Worker's Preferences over Payment Schedules: Evidence from Ridesharing Drivers

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An occupation is usually characterized as a combination of what people do and how much they are paid for it, with little attention to the fact that work arrangements also define *when* people are paid for their labor. This paper advances this discussion by investigating (a) how much value workers assign to having a shorter interval between their tasks and the associated compensation and (b) what explains potential differences in such valuation between workers. Using a large-scale survey experiment with ridesharing drivers in Brazil, I document that the median driver would be willing to forgo at least a third of their earnings to be paid on the same day of their rides, compared to the alternative of being paid a month later. Text analysis methods indicate that a prompt remuneration tends to be critical if working extra hours is one's primary adjustment mechanism in response to financial emergencies. Finally, I provide experimental evidence that increasing the salience of their household budget can make workers marginally less likely to prefer immediate compensation at any cost.

Keywords: Work Contracts; Financial Constraints; Time Preferences; Self-employment; Gig Economy; Ridesharing; Brazil.

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

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I. Introduction

A job is usually characterized as a combination of a task (what the workers are expected to do) and a compensation (how much they are paid for their labor), with little attention to the fact that work arrangements also define *when* workers are paid. This paper advances this discussion by investigating (a) how much value people assign to having a short interval between their tasks and the associated compensation and (b) what factors can help explaining potential differences in such valuation between workers.

Even though it is intuitive to expect a trade-off between quicker versus larger earnings in the labor market, the analysis of the value of different payment schedules in a real-world setting is challenging, since this feature is often related to other job attributes. Occupations that pay shortly after a task (we can think of daily construction workers, hairdressers working on their own, or taxi drivers) are in many ways different from jobs with longer payment terms (such as office workers with monthly paychecks, or consultants paid only at the completion of a long project). Without imposing further assumptions, it is difficult to isolate the marginal importance of the payment timing for the people we observe in one group of occupations or another.

This research addresses this challenge by focusing on the particular case of ridesharing drivers. These workers offer their transportation services to final clients using the intermediation of a digital platform that sets the rules for the transactions. For the purposes of the question at hand, this setting has three unique advantages: (a) all workers performs a homogeneous, well-defined task, (b) the time to remuneration is a salient feature of the activity, and (c) it can be changed without affecting the nature of the job. Since the platform charges the client at the end of a ride, the drivers could receive their share in the same day or anytime after that, depending only on the platform's policy.

To explore this setting, I run a survey experiment with over 14,000 drivers working with a major ridesharing platform in Brazil. The key outcome of interest is the drivers' reported preference when facing a hypothetical choice between being paid the usual rate per kilometer on the same day of the ride, or receiving a higher rate 30 days after the ride. This choice is repeated three times, each time with a different multiplier for the later payment, following an unfolding brackets methodology. As a result, it is possible to identify an interval of forgone earnings representing the relative importance of same day remuneration for each individual.

The results document an extremely high preference for quick payment contracts, as the median driver would rather be paid the same day than receiving about 1.5 times as much within 30 days. In terms of intertemporal discounting, this preference implies a rate of about 50% per month. From a different angle, this choice is equivalent to foregoing a third of your potential nominal earnings (0.5 out of 1.5) in exchange for this particular payment rule. This is the perspective that I favor in the remainder of this paper, and the share of forgone earnings will be referred to as the individual *willingness to pay* (*WTP*) *for same day remuneration*.

The use of a WTP framework has three advantages. First, this measure is agnostic on the underlying functional form linking choices and utility. In other words, all my claims will refer specifically to the comparison of same day contracts versus 30 days contracts. Second, this summary measure has a natural scale that goes from zero (not willing to renounce any earnings to be paid the same day) to almost one (willing to use nearly all earnings to be paid the same day). More importantly, it is meant to be more generic than time preferences, in the sense that pure time discounting can help rationalize the choices I document, but need not be the only channel. An additional benefit is that the results can be contrasted to other discrete choice experiments that manipulate the valuation of job attributes in terms of relative earnings change.

What can justify such extreme preferences? To study it further, I look at the driver's answers to the open-ended questions. The participants report that they would not be able to support their family consumption and pay the working expenses — gas and car repairs — during a whole month without this income source, which can make the waiting period impracticable at any rate. This is coherent with a strong liquidity restriction.

A more structured text analysis points to another reason: a quick remuneration tends to be critical if working extra hours is the driver's primary adjustment mechanism in response to financial emergencies. Indeed, people who report that they would increase how much they work if they had to cover an unexpected expense are more likely to give priority to same day payment, while those who can tap on emergency savings or use their credit card are more likely to prefer a larger payment later.

Finally, the descriptive results are complemented by the experimental dimension of this study, whereby I investigate whether being exposed to those two questions in itself can affect the contract choice. A third of the respondents were randomly asked how they would cover a financial emergency equivalent to roughly three weeks' worth of earnings. Another third was asked how they would spend a similar amount if they were to receive it unexpectedly. The reference group had no open-ended text question before the contract choice.

The main experimental result is that an increase in the salience of one's household financial conditions, as triggered by a reflection on how to address a financial emergency or how to spend an unexpected income, can lead to a marginal decrease in the perceived importance of same day compensation. Put otherwise, drivers exposed to the budget questions assigned more importance to be paid more instead of faster.

In my most conservative specification, using a doubly robust method combined with interval regression, the treatment leads to a reduction of 1.5 percentage points in the average willingness to pay for same day remuneration, out of a reference level of about 40 percent. Ancillary analysis suggest that the bulk of the effect takes place at the top end of the distribution, as both treatments reduce the share of people choosing same day remuneration against very large multipliers (1.5, 2 or 3 times).

An important limitation of these results is imposed by the nature of the hypothetical, non-incentivized elicitation mechanism. To be transparent, the preferences reported by the drivers can 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 experts when it comes to reasoning in terms of kilometer fares. As their available income is a function of the the earnings from their rides, we can expect that they are able to anticipate the real consequences of marginal changes in payment rules better than the rest of the population would be.

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 elicitation of willingness to pay for short payment terms put forth here is close in spirit to the elicitation of willingness to pay for work flexibility (Mas and Pallais 2017; 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). 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 this much smaller literature, my findings contrast with the series of studies that manipulate payment timing 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 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, justifying the interpretation that the results reflect primarily a demand for safe savings devices that allow the workers to purchase large indivisible goods. In this paper, the contracts differ only in the *interval between the work task and the respective pay* (either $t + 0$ or $t + 30$) and neither option allow the accumulation of earnings over multiple days. As a consequence, the results are clean from 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 wordclouds and keyword analysis to study partisan differences in people's concerns regarding taxation in the United States. See also Gentzkow, Kelly, and Taddy (2019) and Ash and Hansen (2023) for an overview of recent developments in the analysis of text in economics.

Finally, my results complement the recent debate on the costs and benefits of platform work. The available literature has consistently argued that flexibility in working hours is the primary benefit of the digital gig economy. It appears as the feature most appreciated by gig workers, and as the key reason why people choose this form of occupation. This paper shows that this view is incomplete because it fails to consider that gig work is also a way to secure income faster, both in the sense that it has low entry barriers and that the time period between the task and the associated payment is shorter than in other occupations. Notably, the payment schedule does not show up in the results from previous surveys and experiments for a simple reason: so far, researchers have asked workers to choose from menus that did not include this feature (Hall and Krueger 2018). This papers shows that this is a first order feature: consistent with the high implicit value documented in the discrete choice elicitation, the option to make money fast is also the most cited reason to start ridesharing.

The remainder of this paper is organized as follows. Section II describes the operation of the ridesharing activities in Brazil, with a focus on the rules that determine the drivers' payout. Section III describes the survey design, the preference elicitation method, the experimental manipulation, and provides an overview of the sample. Section IV reports a set of 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

Ridesharing platforms are companies that intermediate the supply and demand of personal transportation services using digital applications. When a client requests a ride in such platforms, this task is proposed to available drivers in that geographic area, who can accept it under the posted rates. In all of 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 records, 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 employers 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 labor protection benefits (such as temporary work incapacity, maternity leave, and retirement pension) to contributing workers. While any platform driver could pay social security contributions as individual own-account workers, this participation was not enforced, and coverage was effectively depending on the driver's initiative.(Education and Research in Innovation (CEPI) 2021). Furthermore, drivers were not subject to the national minimum wage nor to the 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. When demand is high, the platforms offer temporary multipliers to attract more drivers.

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

Note that, in contrast to most work arrangements, the platform has a large autonomy to set (and to change) the details of their payment policy, including the base rates and the timing. At the time of the experiment, the default flow was the following: 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 at the drivers' bank account once a week.

While the major platforms all adopted a similar policy on payment timing, 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 companies have already introduced mechanisms allowing drivers to access their outstanding balance before the weekly deposit date, but these alternatives require the use a payment card provided by the platform, which can be subject to transaction fees. There is no public information regarding the adoption of such payment devices by the drivers.

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, Pesquisa Nacional Por Amostra de Domicílios Contínua).

III. Experimental Design

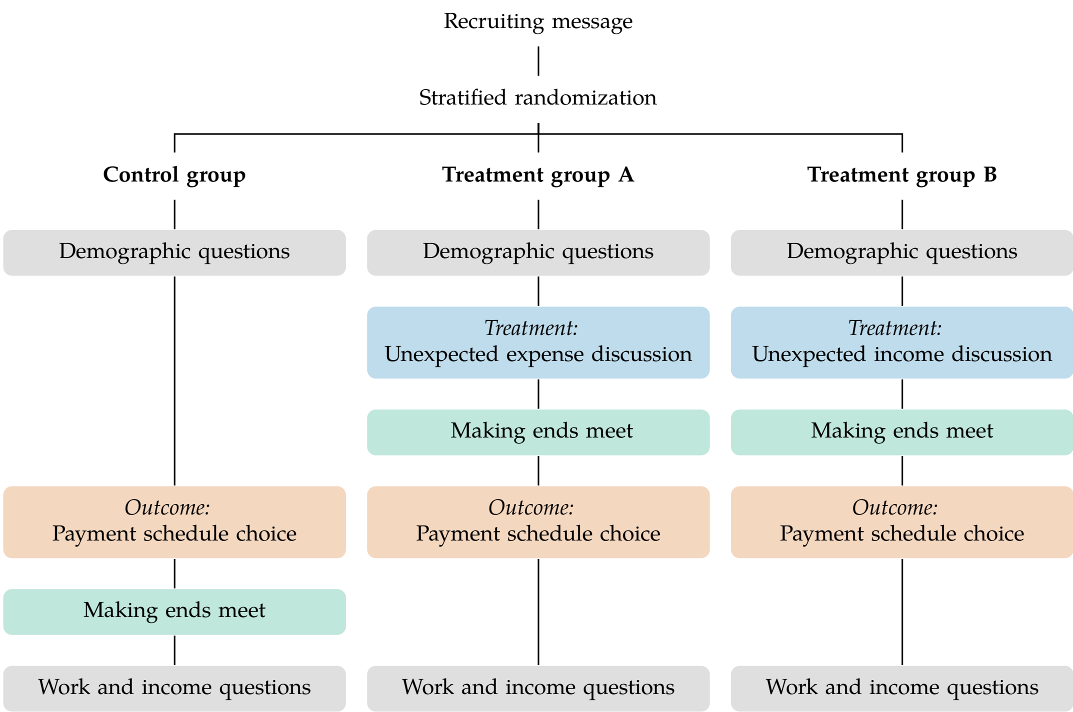
The experiment was implemented with one of the leading ridesharing platforms in Brazil. An invitation to participate in the survey was distributed to the mobile phone of all drivers registered with this company in the afternoon of 24th of January 2023. A reminder was sent two days later, and the data collection was concluded on the 31st. Within this period, 14,265 drivers participated in the survey.

To evaluate the consequences of

different financial concerns on the driver's perceived financial stress, respondents were randomly exposed to questions that making their domestic budget more salient. In the control group, drivers in the control group reported their demographic information, their preferred payment scheduled, how easy it is to make ends meet in their household, and other aspects of their working routine, as shown in figure 1.

The randomization was stratified by region, with the region 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. The objective of the stratification was to improve balance between the treatment groups.

Figure 1
The sequence of the survey blocks according to the assignment group



In addition to these background questions, respondents in the first treatment group were also presented with a vignette inviting them to discuss how they would deal with an unexpected expense in the amount of R$ 1400 (about US$ 270, slightly above the monthly minimum wage). Finally, drivers in the last treatment arm were asked how they would spend an unexpected gain of R$ 1400.

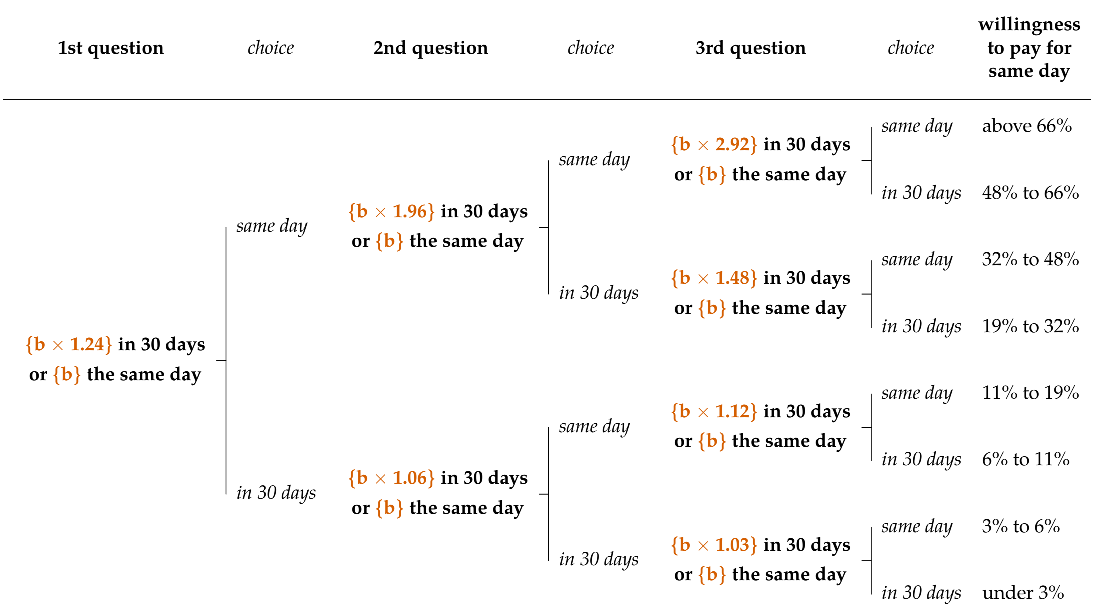
The main outcome of interest is the drivers' reported preferences when facing the hypothetical choice between receiving the usual fare soon after a ride, versus receiving a higher fare within 30 days. The question reads:

> *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 long for it to be deposited.*
>
> *If you could choose, which of those options would work best for you?*
>
> [ ] *I'd prefer {base rate} per km, deposited always the same day of the ride.*
> [ ] *I'd prefer {1.24 × base rate} per km, deposited always 30 days after the ride.*

The bracketed values were calculated dynamically according to the geographical region of the driver, such that the baseline rate b for the same day option matches the actual kilometer rate that the respondent is used to see in their rides, contributing to the realism of the exercise. The 30 days rate is calculated using a fixed multiplier 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). This strategy ensures that the relative monetary increases are the same for drivers in Manaus, Salvador or São Paulo, even though they see different values.

The mechanism is designed to identify 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. The unfolding protocol is repeated three times, leading to a total of eight indifference intervals, as show in figure 2.

Figure 2
Sequences of possible contract choices and the corresponding rates



This elicitation strategy (also called "titration", "unfolding brackets", "bisection", or "staircase method") has a long tradition in lab applications for behavioral economics. It is internally consistent and requires only a small set of brief questions, which are desirable properties for a mobile survey. The crucial novelty relative to previous investigations using the same protocol is that here it is employed to a recurring payment rule in an applied labor market context.

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

Another concern refers to potential status quo bias, if the alternatives were to 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 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 important to close the accumulation channel.

This paper acknowledges that reported choices for hypothetical scenarios may 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 detailed methodological discussion, Read (2005) stresses that incentives are not unconditionally necessary nor sufficient for valid results and notes that applied researchers should instead ponder what role a monetary payoff would play in a given elicitation design. In the present case, to recover unbiased results, we require that the subjects (a) understand the alternatives, (b) correctly anticipate their choice were these choices to have material consequences, and (c) have no systematic reason to misrepresent their preferences. These assumptions are plausible in this setting because the focus of the experiment is close to the subjects' familiar working routine. In other words, I assume that adult drivers do not need extra incentives to understand how kilometers translate into income and to anticipate what consequences a change in the payment timing would have for them.

IV. Descriptive Results

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 closely the general composition of the working population in Brazil, as detailed in table 1.[1]

The striking exception is that men represent 93.2% among the ridesharing drivers, in contrast to 54.8% in the workforce. Such a strong gender unbalance, however, is typical for this industry, particularly in low- and middle-income countries.[2] For completeness, I replicate

[1] Throughout this section, the comparisons with the general working population is restricted to adults living in urban areas, since drivers are required to be above 18 years and the ridesharing platforms are active primarily in cities.

[2] The International Labour Office reports that females are, 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).

the descriptive statistics keeping only males in both the sample of drivers and in the general workforce in table 9, available in the appendix.

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

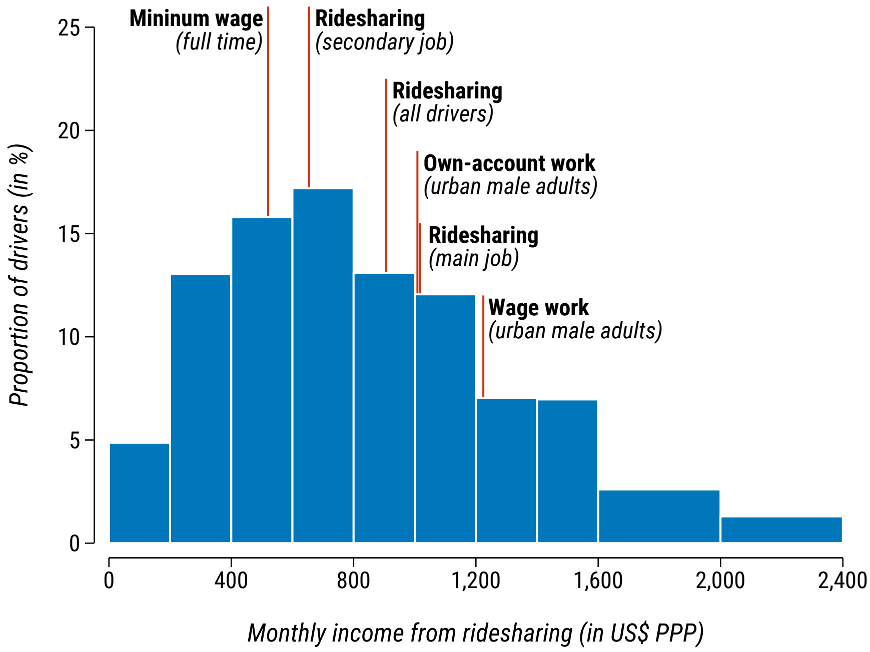
Characteristics of the ridesharing drivers in the survey and corresponding summaries for urban adult workers in Brazil (*continued*)

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

The drivers report an average net income from ridesharing of R$ 2,267 per month, after their regular working expenses such as fuel and maintenance, which is equivalent to about US$ 900, if we adjust for purchase power parity. This monthly value value is 1.7 times the national minimum wage for a full-time formal employment position in Brazil. On the other hand, it is about 20% less than the average monthly income earned by the general workforce in the same period (or 26% less, if we compare only male drivers with the male working population).

Figure 3
Distribution of monthly work earnings for the ridesharing drivers and average earnings from different groups of workers in the labor market



Going beyond the general average, it is possible to identify two very distinct profiles: intense drivers, for whom this activity is their sole or main job (in the sense that it is their main source of work income), and part-time drivers, who use it as a secondary job. Intense 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, workers who use ridesharing to complement their household income report driving 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 part-time drivers are able to earn about 14% more per hour (US$ 4.2 vs US$ 4.9 in PPP terms), suggesting that they might be able to optimize their driving routine and to respond to changing demand more strongly than intense drivers, who are working both in good and bad times.

My data does not allow us to take a clear position on whether Brazilian ridesharing drivers have daily earnings targets or respond to changing opportunities, as discussed in the literature on the labor supply of taxi drivers (Camerer et al. 1997; Farber 2008; Crawford and Meng 2011; Thakral and Tô 2021). However, the reported behavior of intense drivers appears to maximize monthly earnings, instead of hourly earnings. For 64% of the intense drivers, the marginal dollar from work remains more valuable than resting after 8 driving hours in a typical working day.

It is remarkable that the polarization between intense drivers and part-time drivers mirrors in many ways the differences between own-account workers and employees in the general workforce. In each of these comparisons, both intense drivers and own-account workers are less educated, have lower earnings per hour, are less likely to contribute to a pension system, and are more likely to live in a poor household (with poverty defined here using the threshold of US$ 5.5 daily per capita).

MAIN REASON TO DRIVE

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					
Adults in the household	2.38	2.40	0.606	2.36	0.366
Kids 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

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)
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	.
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	0.03	0.04	0.803	0.04	0.449
Northeast	0.12	0.12	.	0.11	.
Central-West	0.34	0.35	.	0.36	.
Southeast	0.39	0.39	.	0.38	.
South	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	.	0.109		0.000	

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

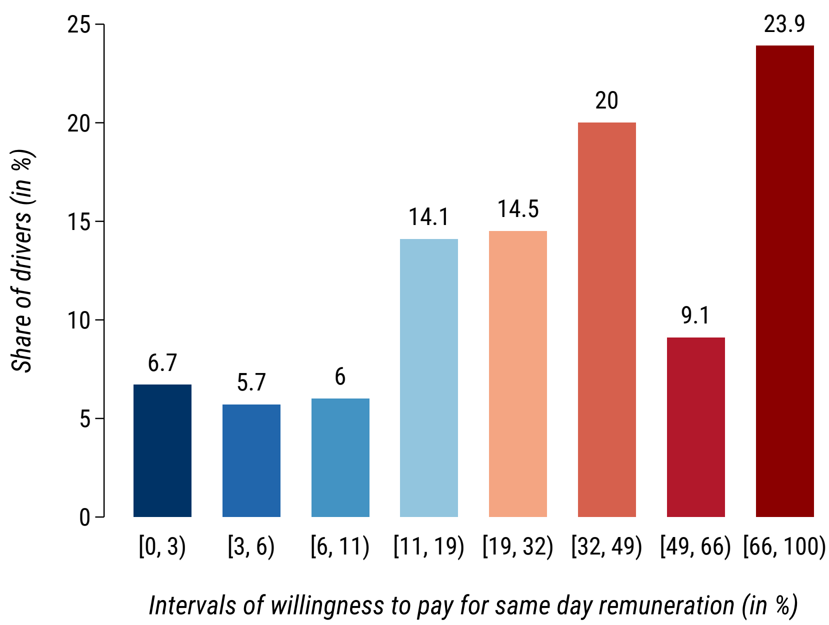
	Control group (n = 2,672)	*Treatment group A: unexpected expense* (n = 2,597)		*Treatment group B: unexpected income* (n = 2,873)	
	mean (1)	*mean* (2)	*p-value* (1) = (2)	*mean* (3)	*p-value* (1) = (3)

Notes: [1] The baseline sample is composed by 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 significante test reports the p-value associated with the F-test from a regression of the treatment indicator on all covariates displayed in the table.

A. The value of a short time to payment

A key finding from this research is that the possibility to quickly convert work into cash is extremely valuable for the ridesharing drivers. To be more precise, about 1 in every 4 drivers prefer to be paid the same day than to be paid nearly 3 times as much within a month, the most extreme trade-off considered in the survey. This group is depicted by the dark red bar in figure 4, and their choice reveals that they would only prefer a later payment under an increase of about 3 times as much relative to their usual rate (2.92 times, or 192 percent increase) or more.

Figure 4
Distribution of drivers over the rates implied by their preferred contracts



Taken at face value, a discount rate of 192 percent per month is extremely high by any standards. The current inflation rate in Brazil is under 0.4 percent per month, and reference interest rates in the financial system are around 1 percent per month. In our preferred interpretation, the choices reported by the drivers reflect a combination of (a) a very high present value of liquidity and (b) the option value of being able to quickly address expenses via extra labor supply.

This view is supported by the different distribution of preferences over the income levels within the drivers' population. Notably, the lower is the total household income per capita, the more critical is the option to quickly access one's work earnings as a driver.

Figure 5

Distribution of willingness to pay for same day remuneration by quintile of driver's household income per capita

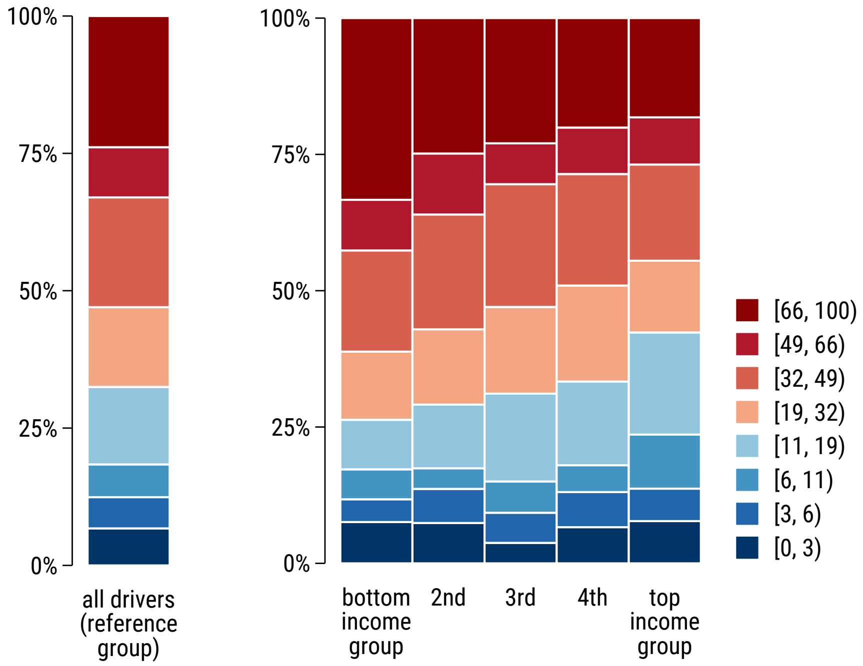
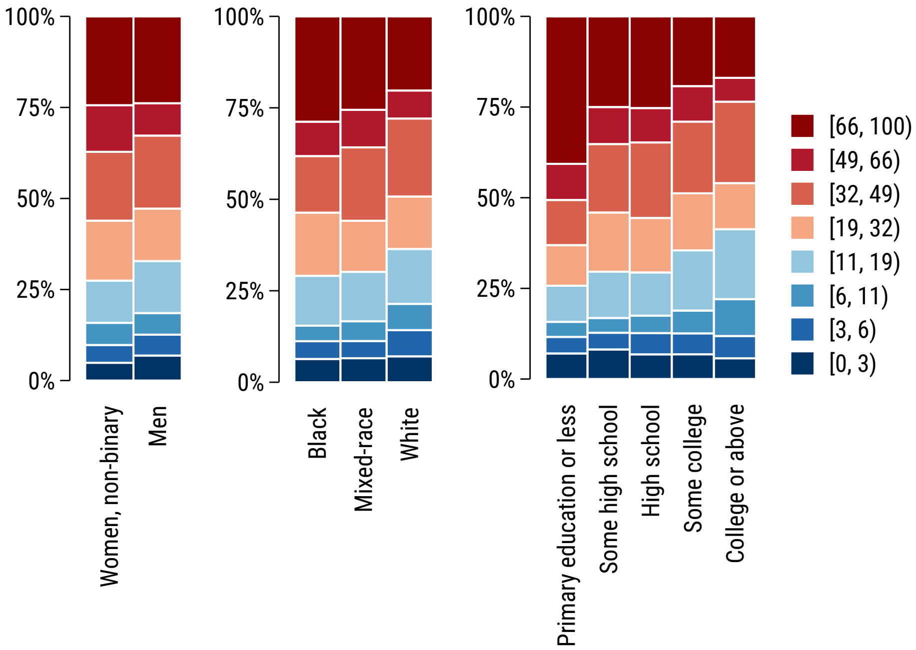
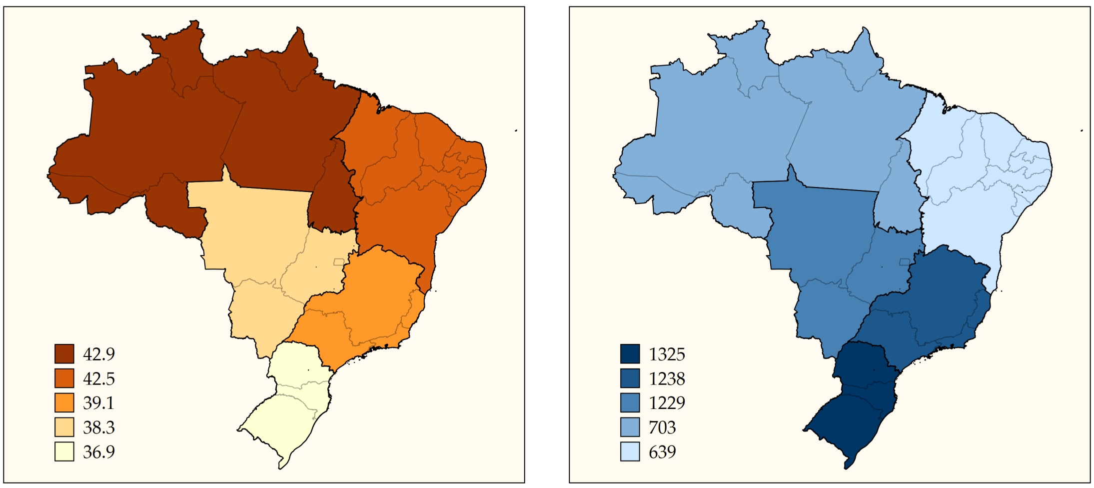


Figure 6
Distribution of willingness to pay for same day remuneration by demographics



At a geographical level, there is a clear correlation between the average poverty in the area and how likely a driver would be to privilege fast payments over large payments.

Figure 7
Payment preferences and median income level by geographic macroregion



(*a*) **Average willingness to pay for same day remuneration by geographical macroregion, as measured in the ridesharing driver's survey**

(*b*) **Median household income per capita by geographical macroregion, as measured in the national household survey (PNADC)**

There is a large variety of driver profiles, but the group looking for access to faster income stands out. The survey asks the drivers for the main reason why they have chosen to drive. About 30 percent of them point to the possibility of earning income fast, followed by 20 percent highlighting the flexibility to choose their working hours. In line with our proposed interpretation, those who are motivated by faster income are also less likely to accept being paid later, even at very high multipliers.

B. Text Analysis

[to be done]

Where a misspelled word was ambiguous, I would look back to the context in which it was applied to clarify which term was meant to be used.

Different verb declination (says, say, said), we keep the infinitive

frequent verbs can be droppes among stopwords (to be), I keep them

Adjectives and substantives (honest, honesty), we keep honesty

Adjectives and adverbs (facil, facilmente) we keep fail

Substantives with same root (dinheiro, dinheirinho, documento, documentacao) we keep the simplest one

Verbs and substantives with same root (invest, investment), we keep one of them

In all cases, the term that labels the root is immaterial to the analysis, that is, after collapsing invest and investment, either can label this group. Whenever possible, priority to labels that are less prone to ambiguitiy when translated to English (poupar and poupanca, save and savings, save also associated with religion in English)

Some of that is immaterial in English (I say, I would say, I would focus and the focus, pay, primeiro e primeiramente, valor, valorizar, valorioz)

The list is specific to this universe of words

Plurals in Portuguese are similar to English, in that the regular forms simply add an "s" to the singular word (as in "aplicativo" and "aplicativos"). However, it does mean that one can safely remove the final "s" whenever it appears. For example, one the most frequent words in the present corpora, "Deus" ("God"), would become "Deu" ("gave"). For that reason, plural forms were reviewed and removed individually.

Words that share a common root are grouped together (happy and happyness)

There is a recurring topic on car parts (expected) plus school materials and particular forms of taxes (given the timing of the survey).

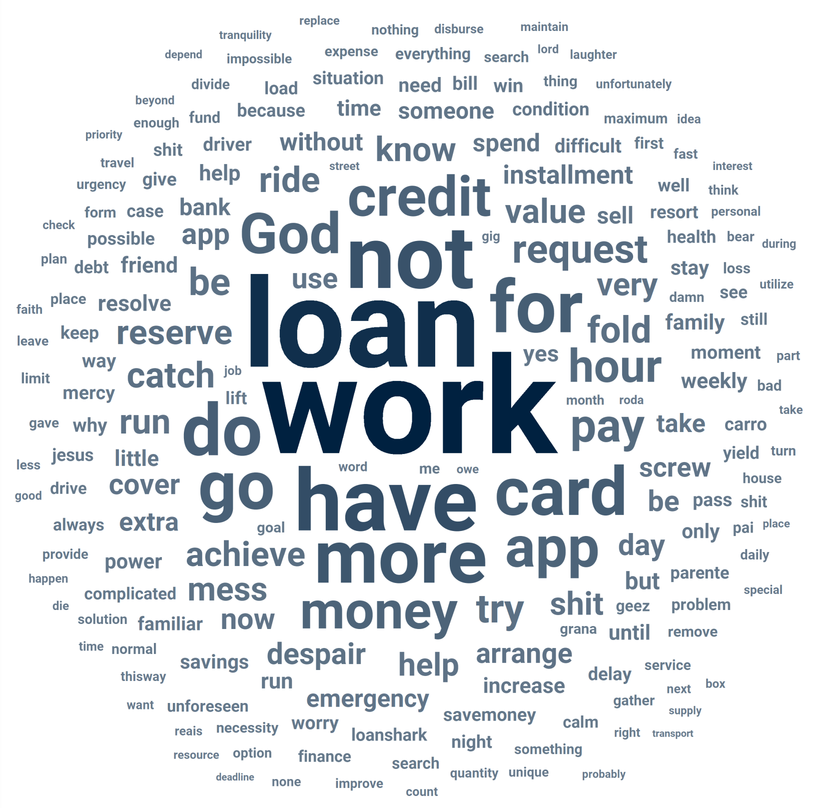
Widespread use of religious words (bless, harvest, tithe, glory, church, donate, god, jesus, pray, sow, prover).

The cleaning was performed in Portuguese.

The translation of the terms into English was done with support of chat gpt. The imput was "Translate the following list of words from Portuguese to English, posting each word in a new line, with the original word in Portuguese separated from its translation in English by an empty space:". The output was revised and adapted with the context in mind.

Figure 8

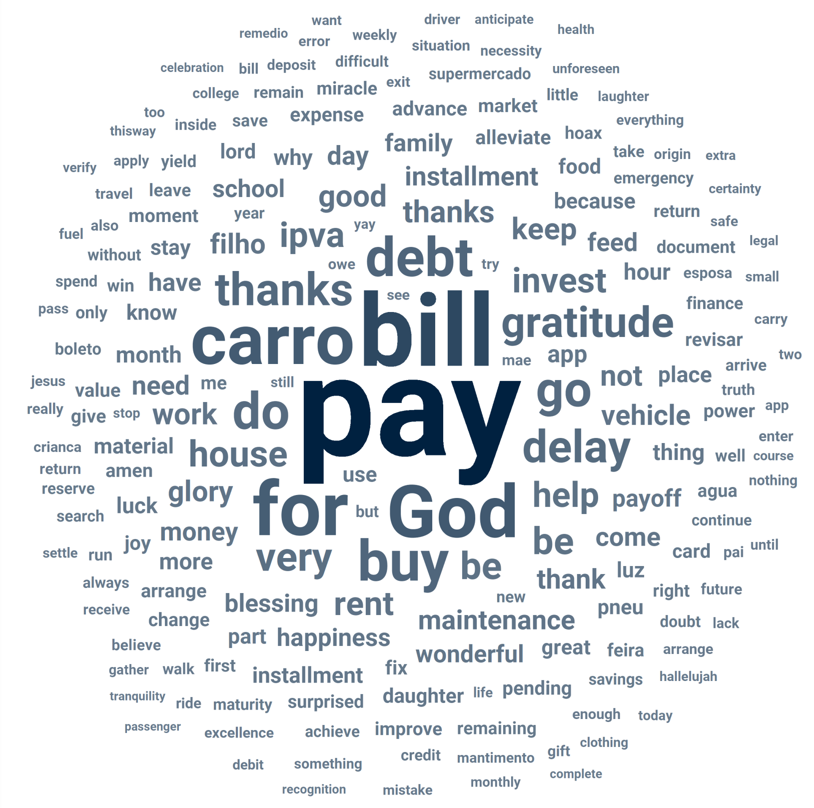
Top 100 terms mentioned by drivers when discussing how they would cover an unexpected expense



Notes: a

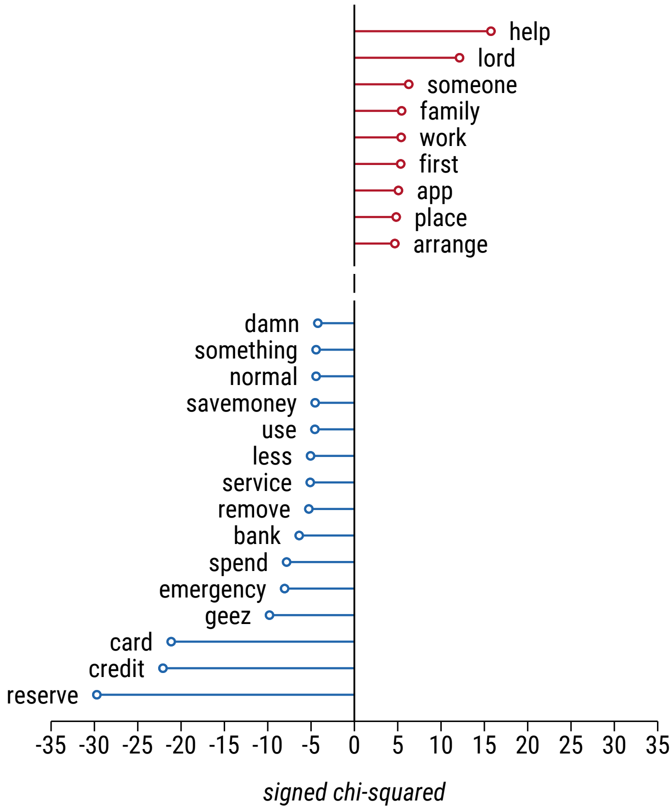
Figure 9

Top 100 terms mentioned by drivers when discussing what they would do with an unexpected income



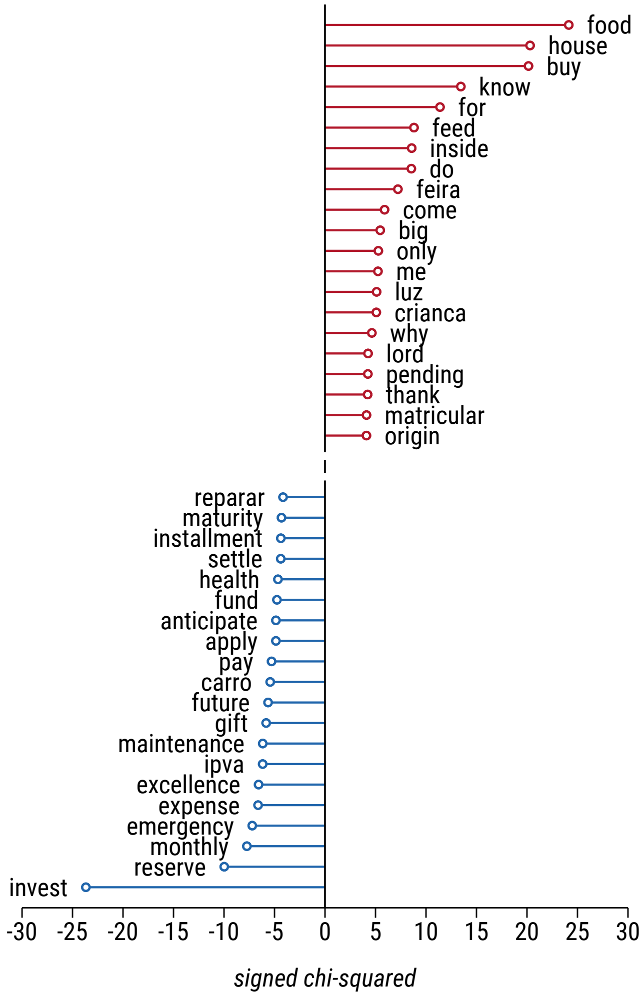
Notes: a

Figure 10
Keywords from emergency expenses discussion



Notes: The plot includes words that were mentioned by more than 1/1000 of the responses and have a chi-squared statistic of at least 3.84, which is the critical value for 5% significance in a test with two groups. The break in the axis is a reminder that the large majority of words have a keyness statistic in the interval [-3.84, 3.84] and are omitted.

Figure 11
Keyness measure for income discussion



Notes: The plot includes words that were mentioned by more than 1/1000 of the responses and have a chi-squared statistic of at least 3.84, which is the critical value for 5% significance in a test with two groups. The break in the axis is a reminder that the large majority of words have a keyness statistic in the interval [-3.84, 3.84] and are omitted.

V. Experimental Results

The average treatment effects are estimated via OLS:

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

where *Expense Discussion* and *Income Discussion* are indicators for random assignment to one of the treatment arms. The estimation 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 contribute to increase 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 contributes to controlling for such imbalance.

The main experimental result is that the increased salience regarding one's household financial conditions (as induced by the expense and income questions) lead to a small decrease in the importance of same day compensation, as reported in table 3.

The baseline estimates (columns 2 and 3) suggest that the average willingness to pay for same day remuneration is at least 1.5 percentage points lower for the drivers that have previously discussed their household budget, either from the perspective of addressing an extra expense or using some extra income.

Interestingly, this effect is not homogeneous over the underlying distribution of preferences for payment timing. To investigate who is pulling this average, 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.

Table 3
Average effect of the different budget discussions on the willingness to pay 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)	(0.7)
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 (defined as capital and non-capital areas, for each state), which is the same level adopted in the stratified randomization of the treatment. For the interval regression, the estimation results are bootstrapped over 500 replications.

Table 4
Treatment effects on the probability of choosing a contract with an implicit price 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)

Notes: The standard errors (reported in parenthesis under the point estimate) are clustered at the regional level (defined as capital and non-capital areas, for each state), which is the same level adopted in the stratified randomization of the treatment.

A. Mechanisms

Table 5
Average effects of the different budget discussions 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 different 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 caused by eventual imbalances between treatment groups.

As summarized in table 6, the doubly robust estimates reiterate that the increased salience of the household financial conditions induced by the expense and income questions lead 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 -1.44 and -1.54 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. As before, the most conservative estimation is reported in column 3, in which the covariate adjustment and the IPW are applied with an interval regression 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 6
Doubly robust estimation of the average effect of the different budget discussions on the willingness to pay for same day remuneration

	outcome: WTP midpoint		*outcome: WTP interval*
	Difference in Means	Doubly Robust Method: Covariate Adjustment via Regression and Inverse Probability Weights	Doubly Robust Method: Covariate Adjustment via Interval Regression and Inverse Probability Weights
	(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)	(0.6)
Reference level			
Control group mean	39.9	40.2	38.9
	(0.7)	(0.6)	(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 (defined as capital and non-capital areas, for each state), which is the same level adopted in the stratified randomization of the treatment. In the doubly robust estimators (2 and 3), the stardard errors also account for the variation coming from the estimation of the inverse probability weights (IPWs): in (2), the errors are calculated analytically, as the weigths and the main regression coefficients are estimated together via GMM; in (3), the two steps are bootstrapped over 500 replications.

Table 7

Doubly robust estimation of the treatment effects on the probability of choosing a contract with an implicit price above a given threshold

	Regression Adjusted with Inverse Probability Weights						
	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	8142	8142	8142	8142	8142	8142	8142

Notes: The standard errors (reported in parenthesis under the point estimate) are clustered at the regional level (defined as capital and non-capital areas, for each state), which is the same level adopted in the stratified randomization of the treatment, and also account for the variation coming from the estimation of the inverse probability weights (IPWs).

Table 8
Doubly robust estimation of the average effect of the treatments on the time to choose a contract

	outcome: Seconds on Q1	*outcome: Seconds on Q2*	*outcome: Seconds on Q3*	*outcome: Total seconds*
	Covariate Adj. via Regression and IPW	Covariate Adj. via Regression and IPW	Covariate Adj. via Regression and IPW	Covariate Adj. via Regression and IPW
	(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: 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 research explores the context of the ridesharing activity in Brazil to study the relative value of a short time to remuneration from the perspective of the workers. This setting is particularly well-suited for the elicitation method I implement because payment timing is salient for this population and a change in this policy is a real possibility. In short, ridesharing drivers are in a unique position to compare contracts that vary only in the payment timing, an exercise that could sound implausible in other sectors where compensation time is constrained by technical reasons, formal regulations or informal norms.

The question of the worker's paychecks' timing has received much less attention in the labor economics literature than other components of an occupation. One potential explanation is that most of the research is done in developed countries, where the large majority of the labor force is working in firms, typically under a fixed payment scheme. In developing countries, where informal arrangements and self-employment is more common, there is a larger variance in payment timing and it can be a salient feature in occupational choice. Moreover, as alternative forms of work such as digital gigs and platform work continue to engage an increasing number of people in both rich and poor countries, non-standard payment schedules can also become more salient.

The findings from this study suggest two main conclusions. First, the ridesharing services are an increasingly popular work alternative precisely because they can offer payment schedules that are valuable for workers under financial stress. We document a variety of driver profiles, but the strong preference for fast work income stands out among the fundamental reasons to drive. It seems plausible to extend this conclusion for any other platform work offering similar payment conditions (easy entry; engagement defined on a task-by-task basis; short time to payment), but we should pursue further research to document it.

Secondly, if an important share of drivers are motivated by strong liquidity constraints, and if this work does not lead to human or financial capital accumulation, they could be locked into a low income equilibrium. Therefore, the next steps in this research agenda is to investigate if this form of occupation leads to net welfare gains for the workers, by providing them a viable source of income, or net welfare losses, by limiting their capital accumulation in the long run.

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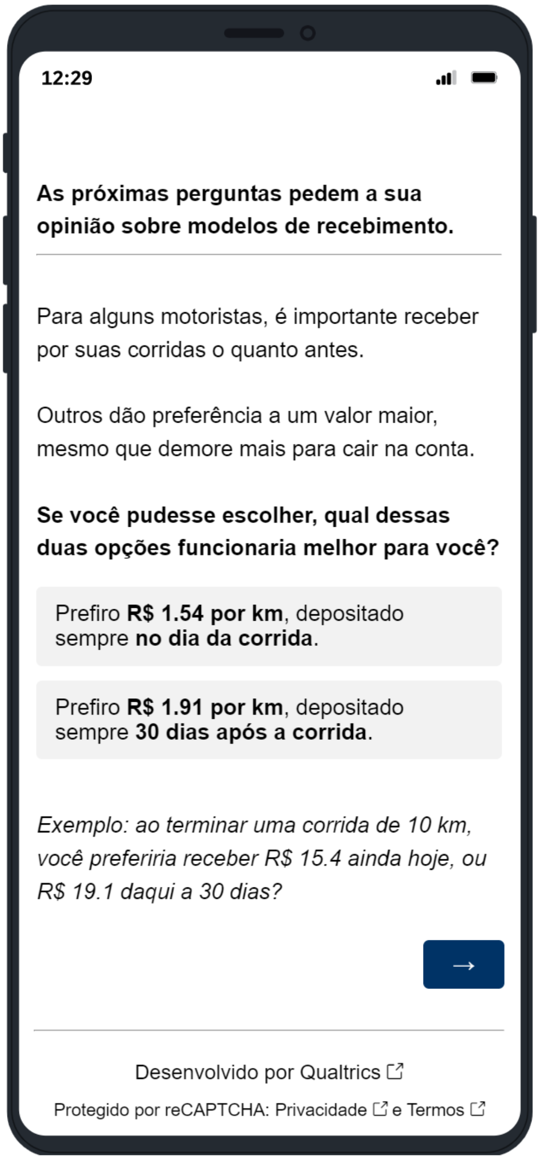
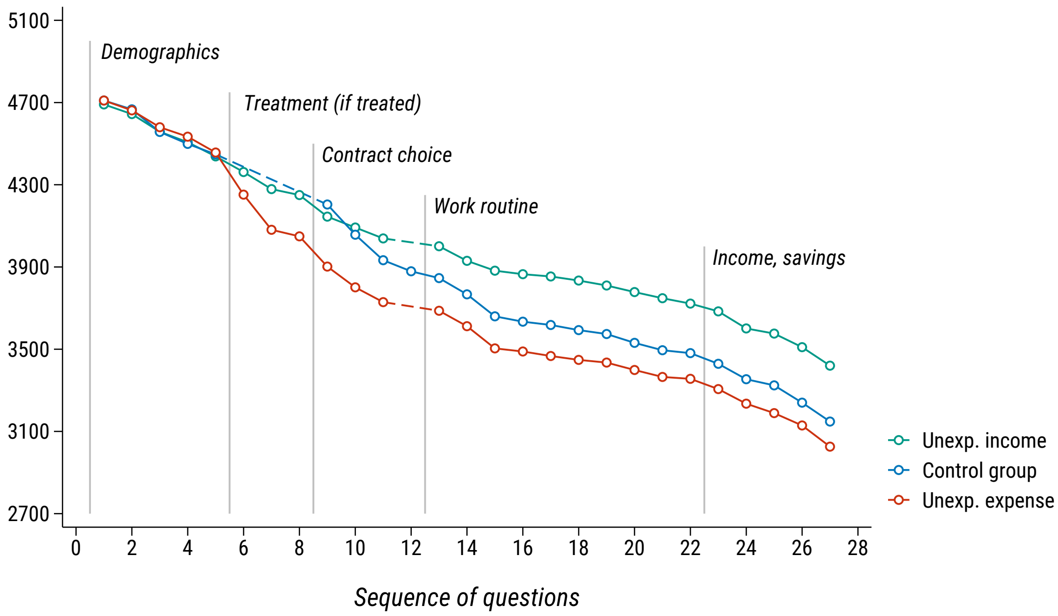
Appendix I: Example of the survey interface



Appendix II: Additional figures and tables

Figure 12

Number of active respondents throughout the sequence of possible questions in the survey, split by treatment condition



Notes: A respondent is considered to be active in the survey until the last question they submit an answer to. The number of respondents in the control group is depicted as constant along the treatment questions, as they skip this block by the design.

Table 9

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

	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)

Table 9

Characteristics of the male ridesharing drivers in the survey and corresponding summaries for male urban adult workers in Brazil (*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.*
1 to 2 years	16.6	(0.36)	16.0	(0.43)	17.9	(0.76)	10.3	(0.17)	7.1	(0.26)	12.2	(0.23)
2 to 4 years	29.8	(0.44)	31.0	(0.55)	26.7	(0.88)	21.8	(0.22)	21.4	(0.40)	22.4	(0.28)
More than 4 years	20.5	(0.39)	22.8	(0.50)	15.3	(0.72)	45.5	(0.29)	54.9	(0.51)	39.0	(0.35)
Social indicators (share in %)												
Contributes to a pension system	43.4	(0.55)	31.5	(0.61)	76.3	(0.93)	66.9	(0.29)	32.7	(0.50)	81.6	(0.28)
Household inc. per cap. < USD 5.5/day	11.0	(0.33)	12.0	(0.40)	8.4	(0.57)	8.4	(0.16)	9.0	(0.29)	4.9	(0.14)
Country region (share in %)												
North	8.7	(0.25)	8.4	(0.33)	8.4	(0.55)	7.8	(0.15)	8.8	(0.25)	7.3	(0.17)
Northeast	20.5	(0.35)	20.7	(0.48)	19.6	(0.79)	21.6	(0.26)	23.0	(0.42)	20.0	(0.30)
Southeast	46.9	(0.44)	48.2	(0.59)	44.7	(0.99)	47.2	(0.36)	45.7	(0.57)	48.0	(0.46)
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 are 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.

Appendix III. Survey questionnaire design

A. Sequence of question blocks by group

IF group = {reference group}

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

IF group = {discuss income sources}

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

IF group = {discuss income uses}

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

B. Survey questionnaire in the original language

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: Outcome 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 $\times$ 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 $\times$ 10} ainda hoje, ou R$ {taxa de referência da região $\times$ 1.03 $\times$ 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.

[______________________]