Workers' Preferences over Payment Schedules: Evidence from Ridesharing Drivers

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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 paper 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.

Keywords: Platform Work; Gig Economy; Self-employment; Labor Supply; Financial Constraints; Time Preferences; Digital Economics.

JEL codes: D91; J22; J24; J31; M52.

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I. 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 paper, 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 paper 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.

This paper 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)

[1] For a documentation of these stylized facts, 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).

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 a marginally lower importance to be paid faster (or, equivalently, a 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 paper 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 time preference, where subjective discount parameters are typically inferred from choices over when to receive arbitrary gifts, 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 paper 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 paper, 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 paper 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 paper 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 paper is organized as follows. Section II describes the operation of the ridesharing activities in Brazil, focusing on the rules that determine the drivers' payout. Section III describes the survey design, the preference elicitation method, and the experimental manipulation, and provides an overview of the sample. Section IV 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 V 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 VII concludes with a discussion of the implications of the results and directions for further research.

II. 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, this task is proposed to available drivers in that geographic area, who can accept it under the posted rates. In this paper, 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.

III. Experimental Design

The survey experiment was implemented with one of the leading ridesharing platforms in Brazil. An invitation to participate was distributed to the mobile phones of all drivers registered with this company on the afternoon of the 24th of January, 2023. A reminder was sent two days later, and the data collection was concluded on the 31st. Within this period, I document the participation of 14,265 drivers, making it one of the largest surveys with platform workers to date.[3]

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.

A. 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 question reads:

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 × b} per km, always deposited 30 days after the ride.

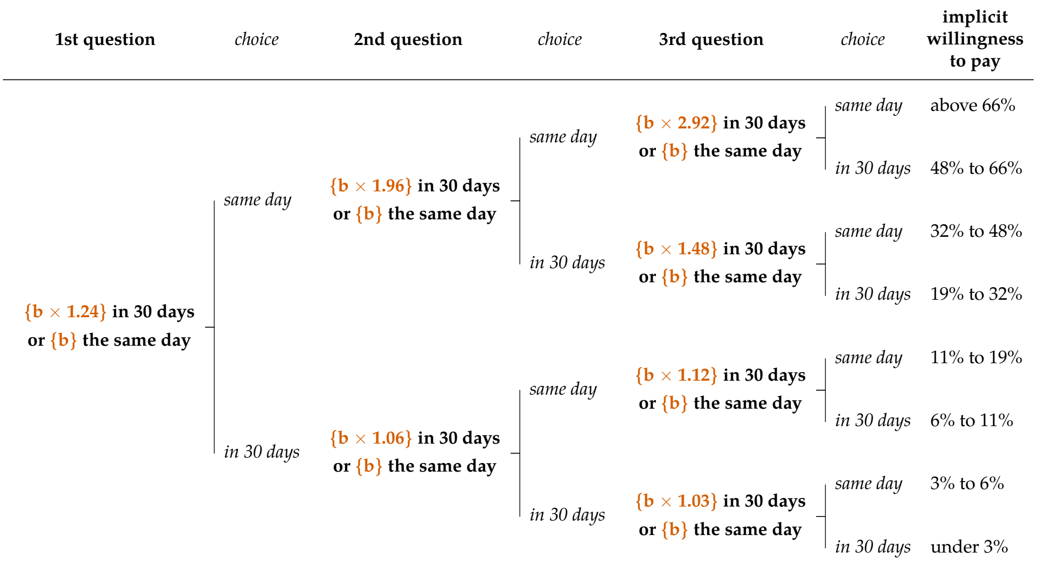
The bracketed values were calculated dynamically according to the geographical region of the driver, such that the baseline rate b for the same-day option matches the actual

[3] This number refers to all individuals who agreed to participate and were assigned to a treatment 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. This figure excludes (a) 35 cases flagged by the survey software as potentially repeated responses by the same individual and (b) 7 observations coming from the only two strata with less than 20 observations each. It is not possible to calculate the precise response rate because the total number of drivers registered with the company is confidential business information, but it is plausible to estimate that the sample represents several percent of the underlying population of drivers.

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



Notes: The multipliers were set with the objective of balancing precision (that is, 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 wage workers in general 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 pick their preferred choice. The unfolding protocol is repeated three times, leading to eight indifference intervals.

The interpretation proposed in this paper 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 paper, all mentions of WTP should be understood in these terms.

An alternative interpretation would be to frame the results in terms of pure time discount, inferring a subjective monthly discount rate of at least 24% from the aforementioned choice. This paper favors the use of a WTP framework instead, for the following reasons. First, the WTP is agnostic on the underlying functional form linking utility and different choices over deferred payment, while discounting requires some extra 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 generic concept than time preference in that heterogeneity in pure time discounting is likely to be a reason behind the choices I document but need not 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.[4]

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 paper 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.

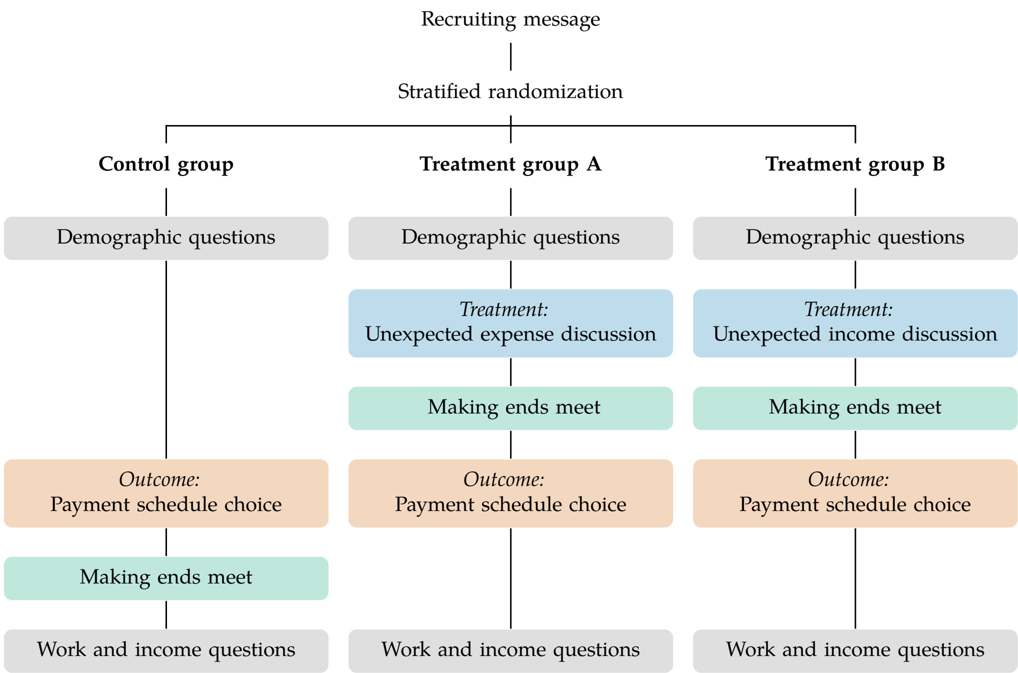
[4] In practice, if one still prefers the time discount perspective, the qualitative results would remain valid, but the magnitudes would require the appropriate conversion following the ancillary assumptions, for instance, using an exponential functional form and a monthly frequency.

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.

B. 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
The sequence of the survey blocks according to the assignment group



Notes: 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 blocks propose either the following unexpected expenses 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, first word that comes to mind, and what would you do).

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

IV. 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 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 with other attributes, in particular their total household income per capita, support the interpretation that such distribution is partially driven by structural material scarcity.

A. Who are the Ridesharing Drivers?

The ridesharing drivers in this study are predominantly young adults (52.4% are less than 38 years old), who identify themselves as black or mixed-race (62.8%), and have high school education or less (63.1%). In most cases, they live with another adult (57.6%) and at most one child (70.3%). Considering those attributes, the drivers reflect the diversity of the working population in Brazil, as detailed in table 1. To avoid the risk of comparing groups whose attributes lie on non-overlapping supports, the reference working population is restricted to adults (18 years old and above) living in urban areas.

The striking exception is that men represent 93.2% among the ridesharing drivers, in contrast to 54.8% in the workforce. However, the gender unbalance is typical for this industry, particularly in low- and middle-income countries.[5] For completeness, table 8 (in the appendix) replicates the descriptive statistics from table 1, but keeping only men in both the drivers' sample and in the general workforce. 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. As expected, these changes are more visible among the general working population than among drivers, as female drivers are a small share and thus have a lower impact on the averages.

[5] 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 Unites 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).

Table 1

Characteristics of the ridesharing 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)
Household composition												
N. of adults (age 18+) in the household	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) in the household	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)

Table 1

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

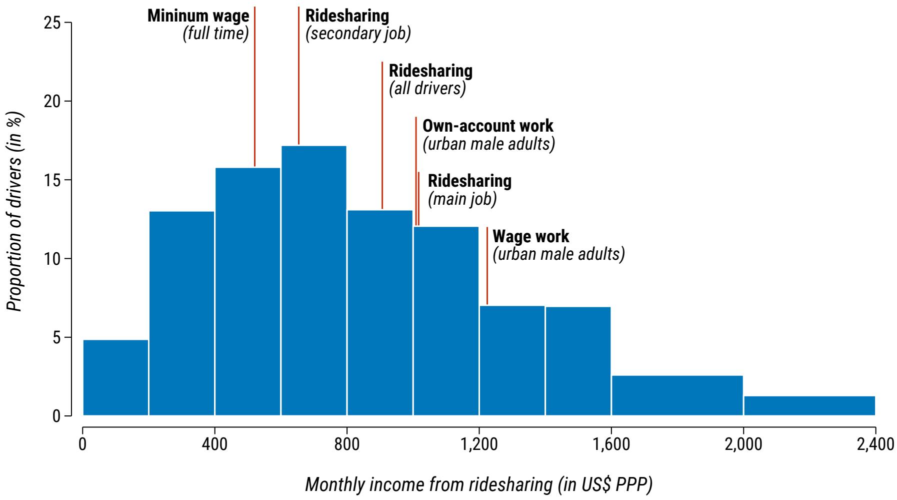
	Ridesharing Drivers Survey						*National Household Survey (PNADC)*					
	All drivers		*Driver as main job*		*Driver as secondary job*		*Adult urban workforce*		*Adult urban own-account workers*		*Adult urban employees*	
	stat.	*s. e.*	*stat.*	*s. e.*	*stat.*	*s. e.*	*stat.*	*s. e.*	*stat.*	*s. e.*	*stat.*	*s. e.*
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)
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 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.

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 (refer to 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 than 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



Notes: The red reference lines mark the average work earnings for the different reference groups. The underlying values can be found at table 8 in the appendix.

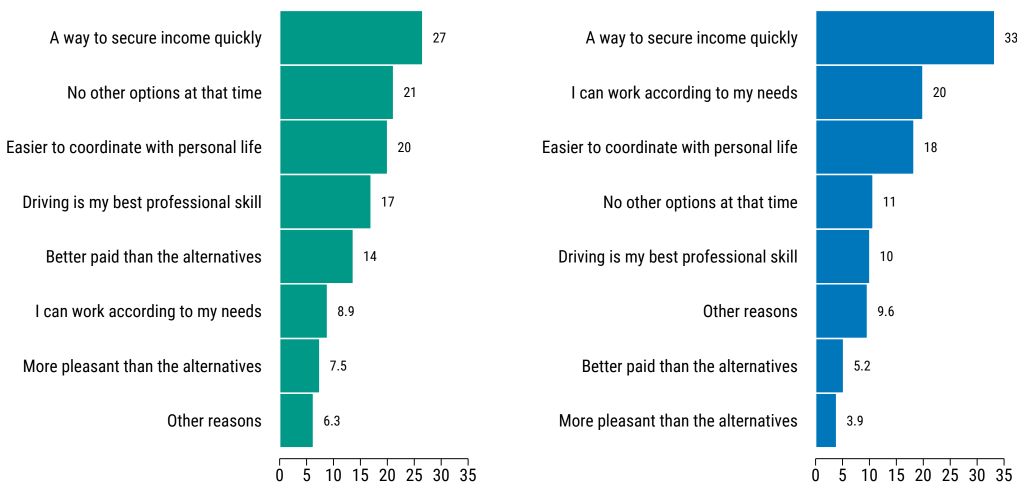
Going beyond the general average, it is possible to identify two very distinct profiles in this population: 3/4 of the drivers engage in ridesharing as their the sole or main occupation (in the sense that it represents their main income source), while 1/4 use it as a supplementary activity. Primary job 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 a poorer household, 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.

Figure 4
Most important reasons for taking up ridesharing, by driver type



(a) Main job drivers **(b) Secondary job drivers**

Notes: The questionnaire presented this set of alternatives in random order to the respondents to avoid sequence bias. The total share of responses add to more than 100 percent because people could choose more than one option.

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.

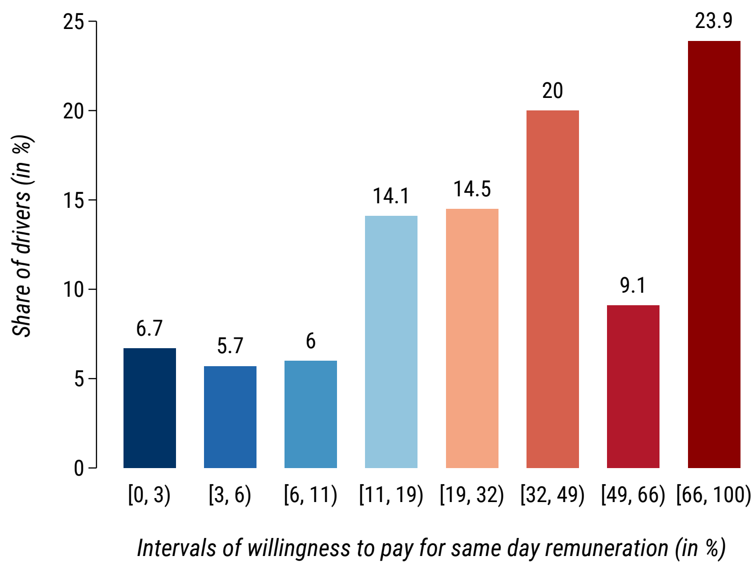
The caveat about these results is that the wording "a way to secure income quickly" can potentially cover two distinct senses for "quick": (a) the low entry barrier that allows people to start working faster relative to the counterfactual of searching for a match with a company and (b) the short time 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 next section, we take a step further in this investigation with the results from the WTP protocol, which have the double benefit of eliminating the 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).

B. How Much do Drivers Value a Short Time to Payment?

The main finding from the preference elicitation protocol is that the possibility to quickly convert 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 (implying a WTP of at least 32%), and almost 1 in every 4 drivers would take same day against roughly 3 times as much in a month (WTP of 66% or more). Taking the midpoint of each interval weighted by their mass, the estimated average is close to 40%.

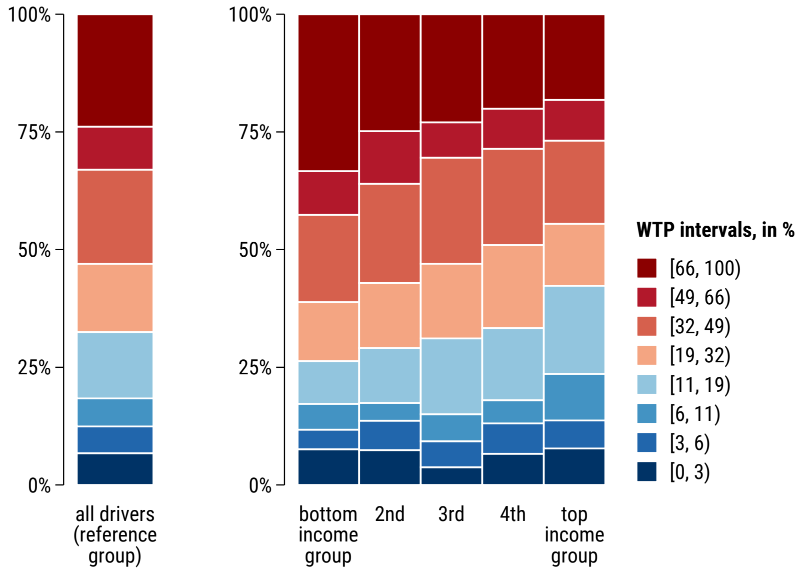
Figure 5
Distribution of preferences for same-day remuneration



High inflation and high interest rates could be a trivial reason 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.

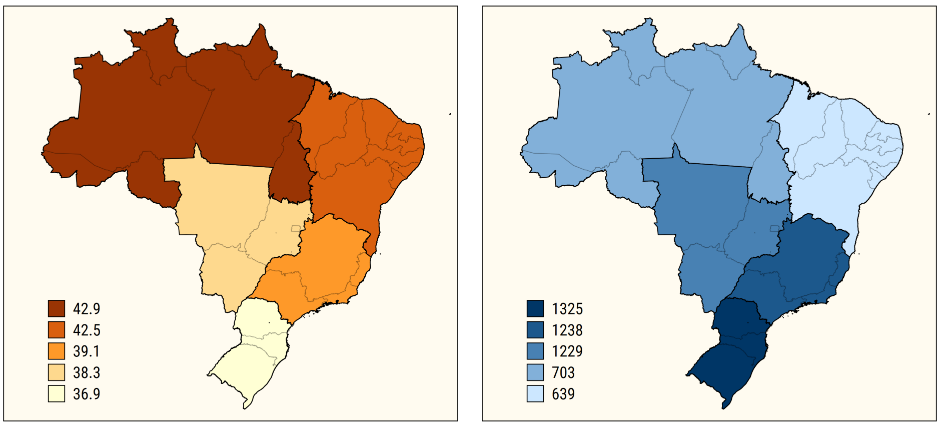
Instead, these extreme preferences appear to partly reflect a context of structural resource scarcity and missing financial instruments, which makes one's labor a source of both domestic solvency *and* liquidity. This view is supported by the monotonic association between contract choices and poverty: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

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



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, in the opposite direction: drivers in the poorest regions are the ones who favor quick payment the most, as shown in figure 7.

Figure 7
Payment preferences and median income level by geographic macroregion



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

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

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 the application process for 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.

One may argue that part of the dislike of being paid later also comes from the potential risk of earnings theft. A worker may fear that, in extremis, if the company goes bankrupt at some point, it might not pay what it owes to the drivers. However, this factor is unlikely to play a large role in the results because most drivers have a track record of at least a few months working with this company, which contributes to minimize the perception of default risk compared to a firm one just met for the first time. Even in the unlikely event of bankruptcy, the class of workers, service providers and contractors have priority in the liquidation. In short, this risk could impose a discount of a few percentage points for a payment taking place a year in the future or longer, but much less so for a monthly interval.

V. Experimental Results

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

After that, I apply text analysis on 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 the analysis of the treatment effects. The main results suggest that both treatments (either a discussion about emergency expenses or the use of an unexpected income) are inducing ridesharing drivers to decrease the importance they assign to immediate payment and increasing the probability they choose a larger payment instead. The section concludes with a discussion of potential cognitive mechanisms behind such an effect.

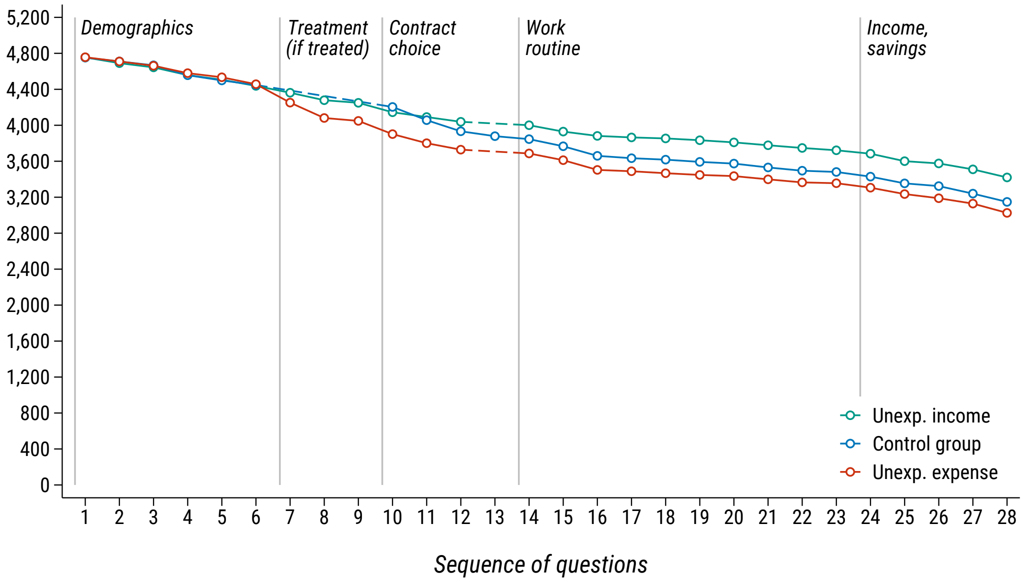
A. Working Sample and Treatment Randomization Balance

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 in their mobile phone, among many other reasons leading them to drop out at some point. With that in mind, the survey was designed to be concise and achieved a relatively high completion rate. From the 14,265 individuals who responded 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 8 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 an hypothetical scenario with a surprise income were less likely to drop out (in green), in comparison to the control group (in blue).

Figure 8

Number of active respondents throughout the survey, by treatment condition



Notes: 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 whether 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 expenses 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 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).

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.

Table 2
Summary statistics and randomization balance for the baseline sample

	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+) in the household	2.38	2.40	0.606	2.36	0.366
N. of kids (age < 18) in the household	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
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	.

Table 2
Summary statistics and randomization balance for the baseline sample (*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)*
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	.
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.

B. 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, an 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.

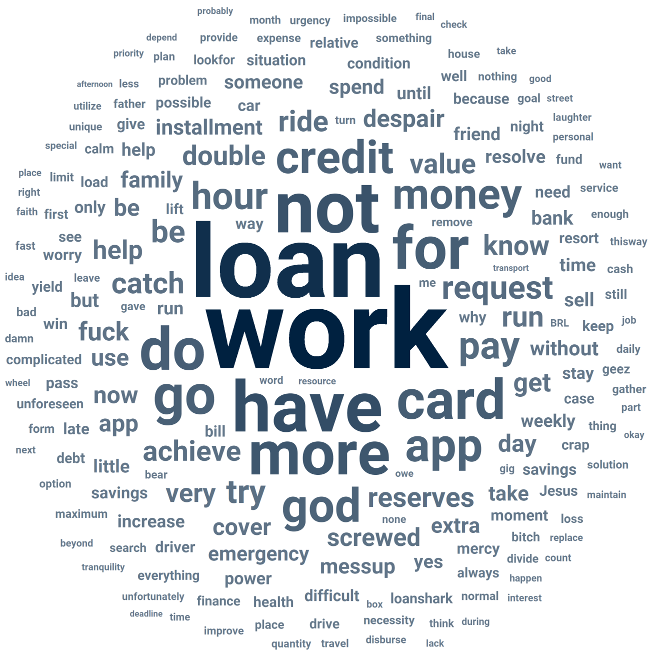
The cleaning consists in harmonizing these terms. As a first step, all characters are transformed to lowercase (for example, "App" to "app"), punctuation and diacritical marks are removed ("gratidão" to "gratidao"). Next, I split words that are unintentionally merged ("boahora" to "boa hora"), correct 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 9, in which size and color intensity are proportional to how often the drivers mention them. The same representation using the original terms in Portuguese is available in figure 14 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.

Figure 9

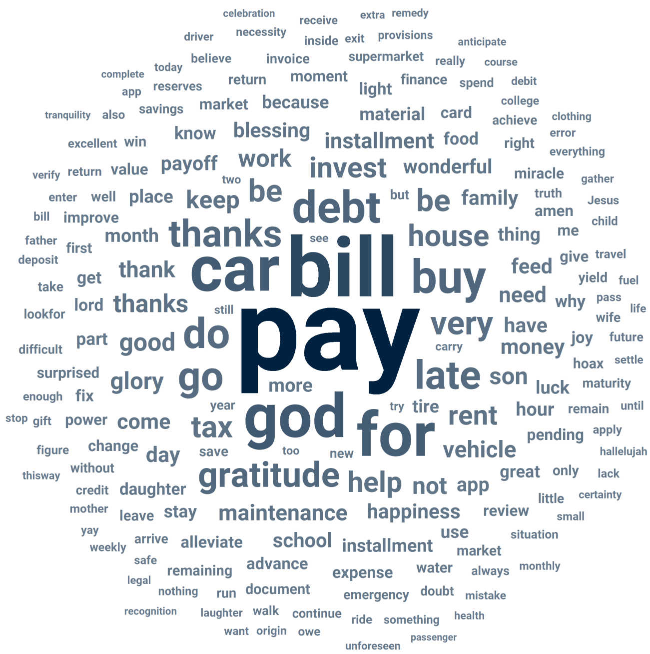
Most frequent terms mentioned by drivers when discussing how they would cover an unexpected expense



Notes: 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 10

Most frequent terms mentioned by drivers when discussing what they would do with an unexpected income



Notes: 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.

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

Looking at the mirror image of this problem, the second set of answers include 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 10 is dominated by a single term: "pay". In this context, the most common reaction appears to guided by concerns with recurring household bills and outstanding debts.

It is interesting to note that in the religious terms have a clear presence 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 the word clouds are useful to highlight the predominant topics, they must be complemented with other strategies that are better suited to uncover the associations between the responses and other observable features. In particular, we want to study which terms are disproportionally adopted by the individuals who also show a very strong preference for quick payment rules.

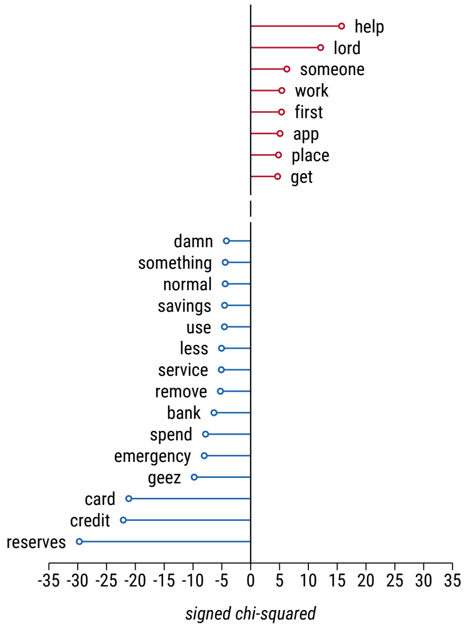
For simplicity, I divide the drivers into two groups: the top third of the distribution (those who claim to prefer same-day payment over 2 or 3 times larger rates) and the rest. The keyword analysis in this case is analogous to a chi-square test for a contingency table, in which we study whether a given 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 11. At 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 reflects 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 12.

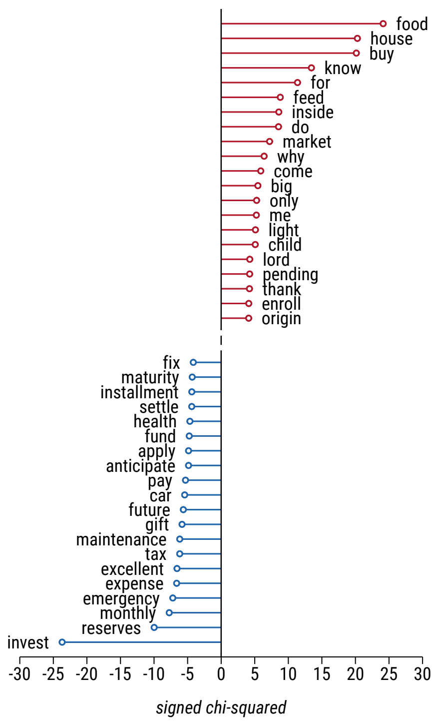
A criticism to this type of analysis is that words lose much of their meaning outside a sentence. While this remains an important caveat in this paper, the concern is partially mitigated by the constraints imposed by the text collection strategy. We have the benefit of recording responses that are not bounded by a small pool of close-ended alternatives, while being sufficiently tied to the context to give us confidence in their interpretation. For

Figure 11
Keywords from the liquidity discussion that distinguish the drivers with the strongest preference for same-day payment



Notes: 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 12
Keywords from the consumption discussion that distinguish the drivers with the strongest preference for same-day payment



Notes: 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.

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.

C. 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 OLS:

$$Y_i = \alpha + \beta_{exp}\ \textit{Expense Discussion}_i + \beta_{inc}\ \textit{Income Discussion}_i + \gamma X_i + \epsilon_i \qquad (1)$$

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 expenses 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, an specification that is more general because it formally incorporates the fact that the outcome is always observed between two boundaries.

Table 3
Average 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.

Interestingly, 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 reduces 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.

D. 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? Having established that magnitude and signs of the effects are similar, I propose we look at what the treatments have in common: that is, both require a costly information retrieval that puts the trade-off into a more complex context. People in the control group may also choose to go through the same long mental process before picking their contracts, but they were not explicitly primed to.

If it is true that treated drivers end up facing a relatively harder trade-off because they consider their options within a richer reference point available to them, they would pay more attention to the alternatives and would take longer to choose. While I cannot measure attention directly, response times are precisely recorded.

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 interesting 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 appear to be taking the time to contemplate contracts that pay them more.

Table 5
Average 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*
	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.

VI. 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.

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 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 6
Doubly robust estimation of the average effects of budget salience on the WTP for same-day remuneration

	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.

Finally, table 7 reports the 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).

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.

VII. Discussion

This paper 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. What is more striking, the workers who would benefit the most from higher earnings are the ones most likely to refuse them.

A simple justification for this puzzling result is that choices that pay faster are valuable because they address the pressing needs of today. This paper takes a step further and claims that labor market activities that convert labor into cash faster are valuable because they can address pressing needs *whenever then happen*.

Under this perspective, the contract with same-day payment also appears to be the *safest choice*, since it guarantees that some liquidity will be available when needed, despite the lower average hourly earnings. Since it requires the lowest amount of financial planning, it emerges as the default option for the average ridesharing driver.

The conclusion that the fast payment can be an safe, intuitive, automatic choice for many workers in this population is supported by the results of the experimental intervention. Simple questions about an 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 allow 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. Another implication of this paper is that this dimension can be consequential and merits further research. In the context of developing countries, short payment timing appears as another layer in the long literature on informal arrangements and self-employment. Nevertheless, as platforms and other non-standard work arrangements employ an increasing number of people globally, payment schedules can become a more salient margin in labor markets of both rich and poor countries.

More concretely, as policymakers are actively moving to regulate platform work, this paper invites them to consider that their relatively rapid payment is a feature appreciated by the people that 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 I: Additional Figures and Tables

Figure 13
Distribution of preferences for same-day remuneration by demographics

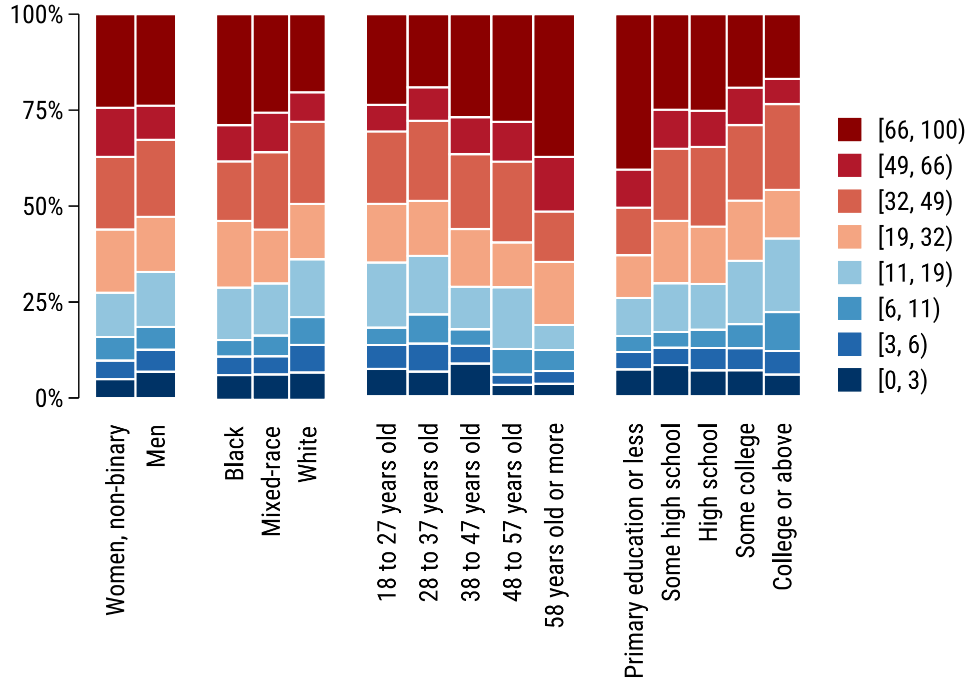


Table 8
Characteristics of the male ridesharing drivers in the survey and corresponding summaries for male urban adult workers

	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+) in the household	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) in the household	1.1	(0.01)	1.1	(0.01)	1.1	(0.02)	0.7	(0.01)	0.7	(0.01)	0.8	(0.01)
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)

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.*
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)
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 invidividuals 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+) in the household	2.4	(0.01)	2.4	(0.01)	2.4	(0.02)
N. of kids (age < 18) in the household	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)
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)
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)

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

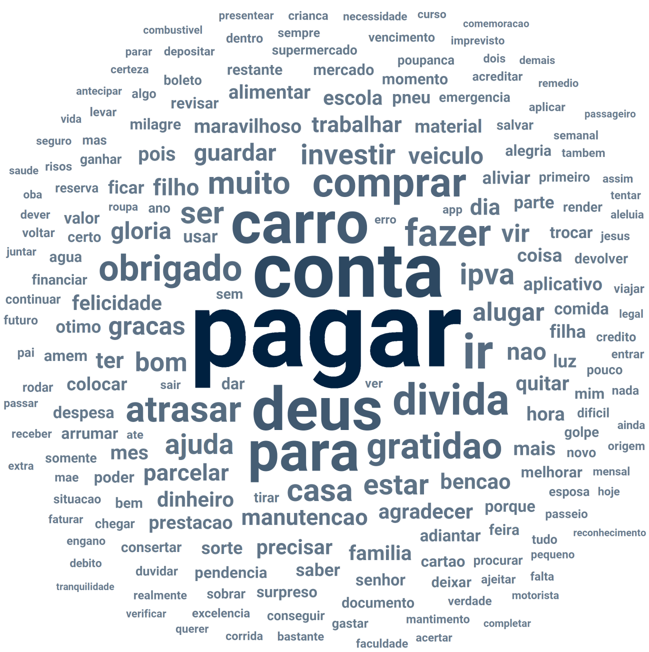
	All drivers		*Driver as main job*		*Driver as secondary job*	
	stat.	*s. e.*	*stat.*	*s. e.*	*stat.*	*s. e.*
3 apps	18.5	(0.37)	19.2	(0.45)	17.0	(0.72)
More than 3	3.7	(0.18)	3.8	(0.22)	3.6	(0.36)
Vehicle ownership						
Rented from friend, family	12.2	(0.31)	13.9	(0.39)	7.5	(0.51)
Rented from agency	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)
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 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.

Figure 14
Most frequent terms mentioned by drivers when discussing how they would cover an unexpected expense (in Portuguese)

Notes: 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.

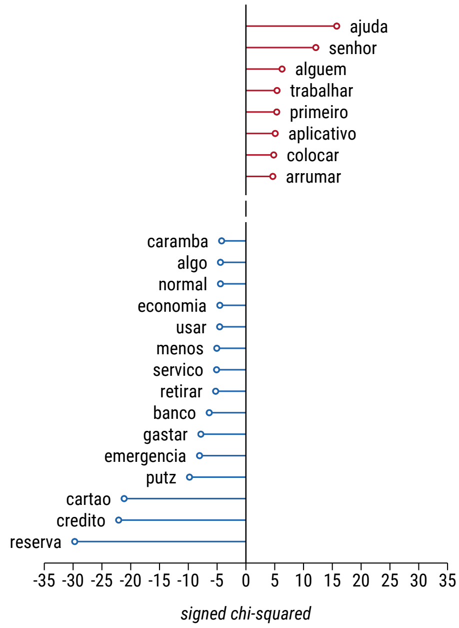
Figure 15
Most frequent terms mentioned by drivers when discussing what they would do with an unexpected income (in Portuguese)



Notes: 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 16

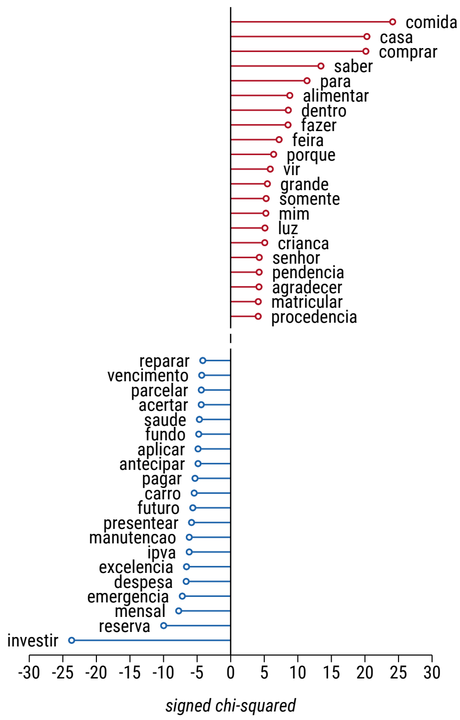
Keywords from the liquidity discussion that distinguish the drivers with the strongest preference for same-day payment (in Portuguese)



Notes: 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 17

Keywords from the consumption discussion that distinguish the drivers with the strongest preference for same-day payment (in Portuguese)



Notes: 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.

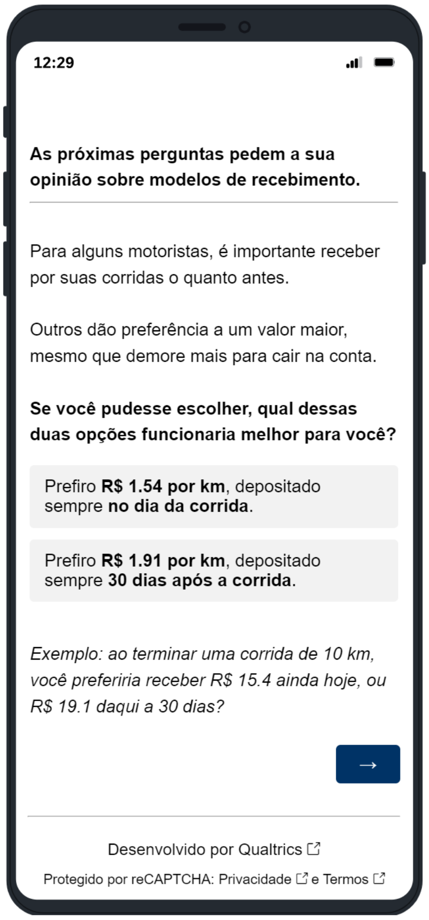
Table 10
Doubly robust estimation of the effects of budget salience on the time to choose a contract

	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.

Appendix II: Survey Instrument

Figure 18
Interface of the survey instrument



A. Survey Questionnaire (in Portuguese)

Block 1: Geo Region

1.1. state

Onde você costuma fazer a maior parte de suas corridas como motorista de aplicativo?

[ ] 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

Na região da capital ou em outras regiões?

[ ] Região de {nome da capital correspondente} e arredores
[ ] Em outra cidade de Alagoas

Block 2: Demographics

2.1. gender

Qual seu gênero?

[ ] Masculino
[ ] Feminino
[ ] Outro
[ ] Prefiro não dizer

2.2. race

Com qual dessas opções você se identifica mais?
[ ] Branco(a)
[ ] Pardo(a)
[ ] Negro(a)
[ ] Indígena
[ ] Asiático(a)

2.3. age

Qual sua idade?
[ ] Entre 18 e 22 anos
[ ] Entre 23 e 27 anos
[ ] Entre 28 e 32 anos
[ ] Entre 33 e 37 anos
[ ] Entre 38 e 42 anos
[ ] Entre 43 e 47 anos
[ ] Entre 48 e 52 anos
[ ] Entre 53 e 57 anos
[ ] Entre 58 e 62 anos
[ ] Entre 63 e 67 anos
[ ] 68 anos ou mais

2.4. schooling

Qual sua escolaridade?
[ ] Sem ensino formal
[ ] Fundamental (1º ao 9º ano) incompleto
[ ] Fundamental (1º ao 9º ano) completo
[ ] Médio (1º ao 3º ano) incompleto
[ ] Médio (1º ao 3º ano) completo
[ ] Superior (faculdade) incompleto
[ ] Superior (faculdade) completo
[ ] Pós-graduação incompleta
[ ] Pós-graduação completa

2.5. hh_adults

Quantos adultos (18 anos ou mais) moram no seu domicílio, incluindo você?
[ ] 1 adulto (apenas eu)
[ ] 2 adultos
[ ] 3 adultos
[ ] 4 adultos
[ ] 5 adultos
[ ] 6 adultos ou mais

2.6. hh_kids

Quantas crianças e jovens (até 18 anos) moram no seu domicílio?
[ ] nenhuma criança / jovem
[ ] 1 criança / jovem
[ ] 2 crianças / jovens
[ ] 3 crianças / jovens
[ ] 4 crianças / jovens
[ ] 5 crianças / jovens
[ ] 6 crianças / jovens ou mais

Block 3: Contract Choice

As próximas perguntas pedem a sua opinião sobre modelos de recebimento.

Para alguns motoristas, é importante receber por suas corridas o quanto antes. Outros dão preferência a um valor maior, mesmo que demore mais para cair na conta.

3.1. s_or_l

Se você pudesse escolher, qual dessas duas opções funcionaria melhor para você?
[ ] Prefiro R$ {taxa de referência da região} por km, depositado sempre no dia da corrida.
[ ] Prefiro R$ {taxa de referência da região × 1.24} por km, depositado sempre 30 dias após a corrida.

Exemplo: ao terminar uma corrida de 10 km, você preferiria receber R$ {taxa de referência da região × 10} ainda hoje, ou R$ {taxa de referência da região × 1.24 × 10} daqui a 30 dias?

IF s_or_l = {no dia da corrida}

3.2. sas_or_las

E neste caso, qual dessas duas opções funcionaria melhor para você?
[ ] Prefiro R$ {taxa de referência da região} por km, depositado sempre no dia da corrida.
[ ] Prefiro R$ {taxa de referência da região × 1.96} por km, depositado sempre 30 dias após a corrida.

Exemplo: ao terminar uma corrida de 10 km, você preferiria receber R$ {taxa de referência da região × 10} ainda hoje, ou R$ {taxa de referência da região × 1.96 × 10} daqui a 30 dias?

IF s_or_l = {30 dias após a corrida}

3.3. sal_or_lal

E neste caso, qual dessas duas opções funcionaria melhor para você?
[ ] Prefiro R$ {taxa de referência da região} por km, depositado sempre no dia da corrida.
[ ] Prefiro R$ {taxa de referência da região × 1.06} por km, depositado sempre 30 dias após a corrida.

Exemplo: ao terminar uma corrida de 10 km, você preferiria receber R$ {taxa de referência da região × 10} ainda hoje, ou R$ {taxa de referência da região × 1.06 × 10} daqui a 30 dias?

IF sas_or_las = {no dia da corrida}

3.4. sass_or_lass

E neste caso, qual dessas duas opções funcionaria melhor para você?
[ ] Prefiro R$ {taxa de referência da região} por km, depositado sempre no dia da corrida.
[ ] Prefiro R$ {taxa de referência da região × 2.92} por km, depositado sempre 30 dias após a corrida.

Exemplo: ao terminar uma corrida de 10 km, você preferiria receber R$ {taxa de referência da região × 10} ainda hoje, ou R$ {taxa de referência da região × 2.92 × 10} daqui a 30 dias?

IF sas_or_las = {30 dias após a corrida}

3.5. sasl_or_lasl

E neste caso, qual dessas duas opções funcionaria melhor para você?
[ ] Prefiro R$ {taxa de referência da região} por km, depositado sempre no dia da corrida.
[ ] Prefiro R$ {taxa de referência da região × 1.48} por km, depositado sempre 30 dias após a corrida.

Exemplo: ao terminar uma corrida de 10 km, você preferiria receber R$ {taxa de referência da região × 10} ainda hoje, ou R$ {taxa de referência da região × 1.48 × 10} daqui a 30 dias?

IF sal_or_lal = {no dia da corrida}

3.6. sals_or_lals

E neste caso, qual dessas duas opções funcionaria melhor para você?
[ ] Prefiro R$ {taxa de referência da região} por km, depositado sempre no dia da corrida.
[ ] Prefiro R$ {taxa de referência da região × 1.12} por km, depositado sempre 30 dias após a corrida.

Exemplo: ao terminar uma corrida de 10 km, você preferiria receber R$ {taxa de referência da região × 10} ainda hoje, ou R$ {taxa de referência da região × 1.12 × 10} daqui a 30 dias?

IF sal_or_lal = {30 dias após a corrida}

3.7. sall_or_lall

E neste caso, qual dessas duas opções funcionaria melhor para você?
[ ] Prefiro R$ {taxa de referência da região} por km, depositado sempre no dia da corrida.
[ ] Prefiro R$ {taxa de referência da região × 1.03} por km, depositado sempre 30 dias após a corrida.

Exemplo: ao terminar uma corrida de 10 km, você preferiria receber R$ {taxa de referência da região × 10} ainda hoje, ou R$ {taxa de referência da região × 1.03 × 10} daqui a 30 dias?

Block 4: Making Ends Meet

4.1. making_ends_meet

Em geral, como tem sido fechar as contas no final do mês na sua casa?
[ ] Muito simples
[ ] Simples
[ ] Relativamente simples
[ ] Nem simples, nem complicado
[ ] Relativamente complicado
[ ] Complicado
[ ] Muito complicado

Block 5: Work and Income

5.1. how_long_app

Faz quanto tempo que você trabalha como motorista de aplicativo?
Caso já tenha parado por mais de três meses, considere apenas o tempo desde que voltou.
[ ] Menos de um mês
[ ] Entre um mês e 3 meses
[ ] Entre 3 meses e 6 meses
[ ] Entre 6 meses e um ano
[ ] Entre um ano e dois anos
[ ] Entre dois e quatro anos
[ ] Mais que quatro anos

5.2. previous_state

Qual era sua situação no mês anterior ao que começou (ou retomou) o trabalho por aplicativo?
[ ] Estudante
[ ] Desempregado(a)
[ ] Trabalhando por conta própria
[ ] Empregado(a) em tempo integral
[ ] Empregado(a) em tempo parcial
[ ] Afastado(a) por doença ou outra incapacitação
[ ] Cuidando da casa e/ou da família em tempo integral
[ ] Aposentado(a)
[ ] Outra situação

IF previous_state = {Desempregado(a)}

5.3. previous_state_unemp

No mês anterior ao que começou (ou retomou) o trabalho por aplicativo, você estava buscando trabalho?
[ ] Sim
[ ] Não

IF previous_state = {Empregado(a) em tempo integral} OR {Empregado(a) em tempo integral}

5.4. previous_state_emp

No mês anterior ao que começou (ou retomou) o trabalho por aplicativo, você tinha carteira assinada?

[ ] Sim
[ ] Não

IF previous_state = {Trabalhando por conta própria}

5.5. previous_state_oaw

No mês anterior ao que começou (ou retomou) o trabalho por aplicativo, você tinha CNPJ ou outro registro formal?

[ ] Sim
[ ] Não

5.6. main_reasons

Naquele momento, o que levou você a começar (ou retomar) o trabalho por aplicativo?

Levando em conta as outras ocupações que eu poderia exercer, decidi ser motorista porque...

[ ] pagava melhor do que as outras opções.
[ ] era mais agradável do que as outras opções.
[ ] era mais fácil de conciliar com minha vida pessoal.
[ ] poderia trabalhar de acordo com a necessidade do mês.
[ ] era uma forma de garantir renda rapidamente.
[ ] dirigir é minha maior habilidade profissional.
[ ] não havia outras opções naquele momento.
[ ] tinha outros motivos: [____________________________]

5.7. how_many_apps

Com quantos aplicativos você trabalha atualmente?

[ ] 1
[ ] 2
[ ] 3
[ ] mais que 3

5.8. working_vehicle

Qual opção descreve melhor o seu veículo de trabalho atualmente?

[ ] Veículo próprio, pago
[ ] Veículo próprio, ainda pagando
[ ] Veículo alugado de uma agência
[ ] Veículo alugado de um parente ou amigo
[ ] Veículo alugado via parceria da plataforma
[ ] Veículo emprestado

5.9. work_days_per_week

Quantos dias por semana você costuma trabalhar como motorista, em média?
[ ] Menos que 1 dia por semana
[ ] 1 dia por semana
[ ] 2 dias por semana
[ ] 3 dias por semana
[ ] 4 dias por semana
[ ] 5 dias por semana
[ ] 6 dias por semana
[ ] 7 dias por semana

5.10. work_hours_per_day

Por quantas horas você costuma dirigir durante uma jornada de trabalho, em média?
[ ] Menos que uma hora
[ ] 1 hora
[ ] 2 horas
[ ] 3 horas
...
[ ] 22 horas
[ ] 23 horas
[ ] 24 horas

5.11. other_jobs

Você exerce outras atividades remuneradas além de motorista atualmente?
[ ] Sim, outras atividades por conta própria
[ ] Sim, empregado(a) tempo integral
[ ] Sim, empregado(a) tempo parcial
[ ] Não, motorista é minha única atividade remunerada atualmente

IF other_jobs = {Sim, outras atividades por conta própria}

5.12. other_jobs_oaw

Nessa outra atividade por conta própria, você tem CNPJ ou outro registro formal?
[ ] Sim
[ ] Não

IF other_jobs = {Sim, empregado(a) tempo integral} OR {Sim, empregado(a) tempo parcial}

5.13. other_jobs_emp

Nesse outro emprego, você tem carteira assinada?
[ ] Sim
[ ] Não

IF other_jobs ≠ {Não, motorista é minha única atividade remunerada atualmente}

5.14. main_or_second_inc

A atividade de motorista é atualmente...
[ ] minha fonte de renda principal.
[ ] uma fonte de renda complementar.

5.15. looking_for_a_job

Você está buscando emprego atualmente?
[ ] Sim
[ ] Não

5.16. driver_income

Qual é seu ganho líquido mensal como motorista, aproximadamente?
Considere a renda disponível para você depois de descontar o combustível e os outros custos do carro.
[ ] Menos de R$ 500 por mês
[ ] R$ 500 a R$ 1 000 por mês
[ ] R$ 1 000 a R$ 1 500 por mês
[ ] R$ 1 500 a R$ 2 000 por mês
[ ] R$ 2 000 a R$ 2 500 por mês
[ ] R$ 2 500 a R$ 3 000 por mês
[ ] R$ 3 000 a R$ 3 500 por mês
[ ] R$ 3 500 a R$ 4 000 por mês
[ ] R$ 4 000 a R$ 5 000 por mês
[ ] R$ 5 000 a R$ 6 000 por mês
[ ] R$ 6 000 a R$ 7 000 por mês
[ ] R$ 7 000 a R$ 8 000 por mês
[ ] R$ 8 000 a R$ 10 000 por mês
[ ] Mais de R$ 10 000 por mês

5.17. hh_income

Qual a renda total do seu domicílio, aproximadamente?
Considere as rendas de todos os moradores, incluindo seu ganho líquido como motorista e outras atividades.
[ ] Menos de R$ 500 por mês
[ ] R$ 500 a R$ 1 000 por mês
[ ] R$ 1 000 a R$ 2 000 por mês
[ ] R$ 2 000 a R$ 3 000 por mês
[ ] R$ 3 000 a R$ 4 000 por mês
[ ] R$ 4 000 a R$ 5 000 por mês
[ ] R$ 5 000 a R$ 6 000 por mês
[ ] R$ 6 000 a R$ 7 000 por mês
[ ] R$ 7 000 a R$ 8 000 por mês
[ ] R$ 8 000 a R$ 10 000 por mês
[ ] R$ 10 000 a R$ 12 000 por mês
[ ] R$ 12 000 a R$ 15 000 por mês
[ ] Mais de R$ 15 000 por mês

5.18. savings

Quanto dos seus ganhos líquidos como motorista você costuma guardar no fim do mês?

[ ] Quase nada (0% a 10%)
[ ] Uma pequena parte (10% a 25%)
[ ] Uma boa parte (25% a 40%)
[ ] Aproximadamente metade (40% a 60%)
[ ] Uma parte grande (60% a 75%)
[ ] A maior parte (75% a 90%)
[ ] Quase tudo (90% a 100%)

IF savings > 10%

5.19. savings_destination

Quais os principais objetivos dessas reservas?

[ ] Emergências do trabalho (carro quebrou, fiquei doente, etc.)
[ ] Emergências domésticas (casa, família, etc.)
[ ] Uma formação profissional
[ ] Um novo negócio
[ ] Lazer e férias
[ ] Guardar para aposentadoria
[ ] Compra de um bem (casa, carro, eletrodoméstico, etc.)
[ ] Evento pessoal (aniversário, casamento, etc.)
[ ] Minhas reservas não têm destinação específica
[ ] Outros objetivos: [____________________________]

5.20. pension

Você contribui para alguma aposentadoria atualmente?

[ ] Pago INSS por conta própria como contribuinte individual ou MEI
[ ] Pago INSS como funcionário de uma empresa
[ ] Pago uma previdência privada
[ ] Não pago nenhuma aposentadoria atualmente
[ ] Não saberia responder

IF pension = {não pago nenhuma aposentadoria atualmente}

5.21. why_no_pension

Quais os principais motivos para você não pagar uma aposentadoria atualmente?

[ ] Gostaria de pagar aposentadoria, mas não sei como funciona
[ ] Gostaria de pagar aposentadoria, mas as mensalidades são muito altas
[ ] Gostaria de pagar aposentadoria, mas não sobra dinheiro para isso
[ ] Já estou guardando por minha conta, com o que sobra no mês
[ ] Já estou guardando por minha conta, uma quantia fixa por mês
[ ] O retorno é muito baixo, não vale a pena
[ ] É muito cedo para pensar nisso
[ ] Não confio nos sistemas de aposentadoria
[ ] Já recebo uma aposentadoria atualmente
[ ] Outros motivos: : [____________________________]

Block 6: Open Feedback

6.1. feedback

Muito obrigado por sua atenção!

Se quiser, você pode deixar um comentário sobre o levantamento.

De modo geral, o que você achou das questões? Teve alguma dificuldade ou incômodo?
[____________________________]

Block 7: Discuss Income Sources

Agora vamos considerar uma situação hipotética.

Imagine que você recebeu a notícia de uma emergência doméstica (um reparo urgente em casa, ou um tratamento de saúde que não pode esperar).

Por causa disso, você terá que desembolsar R$ 1 400 além do previsto essa semana.

7.1. priming_income_sources_word

Qual a primeira palavra que vem à sua mente numa situação assim?
[____________________________]

7.2. priming_income_sources_descr

Na prática, como você cobriria esse gasto imprevisto de R$ 1 400 neste momento?
Pense na situação e descreva suas opções em algumas palavras.
[____________________________]

Block 8: Discuss Income Uses

Agora vamos considerar uma situação hipotética.

Imagine que você recebeu a notícia de um pagamento surpresa (resultado de um sorteio ou de um reembolso inesperado, por exemplo).

Por causa disso, você receberá um depósito extra de R$ 1 400 essa semana.

8.1. priming_income_uses_word

Qual a primeira palavra que vem à sua mente numa situação assim?
[____________________________]

8.2. priming_income_uses_descr

Na prática, o que você faria com esse ganho imprevisto de R$ 1 400 neste momento?
Pense na situação e descreva suas opções em algumas palavras.
[____________________________]