6	(0.47)	54.7	(0.57)	61.2	(0.94)
Own car, fully paid	19.3	(0.38)	17.7	(0.43)	24.5	(0.83)
Share of work income usually saved						
Less than 10%	70.9	(0.45)	72.9	(0.52)	65.1	(0.94)
Between 10% and 25%	19.3	(0.39)	18.7	(0.45)	21.5	(0.81)
More than 25%	9.8	(0.30)	8.4	(0.32)	13.4	(0.67)
Social security						
Not currently contributing	53.1	(0.52)	63.8	(0.58)	22.5	(0.86)
Public system (as individual)	22.2	(0.43)	24.0	(0.52)	16.7	(0.77)
Public system (as employee)	15.6	(0.38)	3.5	(0.22)	50.5	(1.03)
Private system	2.3	(0.15)	1.5	(0.15)	4.5	(0.43)
Does not know	6.9	(0.26)	7.2	(0.31)	5.7	(0.48)
Country region						
North	8.8	(0.24)	8.5	(0.32)	8.3	(0.53)
Northeast	20.0	(0.34)	20.3	(0.46)	19.3	(0.76)
Southeast	46.7	(0.42)	48.0	(0.57)	44.6	(0.96)
South	13.6	(0.29)	12.8	(0.38)	16.4	(0.71)

Table 9 – Descriptive statistics when ridesharing is their main or secondary job *(continued)*

	All drivers		*Driver as main job*		*Driver as secondary job*	
	stat.	*s. e.*	*stat.*	*s. e.*	*stat.*	*s. e.*
Central-West	10.9	(0.26)	10.4	(0.35)	11.4	(0.61)
Survey sample						
Number of observations	14,265		7,741		2,708	

Notes: [1] The drivers' survey was conducted by the author between the 24th and the 31st of January 2023 and its underlying population is all drivers working with a leading ridesharing company in Brazil. [2] The figures regarding to the general workforce are calculated using the microdata from Brazil's official labor survey, refer to the full year of 2022, and are weighted to be representative of the active population above 18 years old and living in urban areas. In particular, I use the data collected by PNADC's 5th interview with the sampled households, which records household income from all sources. [3] For all variables and all subpopulations, the statistics are calculated using the available responses required for that specific item, and therefore the number of observations may vary for different attributes. The sample size for all drivers represents to the number of unique individuals who participated in the survey, while the combined number primary job drivers and secondary job drivers refer to the respondents for whom there is sufficient information for this breakdown. [4] Monetary values from PNADC are reported in January 2023 equivalent terms. [5] Work-related statistics (such as *work income*, *work hours* and *how long in this job*) are specific to the occupation indicated in the column. [6] The *household income per capita* is composed of all income sources from all invididuals in a given household. [7] Non-male drivers are composed by 6.7% of female drivers and 0.1% of respondents who do not identify neither as male nor female; PNADC has no comparable gender information.

Table 10 – Doubly robust estimation of the effects of budget salience on the time to choose a contract

	outcome: seconds on q1	*outcome: seconds on q2*	*outcome: seconds on q3*	*outcome: total seconds*
	IPW and Covariate Adj. via Regression	IPW and Covariate Adj. via Regression	IPW and Covariate Adj. via Regression	IPW and Covariate Adj. via Regression
	(1)	(2)	(3)	(4)
Treatment A:				
Unexpected expense discussion	2.3	1.1	1.2	4.8
	(0.8)	(0.4)	(0.3)	(1.5)
Treatment B:				
Unexpected income discussion	0.9	0.8	1.3	3.0
	(1.0)	(0.5)	(0.3)	(1.8)
Reference level:				
Control group mean	50.1	22.5	15.9	90.5
	(1.0)	(0.4)	(0.2)	(1.4)
Number of observations	8,142	8,142	8,142	8,142

Notes: Response times are winsorized at 1 percent. The standard errors (in parenthesis) are clustered at the regional level and account for the joint estimation of the inverse probability weights (IPWs). The additional controls, both in the regression and the propensity estimation, are the same covariates adopted in the baseline estimation.

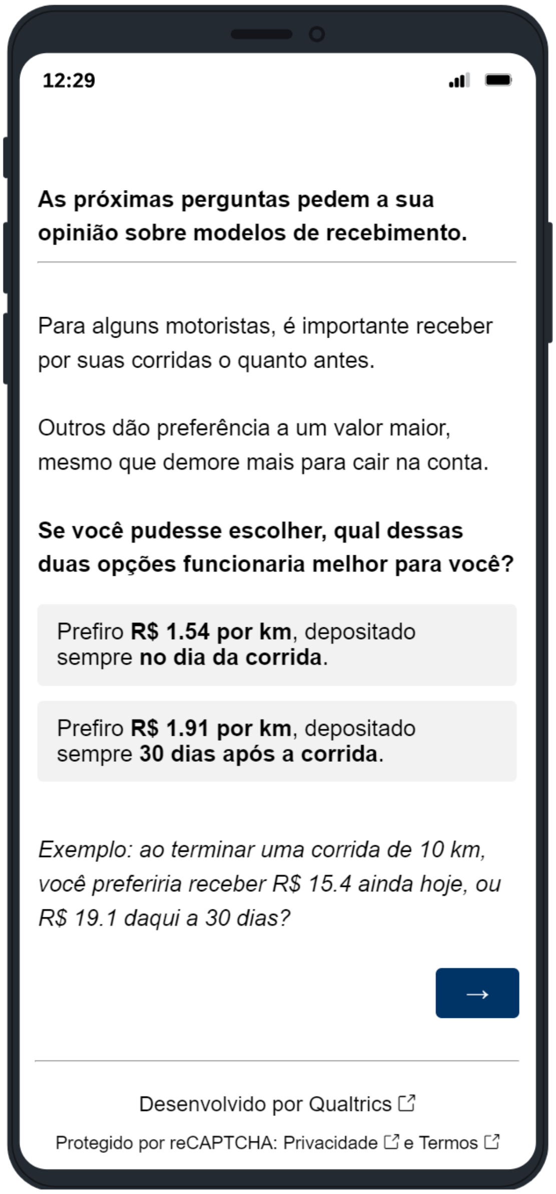

FIGURE 19 – Interface of the survey instrument

Appendix B. Survey questionnaire (English translation)

Sequence of question blocks by group

if group = {reference group}

Block 1: Geo Region
Block 2: Demographics
Block 3: Outcome contract choice
Block 4: Making ends meet
Block 5: Work and income
Block 6: Open feedback

if group = {discuss income sources}

Block 1: Geo Region
Block 2: Demographics
Block 7: Discuss income sources
Block 4: Making ends meet
Block 3: Outcome contract choice
Block 5: Work and income
Block 6: Open feedback

if group = {discuss income uses}

Block 1: Geo Region
Block 2: Demographics
Block 8: Discuss income uses
Block 4: Making ends meet
Block 3: Outcome contract choice
Block 5: Work and income
Block 6: Open feedback

Block 1: Geo Region

1.1. state

Where do you usually make your rides as an app driver?

[ ] Acre
[ ] Alagoas
[ ] Amapá
[ ] Amazonas
[ ] Bahia
[ ] Ceará
[ ] Distrito Federal
[ ] Espírito Santo
[ ] Goiás
[ ] Maranhão
[ ] Mato Grosso
[ ] Mato Grosso do Sul
[ ] Minas Gerais
[ ] Pará
[ ] Paraíba
[ ] Paraná
[ ] Pernambuco
[ ] Piauí
[ ] Rio de Janeiro
[ ] Rio Grande do Norte
[ ] Rio Grande do Sul
[ ] Rondônia
[ ] Roraima
[ ] Santa Catarina
[ ] São Paulo
[ ] Sergipe
[ ] Tocantins

1.2. capital

In the capital or in other areas?

[ ] {State capital} and surrounding areas
[ ] Another city of {State}

Block 2: Demographics

2.1. gender

Your gender?
[ ] Male
[ ] Female
[ ] Other
[ ] Prefer not to answer

2.2. race

With which of these options do you identify yourself most?
[ ] White
[ ] Brown
[ ] Black
[ ] Indigenous
[ ] Asian

2.3. age

How old are you?
[ ] Between 18 and 22 years old
[ ] Between 23 and 27 years old
[ ] Between 28 and 32 years old
[ ] Between 33 and 37 years old
[ ] Between 38 and 42 years old
[ ] Between 43 and 47 years old
[ ] Between 48 and 52 years old
[ ] Between 53 and 57 years old
[ ] Between 58 and 62 years old
[ ] Between 63 and 67 years old
[ ] 68 years old or more

2.4. schooling

What is your schooling degree?
[ ] No schooling
[ ] Primary school, incomplete
[ ] Primary school, complete
[ ] Secondary school, incomplete
[ ] Secondary school, complete
[ ] Bachelor's degree (college), incomplete
[ ] Bachelor's degree (college), complete
[ ] Graduate school, incomplete
[ ] Graduate school, complete

2.5. hh_adults

How many adults (18 years or older) live in your household, including you?

[ ] 1 adult (just me)
[ ] 2 adults
[ ] 3 adults
[ ] 4 adults
[ ] 5 adults
[ ] 6 adults or more

2.6. hh_kids

How many children and teenagers (up to 18 years old) live in your household?

[ ] no children / teenager
[ ] 1 children / teenager
[ ] 2 childrens / teenagers
[ ] 3 childrens / teenagers
[ ] 4 childrens / teenagers
[ ] 5 childrens / teenagers
[ ] 6 childrens / teenagers or more

Block 3: Contract Choice

The next questions ask you for your opinion on payment models.

For some drivers, it's important to get paid as soon as possible. Others prefer a higher amount, even if it takes longer to arrive in their account.

3.1. s_or_l

If you could choose, which of these two options would work best for you?
[ ] I prefer R$ {reference rate} per km, always deposited on the day of the ride.
[ ] I prefer R$ {reference rate × 1.24} per km, always deposited 30 days after the ride.

Example: at the end of a 10 km ride, would you prefer to receive R$ {reference rate × 10} today, or R$ {reference fee × 1.24 × 10} in 30 days?

if s_or_l == {on the day of the ride}

3.2. sas_or_las

And in this case, which of these two options would work best for you?
[ ] I prefer R$ {reference rate} per km, always deposited on the day of the ride.
[ ] I prefer R$ {reference rate × 1.96} per km, always deposited 30 days after the ride.

Example: at the end of a 10 km ride, would you prefer to receive R$ {reference rate × 10} today, or R$ {reference fee × 1.96 × 10} in 30 days?

if s_or_l == {30 days after the ride}

3.3. sal_or_lal

And in this case, which of these two options would work best for you?
[ ] I prefer R$ {reference rate} per km, always deposited on the day of the ride.
[ ] I prefer R$ {reference rate × 1.06} per km, always deposited 30 days after the ride.

Example: at the end of a 10 km ride, would you prefer to receive R$ {reference rate × 10} today, or R$ {reference fee × 1.06 × 10} in 30 days?

if sas_or_las == {on the day of the ride}

3.4. sass_or_lass

And in this case, which of these two options would work best for you?
[ ] I prefer R$ {reference rate} per km, always deposited on the day of the ride.
[ ] I prefer R$ {reference rate × 2.92} per km, always deposited 30 days after the ride.

Example: at the end of a 10 km ride, would you prefer to receive R$ {reference rate × 10} today, or R$ {reference fee × 2.92 × 10} in 30 days?

if sas_or_las == {30 days after the ride}

3.5. sasl_or_lasl

And in this case, which of these two options would work best for you?
[ ] I prefer R$ {reference rate} per km, always deposited on the day of the ride.
[ ] I prefer R$ {reference rate × 1.48} per km, always deposited 30 days after the ride.

Example: at the end of a 10 km ride, would you prefer to receive R$ {reference rate × 10} today, or R$ {reference fee × 1.48 × 10} in 30 days?

if sal_or_lal == {on the day of the ride}

3.6. sals_or_lals

And in this case, which of these two options would work best for you?
[ ] I prefer R$ {reference rate} per km, always deposited on the day of the ride.
[ ] I prefer R$ {reference rate × 1.12} per km, always deposited 30 days after the ride.

Example: at the end of a 10 km ride, would you prefer to receive R$ {reference rate × 10} today, or R$ {reference fee × 1.12 × 10} in 30 days?

if sal_or_lal == {30 days after the ride}

3.7. sall_or_lall

And in this case, which of these two options would work best for you?
[ ] I prefer R$ {reference rate} per km, always deposited on the day of the ride.
[ ] I prefer R$ {reference rate × 1.03} per km, always deposited 30 days after the ride.

Example: at the end of a 10 km ride, would you prefer to receive R$ {reference rate × 10} today, or R$ {reference fee × 1.03 × 10} in 30 days?

Block 4: Making Ends Meet

4.1. making_ends_meet

Overall, how easy is it to make ends meet in your household?

[ ] Very easy
[ ] Easy
[ ] Relatively easy
[ ] Neither easy nor hard
[ ] Relatively hard
[ ] Hard
[ ] Very hard

5.1. how_long_app

How long have you been working as an app driver?
If you have stopped this activity for over 3 months, consider only the period since you resumed it.
[ ] Less than a month
[ ] Between one and 3 months
[ ] Between 3 and 6 months
[ ] Between 6 months and one year
[ ] Between one and 2 years
[ ] Between 2 and 4 years
[ ] More than 4 years

5.2. previous_state

What was your situation the month before you started (or resumed) working with ridesharing apps?
[ ] Student
[ ] Unemployed
[ ] Self-employed worker
[ ] Full-time employee
[ ] Part-time employee
[ ] On leave due to long illness or other incapacity
[ ] Taking care of the household full-time
[ ] Retired
[ ] Other

if previous_state == {Unemployed}

5.3. previous_state_unemp

In the month before you started (or resumed) working with ridesharing apps, were you looking for a job?
[ ] Yes
[ ] No

if previous_state == {Full-time employee} or {Part-time employee}

5.4. previous_state_emp

In the month before you started (or resumed) working with ridesharing apps, were you a formal employee?
[ ] Yes
[ ] No

if previous_state == {Self-employed worker}

5.5. previous_state_oaw

In the month before you started (or resumed) working with ridesharing apps, did you have a formal registration as a self-employed worker?
[ ] Yes
[ ] No

5.6. main_reasons

At that moment, what led you to start (or resume) this activity?
Taking into account the other activities I could do, I decided to be a driver because...
[ ] it paid me more than my other options.
[ ] it was more enjoyable than my other options.
[ ] it was easier to conciliate with my personal life.
[ ] allowed me to work according to my current needs.
[ ] I could secure some income quickly.
[ ] driving is my best professional skill.
[ ] there were no other options available at that moment.
[ ] I had other reasons: [______________________________]

5.7. how_many_apps

How many apps do you currently work with?
[ ] 1
[ ] 2
[ ] 3
[ ] more than 3

5.8. working_vehicle

Which option best describes your current work vehicle?
[ ] Own car, paid for
[ ] Own car, still paying for it
[ ] Car rented from an agency
[ ] Car rented from a friend/family member
[ ] Car rented via the app's partners
[ ] Borrowed vehicle

5.9. work_days_per_week

How many days a week do you usually work as a driver, on average?

[ ] Less than 1 day per week
[ ] 1 day per week
[ ] 2 days per week
[ ] 3 days per week
[ ] 4 days per week
[ ] 5 days per week
[ ] 6 days per week
[ ] 7 days per week

5.10. work_hours_per_day

How many hours do you usually drive during a work day, on average?

[ ] Less than 1 hour
[ ] 1 hours
[ ] 2 hours
[ ] 3 hours
...
[ ] 22 hours
[ ] 23 hours
[ ] 24 hours

5.11. other_jobs

Do you currently have any paid activities other than driving?

[ ] Yes, other activities as a self-employed worker
[ ] Yes, as a full-time employee
[ ] Yes, as a part-time employee
[ ] No, driving is currently my only paid activity

if other_jobs == {Yes, other activities as a self-employed worker}

5.12. other_jobs_oaw

In this other activity, do you have a formal registration as a self-employed worker?

[ ] Yes
[ ] No

if other_jobs == {Sim, empregado(a) tempo integral} or {Sim, empregado(a) tempo parcial}

5.13. other_jobs_emp

In this other employment, are you a formal employee?
[ ] Yes
[ ] No

if other_jobs ≠ {No, driving is currently my only paid activity}

5.14. main_or_second_inc

The driving activity is currently...
[ ] my main income source.
[ ] a secondary income source.

5.15. looking_for_a_job

Are you currently looking for a job?
[ ] Yes
[ ] No

5.16. driver_income

What is your monthly net income as a driver, in approximate terms?
Consider the income available to you after paying for fuel and the other car costs.
[ ] Less than R$ 500 per month
[ ] R$ 500 to R$ 1,000 per month
[ ] R$ 1,000 to R$ 1,500 per month
[ ] R$ 1,500 to R$ 2,000 per month
[ ] R$ 2,000 to R$ 2,500 per month
[ ] R$ 2,500 to R$ 3,000 per month
[ ] R$ 3,000 to R$ 3,500 per month
[ ] R$ 3,500 to R$ 4,000 per month
[ ] R$ 4,000 to R$ 5,000 per month
[ ] R$ 5,000 to R$ 6,000 per month
[ ] R$ 6,000 to R$ 7,000 per month
[ ] R$ 7,000 to R$ 8,000 per month
[ ] R$ 8,000 to R$ 10,000 per month
[ ] Mais de R$ 10,000 per month

5.17. hh_income

What is the total income in your household, in approximate terms?
Consider all the incomes of all the residents, including your net income as a driver and your other activities.
[ ] Less than R$ 500 per month
[ ] R$ 500 to R$ 1,000 per month
[ ] R$ 1,000 to R$ 2,000 per month
[ ] R$ 2,000 to R$ 3,000 per month
[ ] R$ 3,000 to R$ 4,000 per month
[ ] R$ 4,000 to R$ 5,000 per month
[ ] R$ 5,000 to R$ 6,000 per month
[ ] R$ 6,000 to R$ 7,000 per month
[ ] R$ 7,000 to R$ 8,000 per month
[ ] R$ 8,000 to R$ 10,000 per month
[ ] R$ 10,000 to R$ 12,000 per month
[ ] R$ 12,000 to R$ 15,000 per month
[ ] Mais de R$ 15,000 per month

5.18. savings

How much of your net income as a driver do you usually save at the end of the month?
[ ] Nearly nothing (0% to 10%)
[ ] A small share of it (10% to 25%)
[ ] A good share of it (25% to 40%)
[ ] Approximately half of it (40% to 60%)
[ ] A large share of it (60% to 75%)
[ ] Most of it (75% to 90%)
[ ] Nearly all of it (90% to 100%)

if savings > 10%

5.19. savings_destination

What are the main purposes of these reserves?
[ ] Possible emergencies related to work (my car broke down, I got sick, etc.)
[ ] Possible domestic emergencies (home, family)
[ ] Future professional training
[ ] A new business
[ ] Leisure and holidays
[ ] Saving for retirement
[ ] Buying a specific good (house, car, appliance, etc.)
[ ] Specific personal event (birthday, wedding, etc.)
[ ] My reserves do not have a specific purpose
[ ] Other objectives: [___________________________]

5.20. pension

Do you currently contribute to a pension?
[ ] I contribute to the public system as a self-employed
[ ] I contribute to the public system as an employee
[ ] I contribute to a private pension scheme
[ ] I don't contribute to any pensions at the moment
[ ] I wouldn't know how to answer that

if pension == {I don't contribute to any pensions at the moment}

5.21. why_no_pension

What are the main reasons you don't contribute to a pension at the moment?
[ ] I would like to, but I don't know how it works
[ ] I would like to, but the contributions are too expensive
[ ] I would like to, but there is no money left for that
[ ] I am saving by myself with what is left at the end of the month
[ ] I am saving by myself with a fixed monthly amount
[ ] The returns are too low, it is not worth it
[ ] It is too early to think about that
[ ] I do not trust the pension system
[ ] I am already retired
[ ] Other reasons: [__________________________]

Block 6: Open Feedback

6.1. feedback

Thank you very much for your attention!

If you like, you can leave a comment on the survey.

In general, what did you think of the questions? Did you have any difficulties or discomfort?
[__________________________]

Block 7: Discuss Income Sources

Now, let's consider a hypothetical situation.

Imagine that you have received news of a domestic emergency (an urgent home repair, or a health treatment that cannot wait).

Because of this, you'll have to disburse R$1,400 more than expected this week.

7.1. priming_income_sources_word

What's the first word that comes to mind in a situation like this?
[________________________]

7.2. priming_income_sources_descr

In practice, how would you cover this unforeseen expense of R$ 1,400 right now?
Think about the situation and describe your options in a few words.
[________________________]

Block 8: Discuss Income Uses

Now, let's consider a hypothetical situation.

Imagine you received news of a surprise payment (the result of a lottery or an unexpected refund, for example).

Because of this, you will receive an extra deposit of R$ 1,400 this week.

8.1. priming_income_uses_word

What's the first word that comes to mind in a situation like this?
[________________________]

8.2. priming_income_uses_descr

In practice, what would you do with this unexpected gain of R$ 1,400 right now?
Think about the situation and describe your options in a few words.
[________________________]