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Thiago Scarelli

Occupational Choices and Liquidity Constraints in Developing Countries

Sous la direction de
David N. Margolis — CNRS, Université Paris 1 Panthéon-Sorbonne, PSE

Président du jury
Nicolas Jacquemet — Université Paris 1 Panthéon-Sorbonne, PSE

Rapporteurs
Béatrice Boulu-Reshef — Université d'Orléans
Gabriel Ulyssea — University College London

Examinateurs
Luc Behaghel — INRAE, PSE
Anett John — University of Birmingham

My great-grandmother was born in the 1920s, but no one seems to remember exactly when.

She was a cheerful, talkative woman, yet strict and stubborn. As my grandfather recalls, his mother would always have things her way. Like the dresses she sewed for herself: a row of buttons on the front, so that she would need no help getting dressed, and two pockets at the height of her hands, where she stored her straw cigarettes.

She entered a classroom for the first time in the 1970s, her curly hair already white, joining an adult education program close to her home. In the evenings, under the lamplight, she would share her progress with her oldest grandchild, my mother, who was almost a teenager by then.

"Look here," she would show with great pride, "that is my name." In big round letters, the notebook read *Olivia Maria Ferreira*.

This thesis is dedicated to her memory.

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Summary

Summary of the thesis (English)

This thesis studies the link between workers' liquidity and their labor market outcomes. More precisely, we examine the hypothesis that the immediate availability of resources (or the lack thereof) may affect people's propensity to work by themselves. Since financial constraints tend to be more widespread and more severe in poor and middle-income countries, most of our attention is dedicated to this context, with a particular focus on Brazil.

To motivate the problem at a broad level, the first chapter examines the composition of the working population in local labor markets across the developing world. We document that, despite the diversity in the composition of those markets, own-account and family workers are consistently overrepresented among the poorest members of the employed population.

The second chapter, coauthored with David N. Margolis, builds on the hypothesis that intertemporal considerations can help explain the link between material scarcity and self-employment. In simple terms, we note that people may work on their own at any time, but can only take a potentially better-paid wage job after spending some time looking for it. We formalize this intuition under the job search framework and show that a sufficiently high subjective discount rate can justify the choice for own-account work even when it pays less than wage work. With this simple model, we estimate the lowest discount rate that is consistent with the occupational choice of urban own-account workers in Brazil. We find that at least two-thirds of those workers appear to discount the future at rates superior to those available in the formal credit market, which suggests constrained occupational choice. Finally, we show that our estimated lower bound of the time discount rate is positively associated with food, clothing, and housing deprivation.

To relax the assumptions imposed by our model in chapter two, the final chapter explores the question of pay schedules with a reduced form empirical strategy that elicits preferences directly in the field. We ran a large-scale survey experiment with ridesharing drivers in Brazil and found that the median Brazilian driver would rather be paid the same day than receive a fare 1.48 times higher after a 30-day waiting time. 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. Further analysis provides evidence that such a strong preference for fast payment reflects a structural context of resource scarcity and liquidity constraints, combined with a modest degree of behavioral heuristics that favor quick pay as a default safe choice. This chapter also contributes to the gig work debate by emphasizing that digital platforms are best positioned to offer agile pay schemes, which help workers address liquidity shortages in the short run but might induce poverty traps over the long run.

Sommaire de la thèse (français)

Cette thèse étudie le lien entre la liquidité des travailleurs et leurs résultats sur le marché du travail. Plus précisément, nous examinons l'hypothèse selon laquelle la disponibilité immédiate des ressources (ou leur absence) peut affecter la propension des individus à travailler pour leur propre compte. Étant donné que les contraintes financières tendent à être plus répandues et plus sévères dans les pays pauvres et à revenu intermédiaire, la majeure partie de notre attention est consacrée à ce contexte, avec un accent particulier sur le Brésil.

Pour motiver le problème à un niveau général, le premier chapitre examine la composition de la population active sur les marchés du travail locaux à travers le monde en développement. Nous constatons que, nonobstant la diversité de la composition de ces marchés, les travailleurs indépendants et les travailleurs familiaux sont constamment surreprésentés parmi les membres les plus pauvres de la population de travailleurs.

Le deuxième chapitre, coécrit avec David N. Margolis, s'appuie sur l'hypothèse selon laquelle les considérations intertemporelles peuvent contribuer à expliquer le lien entre la pauvreté matérielle et le travail indépendant. En termes simples, nous constatons que les agents peuvent travailler à leur compte à tout moment, mais qu'ils ne peuvent accepter un emploi salarié potentiellement mieux rémunéré qu'après avoir passé un certain temps à le chercher. Nous formalisons cette intuition dans le modèle classique de recherche d'emploi et montrons qu'un taux subjectif d'escompte du temps suffisamment élevé peut justifier le choix d'un travail à son compte même s'il est moins bien rémunéré qu'un emploi salarié. Avec ce modèle simple, nous estimons le taux d'escompte du temps le plus bas compatible avec le choix professionnel des travailleurs urbains à leur compte au Brésil. Nous constatons qu'au moins deux tiers de ces travailleurs semblent actualiser l'avenir à des taux supérieurs à ceux disponibles sur le marché du crédit formel, ce qui suggère un choix professionnel contraint. Enfin, nous montrons que notre estimation de la borne inférieure du taux d'escompte est positivement associée à la privation de nourriture, de vêtements et de logement.

Pour assouplir les hypothèses imposées par notre modèle dans le deuxième chapitre, le dernier chapitre explore la question des calendriers de paiement avec

une stratégie empirique en forme réduite qui élicite les préférences directement sur le terrain. Nous avons mené une expérience de sondage à grande échelle avec des chauffeurs de VTC au Brésil et avons constaté que le chauffeur brésilien médian préfère être payé le jour même plutôt que de recevoir un tarif 1,48 fois plus élevé après un délai de 30 jours. Ce choix équivaut à renoncer à un tiers de ses revenus nominaux par unité d'effort (0,48 sur 1,48) en échange du bénéfice d'être payé plus rapidement. Une analyse plus approfondie fournit des preuves qu'une telle préférence pour un paiement rapide reflète un contexte structurel de pauvreté des ressources et de contraintes de liquidité, combiné à un degré modeste d'heuristiques comportementales favorisant le paiement rapide comme choix par défaut. Ce chapitre contribue également au débat sur le travail à la demande en soulignant que les plateformes numériques sont les mieux placées pour offrir des régimes de paiement agiles, qui aident les travailleurs à faire face aux pénuries de liquidités à court terme, mais pourraient induire des pièges de pauvreté à long terme.

Introduction

This thesis studies the link between workers' liquidity and their labor market outcomes. More precisely, we examine how the immediate scarcity of resources could affect people's choices in the labor market. In the following chapters, we present evidence that financial stress can push people to prioritize work arrangements that pay fast over options that pay more, and we argue that this trade-off contributes to the prevalence of many forms of easily accessible but poorly paid self-employment in the developing world. The rest of this introduction defines the key concepts we adopt in this discussion, presents the general argument, lays out the structure of the thesis, and contrasts our approach with the related literature.

Conceptual framework

The fundamental propositions we will develop throughout the thesis are built around the concepts of *scarcity*, *liquidity*, *constraint*, and *time discounting*, and their particular applications in the context of the labor market. While these are related ideas, they should not be taken as synonyms.

We understand *scarcity* as a condition of deprivation, be it momentary or persistent, close to the meaning adopted by Shah, Mullainathan, and Shafir (2012) and Mullainathan and Shafir (2013). While the whole field of modern Economics is shaped by the assumption that resources are always scarce relative to the agents' unbounded wants, we take scarcity here in its common usage as material insufficiency or a shortage of consumption goods relative to some basic needs.

A cause for scarcity is insufficient *liquidity*, defined as an individual's ability to access cash (or other liquid financial resource) in the short term. The defining aspect of liquidity is its temporality: workers with the potential to earn or access abundant resources in the future may face liquidity shortages if they cannot use these resources for consumption purposes in the present.

A priori, such intertemporal exchange should happen in the financial market, and the price for the trade would be a function of the prevailing interest rates. If such transactions do not take place, even when the parties involved would likely benefit from it, we may speak of a *constraint*, a market limitation related to the economic environment under which the agent operates, as discussed by Stiglitz and Weiss (1981).

Finally, we use *time discount rate* as a parameter that summarizes the many considerations underlying an individual's priorities in intertemporal problems. If a worker perceives resources today as being more important than the same resources in the future, we say they *discount* the value of such future resources. However, note that we need not see this subjective time discount rate as a fixed preference, a psychological individual trait, or an exogenous taste parameter. Instead, we assume that the effective discount rates that emerge from people's revealed economic choices reflect a range of determinants, including the contingent context where they occur. By doing so, we adopt *time discounting* as a concept that is more general than *time preference*, as suggested by Frederick, Loewenstein, and O'Donoghue (2002). Variations of this perspective also appear in Fisher (1930), Lawrance (1991), Pender (1996), Tanaka, Camerer, and Nguyen (2010), Haushofer and Fehr (2014), Bernheim, Ray, and Yeltekin (2015), Carvalho, Meier, and Wang (2016), Di Falco et al. (2019), Bartoš et al. (2021), and Dean and Sautmann (2021), among others. In broad terms, we follow this literature in admitting that (i) many causes drive intertemporal choices; and that (ii) while observed behavior is generally insufficient to identify pure time preferences in the field, it can be informative about liquidity constraints.

The liquidity → labor → liquidity nexus

The fundamental objective of this thesis is to contribute to our understanding of the many links between liquidity and labor. As a starting point, let us consider the most direct part of this relationship: paid work affects one's liquidity, as the associated remuneration increases cash immediately available relative to the counterfactual of no paid work. This is a trivial link, so much so that measures of earnings and cash holding are used as success indicators in evaluating labor market interventions. A policy that fosters workers' liquidity is often considered a desirable one.

Now, we turn to the other direction of this relationship: the consequences of liquidity on the different choices people make regarding their labor supply. From this perspective, the links are more complex. According to literature following the classic work from Evans and Jovanovic (1989), nascent entrepreneurs often rely on their own liquidity to set up their businesses. When that is the case, the immediate availability of financial resources increases the likelihood that someone becomes self-employed, whereas liquidity constraints keep people as wage employees instead.

This thesis argues that the exact opposite may occur, in the sense that *the lack of liquidity could push people towards self-employment and away from wage* *employment*. The reason for turning the classic constrained entrepreneurship argument on its head is based on the fact that not every self-employed is the same. Entrepreneurs and employers do require capital upfront, but those constitute only a few percentage points of the whole active population, both in developed and developing economies (International Labour Organization 2022). In contrast, the bulk of the self-employed in the world is composed of people simply working by themselves (also called own-account workers), primarily in poor and middle-income countries, where they perform activities with a low entry barrier. In this context, self-employment can be the most accessible source of liquidity for a worker, which is particularly important in a context of scarcity and when wage employment takes a long time to find.

The following chapters will examine the assumptions and implications associated with this argument in more detail. First, if scarcity pushes people into self-employment, we should find that the poorest workers in a given market are the most likely to take it up, which we document in Chapter 1. Second, if people do start working on their own instead of investing time into finding better-paid employment, such behavior can carry some information about their intertemporal priorities, which we explore in Chapter 2. Finally, if prompt remuneration is indeed a relevant job feature for constrained workers, we should be able to elicit the gradient of its valuation in a discrete choice experiment in the field, which we do in Chapter 3.

Chapter 1: Stylized facts on own-account work

The first chapter looks at the composition of the working population in local labor markets across the developing world. To cover as many different markets as possible, we use individual-level data from national censuses and define the geographical dimension of a labor market as the first (largest) subnational level available in each country (generally comparable to the level of a State in the United States). In light of the available data, we infer the relative wealth of a given worker from the observable aspects of their household (that is, their durable assets and the general housing infrastructure), as summarized by the scores of the first component from a Principal Component Analysis (PCA). The idea is to reduce the complex structure of housing conditions down to its most informative dimension (understood as the dimension that captures the largest share of the underlying dispersion of the attributes), as it allows for a meaningful ranking of workers' material living conditions.

This exercise leads to three results that are relevant to the present discussion. First, we find a huge diversity in the structure of subnational labor markets. For instance, the share of wage employment may range from nearly absent to largely dominant, reflecting a significant heterogeneity among labor markets in developing countries. Second, despite such variety, employers rarely represent more than a few percent of the working population in any given region. This means that the dynamics of self-employment in developing countries are fundamentally driven by the own-account workers. Finally, we document that the workers at the bottom of the wealth distribution of a given region are systematically overrepresented within own-account work and contributing family work. Put otherwise, we find that the poorest workers have a stronger propensity to be outside the context of a firm.

One of the objectives of this chapter is to investigate labor market patterns that hold across a large sample of developing countries. By doing so, we can go beyond the particularities of one institutional context and document more fundamental regularities. In this sense, our work is close to Donovan, Lu, and Schoellman (2023), who harmonized labor force microdata from 49 countries to study patterns in labor market transitions according to the country's development level. The key distinction between both approaches is one of stock and flow: while we focus on the labor market structure at a fixed point in time (as documented by the censuses), they investigate the movements between labor market states (using rotating panels). For this reason, their results are an interesting complement to ours. Most notably, they find that labor market flows are systematically more intense in developing countries and clarify that such dynamism is primarily a consequence of the high transition rates in and out of self-employment in those economies. Conversely, when looking only at the formal, well-paid employees, they find broadly similar flows around the globe. These results support our views in two ways. First, it offers yet another evidence that self-employment is a crucial feature of labor markets in developing economies. Second, the exceptionally high transition rates they find for self-employment in poor countries support the interpretation that this labor market status is characterized by activities with low entry barriers in such a context.

These statistical regularities, however robust, cannot pinpoint the mechanism behind the association between material circumstances and occupational choices. In particular, the poverty gaps we find could be driven by systematic differences in the human capital of people inside and outside the firms. Hence, if we are to claim that scarcity and liquidity constraints contribute to self-employment, we must clarify how these constraints operate in the occupational choice process.

Chapter 2: Occupational choice as an intertemporal problem

The subsequent chapter, coauthored with David N. Margolis, aims to address these critiques by providing more structure to the problem faced by the worker. The insight here is that the fundamental choice faced by an individual joining the labor market is between working by themselves versus looking for a job elsewhere. Following the well-established literature on frictional labor markets, we note that people do not jump straight into a wage job — but they can choose to search for one, and eventually, they may find an employer willing to present an acceptable offer. Own-account work, in contrast, depends primarily on one's own initiative, especially when taking up the types of activities that are the most common for the self-employed in developing countries, which require little capital or paperwork.

We formalize this intuition under the standard job search framework and show how a sufficiently high subjective discount rate can justify the choice of own-account work even when it pays less than wage work. With this simple model, we estimate a lower bound for the discount rate that is compatible with the observed occupational choice of urban own-account workers in Brazil. We find that at least two-thirds of those workers appear to discount the future at rates superior to those available in the formal credit market, which suggests constrained occupational choice. Our results indicate that the idea of "necessity" can be better understood as a high value for present consumption since the estimated lower bound of the time discount parameter is also shown to be significantly associated with other measures of food, clothing, and housing deprivation.

A potential critique of this modeling choice is that the core of the problem could be framed in terms of liquidity alone, without a time discount. In its simplest form, the argument would be that workers turn to self-employment when they do not have enough cash to meet their needs. However, such formulation requires many arbitrary assumptions to be empirically operational. For instance, which threshold defines "not having enough"? How do we set a minimum subsistence basket that matches the idea of "needs"? How does it change with household composition? To avoid these discretionary components, we turn to discount rates as the summary for consumption urgency. In our approach, the discount rate emerges from the frictional job market framework; it is not an ad hoc element we introduce. Furthermore, it allows us to claim that the revealed choice of a worker is consistent with a liquidity-constrained decision because the market's discount rate is a natural reference point to gauge a liquidity constraint. In this sense, our empirical approach is similar to the reasoning from Pender (1996), in that the distance between individuals' effective discount rates and the banks' rates serves as evidence of market failures and misallocation.

Another concern with our approach is that measures of discount rates over monetary rewards may not identify pure time preferences but instead reflect liquidity constraints, as recently articulated by Dean and Sautmann (2021) and others. We argue that this is a lesser problem for the objectives of this chapter, as we do not aim to estimate pure time preference parameters. The key objective is to capture time discount rates that are consistent with the choices we observe in the labor market. In our preferred interpretation, these rates are precisely taken as a measure of liquidity constraint.

Nevertheless, we acknowledge that the semi-structural nature of the estimation protocol carries strong assumptions, as discussed in detail in the body of the chapter. The next step is to look for evidence of liquidity constraints in the labor market using a reduced-form design.

Chapter 3: Payment schedule preferences in the field

The final chapter presents an empirical strategy that elicits preferences for different work pay schedules, imposing as little structure as possible. Our line of inquiry implies that a large share of the people working by themselves in developing countries could be taking up these activities to secure some income quickly. If this is true, we should expect that (1) workers assign some positive value to the benefit of being paid sooner and (2) the preference for such benefit is directly proportional to their financial stress. To test these hypotheses, we conduct a large-scale discrete choice experiment with ridesharing drivers in Brazil.

The economic context of ridesharing drivers offers some desirable properties for this research strategy. In particular, the task is largely homogeneous, allowing us to put aside considerations about tastes and amenities, which usually are confounders when studying compensating differentials between occupations. Furthermore, remuneration rules are defined at the platform's discretion and can change without affecting the fundamental nature of the job, which means that the payment schedule is a plausible and salient margin of adjustment. Finally, gig work compensation is not (yet) bound by social and formal norms to the same extent as other well-regulated activities.

In practice, we partnered with a major ridesharing platform in Brazil and recruited over 14,000 active drivers for a survey experiment. The outcome of interest is the drivers' reported preference when faced with a hypothetical comparison between being paid their usual kilometer rate on the same day of their rides or receiving a higher rate 30 days after their rides. We find that the median Brazilian driver would rather be paid the same day than receive a fare 1.48 times higher after a 30-day waiting time. 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. Further analysis provides evidence that such a strong preference for fast payment reflects a structural context of resource scarcity and liquidity constraints, combined with a modest degree of behavioral heuristics that favor quick pay as a default safe choice.

Contributions to the literature

An important part of our argument relates to the consequences of scarcity for people's economic choices. The literature provides evidence that poverty in itself can trigger fundamental changes in behavior because it causes tunneling (an excessive focus on immediate problems) and consumes mental bandwidth (the finite ability to command executive control and perform cognitive tasks) as it draws attention away from all other tasks (see Shah, Mullainathan, and Shafir 2012; Mani et al. 2013; Mullainathan and Shafir 2013; Mani et al. 2020). Our contribution is to examine a new channel through which scarcity could affect people's priorities *in the labor market*.

In general terms, it is intuitive to expect that scarcity affects workers by increasing the marginal utility of cash relative to other work amenities. However, the novel channel we stress here refers to the *schedule of work remuneration*: facing a menu of payment flows, workers under financial constraints may favor the jobs with quicker remuneration schemes.

The role of the remuneration schedule is particularly intriguing for a simple reason: it should not matter. Under complete markets, any potential intertemporal arbitrage would happen in the financial sector, and choices between different flows would be reduced to taking the alternative with the highest present value, a result summarized in Frederick, Loewenstein, and O'Donoghue (2002). However, our findings suggest that *work arrangements can take the role of financial instruments* when those are missing — and that are priced as such. In simple terms, an activity that offers the option to promptly convert labor effort into cash is, by definition, more liquid than the alternatives, and it should be no surprise that liquid instruments offer low returns. Moreover, those "liquid occupations" can even offer implicit returns below the market's when they are a worker's primary liquidity source.

Regarding the general consequences of cash-in-hand in the labor market, we complement the findings from Kaur et al. (2021), who manipulates the payment time of manufacturing workers in India and find that financial concerns (in the cash-poor days) decrease workers' productivity. While we believe such patterns play a larger role in developing countries, it is worth noting they also affect workers in rich economies. Looking at the Austrian labor market, Card, Chetty, and Weber (2007) find that severance pay increases the unemployment spell and conclude that such a reaction to lump sum liquidity is evidence of credit constraint. Another paper closely related to ours is Carvalho, Meier, and Wang (2016), who study cognitive function, intertemporal and risk choices with a sample of low-income US households before and after payday. While they find no difference in cognitive capacity or risk behavior, the authors document that the behavior of before-payday participants is consistent with a higher present bias, a result likely due to binding liquidity constraints.

Our discussion also builds on the distinction between two forms of self-employment. While the literature has proposed various names for these ideal types, the common element is their motivation: people in the first group are said to be self-employed by their choice, while people in the second group would arguably do something else if they could (see Fields 2014; Gindling and Newhouse 2014; La Porta and Shleifer 2014; Margolis 2014; Levine and Rubinstein 2017). Despite its intuitive appeal, drawing the borders between these groups remains an empirical challenge, as it requires identifying who is not doing what would be best for them and why. Our contribution is to provide a simple criterion for contained own-account work by combining familiar elements from the frictional labor markets framework and the financial constraints literature. In a nutshell, constrained own-account workers would gain from having another activity but take self-employment anyway to address their immediate consumption needs. We can tell them apart because the minimum time discount rate compatible with their revealed occupational choice is strictly superior to the market's rate, which suggests that they do not operate under market prices.

To emphasize the novelty of this approach, let us recall that a standard explanation for the distribution of occupations and the persistence of return gaps is that different workers have different productivity for different tasks, in the spirit of Roy (1951) and Lucas (1978). In the standard framework, one's productivity (or "talent") is exogenously assigned, and workers self-select into an occupation based on their relative advantages. At its core, the present thesis complements this view by describing an alternative mechanism that rationalizes the existence of return gaps based on endogenous, context-driven components — without sacrificing individual rationality and self-determination.

Notably, the role played by time discount as a driver of permanent wealth inequality in our context echoes, to some extent, the discussion introduced by Ramsey (1928) in a research paper that became the foundation of the modern economic theory of savings. After describing how discounted marginal utility affects savings and consumption decisions over the life cycle, Ramsey concludes the manuscript with an extension of his model "to take account of variations in the rate of discount from family to family" and claims that, under preference heterogeneity in time discount, "equilibrium would be attained by a division of society into two classes, the thrifty enjoying bliss and the improvident at the subsistence level". The "Ramsey's conjecture" inspired a long literature that has supported its broad implications (see Becker 2006; Mitra and Sorger 2013; Epper et al. 2020). In this family of models, patient individuals become wealthier than their impatient peers due to *differences in their savings behavior* that follow from exogenous intertemporal priorities. Our innovation is to describe a variation of this structure where patient individuals become wealthier because of *differences in their behavior in the labor market*.

In this sense, our perspective relates to the recent work from Hardy, Kagy, and Song (2022), who show that poor traders are often willing to accept lower prices for their goods than richer ones. According to their results, a decrease of one standard deviation in the liquidity of a garment maker in Ghana is associated with 5% lower final prices in real bargaining exercises, a robust relationship that they also find using a controlled field experiment. It is reasonable to expect some degree of classic market differentiation to take place in this setting, with some garment makers producing superior goods and commanding higher prices for them. However, their findings suggest something more interesting: the traders' contingent liquidity in itself contributes to systematic return gaps for a similar labor effort. They note that such a result could be justified by risk aversion, differences in aspirations, or subsistence needs. In any case, as the authors put it, one "gotta have money to make money".

Investigating the micro-foundations of labor market structures is all the more relevant given the accumulation of evidence pointing to an "excess" of self-employment in poor countries, including advances in how to define and identify it. In a rare example of large-scale manipulation of a labor market, Breza, Kaur, and Shamdasani (2021) hired about 1/4 of the male labor force in a sample of villages in Odisha, India. During peak months, when employment demand is higher due to agricultural seasonality, local wages increased and local employment decreased, relative to the sample of control villages, showing that the experiment effectively created competition for the local employers. In contrast, during lean months, removing 1/4 of the workforce from the market had no impact on the average wage for the remaining workers but did reduce the amount of self-employment in treated villages. The authors conclude that at least 24% of all self-employment observed in the lean season is due to *labor rationing*. From our perspective, the idea of labor rationing coincides with the absence of immediately accessible wage positions at the prevailing market remuneration.

With respect to the time dimension, we know that the tendency to avoid allocating resources to activities that pay off in the long term remains a barrier to higher welfare in multiple aspects of life. Examples of underinvestment in the developing world are documented in the context of fertilizer adoption in Kenya (Duflo, Kremer, and Robinson 2011), bednets in India (Tarozzi et al. 2014), fuel-efficient cookstoves in Uganda (Levine et al. 2018), crop insurance in Kenya (Casaburi and Willis 2018), education in Colombia (Carrillo 2020), and water chlorination in Kenya (John and Orkin 2022), despite the high expect return in all these cases. Our contribution is to stress how searching for a wage job can be considered an investment, and as such, it can be subject to similar behavioral and liquidity constraints.

Still within the development literature, the research on payment timing that is closest to ours leads to strikingly opposing results, showing that workers are often willing to earn *less* in exchange for being paid later (Brune and Kerwin

2019; Casaburi and Macchiavello 2019; Brune, Chyn, and Kerwin 2021). To reconcile both perspectives, we note that their research design examines the choice between a large lump sum versus frequent payouts, while we are primarily interested in the interval to payment, clean of any possible accumulation of resources. Therefore, their results provide evidence that lump sum payments can serve as a secure savings instrument and as a commitment device. In contrast, we provide evidence that immediate payments can serve as a source of liquidity and an insurance mechanism against unexpected shocks. Taken together, all these results agree that the details of the payment flow matter for the workers *because they substitute for financial services* that people cannot access otherwise. In the presence of well-developed and accessible savings and borrowing markets, neither the delay nor the accumulation of the workers' remuneration should affect their payment choices.

While there is a sizeable overlap between the issue of informality and the subjects covered here, we clarify that the discussion of the workers' legal status per se is out of the scope of this thesis. The reason is one of emphasis: the concept of *informality* stresses the fact that the activity does not comply with some (or all) due regulations (Ulyssea 2020), whereas our main concern refers to the differences in the flow of earnings between alternative work arrangements, regardless of their (in)formal status. That said, we note that the tasks performed by poorly paid self-employed workers in developing countries are generally associated with the lowest entry barriers and the least amount of paperwork, which leads to a high coincidence between informality and self-employment driven by liquidity constraints. For that reason, the text provides estimates of formalization rates for the population of interest, whenever they are available, as a relevant part of the context. This dimension may take a more salient place in future work, however, as we move on to investigate the economic trade-offs implicit in alternative formalization schemes for gig workers, as currently discussed by regulators, to the extent that taxes and contributions paid in the present are often a condition for benefits that take place in the future.

To conclude, we stress that the hypothesis examined in this thesis implies a particular form of poverty persistence. When the workers facing the harshest financial conditions are the most inclined to choose labor arrangements that pay faster, they will likely continue to face the same hard choices in future periods, as such arrangements are precisely the ones that pay the least. The complex relationship between labor market outcomes and liquidity generates a negative feedback loop. While none of the chapters alone is sufficient to pin down all the links in this cycle, the thesis's objective is to provide an accumulation of empirical evidence that is consistent with its general mechanisms and pave the way for related investigation in the future.

Chapter 1

Occupations and Wealth in Developing Countries

by Thiago Scarelli

This chapter examines 1,313 regions from 46 developing countries to document that individuals working outside the context of a firm (own-account workers and family workers) are consistently overrepresented among the poorest workers in their labor markets.[1]

JEL: I32, J21.

Keywords: Employment; Poverty; Development.

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1.1 Introduction

To what extent is the workers' occupational category (whether someone is an employer, an employee, an own-account worker, or an unpaid family worker) associated with their material living conditions? Motivated by this question, this short chapter looks at the distribution of employment categories over different wealth levels in 1,313 regions from 46 low- and middle-income countries. We find that, despite a wide diversity in the composition of those markets, own-account and family workers are consistently overrepresented among the poorest members of the employed population.

These results contribute to the literature on the composition of the labor supply by examining the labor markets at a subnational level, complementing the patterns established with national aggregates. Moreover, it estimates workers' wealth from observable household living conditions, an approach that improves the coverage of the working population relative to comparisons based on monetary labor income.

1.2 Data source and sample description

This study explores microdata from the national censuses collected and harmonized in the IPUMS International database (Minnesota Population Center 2020). The universe of interest comprises all countries classified by the World Bank as low, lower-middle, or upper-middle income in the reference year of their censuses. The final sample is restricted to censuses that include sufficient information on the employment status of the working population, and a comprehensible set of indicators on the material living conditions in the household, as detailed in the following sections. If more than one census edition is available, we keep only the latest one, and waves collected before 2000 are disregarded.

The final sample is broad in terms of geography (20 countries from Africa, 18 from the Americas, and 8 from Asia) and in terms of income level (14 low-income countries, 21 lower-middle, and 11 upper-middle), representing a total of 1.32 billion people.[2]

2. In alphabetical order, it includes Armenia (2011), Benin (2013), Bolivia (2012), Botswana (2011), Brazil (2010), Burkina Faso (2006), Cambodia (2008), Cameroon (2005), Colombia (2005), Costa Rica (2011), Dominican Republic (2010), Ecuador (2010), Egypt (2006), El Salvador (2007), Fiji (2014), Ghana (2010), Guatemala (2002), Haiti (2003), Honduras (2001), Indonesia (2010), Jamaica (2001), Jordan (2004), Laos (2005), Lesotho (2006), Liberia (2008), Malawi (2008), Malaysia (2000), Mali (2009), Mexico (2015), Morocco (2014), Nepal (2011), Nicaragua (2005), Panama (2010), Paraguay (2002), Peru (2007), Rwanda (2002), Senegal (2013), Sierra Leone (2015), South Sudan (2008), Sudan (2008), Suriname (2012), Tanzania (2012), Togo (2010), Uganda (2014), Venezuela (2001), and Zambia (2010). In most cases, the microdata represents a 10% random sample from the original census, with the exceptions of Malaysia (2%), Mexico (9.5%), Nepal (12%), South Sudan (7%), and Sudan (16.6%). China and India are not in the sample because the available data lack crucial variables, and their absence may represent the main limitation to the generalizability of our findings.

1.3 The employment categories

The analysis focuses on employed individuals of a given region (i.e., excluding the inactive and the unemployed) between the ages of 15 and 64. In all that follows, the term "workers" will refer to this specific population.

We classify the workers into four categories, according to their primary occupation: [a] *employers*, who own the firm where they work and regularly engage other employees to contribute to the production under their authority; [b] *employees*, who work in exchange for pay under an agreement with a firm; [c] *own-account workers*, who perform an autonomous economic activity without regularly engaging other employees; and [d] *contributing family workers*, who support the activity of another family member without expectation of regular pay.

While the related literature may adopt the term "self-employed" in reference to both employers and own-account workers, this chapter distinguishes those two groups. We also clarify that, for the purposes of this analysis, the categories are independent of the legal status of the activity: both formal and informal employers are considered employers, and similarly for all other workers.

In practical terms, those groups can be readily identified in the IPUMS database, as they represent a subset of the classification proposed in the International Classification of Status in Employment (ICSE) (International Labour Office 2020). The single analytical adjustment we make consists of moving domestic workers from employees into own-account workers, when the information is available, since they are closer to autonomous service providers than employees who contribute to a firm's production. However, this group is relatively small, and the results are quantitatively similar without adjustment. The remaining work activities (apprentices, unknown, others, or missing) are removed from the sample.

1.4 An index of household wealth

Monetary measures of socioeconomic status based on asset holdings, income, or consumption require data that is not systematically available for representative samples in developing countries. To overcome this constraint, we use the information provided by the infrastructure of someone's residence, following a strategy popularized after Filmer and Pritchett (2001) with the same implementation as Bandiera, Elsayed, and Smurra (2022).

The objective is to summarize the set of domestic assets observed for a given household into an index that captures, as much as possible, the variability in the distribution of those assets over all households. In technical terms, the index weights standardized asset indicators by the scores of the first component from a Principal Component Analysis (PCA), estimated separately for each country.

The resulting index is assigned to all household members, assuming they benefit equally from the domestic conditions captured by it.

The set of variables that may enter into the estimation, according to availability, includes: [a] *durable assets* (ownership of the housing unit, radio, telephone, cellphone, refrigerator, washing machine, computer, cars per capita, TVs per capita), [b] *measures of the infrastructures and services* (type of fuel used for cooking, access to electricity, piped water, internet, sewage system, and trash disposal mechanism), and [c] *measures of housing space, quality, and comfort* (household members per room and per bedroom, presence of a toilet, air conditioning, kitchen, bathing facilities, materials used in the floor, walls, and roof of the dwelling).

To minimize the incidence of large clusters with identical indexes, we keep in the sample only the censuses containing at least 20 indicators with non-missing values for more than 85% of the households.[3] The final number of available indicators can range from 20 (in the case of Armenia) to 64 (for Zambia).[4]

1.5 Regional labor markets

The main exercise consists of studying the distribution of workers over different categories of employment and different levels of wealth. One novelty in this chapter is that the analysis takes place at the level of a *regional labor market*, defined as the areas sharing the same urbanization status (either urban or rural) within the first subnational division in a country (be it state, department, region, province, district, or parish, according to the jurisdiction). In other words, a given state's rural and urban areas make up two distinct regional labor markets, and a country can be divided into up to twice as many regional labor markets as there are states.

The use of subnational reference areas leads to a range of analytical units (1,313 regional labor markets from 683 states in 46 countries on three continents). It also defines relatively homogeneous labor markets, helping to control for systematic differences between markets when we compare workers in the same

3. The adoption of a broader range of indicators favors a smoother composite index. On the other hand, restricting the analysis to countries (or households) with a very large number of variables would introduce sample selection. The criteria adopted here are meant to balance those considerations.

4. Take Bolivia as a practical example. Its harmonized census has 18 of the variables mentioned above. Since the categorical ones are broken down into sets of dummies, we have 56 indicators, out of which 50 are available for more than 85% of the households and are retained for the PCA estimation. The scores associated with having a radio, a phone, or access to the internet all have positive signs, implying positive contributions to the index, while having a larger number of people per bedroom lowers the index. The principal component accounts for the fact that there is a correlation between these items, and can accommodate the observation that radios are much more common than internet connections.

region. The smallest labor market in the sample refers to the Dowa District urban areas (Malawi), with 1,120 workers, and the largest comprises the São Paulo State urban areas (Brazil), with 18.5 million workers.

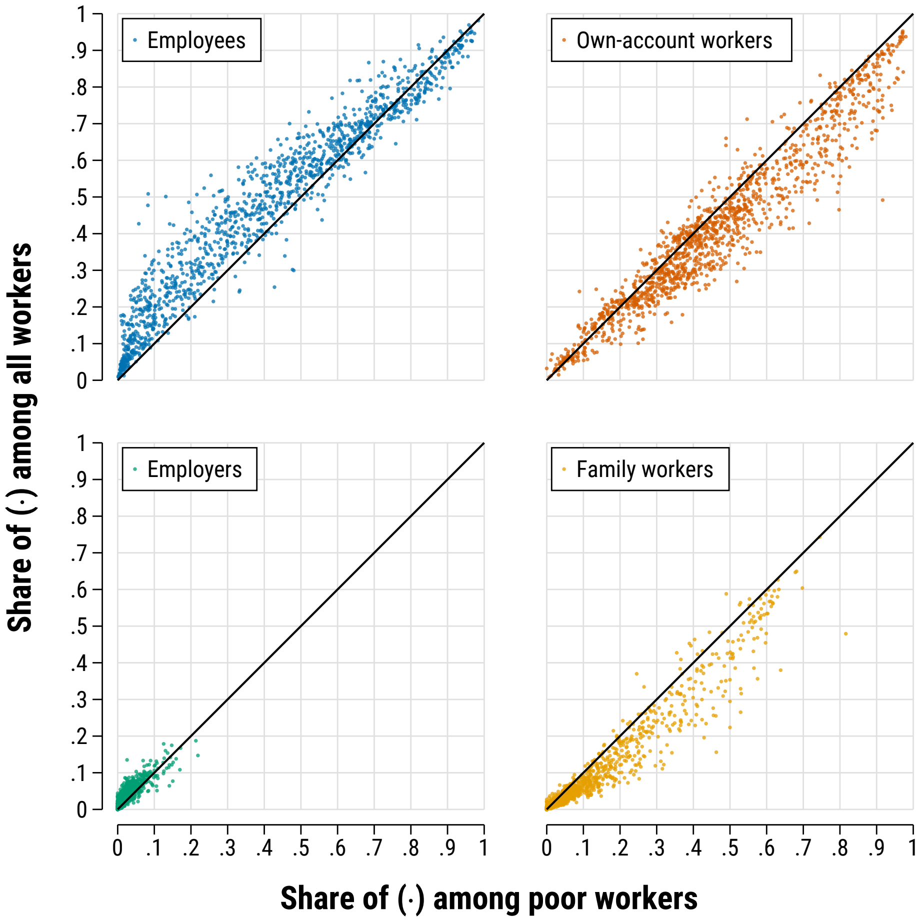
1.6 Results

Regional labor markets in poorer countries tend to have a higher prevalence of own-account workers and family workers. Splitting the sample according to the country's income level, the average share of own-account workers in a regional labor market decreases monotonically from 60.6% (in low-income countries) to 35.4% (lower-middle income) to 27.3% (upper-middle income). Similarly, the average proportion of family workers falls from 14.1% to 9.4% and 2.4%. At the same time, these reductions are matched by an increase in the average share of employees (24.0%, 51.2%, 66.6%). These results are aligned with patterns reported by Gindling and Newhouse (2014) and Bandiera, Elsayed, Smurra, and Zipfel (2022) using evidence aggregated at the national level.

Own-account workers and family workers are consistently overrepresented at the bottom of the wealth distribution in their regional labor market. Figure 1.1 plots the regions over four panels, each focusing on a given employment category. The vertical axis shows how much that category represents among all workers in the region, while the horizontal axis shows how much it represents among poor workers (the ones that fall at the bottom quintile of the wealth index). Hence, dots falling under (over) the 45-degree line represent a region where that category is more (less) common among poor workers than among workers from all wealth groups.

If the composition of the poorest workers in a region were simply a reflection of the general composition of that labor market, the dots would track the 45-degree line. Instead, these plots tell a different story: own-account workers and family workers are consistently overrepresented at the bottom (in 76.4% and 73.0% of the regions, respectively) while employees and employers are consistently underrepresented at the bottom (in 81.6% and 86.4% of the regions).

Figure 1.1. Labor market structure for all workers vs. for poor workers



Notes: Each dot represents a subnational region. The panel plots the share of a given employment category among all workers in that region versus the share of the same category among the poor workers.

1.7 Concluding remarks

The evidence presented here is fundamentally descriptive in nature, yet it suggests some refinements to how we understand the link between work and wealth in the developing world. One could hypothesize that the correlation between own-account work and poverty is driven by the higher presence of such occupations in rural areas. However, our analysis rejects a complete mediation by urbanization: looking only at cities, own-account workers are still predominant in the regional labor markets of the poorest countries (with an average share of 55.5%, 30.7%, and 23.0% in the urban regions from low, lower-middle, and upper-middle income countries), and they continue to be overrepresented among the poorest workers (with a disproportionally larger share at the bottom of the wealth distribution in 78.7% of the urban regional labor markets).

Our findings also point to a polarization between individuals who work within the productive structure of a firm (employers and employees) and those outside it (own-account workers and family workers). This seems to be a fundamental cleavage dimension, leading to other research questions. To what extent is this pattern driven by a structurally higher work efficiency inside the firm? Or is this a consequence of sorting and selection, with firms taking up the most productive workers in the pool and segregating the rest?

Finally, we note that the causality could run from household wealth to occupational choice. Workers in vulnerable living conditions may be unable to invest time and resources into finding a wage job; instead, they can be more likely to work on their own to secure some labor income sooner (for a discussion on this form of constrained own-account work, see the next chapter). The data presented here cannot reject these hypotheses and encourages further investigation of the different mechanisms that may contribute to such labor market cleavages.

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Chapter 2

When You Can't Afford to Wait for a Job: The Role of Time Discounting for Own-Account Workers in Developing Countries

by Thiago Scarelli & David N. Margolis

Frictional labor markets impose a fundamental trade-off: individuals may work on their own at any time, but can only take a potentially better-paid wage job after spending some time looking for it, suggesting that intertemporal considerations affect how people choose their occupation. We formalize this intuition under the job search framework and show that a sufficiently high subjective discount rate can justify the choice for own-account work even when it pays less than wage work. With this simple model, we estimate the lowest discount rate that is consistent with the occupational choice of urban own-account workers in Brazil. We find that at least 65 percent of those workers appear to discount the future at rates superior to those available in the formal credit market, which suggests constrained occupational choice. Finally, we show that our estimated lower bound of the time discount rate is positively associated with food, clothing, and housing deprivation.[1]

JEL: J22, J24, J31, J64.

Keywords: Own-Account Work; Self-Employment; Developing Countries; Financial Constraints; Time Discounting; Brazil.

1. This chapter is forthcoming at the journal *Economic Development and Cultural Change (EDCC)*.

2.1 Introduction

Own-account workers — those who have neither a firm to report to, nor an employee to coordinate with — constitute about 40% of all working individuals in low- and middle-income countries, and often face labor income penalties relative to wage workers within their labor markets (Gindling, Mossaad, and Newhouse 2016; Scarelli 2022). These recurring patterns motivate two questions: Why do some individuals work for a firm while others, despite being observationally similar, work on their own? Under which conditions can we say that their option for low-pay own-account work is a constrained choice?

To address these issues, this chapter builds on the argument that own-account workers, by definition, do not need to match with a firm to start working. Under this perspective, the occupational choice can be summarized as a choice between two return flows: own-account work potentially paying less but starting sooner, versus wage employment potentially paying more but starting later. Hence, with everything else constant, individuals with a stronger consumption urgency would be more likely to work on their own instead of looking for a position in a firm, even when the second option offers them a relatively higher income in all future periods after a job is found. Our proposed channel thus complements the other explanations of the prevalence of own account work that have been proposed in the literature, which rely on individual heterogeneity in skills or tastes, non-monetary returns to work, or exogenous market segmentation, as we review in section 2.2.

The proposed mechanism has three appealing features. First, it is parsimonious to model, in the sense that it does not require appending yet another behavioral parameter to the worker's optimization problem, as we are simply presenting a refined interpretation of the subjective discount rate that is already present in any intertemporal framework. Indeed, our approach is intended to address the challenge of justifying the choice for own-account work without violating individual rationality and without relying on an arbitrary introduction of preferences. The formalization of this mechanism is presented in section 2.3, where we describe the occupational choice issue using the canonical job search framework augmented by the possibility of working on your own. The key insight from the model is that individual heterogeneity in consumption urgency is sufficient to motivate sorting into unproductive own-account work as we observe in low- and middle-income countries. While the baseline specification in the empirical exercises assumes utility to be linear in earnings, the main findings from the theoretical model also hold under risk aversion, as discussed later in section 2.7.

Second, an empirical counterpart of this model can inform us about the subjective discount rates that are consistent with the actual occupational choice of own-account workers. To be concrete, the lowest subjective discount rate that is compatible with choosing to become an own-account worker can be inferred as a function of the gap between their current labor income and the wage they could expect to receive as an employee, given the local market conditions — the larger the gap, the larger the minimum time discount rate required to make own-account work the preferred option. In section 2.4, we present the Brazilian Budget Survey (POF) and the Brazilian Household Survey (PNAD), two nationally representative data sources that we explore in tandem to operationalize these concepts, and in section 2.5 we discuss the estimation of the key components that make up the value of a counterfactual wage job: the minimum wage a person would be willing to accept; how long they would take to find one; how much they could expect to earn after finding one; and how long it would last.

Third, our approach suggests a new dimension to be considered when discussing the issue of constrained self-employment. Under our preferred empirical specification, we estimate that at least 2/3 of the own-account workers in Brazil have selected this occupation due to a particularly high urgency for immediate income, as measured by a subjective discount rate above the discount rate available in the formal credit market. Interpreting these results in the context of our model, we find empirical evidence that poorly paid own-account work imposes itself as the best option because finding a job takes too long, there are pressing needs for consumption, and it is not possible to finance those needs at the market's rate, as discussed in section 2.6.

This chapter assumes that the workers' relative valuation of consumption in the present need not be a fixed personality parameter and could, at least in part, be affected by their current living conditions, in line with the seminal definition of intertemporal discounting.[2] Hence, a context of material scarcity in itself could increase the relative importance assigned to income in the near term and thus drive one's occupational choice. While this hypothesis does not affect the identification of the discount rates, it does change the implications of our findings. In section 2.8, we show that the own-account workers who report financial comfort and access to credit also have a lower estimate of the lower bound of their discount rate; while the opposite is true for those facing housing, clothing, and food deprivation. While these are descriptive results, they are aligned with our proposed mechanism.

These are consequential questions because different mechanisms behind the labor supply choice can lead to different policy recommendations. In particular, our results suggest that policies that smooth consumption during liquidity shocks are likely to support wage employment and lead to long-run income

2. "In general, it may be said that, other things being equal, the smaller the income, the higher the preference for present over future income; that is, the greater the impatience to acquire income as early as possible. It is true, of course, that a permanently small income implies a keen appreciation of future wants as well as of immediate wants. Poverty bears down heavily on all portions of a man's expected life. But it increases the want for immediate income *even more* than it increases the want for future income." (Fisher 1930, p.72, emphasis in the original)

gains by reducing the dependence on readily available (but poorly paid) labor income sources, leading to a more productive occupational structure in the long term. On the other hand, we offer a note of caution for policies aiming at promoting income growth via incentives for "entrepreneurship", as our findings suggest that the majority of own-account workers in the context of a developing country such as Brazil are plausibly taking this occupation as their second-best choice and that these workers could potentially access better-paid jobs without the subsidies, if only they could meet their short-run consumption needs while searching.

2.2 Related literature

The intertemporal tradeoff approach presented in this chapter contrasts with and offers a complement to a classic literature in labor economics that explains occupational choices in terms of comparative advantages, following the tradition of Roy (1951) and Lucas (1978). This approach claims that, all else equal, own-account work would be chosen by those endowed with a particular talent (or taste) for it. This mechanism alone, however, appears to be insufficient to explain a stylized fact in developing economies: the prevalence of own-account workers close to subsistence, who would be willing and able to take a better-paid employment position if they were offered one, as discussed in Banerjee and Duflo (2011) and Fields (2012).

The limitations of the skill heterogeneity view have been partially addressed by the segmented markets hypothesis (see Fields 2009, for a review). This literature argues that a particular sector can be preferable for all agents, but have a rationed number of positions, forcing the workers outside it to queue or to take less desirable occupations. Such an equilibrium, however, generally requires institutional or structural barriers to keep the equilibrium wage persistently above the market-clearing level, such as migration costs, formalization taxes, or a sector-specific minimum wage. Our model is consistent with the segmentation hypothesis, but it can be seen as a generalization of it, in the sense that we do not require extraneous barriers to motivate an income gap in equilibrium: as long as better positions take longer to be found, heterogeneity in time discount rate is enough to sort otherwise similar agents over different occupations.

In this sense, our approach relates to Zenou (2008), which offered an initial formalization of the classic dualism with the tools of the search and matching framework. He describes a free-entry, perfectly competitive informal market, adjacent to a frictional but more productive formal market. In equilibrium, being in informality or looking for a job have both the same instantaneous return, thanks to the mobility condition. This model leads to segmentation, but cannot explain why some workers will be in a given market and not another without imposing that formal workers never look for informal jobs.

Albrecht, Navarro, and Vroman (2009) propose a search and matching labor market model where individuals can take up opportunities in the informal self-employed sector (where every worker is assumed to have the same productivity) or in the formal wage sector (where productivity is heterogeneous). Again, despite the formal/informal terminology, the puzzle they are addressing is analogous to ours, but in their model the workers with the lowest productivity in the formal sector will find it profitable to stay in informality, which explains poorly paid yet voluntary self-employment as a result of heterogeneity in skills. Relative to this work, our approach has the advantage of acknowledging the large differences in productivity found for own-account workers (refer to the discussion in section 2.4), while presenting a segmentation mechanism that does not depend solely on skill heterogeneity in the wage employment market.

The distinction between informality and self-employment is present in Narita (2020), where self-employment, employment in formal firms, and employment in informal firms are modeled as three alternative labor market states. The formality aspect is relevant because the author's focus was on the effect of changes in tax policy for Brazilian firms, but the distinctive trait of the self-employed (own-account workers and employers combined) relative to wage workers in this model is that they are allowed to be low or high skill. More importantly, the subjective discount is assumed to be 0.5% per month (the Central Bank reference rate) homogeneously for all workers, a simplification that is also present in the two previously mentioned references, following the standard practice in this literature.

Given that the discount rate is required in any intertemporal model, it is surprising that the possibility of heterogeneity in this dimension has been systematically overlooked, under the argument of perfect financial markets. An exception is Postel–Vinay and Robin (2002), where the parameters of an equilibrium search model — including the discount rate — are estimated separately for seven categories of employees. Their focus was on explaining the dispersion of labor income between employees in the 1996-1998 greater Paris region, while we are interested in the gap between own-account workers and wage workers in the 2017-2018 urban Brazil, and one must keep those differences in mind when comparing the results. Under this caveat, we note that they find a monotonic ranking between work groups, going from executives (12% annual, or 0.9% monthly) to unskilled manual workers (57% annual, or 3.8% monthly), a gradient that would be consistent and complementary to the results we explore here. Put otherwise, we look at workers whose present needs are even more stringent than those documented for the most vulnerable of the wage workers in a developed country context. Interestingly, the market interest rate that determines the highest discount rate compatible with wage employment in our model (3.8% monthly, the consumer credit rate during the relevant period, as discussed in section 2.5) is remarkably consistent with their results.

In this sense, our estimation strategy also adds to a broader literature on the identification of time discounting. Discount rates have been traditionally elicited via less-sooner vs. more-later discrete choice questionnaires or experiments (see Frederick, Loewenstein, and O'Donoghue 2002; Cohen et al. 2020, for an overview of those methods) and the present chapter is one of the few that proposes to learn about an individual's time discount rate from their choices in the labor market.

In particular, our findings suggest that consumption urgency and liquidity constraints can explain why rational individuals in developing countries fail to make profitable investments, alongside similar results documented in the context of fertilizer adoption in Kenya (Duflo, Kremer, and Robinson 2011), bednets in India (Tarozzi et al. 2014), fuel-efficient cookstoves in Uganda (Levine et al. 2018), and education investments in Colombia (Carrillo 2020). In this context, our contribution is to stress how searching for a job is also an investment, and hence underinvestment mechanisms could hinder it.

Furthermore, we take part in the debate about who is a constrained self-employed worker and how many of them are there — open questions that are of particular relevance for developing countries (see Margolis 2014; Fields 2014, for reviews of this debate). Among the recent developments, Gindling and Newhouse (2014) propose to distinguish "successful entrepreneurship" cases based on whether the self-employed worker (1) is an employer, or (2) lives in a non-poor household. While they have the benefit of demanding little data, those criteria are not fully satisfactory: the first one assumes any self-employed would be aiming to be a growing firm, while some can be successful professional solo workers; and the second conflates success and poverty. An alternative approach, which has been applied mainly to data from Germany and the United States, focuses on whether people started working on their own coming from unemployment (Block and Sandner 2009; Fairlie and Fossen 2018). This criterion would be less informative for developing countries, since it would overlook own-account workers who were simply too constrained to spend time in unemployment in the first place. In all these cases, the sorting criterion is a signal assumed to be correlated with a general idea of "necessity", while the criteria we propose build on established economic theory to describe a potential mechanism through which the material needs manifest themselves — namely, the rate at which one values present resources relative to future resources.

Related to this discussion, we also note that our approach complements the view according to which constrained own-account workers are synonymous with small firms without access to resources to invest. Indeed, experimental interventions suggest that small firms often have returns above the market interest rate and would benefit from extra capital, as documented by de Mel, McKenzie, and Woodruff (2008) using randomized grants to microenterprises in Sri Lanka. However, a range of microcredit initiatives, meant to address this problem, have faced modest take-up and often failed to produce the expected transformative effects on borrowers, as discussed in Banerjee et al. (2015). These disappointing results suggest that alternative policies (such as supporting the transition to better-paid wage jobs) could complement earmarked microcredit, especially if own-account work is often the second-best choice, as we discuss here.

Finally, this work relates to the discussion about how poverty in itself can lead to behaviors that make it harder to escape poverty. Mullainathan and Shafir (2013) argue that scarcity causes tunneling (an excessive focus on immediate problems) and consumes mental bandwidth (the finite ability to command executive control and perform cognitive tasks). We complement this view with the idea that because scarcity makes present consumption seem more important, it can affect labor market behavior in ways that resemble the "suboptimal" decision-making found in other contexts of scarcity and can perpetuate a situation (low income from own account work) that leads to continued scarcity and a form of poverty trap.

2.3 Theory

The parsimonious model we present here is a simple extension of the canonical job search framework in partial equilibrium (see Rogerson, Shimer, and Wright 2005, for a review of this framework) which allows us to highlight the role of time discounting for occupational choice. Agents are assumed to know the exogenous distribution of net wages they could expect to earn as an employee ($F(w)$), how often one might get a job offer when looking for it (λ), the frequency at which those jobs end (δ), and how much one earns, if anything, while unemployed (b). Agents also discount future flows of income at a rate ρ that converts it into a comparable present value. To these standard assumptions, we add that agents know the net labor income they could make by working on their own (y), which reflects any particular occupation-specific skills agents might have. The environment is stationary, in the sense that this set of labor market parameters does not depend on how long the individual has been in a given work state.

For tractability, individuals do not look for a job if they are already working.[3] Furthermore, we abstract from the details of the matching mechanism

3. Extending the model to allow for on-the-job search would not change our conclusions qualitatively, provided that one does not receive more (or better) job offers as an own-account worker relative to the unemployed. We argue this is a plausible assumption because otherwise it would be trivially preferable for any worker to take up own-account work as a strategy to find good jobs faster, and unemployment would virtually disappear (except for particularly high values for unemployment-specific income). Nevertheless, we note that omitting on-the-job search leads to an underestimation of the present value of wage employment. In the context of the intertemporal trade-off we are interested in, adding this omitted piece would imply even higher discount rates for those who decide to be own-account workers instead of investing their

or any strategic behavior from firms when setting wages and assume an optimal stopping rule, whereby individuals sample from a given distribution of offers and stop searching whenever they find an offer above their reservation threshold.

We purposefully assume away any taste parameter — the choice criterion is based exclusively on the discounted flow of monetary returns, although we return to the implications of this assumption below.[4] From a methodological perspective, the challenge is to justify the choice for own-account work without violating individual rationality and without relying on an arbitrary introduction of preferences.

2.3.1 The value of wage employment

The present discounted value of any wage job $W(w)$ depends on the wage w[5] it pays per time interval dt, accounting for the possibility that the job may end at a rate δ, in which case the worker would go back into unemployment, which has value U. Thus, we have the usual flow value for employment:

$$\rho\ W(w) = w + \delta\ \big[U - W(w)\big] \tag{2.1}$$

2.3.2 The value of unemployment

The discounted value of unemployment U (or, equivalently, the value of looking for a wage job) is given by the flow b, summarizing any extra income that is only received while on unemployment, and by the expected gain from actually finding a job that will pay w, given that at rate λ the job-seeker draws an offer from the known distribution $F(w)$.

$$\rho\ U = b + \lambda \int_{w_r}^{\infty} \big[W(w) - U\big]\ dF(w) \tag{2.2}$$

The equation above acknowledges that a job offer is only acceptable if it pays more than a given reservation wage w_r, defined as the lowest income necessary to make the individual indifferent between unemployment and wage employment. Therefore, any wage offer between 0 and w_r is refused, and the individual remains unemployed.

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time into finding a wage job that would open new doors — in which case the lower bound we discuss remains a valid lower bound.

4. In essence, here we take a position similar to Fields (2009, p. 478): "Especially in poor countries, in which large numbers of people value additional goods greatly compared to leisure, the utility-maximization assumption may often be fruitfully replaced by an income-maximization assumption."

5. In developing countries where wage employment can be formal or informal, formal wage offers are subject to employee payroll taxes while informal offers are not. For the purposes of our model, w is the wage provided by the job offer net of payroll taxes.

2.3.3 The reservation wage

By definition, a job that pays the reservation wage has the same value as the unemployment state. Combining this definition with equation (2.1) and equation (2.2):

$$w_r = b + \frac{\lambda}{\rho + \delta} \int_{w_r}^{\infty} (w - w_r)\, dF(w) \tag{2.3}$$

2.3.4 The value of own-account work

The value functions so far follow the canonical results. To add the possibility of own-account work, we make three assumptions.

First, *own-account work is always available*, in the practical sense there is no need to wait for it. By definition, this is an autonomous decision that precludes coordination with third parties. This assumption may seem strong, as one may argue that setting up a new activity may take time — for instance, it might be necessary to find clients. However, we note that someone looking for clients is *already occupied* when doing so, and hence is already an own-account worker, which is fundamentally different from a job-seeker waiting for a call-back.

Second, *the net income generated by the own-account activity is determined by the individual's productivity* and can be summarized in the individual-specific parameter y. Under the assumption that monetary returns define all the utility derived from work, individuals can rank all their possible alternatives under a single dimension. The parameter y can be interpreted as the activity that yields the highest net return among all options available to the individual, given his/her idiosyncratic skills and market constraints. Moreover, since there are no principal-agent issues and no surplus to be shared, the worker is entitled to the full profit y.[6]

Third, there is no exogenous destruction rate for own-account jobs. To be precise, *the probability that an own-account job ends is immaterial to that value of the job*, which is a logical consequence that follows from the two assumptions above and stationarity. If own-account work is always available, even if the current task were to come to an end, in the subsequent period another one with the same value would be available. Because we consider the return y, which fully characterizes the activity, to be an individual-specific parameter, the upcoming task is equivalent to a continuation of the previous one in every relevant aspect.

6. This assumes that the individual does not issue equity to undertake the own-account activity, which seems realistic for the vast majority of own-account work in developing countries. If the individual needs to borrow to finance the own-account work activity, then the cost of reimbursing that debt is deducted from revenues in the calculation of net income y. This also assumes that own account work is not illegal or subject to fines if detected. If it were to be the case, y could be thought of as the return to own account work net of expected fines paid.

Own-account workers can review their occupational decision at every period and pick the best option between looking for a job and working alone. Hence, we can write the value of own-account work $OAW(y)$ as:

$$OAW(y) = \left(\frac{1}{1+\rho\, dt}\right) \left[y\, dt + \max\big(U, OAW(y)\big)\right] \tag{2.4}$$

Under the assumption of stationarity, this expression simplifies further. When the parameters of the labor market are stable, if own-account work is preferred to job searching *at any point in time*, it will be preferred *at all points in time*. Thus, for any own-account worker, it must be that $\max\big(U, OAW(y)\big) = OAW(y)$ in all subsequent periods. For this reason, we have that:

$$OAW(y) = \left(\frac{1}{1+\rho\, dt}\right) \left[y\, dt + OAW(y)\right] \tag{2.5}$$

$$\rho\, OAW(y) = y \tag{2.6}$$

2.3.5 The occupational choice

The usual job search framework assumes that, once the decision to enter the labor market is taken, individuals can be only employed or unemployed. Here we allow workers to take into account what they can earn as own-account workers instead of looking for a job. Own-account work will be chosen if $OAW(y) \geq U$. Equivalently, using equation (2.3) and equation (2.6), the decision can be expressed as:

$$y \geq b + \frac{\lambda}{\rho+\delta} \int_{w_r}^{\infty} (w - w_r)\, dF(w) \tag{2.7}$$

The own-account work decision resembles the classic formulation of the participation decision, except that own-account work provides the outside option instead of inactivity. This interpretation allows us to derive a set of implications for the prevalence of own-account work in the economy. Given that the share of own-account workers is simply the proportion of individuals for whom the inequality above holds,

$$\mathbb{P}\left(y \geq b + \frac{\lambda}{\rho+\delta} \int_{w_r}^{\infty} (w - w_r)\, dF(w)\right) = \text{share of OAW in the workforce.} \tag{2.8}$$

Therefore, people are more likely to work on their own if:

1. *The return to own-account work is high enough.* Individuals with particularly high autonomous productivity are more likely to opt for own-account work.

2. *Unemployment income is low enough.* Lack of an unemployment-specific flow of resources (such as unemployment insurance) decreases the value of the unemployment state.

3. *The arrival rate of offers is low enough.* When individuals expect to wait a long time to receive offers.

4. *The destruction rate of wage jobs is high enough.* When jobs are short-lived, it is not rewarding to wait to get one.

5. *Expected wages are low enough.* Shifting the cumulative distribution of wages to the left decreases the expected return of looking for a job.

6. *The time discount rate is high enough.* When present consumption is a pressing need, it is preferable to secure an income source quickly.

Readers familiar with the precariousness of own-account work in the developing world might dispute the claim that this occupation emerges from a "choice". Are we exaggerating people's possibilities to really select the way they participate in the labor market?

In this regard, we should emphasize that this model does not assume people pick freely between own-account work and a wage job — instead, we claim that people can choose between taking up own-account work and *looking for a wage job*. That subtle distinction is precisely what allows us to reconcile individual agency with the idea that external factors shape and constrain labor market choices, as it describes how these external factors affect the workers' choices.

To fix ideas, consider a setting in which predetermined or contingent factors (such as market conditions, family context, previous labor market experience, or material scarcity) *reduce the number of alternatives in the workers' choice set*. In this context, workers appear to have fewer choices, or no choice at all. The model would represent such a situation by assuming that both options (taking up own-account work or looking for a wage job) are always available, but having an offer arrival rate close to zero or having *relatively* low potential gains to a job were they to actually find one. In terms of our core question, people do not lose the possibility of looking for good jobs when they face urgent consumption needs, but they are less likely to do it because scarcity changes the relative intertemporal benefits associated with this choice. We argue this perspective is richer in the sense that it can conceptually encompass the "there was no choice" explanation[7] and explain why the apparently superior option was not taken without modifying the overall framework.

7. From an empirical perspective, the claim that workers in Brazil indeed face a choice between working by themselves and looking for a job is supported by the relatively frequent transitions observed between the different labor market status, at any age and education levels. This stylized fact is documented by Narita (2020, tables 1, 2, 3 and 5), using data from the labor survey *Pesquisa Mensal de Emprego (PME)* between 2002 and 2007, and it also holds in the PNAD data over the period we focus on. For concreteness, in our working sample, for every 100 individuals

2.3.6 A time discount rate lower bound for own-account workers

Having established that equation (2.7) can describe the occupational decision, we reorganize the terms to express this choice as a condition on the discount rate:

$$\rho \geq \frac{\lambda}{y-b}\int_{w_r}^{\infty}(w-w_r)\,dF(w)-\delta \tag{2.9}$$

Fundamentally, equation (2.9) shows that there can always be a level of subjective time discount that rationalizes the choice of own-account work. It highlights how a strong urgency for present consumption is in itself a sufficient condition to justify a rational take up of own-account work. Concretely, the right-hand side of equation (2.9) provides the lowest level of discount rate that would be compatible with own account work being the optimal decision for a utility-maximizing individual given her constraints.

Note that we can reinterpret equation (2.9) to accommodate the traditional narratives that emphasize relative productivity and non-monetary satisfaction as determinants of occupational choice. Differential productivity in own-account work relative to wage work is reflected in the difference between y and the distribution of w. Likewise, a higher valuation for own-account work, all else equal, can relate to a lower value of b insofar as it leads to a higher likelihood of choosing own-account work for any distribution of w.

Furthermore, this model suggests how some individuals could be permanently stuck with low-paying activities even in the presence of a few better jobs around. A given worker might be allowed to try to change her occupation every day, but as long as equation (2.9) holds, she will prefer the alternative that provides low, but immediate income.

Finally, this argument also points to a way of identifying when the choice for own-account work, which is rational from the perspective of the individual, can be inefficient from the perspective of the aggregate economy. If this occupational choice is driven by a discount rate larger than the discount rate observed in the financial markets, this suggests that access to capital could be driving a situation in which poverty is rooted in labor market decisions (individuals opt for low-earning own account work when they could earn more from wage work) and that there could be potential welfare gains from improving the functioning of capital markets that are not being realized.

who are observed as own-account workers in a given quarter, 5 are unemployed, and 9 are employees the following quarter, on average. If predefined factors were the sole determinant of their careers, own-account workers would never change their labor market status.

2.3.7 Outline of the empirical estimation protocol

The simple theoretical framework presented above explains how individuals with a sufficiently high consumption urgency would be pushed towards own-account work. In what follows, we will use the empirical counterpart of the condition established in equation (2.9) to infer the discount rates implied by the actual occupational decisions observed for the Brazilian own-account workers.

For this purpose, we reexpress the integral from the expression as:

$$\rho \geq \frac{\lambda}{y-b}\left[\mathbb{E}(w \mid w > w_r) - w_r\overline{F}(w_r)\right] - \delta \tag{2.10}$$

and map this inequality into:

$$\rho_i \geq \frac{\mathbb{E}(\lambda \mid X_i)}{y_i - \mathbb{E}(b \mid X_i)}\left[\mathbb{E}(w \mid w > w_r, X_i) - \mathbb{E}(w_r \mid X_i)\,\mathbb{P}(w \geq w_r)\right] - \mathbb{E}(\delta \mid X_i) \tag{2.11}$$

where the relevant parameters are replaced by conditional expectations that can be estimated for each own-account worker i, characterized by a vector of attributes X_i.

The estimation protocol proceeds as follows:

1. $\mathbb{E}(w \mid w > w_r, X_i)$: The expected potential wage is estimated by fitting a selection-corrected linear regression on the log net labor income of employees;

2. $\mathbb{E}(w_r \mid X_i)$: The expected reservation wage is estimated via quantile regression, focusing on low quantiles of net labor income;

3. $\mathbb{E}(b \mid X_i)$: Consistent with the data (see section 2.5.2.5.5), the unemployment-specific income is assumed to be negligible;

4. $\mathbb{E}(\delta \mid X_i)$: The expected job destruction rate is estimated using a proportional hazards duration model for employment with an exponential baseline hazard, allowing for a two-type mixture of unobserved heterogeneity;

5. $\mathbb{E}(\lambda \mid X_i)$: The expected job offer arrival rate is estimated using a proportional hazards duration model for unemployment with an exponential baseline hazard, allowing for a two-type mixture of unobserved heterogeneity, accounting for the probability that a received offer is acceptable and turns into a job;

6. $\mathbb{P}(w \geq w_r)$: the probability that an offer will be acceptable is calculated off the estimated potential wage from (1), the reservation wage from (2),

and the variance of accepted wages under a parametric assumption about the wage offer distribution;

7. y_i: The labor income as an own-account worker is directly observed for those in this occupation.

We interpret the right-hand side of the inequality expressed in equation (2.11) as the lowest value of the subjective discount rate ρ_i that is consistent with the occupational decision revealed by a worker i who expects their labor market prospects to be summarized by the set of parameters listed above. This interpretation will be valid as long as the theoretical relationship in equation (2.10) captures the relevant components of the occupational decision and its counterpart equation (2.11) represents an unbiased empirical translation of it.

In other words, we assume our estimated expected values (in the statistical sense) are analogous to the expectations held by the individuals (in the conventional sense). From a technical perspective, we assume the error components of estimations (1), (2), (4), and (5) to be uncorrelated, in which case revealed preference provides identification of the relevant boundary. In conceptual terms, we take the statistical results to approximate the perception of the individuals when asking themselves "how much can people like me make in a wage job?", "how many months will it take me to find one?" and "how long is this job likely to last?" and combine these answers to uncover a parameter that is harder to observe, namely: "should I forego the income I can make by working for myself right now and try to find something that might pay more in the future?"

The perspective implemented here has two important limitations. First, it assumes that the discounted income flows are a sufficient summary of the value of alternative occupations. By doing so, we neglect the non-monetary dimensions of own-account and wage jobs, in a modeling decision justified in the interest of parsimony but also due to data limitations. The impact of its omission can be seen as affecting the y or w terms: if an individual appreciates own-account work for reasons unrelated to income (such as flexibility or autonomy), the value of monthly payment alone would underestimate the utility derived from this occupation, and we would be overestimating the associated discount rate lower bound.[8] Conversely, if wage positions are valued for reasons unrelated to income (for instance, stability, skill acquisition, or career concerns), the associated minimum discount rate would be higher — in which case, the estimates we present here are still valid lower bounds. Our aggregate conclusions should hold if idiosyncratic preferences balance out at the population level.

8. This omitted preference component can be particularly relevant among employers (the high-end self-employed who have employees working for them), as their personal engagement can plausibly be driven by more than monetary returns. Autonomy, flexibility, status, and identification with the enterprise are more likely to play a role for them. However, we explicitly distinguish own-account workers from employers here, keeping the second group outside the scope of analysis, which can help mitigate this particular bias.

Risk is the second important dimension that is absent from the model. In an effort to keep our specification as close as possible to the simplest job search framework, the valuation equations assume that the utility derived from work is linear on earnings. This modeling specification is restrictive because (a) it implies that workers are risk-neutral, and (b) it assumes that any additional cent would lead to a similar marginal increment in utility. Because this is a consequential modeling decision, we examine points (a) and (b) in detail using extended versions of the model in section 2.7. The key conclusion of that exercise is that allowing for risk aversion would have two consequences, with opposite implications for the estimated discount rate lower bound. On the one hand, since own-account work is likely the riskier option in terms of earnings volatility, we expect the risk neutrality assumption in the baseline specification to underestimate the relative gains from a stable wage job. On the other hand, when utility is marginally decreasing on money, the gap we observe between the two occupations is smaller in utility terms than in monetary terms, which means that the linearity assumption could overestimate the relative gains from a better-paid wage job. Since the net effect is ambiguous, and in the absence of a direct measure of risk aversion at the individual level in our data, we maintain the linear utility assumption as our baseline specification and discuss alternative results in section 2.7.

2.4 Data

2.4.1 The POF and the PNAD surveys

The empirical analysis is based on two large Brazilian surveys. The main data source is the 2017-18 edition of the Household Budget Survey ("Pesquisa de Orçamentos Familiares", or POF), which compiles information on the earnings and expenses of Brazilian households and their members (Instituto Brasileiro de Geografia e Estatística 2019).

From our perspective, the POF survey offers two particular advantages. First, it collects information on earnings using a detailed questionnaire that makes it possible to calculate net disposable labor income in a comprehensive sense (adding extra hours, performance bonuses, and work-related government transfers, deducting taxes) while reducing the mismeasurement one typically finds in labor market surveys when earnings are calculated from responses to a limited number of generic questions. Second, this particular edition of the survey was enriched by a set of questions about personal finance and material living conditions, including food security, which is rare in nationally representative datasets.

Given the quality of this data, POF is taken to be the reference source for most of the estimations in what follows. Unfortunately, it is cross-sectional in nature and does not offer sufficient retrospective information about employment or unemployment spells. We overcome this limitation by using a second dataset, the National Household Survey ("Pesquisa Nacional por Amostra de Domicílios", or PNAD), a regular labor market survey with a rotating panel structure that has been run regularly since 2012. The PNAD is less detailed than POF, but it follows the sampled households for five consecutive quarters, allowing us to observe transitions between labor market states (Instituto Brasileiro de Geografia e Estatística 2018). We note that these surveys include employment information for both formal and informal workers, and thus offer more comprehensive coverage of the Brazilian labor market than administrative datasets that only cover registered firms or formal workers.

Using those two sources in tandem is possible because they represent the same population, adopt nearly identical socioeconomic concepts, and were run simultaneously. Both surveys were designed by the Brazilian statistical office to be nationally representative, and employ a common stratified cluster-based sampling scheme based on Brazil's 2010 national census.[9] Moreover, both surveys compile the basic socioeconomic attributes of the household members (family position, ethnicity, gender, age, and schooling) using the same definitions, and both allow us to infer the general structure of the household similarly. For transparency, we calculate the summary statistics for the population of interest using both sources (see table 2.1), and it is reassuring to see that the first moments of the key variables are similar, even if the very large sample size makes some of the small differences appear statistically significant. Nevertheless, to check the robustness of our results, we rederive weights for the PNAD sample and make its first moments match those of the POF sample exactly in appendix section A.4.

2.4.2 The population of interest

A simple reason why own-account workers may have a low average income at the national level is that this is a common status for rural workers, who often work in activities that have lower average productivity. Furthermore, the land ownership patterns and the social organization of labor are very distinct in rural and urban areas, in ways that could confound the distribution of occupations and the monetary returns to labor. To keep our discussion clean of those considerations, we focus on the population living in urban areas only (85% of Brazil's population). We also restrict the analysis to individuals between 14 and

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9. A master sample divides the country into small neighborhoods of at least 60 households (the Primary Sampling Units, or PSUs), which are organized in mutually exclusive and relatively homogeneous regions (the strata), according to their sociogeographical characteristics. In any given survey, the PSUs are independently sampled within their stratum, and a subset of random households from the sampled PSUs are interviewed (Freitas and Antonaci 2014). In this sense, the POF sample and each of the quarterly inflow waves of PNAD can be seen as separate draws from a common population.

64 years of age (72% of the urban population), as they are more likely to be economically active.

In summary, the universe of analysis includes 125 million urban, working-age individuals (or 60% of all Brazilians) over the 2017-18 period. Among them, 52% are female, 55% are nonwhite (44% mixed ethnicity, 10% black, and 1% others), 84% have completed at most high school (about 13 years of education or less), and 24% are between 14 and 24 years old.

Table 2.1. Overview of the population of interest

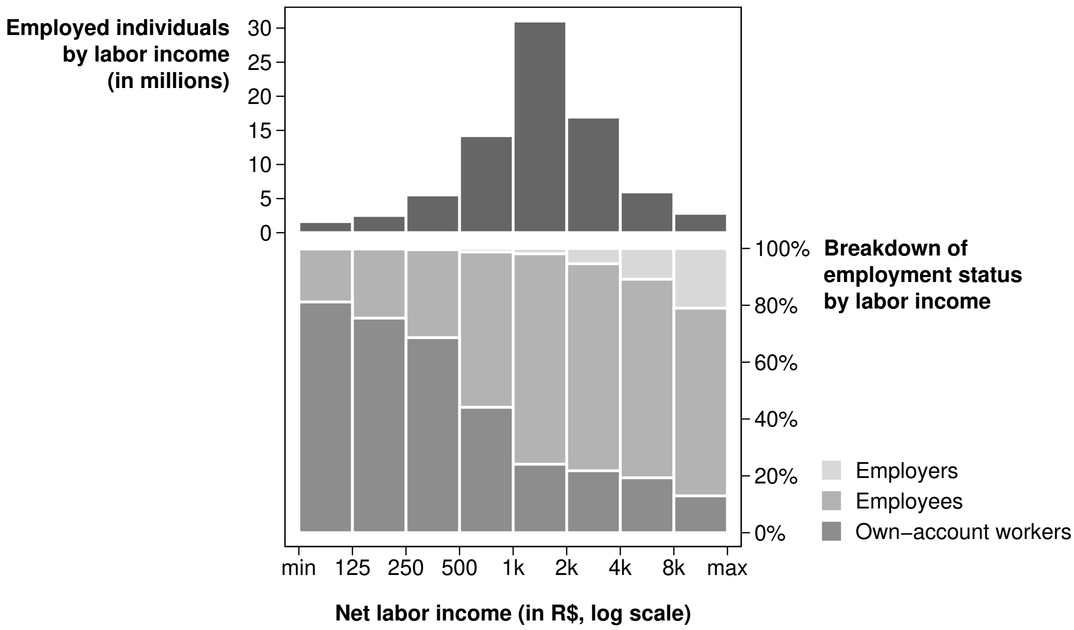
	POF survey (2017/2018)		PNAD survey (2017q1-2018q4)		Difference between surveys	
	A	s. e.	B	s. e.	A - B	p-value
Gender and ethnicity (in %)						
Female	52.31	(0.16)	51.47	(0.06)	0.84	0.000
Nonwhite	54.74	(0.43)	55.43	(0.22)	-0.69	0.149
Education level (in %)						
Less than prim. school	28.08	(0.32)	26.60	(0.16)	1.48	0.000
Primary school	19.19	(0.22)	19.00	(0.09)	0.19	0.430
High school	37.10	(0.28)	38.71	(0.14)	-1.61	0.000
College or above	15.63	(0.37)	15.70	(0.20)	-0.07	0.873
Age group (in %)						
Age 14-24	24.03	(0.21)	24.74	(0.09)	-0.70	0.002
Age 25-34	20.87	(0.22)	23.49	(0.10)	-2.63	0.000
Age 35-44	21.03	(0.22)	21.38	(0.09)	-0.35	0.139
Age 45-54	18.82	(0.20)	17.32	(0.08)	1.50	0.000
Age 55-64	15.26	(0.21)	13.07	(0.08)	2.18	0.000
Survey structure						
Strata	373	.	373	.	.	.
Primary Sampling Units	4,597	.	13,907	.	.	.
Unique households	41,002	.	325,711	.	.	.
Unique individuals	96,175	.	828,326	.	.	.
Observations	96,175	.	2,311,201	.	.	.

Notes: [1] Individual observations are weighted by the inverse of their sampling probability, following the survey design, to render the coefficients meaningful for the population the sample represents. The standard errors around the point estimates are calculated via linearization, accounting for the stratification design, and the p-value was calculated based on the z-statistic of the difference between the estimates. [2] The POF survey conducted interviews between July 2017 and July 2018. In order to capture a similar time window, we use the 8 quarterly rounds of PNAD from 2017 and 2018: four of them overlapping with the data collection interval from POF, plus two quarters before, and two after it. [3] PNAD currently provides unique identifiers to households but not to household members. To track individuals across quarters, we adopt the advanced identification methodology proposed by Ribas and Soares (2008), as implemented in Stata (StataCorp 2015) by the program `-datazoom_pnadcontinua-` (version 1.0) from the Economics Department of PUC-Rio University.

2.4.3 Who are the own-account workers?

Within the population of interest, about 81 million individuals received some form of labor income in the preceding 12 months, according to the POF survey. For 30 million of them, the average monthly amount, net of taxes, was between R$ 1,000 and R$ 2,000 (or US$ 455 to US$ 910, adjusting for purchase power parity), as shown at the top of figure 2.1. In general terms, the distribution of labor income is approximately log-normal, with some excess mass at the right side due to the presence of a minimum wage (R$ 954) that is binding for formal employees.

Figure 2.1. Occupations and labor income



Notes: The calculations refer to the income associated with a worker's primary occupation, net of taxes. The results are representative of urban, working-age (14-64) individuals at the national level. Monetary values in R$, at prices of January 2018. For context, R$ 1,000 here are equivalent to US$ 455, adjusting for purchase power parity.

A more interesting picture emerges as we break down the employment status within each labor income level, at the bottom of figure 2.1. A first stylized fact: own-account workers are a relatively large group, accounting for about a third of all individuals with some labor income in the population of interest.[10] Put otherwise, there is about one own-account worker for every two wage employees in this population, which contrasts with a ratio of 1 to 13 in urban areas of high-income countries, calculated using estimates from the International

10. Note that this share is higher than the official figures (around 25%) because the national statistics office classifies domestic workers as employees, while we count them as own-account workers. We examine the alternative hypothesis, grouping domestic workers with employees, in appendix section A.2. This methodological choice is based on the argument that domestic workers are selling their services to the final consumer, and not selling their labor to a firm, a distinction that puts them closer to those working on their own in the framework proposed here.

Labour Organization (ILO, 2022). This evidence stresses why *urban* own-account work is a central issue for non-rich countries, in complement to the extensive literature on rural self-employment in development economics.

Second, own-account workers are dispersed across all the income ranges —highlighting that this is a heterogeneous category that includes from small service providers to specialized professionals— yet they are heavily concentrated at the bottom of the distribution. In this sense, they contrast with employers, who are negligible at the bottom but make up an increasing share of the working population as we move up the income ladder. This distribution is not unique to Brazil, as own-account workers are systematically overrepresented (and employers, underrepresented) among the poorest working individuals in a large range of low- and middle-income countries (Bandiera, Elsayed, Smurra, and Zipfel 2022; Scarelli 2022). Such a strong empirical distinction between own-account workers and employers is lost if one discusses self-employment in general, and that is why this chapter explicitly defines own-account work as a category in itself, leaving employers out of the scope, as motivated in section 2.2. In what follows, the focus is on the contrast between own-account workers and employees.

Third, urban Brazilians working by themselves are indeed systematically different from those who work for a firm: they comprise a higher share of female and nonwhite workers, and are generally less educated and older, as detailed in table 2.2. These patterns suggest that their prevalence at the bottom of the income distribution reflects differences in the jobs to which those workers can apply and differences in the returns to their skills. The question is whether this observable heterogeneity is sufficient to rationalize their occupational choices. In the next section, we estimate the labor market opportunities that each own-account worker could reasonably expect to face had they decided to look for a wage job, and we argue that part of the remaining variation could be explained by heterogeneity in time discount rates, as some workers have a stronger need for securing income quickly.

But is own-account work really easy to start? So far, we have offered a formal argument, noting that they do not need to match with a firm by definition. A closer inspection of their activities offers further support to this assumption. More than 3/4 of the own-account workers in this population are informal, in the sense that they have neither a registration as a small business nor as an autonomous worker, implying that paperwork does not prevent own-account workers from starting their activities.

Furthermore, own-account workers usually do not require a dedicated store or an office space: nearly half of them work in the place chosen by the client or in the client's home, while 15% work in their vehicle, in a public area, or in other spaces. From the 12% that work from home, most do so in a non-exclusive area, as shown in table 2.3. As a comparison, 64% of the wage employees have a formal contract, and 83% have a dedicated workplace.[11]

Those patterns are consistent with the type of activities the own-account workers are typically running in this context. Looking at the most granular level of the International Standard Classification of Occupations (ISCO), the most common occupations for Brazilian urban own-account workers are domestic cleaners, bricklayers and other construction workers, small shopkeepers and door-to-door salespeople, hairdressers and beauticians, drivers, and care workers — in all cases, occupations with relatively low entry barriers.

2.5 Estimation results

2.5.1 Potential wages

The first step is to estimate the wage a given own-account worker could expect to earn working for a firm, based on the labor income from employees who are observationally similar to them. Higher potential wages make paid employment a more attractive option relative to own-account work, everything else constant, and thus suggest a higher discount would be required to make own-account work preferable.

The statistical specification is a regression of log monthly net labor income on a set of socioeconomic attributes that provide information about the worker's human capital and their relevant labor market. In choosing the covariates, our objective was to be flexible and parsimonious: individuals are split over ethnicity-gender and age-education groups, to capture arbitrarily non-linear effects on those dimensions. All models control for interregional differences, with a region being defined as either the capital, the capital's metropolitan area (if any), or the remaining cities, for each one of the 27 Brazilian States, in a total of 77 mutually exclusive and relatively homogeneous areas.

The main challenge in the estimation of counterfactual earnings for own-account workers comes from the fact that the relationship between wages and observable characteristics must be inferred from the employees, who might have a higher propensity to have wage jobs due to attributes we do not observe. To mitigate this potential selection bias, the wage regression includes a control function intended to capture the role of unobservables, as per (Heckman 1979). To that end, we adopt the classic assumption that attending school or living under a particular household arrangement (say, having young children or elderly people in the household) may affect the probability one is observed in a wage job but does not define how much they can earn, once their human capital and the local market conditions are accounted for. Thus, the excluded variables refer to school attendance (not attending, attending school, attending college) and

11. The workplace statistics refer to 2018, before the widespread adoption of work-from-home following the Covid sanitary emergency. In that context, working in a non-exclusive area of one's house is less a signal of flexibility and more suggestive of constrained improvisation.

household structure (indicators for a rich set of positions within the household, plus the total number of household members by age group), most of which are are statistically significant in the selection equation.[12]

The coefficients for the main equation and the selection equation are reported in table 2.5 in the appendix. Expected wages are increasing in education, and the gap between those who finished college and those with less than primary school increases with age. We also find an effect of ethnicity and gender, increasing from nonwhite females (the reference group), to nonwhite males (+8.5%), to white females (+9.7%), to white males (+30%). Based on these relationships, we can estimate plausible wages for non-employees. [13]

In light of those results, one reason why nonwhites, females, and those without college are overrepresented among own-account workers is that, everything else constant, the jobs they would find in a firm are the worst-paid ones to start with. But this is not the full story, since 82% of Brazilian own-account workers report a net labor income inferior to their potential wage, even after accounting for individual heterogeneity, as shown in figure 2.2.

2.5.2 Reservation wages

Empirical measures of the reservation wage remain an important challenge in applied work, since there are few plausible references for it, especially in developing countries.[14] In the present case, neither POF nor PNAD asks about the lowest wage level individuals would be willing to accept, and hence we need to estimate it.

As a starting point, one could simply take the absolute lowest value observed at conditional cells defined by relevant individual attributes. The main drawback of this nonparametric strategy is that its consistency requires a large number of cells, each with a large number of observations, as the estimation of extrema is much more demanding and much more vulnerable to outliers than the estimation of averages.

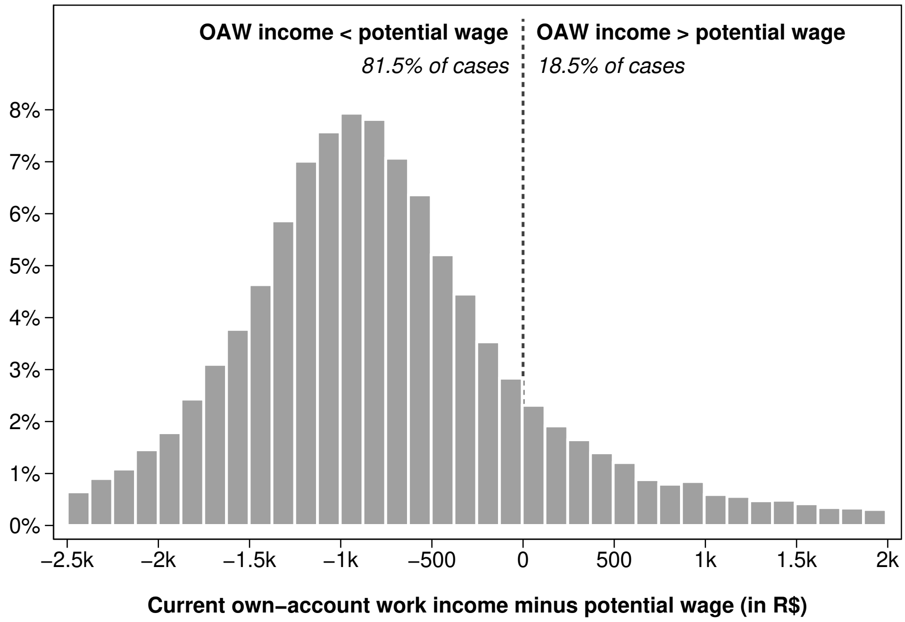
---

12. A generalized Hausman test (Hausman 1978) shows that the coefficients of the wage equation are not the same if we omit the control function (p-value ≈ 0.000), or if we omit the exclusion restrictions in the selection equation (p-value ≈ 0.000), supporting the view that a selection equation is consequential for the estimation of potential wages. It should be noted that, if the exclusion restrictions are invalid, the estimates will be biased in the direction of the correlation of the excluded variables with the earnings equation's disturbance term and their correlation with the included variables of the model. The fact that we have a large number of exclusion restrictions makes the direction of this bias difficult to anticipate.

13. In practice, the fitted values for potential wages are obtained from the linear index composed by the estimated coefficients $\hat{\beta}$ and the individual attributes X_i. To avoid a known transformation bias when translating this index $X_i\hat{\beta}$ back from log into monetary levels, we adopt the "smearing" technique from Duan (1983), which has been shown to perform well in large samples like ours.

14. A notable exception is Krueger and Mueller (2016), who document reservation wages for unemployed workers in New Jersey, US.

Figure 2.2. Distribution of the estimated gap between the labor income received by own-account workers and the wage they could expect to receive as employees



To overcome those difficulties, our strategy is to use quantile regression to predict the conditional expected value *at a sufficiently low rank in the wage distribution*. In the baseline specification, we assume that the 10th percentile of the distribution is a reasonable proxy for the reservation wage, as there may be unsystematic measurement errors in reported wages at the bottom of the distribution.[15] To examine the sensitivity of the results to different cutoffs, we replicate the estimation with 5th and 15th percentiles in appendix section A.3.

The most important difference relative to the previous estimation is that now we introduce family characteristics into the main equation. This econometric choice is motivated by the idea that having children should not affect the wage opportunities a worker expects to see in the market (after correcting for selection), but it can affect the minimum monthly income someone is willing to accept (which is one channel that can lead to the selection itself).

Table 2.6 provides the results of this estimation. Indeed, we find that the presence of dependents in a household (children, young, or senior members) is associated with a decrease of between 3.3% and 4.6% in wages at the 10th percentile level. This result is consistent with a preference for part-time jobs (hence lower monthly earnings), but also with a lower selectivity for offers (due to more urgent family consumption needs).

The signs of the remaining coefficients are largely aligned with what we found in the previous section, although the margins there refer to the average

15. Such noise would not affect the expected wage estimates, as long as it is uncorrelated with observables.

wage, while here they affect the expected wage at the 10th percentile of the wage distribution.

2.5.3 Employment and unemployment duration

To calculate the value of looking for a job, we also need to estimate how long people usually spend in unemployment, and how long wage jobs typically last. Here we follow a long tradition in applied economics that uses duration techniques to model the length of spells in different employment states conditional on covariates.[16] Because our theoretical model assumes agents form expectations for the steady-state, the consistent choice is to use a parametric proportional hazards duration model that fits the duration outcome using an exponential baseline hazard distribution, which imposes that the instantaneous transition rate is independent of the time previously spent in the spell. Our model allows for unobserved heterogeneity to affect transition rates using the approach of Heckman and Singer (1984); see appendix section A.5 for details.

When modeling the transition from unemployment into wage employment, all other transitions from unemployment (namely, into inactivity or self-employment) are treated as censoring events — technically, those changes prevent us from observing a transition into a wage job in the same way that the end of the observation window does. Conversely, in the case of end of employment, we treat all transitions out of employment as the observed end of the spell, since the present discounted value of the job is affected only by its expected duration, regardless of the subsequent state.

As seen in table 2.6, we estimate that males can expect to find wage jobs faster, while job-seekers above 44 years of age would spend more time in unemployment. Interestingly, more educated individuals appear to find jobs at similar rates than less educated ones — but they spend longer in wage employment once a position is found, which makes this occupation more valuable for them, all else equal.

2.5.4 The job offer arrival rate

The previous section described the estimation of the rate at which job-seekers move from unemployment into wage employment (denoted h below). However, the parameter of interest in the model is the rate at which new offers arrive to a job-seeker (λ). Since neither POF nor PNAD collects data on offers, h represents the product of the offer arrival rate λ and the likelihood that an offer is accepted once it has been received,

16. Classic works in this literature include Kiefer (1988) and Meyer (1990). For a comprehensive treatment of these techniques, see Kalbfleisch and Prentice (2002).

$$h = \lambda \mathbb{P}(w > w_r) \tag{2.12}$$

Assuming the wage offer distribution for a given worker is log-normal, centered at the log of the expected wage (w_i), and with standard deviation (σ) common to all workers, we can write

$$h = \lambda \left[1 - \Phi \left(\frac{\log(w_r) - \log(w)}{\sigma} \right) \right] \tag{2.13}$$

Thus, one can recover λ for each individual from the estimated counterparts of h, w, w_r, and σ, according to the expression above. In practice, we find that nearly all offers are good enough to be accepted — equivalently, $\mathbb{P}(w > w_r) \approx 1$ for most individuals — and thus $\lambda \approx h$.[17]

All in all, we estimate that if Brazilian own-account workers were to seek a wage job, it would take them on average 7.6 months to receive an offer, half of them would receive their first offer only after 6 months of looking for it, and they would be willing to accept 95% of these jobs[18]. This result is of interest for it suggests that own-account workers may not be discouraged to look for wage employment because it does not pay enough, but rather because it is too hard to come by.

2.5.5 The expected value of unemployment income

Any income specific to the job-seeking state would increase the value of unemployment, which could be meaningful in a country with an extensive social insurance system. In Brazil, the information available in both surveys used here suggests that unemployment benefits are negligible in practice, as the vast majority of job-seekers report receiving no benefit at all.

This is because unemployment insurance requires an unjustified layoff from formal wage employment and a track record of 12 months of employment over the previous 18 months when applying for it for the first time. Hence, people looking for their first job, coming from short or informal positions, or in a long unemployment spell cannot receive it. Virtually no own-account worker

17. The finding that nearly all offers would be accepted is not surprising. From a theoretical perspective, it is consistent with the idea that, in general equilibrium, firms have no incentive to propose wages below reservation levels (as one finds, for instance, in wage posting-models following Burdett and Mortensen 1998, even though in our case we abstract from any firm behavior.

18. The fact that we estimate a probability of having a wage offer above the reservation wage of 0.95 despite having estimated the reservation wage as the 0.9 quantile of the wage distribution is due to the additional parametric assumptions we impose at this stage (log normality of the offered wage distribution and variance that does not vary with observables) and the fact that the estimated variance of the offer distribution is relatively small.

would qualify, with the major exception of domestic workers, under the same conditions above.

Informal transfers within the individual's network could play a similar insurance role, but those are difficult to observe, even with POF's detailed income data. In any case, missing a permanent or unsystematic transfer does not affect our results, as long as it is independent of one's labor market state.[19]

For these reasons, we take unemployment-specific income b to be negligible in the context of our estimation. This is a conservative assumption since it can only lead to an underestimation of the value of unemployment and, thus, to an overestimation of the implicit discount rate, which means that the lower bound calculated without b remains a lower bound. In terms of our estimates of the share of individuals who would be constrained on formal credit markets (section 2.6.1 below), a non-zero value for b would shift the cumulative density of the estimated discount rate lower bound rightward in figure 2.3, which would imply an even larger share of credit-constrained workers than we currently estimate.

2.5.6 The empirical components of the occupational choice model

Table 2.4 compiles descriptive statistics on estimated components that enter into the empirical counterpart of the occupational decision model. The combination of these components at the individual level according to equation (2.11) provides an estimate for the subjective discount rates that rationalize the revealed preference for own-account work.

2.6 The constrained own-account workers

The main results of this chapter follow from estimating the components of the individual-specific lower bound of the discount rate, inferred for a nationally representative sample of own-account workers. To be precise, the object we recover is the minimum discount rate that makes the present value of own-account work superior to the present value of looking for a wage job, as defined in equation (2.11), based on the full set of results shown in table 2.4 and using microsimulation for the sample of individuals in the POF. Recall that this expression was derived from a parsimonious model for the purposes of understanding the role of time discounting on occupational choice, and all of the caveats expressed in section 2.3 should be borne in mind in this and the following section. Given this context, our estimation results suggest that the lower

19. The availability of income sources other than one's labor income can still affect the value of different occupations in our framework — precisely because they may affect time discounting in itself. Anticipating the findings to be discussed in section 2.6, there is suggestive evidence that own-account workers who can count on transfers have a lower implicit urgency in their occupation decision because transfer income helps alleviate material deprivation.

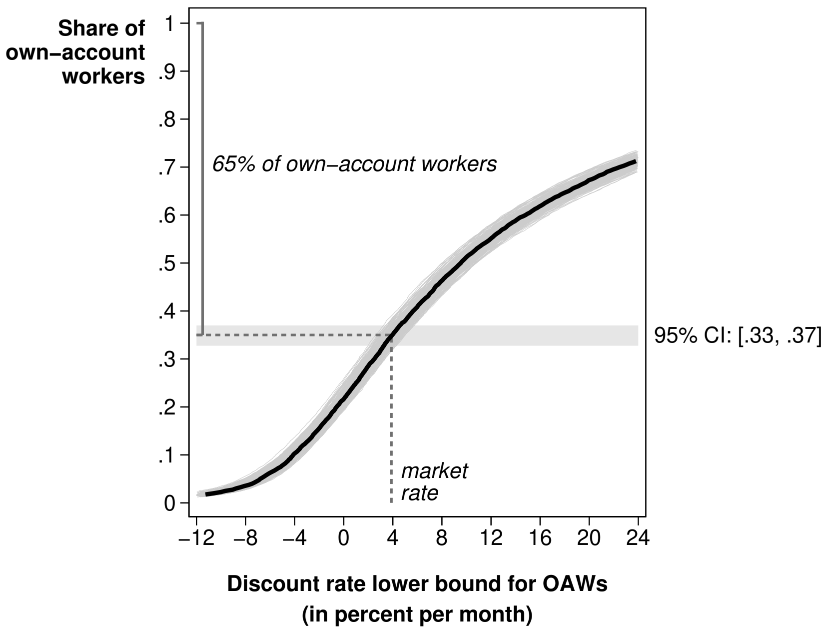
bound of the discount rate in this population has a median of 9.5% per month, and an average of 24% per month, evidence of the salience of the intertemporal trade-off in the occupational choice of Brazilian own-account workers.

2.6.1 Subjective discount rate and access to formal capital markets

To get a sense of what these estimates imply, we compare them to the typical interest rate levels adopted in retail credit operations to finance household consumption. According to the Central Bank, the average rate of consumer credit in the period 2017-18, weighted by total loan volume, was equivalent to 3.8% per month. These are non-earmarked and non-secured credit lines that could be directed to any consumption needs, and their average rate is taken as a reference for the ongoing price at which banks were willing to exchange future and present resources in the period of analysis.

The fact that most own-account workers appear to have a subjective time discount above this credit rate suggests that they could not access the formal credit market — had they been able to borrow at the prevailing rate, they would have done so and chosen to search for wage work instead, under the assumptions of the proposed framework. The cumulative distribution function of the lower bound of ρ, as plotted in figure 2.3, tells us that such financial constraints are binding for at least 2/3 of urban own-account workers in Brazil.

Figure 2.3. Empirical cumulative density of the estimated discount rate lower bound



Notes: The dark curve shows the CDF at the baseline specification, and the grey curves represent each one of the 400 replications of such estimation, leading to the bootstrapped confidence interval described on the right side. The dashed reference line marks the average consumer credit rate for individuals in 2017-18.

This distribution implies that the occupational choice of at most 1/3 of the own-account workers (those at the left of the reference rate) is their first best choice in relative monetary terms, after taking into account income differences and labor market frictions, which leads us to classify those as *unconstrained* *cases*. This share is higher than the 18% who are simply earning more than they could expect to earn as employees (see figure 2.2) since that comparison is missing the intertemporal dimension. The first best choice here does not necessarily mean that those own-account workers have a comfortable material life, since the comparison is always with the individual-specific opportunities in the wage market, an alternative that could well be a precarious one to start with. In contrast, the occupational choice of the remaining own-account workers is their best *constrained* option: it is still the one with the highest present value, but only because they assign strong relative importance to income in the near-term and cannot discount the future using the market rates, but are still able to bypass unemployment by working on their own. In other words, at least 2/3 of the Brazilian urban own-account workers cannot afford to wait for a job.

2.6.2 Subjective discount rate and household conditions

If households facing more precarious material conditions have relatively higher discount rates, one would expect to see them disproportionately among the own-account workers that our model suggests are facing capital market constraints that keep them from looking for wage work. In this section, we present descriptive evidence that supports this hypothesis.

Regressing the estimated discount rate lower bound on a set of living conditions indicators, we find that it tends to be higher for own-account workers (a) without access to financial services, (b) subject to financial stress, (c) with a large share of their budget committed to basic expenses, and (d) who report inadequate housing, clothing, or food availability. The coefficients of interest are summarized in figure 2.4 and the regression output under different specifications are available in table 2.8.

The lack of access to financial services such as a savings account, overdraft facilities, and a credit card are all associated with relatively higher subjective time discounts (+2.7 percentage points to +6.2 percentage points), in line with the mechanism proposed. Notably, the availability of income from sources other than one's occupation (non-labor income, any income from other household members, and systematic transfers) appears to be associated with a lower discount, if we focus on financial indicators only (see model A from table 2.8). However, the association disappears once we control for other markers of actual material precariousness, suggesting that non-labor income may go directly to supporting basic consumption, leaving other urgent needs unmet.

To assess how tight the family budget is, we look at one's perception of how hard it is to make ends meet and find a clear association with the estimated lower-bound discount rate. These subjective indicators are complemented with an analysis of the share of income spent on education, personal goods and services, housing, medicine, and food. In all those categories, we take the top decile as a reference for "spending too much" in a given category. For instance, 10% of the Brazilian urban, working-age individuals are in a household where food expenses account for more than 35% of total expenses — and we find that the own-account workers in this group tend to have a higher implicit lower bound discount rate, all else constant. Interestingly, the same holds for medicine or housing expenses, but the opposite is true for personal and education expenses, categories that individuals may consider to be non-essential items. The fact that own-account workers with lower urgency also tend to be members of families that spend more on education is consistent with the view that education is an investment and people with lower discount rates are more willing to invest.

We conclude by documenting a strong association between basic deprivation (housing, clothing, and food inadequacy) and the estimated lower bound of the discount rate. All else constant, members of families facing hunger are also more likely to take up own-account work that pays less than what they could find in wage employment, and the association with the estimated lower bound of the discount rate is monotonically increasing with the degree of food insecurity. This is a dire translation of the empirical content of the otherwise abstract idea of "urgency" we refer to in this chapter.

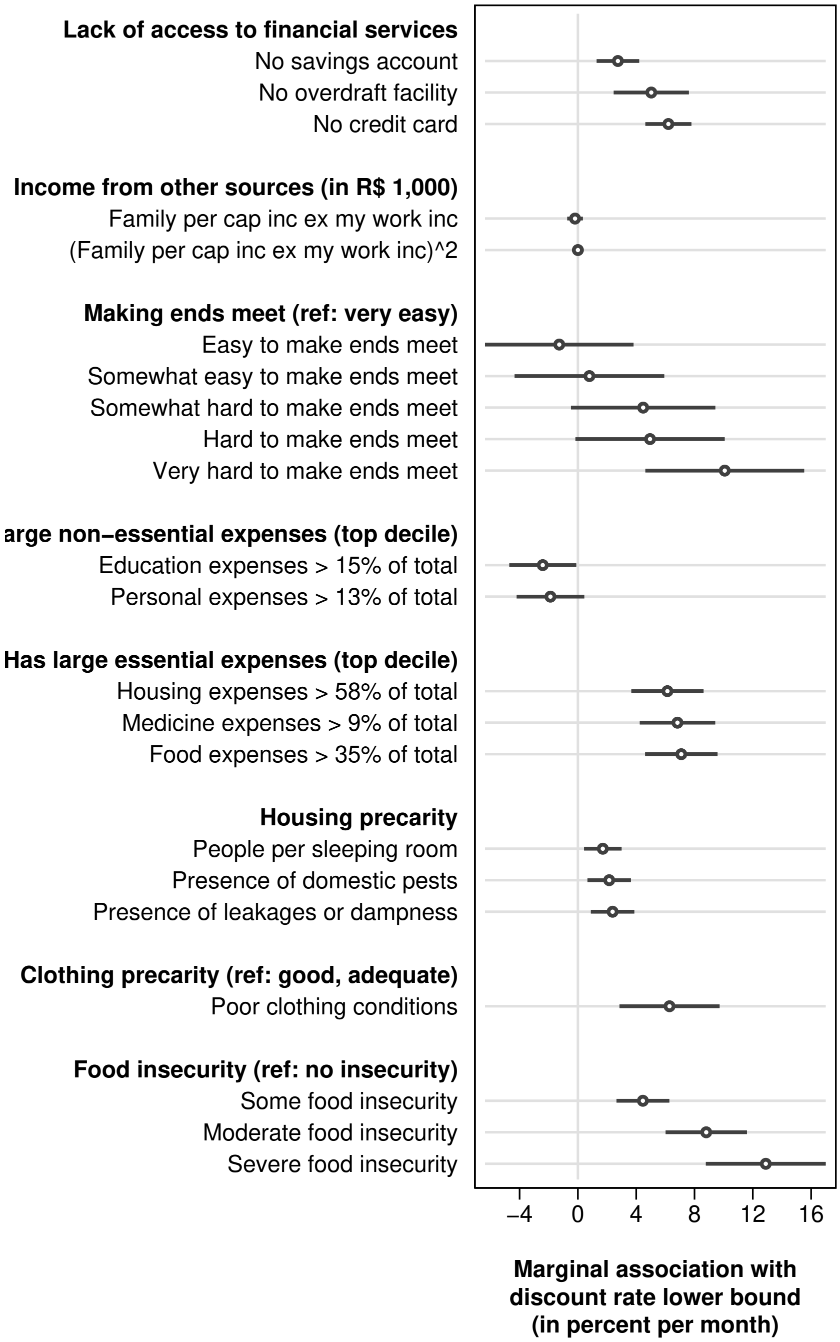
These results are also coherent with a body of research that has consistently documented a negative association between socioeconomic status and time discounting under the traditional measurement protocols (see Green et al. 1996; Harrison, Lau, and Williams 2002; Kirby et al. 2002; de Wit et al. 2007; Reimers et al. 2009; Tanaka, Camerer, and Nguyen 2010; Haushofer and Fehr 2014; Cassar, Healy, and von Kessler 2017; Di Falco et al. 2019).

Nevertheless, we take this evidence with caution. In the absence of exogenous variation in living conditions, it remains unclear how much of the association is due to financial stress leading to the choice of an occupation with lower short-term returns, and how much of it is due to low returns leading to financial stress. All in all, it is reasonable to expect that both reinforce each other (and the associated occupational choice), which would characterize a form of low-income occupational trap.

2.7 Consumption urgency and risk aversion

This chapter has shown how heterogeneity in income urgency can be sufficient to motivate sorting into low-paid own-account work and has provided empirical evidence consistent with the idea that income urgency is a key explanatory factor for a large share of the own-account workers in Brazil. However, these results were all shown under the specific assumption of risk neutrality. In this section, we explore how risk and risk aversion could affect our main conclusions.

Figure 2.4. Association between the estimated discount lower bound of own-account workers in Brazil and the material conditions of their household



Notes: The line around the point estimate represents the 95% confidence interval, with standard errors clustered at the PSU level. Additional controls include ethnicity, gender, age, education, position of the worker in the family, family composition, and region.

2.7.1 Earnings volatility as a disamenity

A simple way to incorporate an occupation-specific risk into the theoretical model discussed in section 2.3.5 is to treat the variability of income for own-account workers as a disamenity which decreases the payoff to own-account work by a monetary equivalent, say ζ. In this case, we could rewrite equation (2.7) as follows:

$$y - \zeta \geq b + \frac{\lambda}{\rho + \delta} \int_{w_r}^{\infty} (w - w_r)\, dF(w) \tag{2.14}$$

The omission of this job component in our preferred empirical specification would imply a relative overestimation of the benefits from own-account work. In this case, the actual time discounting factor ρ required to push people into this occupation (that pays less and also carries higher risks) would be higher than our baseline result. Our baseline result thus becomes an (even more) conservative estimate of the lower bound of ρ that is compatible with observed own-account work, and would imply that a larger share of own account workers are credit-constrained than what we estimate in our baseline specification.[20]

The evidence in the literature from developed countries tends to support this interpretation, as wage workers dislike uncertainty in earnings while self-employed are, on average, more tolerant of it. Using data from Germany, Bonin et al. (2007) documents that workers who have explicitly reported a lower willingness to take risks (as elicited by survey questions) tend to work in occupations with lower earnings risk (defined as the occupation-specific residual dispersion in earnings). The same data source also confirms that self-employed individuals tend to be more open to risks (Caliendo, Fossen, and Kritikos 2009; Dohmen et al. 2011; Caliendo, Fossen, and Kritikos 2014), which is aligned to results documented for Finland (Ekelund et al. 2005) and the United States (Brown et al. 2011).

Moreover, efforts to compare risk attitudes at a global level consistently find that individuals in poorer countries, where own-account work is far more prevalent, are more tolerant to risk than those in rich countries, on average. This finding is reported by Rieger, Wang, and Hens (2015), who looked at 6 912 university students in 53 countries, l'Haridon and Vieider (2019), who explored a sample of 2 939 people in 30 countries, and by Falk et al. (2018), who compiled results for 80 000 people in 76 countries.

In a context that is much closer to ours, Falco (2014) experimentally elicits risk aversion in Ghana and also finds that the self-employed tend to have a higher tolerance to risk. This result is particularly relevant for us because he concludes that, in practice, the volatility in earnings is a form of risk that is more important than the uncertainty associated with the process of queuing for a job.

In summary, if earnings risk in own-account work represents a disamenity due to risk aversion, assuming risk neutrality in the baseline specification may lead us to underestimate the lower bound of the discount rate that is compatible with the observed own-account work in Brazil, but that this underestimation is likely to be small due to the fact that (a) workers in self-employment and (b)

20. We thank two anonymous referees for highlighting this point.

people in developing countries are less risk averse than wage workers. In other words, adopting a utility function that is linear in labor income is likely a better approximation for own-account workers in Brazil than for wage employees in France.

2.7.2 Concave utility function

More generally, we can consider the consequences of allowing the utility function to be a concave function of income. This differs from section section 2.7.2.7.1 in that the concavity of the utility function alters the utility gain/loss associated with a difference in nominal income values, relative to the case of risk neutrality and can, therefore, change the point estimate of the lower bound of ρ.

For this exercise, we suppose workers have a constant relative risk aversion (CRRA) utility function of the form $U(x) = \frac{x^{1-\gamma}}{1-\gamma}$. Assuming CRRA utility on all forms of income, combining equation (2.1), equation (2.2) and equation (2.6) leads to the following inequality that determines the choice in favor of own-account work:

$$y^{1-\gamma} \geq b^{1-\gamma} + \frac{\lambda}{\tilde{\rho} + \delta} \int_{w_r}^{\infty} \left(w^{1-\gamma} - w_r^{1-\gamma} \right) dF(w). \tag{2.15}$$

As before, the relationship can be expressed as a condition on the discount rate, which we note $\tilde{\rho}$ to make the distinction with ρ from equation (2.9):

$$\tilde{\rho} \geq \frac{\lambda}{y^{1-\gamma} - b^{1-\gamma}} \int_{w_r}^{\infty} \left(w^{1-\gamma} - w_r^{1-\gamma} \right) dF(w) - \delta. \tag{2.16}$$

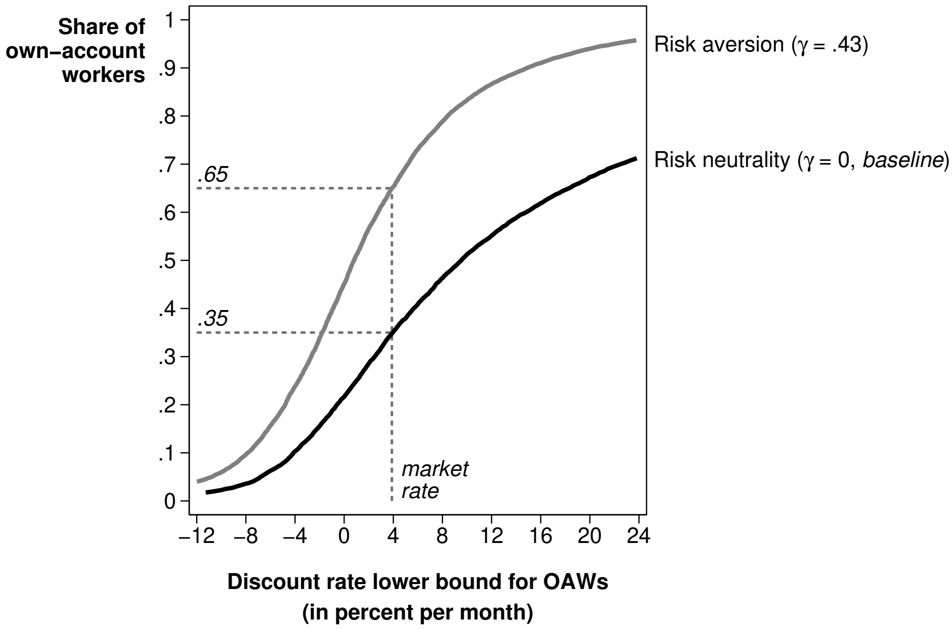
This inequality confirms that the qualitative theoretical results obtained at baseline remain valid. As long as income provides positive utility and individuals are not risk loving (i.e. $0 < \gamma \leq 1$), all of the income variables in equation (2.16) are subject to the same, monotonically increasing, transformation. By the chain rule, this implies that all of the partial derivatives of $\tilde{\rho}$ with respect to variables on the right-hand side of the inequality in equation (2.16) do not change sign, and thus the directional results of section 2.3.5 still hold. In particular, it is still true that for any realistic set of parameters capturing labor market conditions, there exists a sufficiently high consumption urgency that rationalizes taking up low-paid own-account work immediately.

However, as we cannot isolate the risk aversion parameter in equation (2.16), calculating the potential gap between $\tilde{\rho}$ and ρ (the potential bias due to the simplifying linearity assumption) is not straightforward. Moreover, the derivative of the right side of equation (2.16) with respect to $\tilde{\rho}$ has an ambiguous sign.

In practice, we can evaluate the potential bias by calibrating the model in equation (2.16) with a particular value for γ and comparing the results to the baseline case where $\gamma = 0$. The ideal approach would need risk aversion to be individual-specific, but this requirement cannot be implemented directly in our case, as we lack credible information about individual risk attitudes. As a compromise, we adopt a common risk aversion coefficient for all own-account workers at the level of 0.43, which is the average risk aversion reported by Falco (2014) for his sample of self-employed and wage workers. This value offers a benchmark for the extreme case in which all own-account workers are homogeneously risk averse and share the same risk aversion as wage workers, in contrast with the baseline case where all are risk neutral, as shown in figure 2.5.[21]

The conclusion of this calibration exercise is that, for the set of empirical parameters we have, assuming linear utility with respect to all income sources overestimates own-account workers' subjective discount rate, as the cumulative distribution of ρ (dark curve) dominates the distribution of $\tilde{\rho}$ (gray curve).

Figure 2.5. Empirical CDF of the estimated discount rate lower bound under risk aversion



Notes: The dark blue line reports the results for the baseline specification, where own-account workers are assumed to be risk neutral, and the light blue color corresponds to results for the alternative specification, where own-account workers have a homogeneous relative risk aversion of 0.43, following the average estimate of Falco (2014).

Intuitively, this result follows from the fact that, with concave utility, the gains from getting a wage job (relative to the earnings from own-account work) are smaller.[22] In our setting, own-account work can be already attractive even

21. Note that this is a conservative exercise because Falco (2014) notes that the self-employed in his data are less risk averse, although the paper only reports the average value of this parameter combining self-employed and wage workers.

22. It is interesting to note that early work by Weiss (1972) arrives at a similar conclusion when addressing an analogous problem, but in a different context. In that paper, the author infers the intertemporal rate of return associated with having a Ph.D. in the United States for different occupations under a range of degrees of risk aversion. He finds that coefficients above 0.4 imply implausibly low (and even negative) returns from education and concludes that "the dominating factor is the introduction of decreasing marginal utility, which reduces the profitability of investment".

with a modest consumption urgency, given that the marginal benefit of somewhat better pay is increasingly small for risk-averse workers.

Assuming that risk and time discounting are independent[23] and that actual risk preferences at the individual level fall somewhere between 0 and 0.43, we can conclude that the empirical estimation of the discount rate implied by the occupational choices would fall somewhere between the lines depicted above, with the conclusion that the share of credit-constrained own account workers would be some lower, but still large (at least 35% of the total).

Taking stock of both extensions presented in this section, it appears that (a) neglecting the earnings volatility in own-account work can overestimate its value and (b) not allowing for decreasing returns to income can overestimate the relative gains from wage work. The magnitude of the remaining bias, if any, is unclear, given that (a) and (b) act in opposite directions and considering the accumulated evidence from the literature that the self-employed are closer to risk neutrality than the general population. Future work should investigate this issue by designing strategies that allow for the measurement of heterogeneity at the individual level in both time and risk dimensions.

2.8 Concluding remarks

In this chapter, we discuss how the individual time discount rate — understood as a measure of subjective consumption urgency — can play a role when individuals decide between working by themselves or trying to work for a firm, particularly in the high-friction, low-liquidity context of labor markets in developing countries. We highlight that this approach leads to a novel definition of constrained own-account work, which we estimate to be the case for at least 65% of own-account workers in Brazil, assuming our estimates of the labor market parameters are sufficiently close to how workers perceive their potential labor opportunities. Finally, we provide suggestive evidence that financial stress and material precariousness are strongly associated with a higher subjective discount lower bound as estimated on Brazilian urban own-account workers.

Our model offers a note of caution to the classic view according to which liquidity constraints would *prevent people from working on their own*, and thus initiatives that improve access to credit (such as microcredit) would allow a larger number of people to do so. We argue that liquidity constraints could *prevent people from searching for a wage job*, pushing them into own-account work instead. This apparent contradiction is partly due to the confusion between

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23. There is no consensus in the literature regarding the significance or the sign of the correlation between risk aversion and time disconting (Andersen et al. 2008; Booij and van Praag 2009; Andreoni and Sprenger 2012; Woelbert and Riedl 2013; Falk et al. 2018).

low-end self-employment and high-end entrepreneurship, and we hope our discussion about own-account work contributes to a more nuanced understanding of this type of work.

From a public policy perspective, the model (1) highlights the relevance of programs that insure consumption during income shocks in general, and (2) points out why part of own-account workers should be targeted by labor market policies that support transitions into wage jobs, even though they are already working. Unemployment is often taken as the marker of the highest labor market vulnerability, but those observed in unemployment can at least afford to invest time in job searching.

Absent such financial support, agents facing frictional labor markets and imperfect financial markets could rationally drift into unproductive own-account work to bypass the job search period and get permanently stuck in a low-consumption equilibrium. According to our estimates, this is not a remote possibility — it can be the driver for a clear majority of own-account workers in a developing country.

Table 2.2. Descriptive statistics by labor market status

	Own-Account Workers	Employees
Subpopulation size (in millions)	22.6	50.9
Ethnicity and gender (in %)		
Nonwhite female	29.3	21.0
White female	20.4	21.7
Nonwhite male	29.0	31.7
White male	21.3	25.7
Education level (in %)		
Less than prim. school	33.9	15.1
Primary school	18.3	13.8
High school	35.9	46.2
College or above	11.9	24.9
Age group (in %)		
Age 14-24	8.6	18.4
Age 25-34	22.6	31.0
Age 35-44	27.8	25.9
Age 45-54	25.2	17.1
Age 55-64	15.9	7.6
Formal work status (in %)	24.0	64.3
Usual workplace (in %)		
Dedicated store, office	26.3	83.2
Place chosen by client, employer	21.6	7.0
Client's, employer's home	25.1	0.3
Worker's home (dedicated area)	4.8	0.1
Worker's home (shared area)	7.2	0.2
Worker's vehicle	5.9	3.8
Public space	5.7	0.9
Other places	3.3	4.5

Notes: [1] These summary statistics were calculated using the National Household Survey (PNAD) and refer to all working-age individuals (14-64 years old), living in Brazil's urban areas, who reported being occupied as either own-account workers or wage employees. [2] The results represent the average over the 8 quarters of 2017-18, with the exception of the workplace information, which is only available for the 4 quarters of 2018. [3] Employment status, formality status, workplace, and occupation all refer to an individual's main employment. [4] A worker is assigned a formal work status by having a register either as a worker ("carteira assinada") or as a small business ("CNPJ"). [5] The group of own-account workers includes domestic workers, who are by default defined as employees in the official figures from the Brazilian statistical office. This methodological decision is adopted throughout this chapter. An overview of the results under the standard classification is available in the appendix.

Table 2.3. Most frequent occupations by labor market status (in %)

	Own-Account Workers	Employees
1st	Domestic Cleaners, Helpers: (17.2)	Office Clerks: (6.3)
2nd	Bricklayers: (8.2)	Shop Sales Assistants: (6.2)
3rd	Shopkeepers: (6.9)	Cleaners, Helpers in Offices, Stores: (4.2)
4th	Door-to-door Salespersons: (4.6)	Security Guards: (2.3)
5th	Hairdressers: (3.6)	Primary School Teachers: (2.3)
6th	Beauticians: (3.4)	Heavy Truck Drivers: (2.3)
7th	Car, Taxi and Van Drivers: (3.3)	Cashiers and Ticket Clerks: (1.9)
8th	Child Care Workers: (2.5)	Building Construction Labourers: (1.7)
9th	Home-based Personal Care Workers: (2.1)	Nursing Associate Professionals: (1.7)
10th	Building Construction Labourers: (2.1)	Receptionists: (1.6)

Notes: The reported occupations are the most granular category (level 4) in the International Standard Classification of Occupations (ISCO). See also the notes for table 2.2

Table 2.4. Summary of the empirical components of the model

	mean	std. dev.	25th centile	50th centile	75th centile
Transition components					
Estimated job offer arrival rate [λ]	0.19	0.12	0.11	0.17	0.25
Estimated job destruction rate [δ]	0.12	0.07	0.07	0.10	0.14
Estimated prob. of acceptable offer [$P(w \geq w_r)$]	0.94	0.04	0.92	0.95	0.97
Earnings components (in R$)					
Estimated reservation wage [w_r]	860	401	589	806	1,048
Observed income from own-account work [y]	1,443	1,778	483	995	1,748
Estimated potential wage [$w \mid w > w_r$]	2,089	942	1,499	1,895	2,396

Notes: The summary statistics refer to the model parameters estimated for the 20,424 individuals observed in own-account work in the POF survey (2017/2018) within the population of interest. The results are weighted following the survey design to make them representative of the population the sample represents.

2.9 Acknowledgements

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Appendix for Chapter 2

A.1 Estimation output tables

Table 2.5. Estimation of potential wages with adjustment for selection

	Main equation log wage		Selection equation P(status = employee)	
	coef.	s.e.	coef.	s.e.
Ethnicity and gender				
Nonwhite female	.	.	.	.
White female	0.093	(0.016)	-0.002	(0.018)
Nonwhite male	0.082	(0.013)	0.473	(0.016)
White male	0.264	(0.015)	0.270	(0.019)
Age and education				
14-24, less than prim. school	.	.	.	.
14-24, primary school	-0.076	(0.038)	0.382	(0.036)
14-24, high school	-0.004	(0.036)	0.599	(0.039)
14-24, college or above	0.237	(0.054)	0.995	(0.075)
25-34, less than primary school	0.194	(0.039)	0.211	(0.044)
25-34, primary school	0.203	(0.040)	0.384	(0.047)
25-34, high school	0.264	(0.035)	0.683	(0.039)
25-34, college or above	0.666	(0.042)	1.047	(0.046)
35-44, less than primary school	0.317	(0.038)	-0.021	(0.043)
35-44, primary school	0.306	(0.041)	0.303	(0.047)
35-44, high school	0.468	(0.036)	0.516	(0.040)
35-44, college or above	0.963	(0.042)	1.006	(0.051)
45-54, less than primary school	0.454	(0.038)	-0.184	(0.041)
45-54, primary school	0.505	(0.041)	-0.044	(0.049)
45-54, high school	0.673	(0.038)	0.266	(0.044)
45-54, college or above	1.152	(0.050)	0.868	(0.058)
55-64, less than primary school	0.577	(0.039)	-0.543	(0.044)
55-64, primary school	0.625	(0.049)	-0.322	(0.059)
55-64, high school	0.870	(0.048)	-0.130	(0.051)
55-64, college or above	1.445	(0.056)	0.254	(0.061)
Current schooling status				
Not currently studying	.	.	.	.
Attending school	.	.	-0.584	(0.033)
Attending college or above	.	.	0.114	(0.022)
Household position				
Head, with partner, no kids	.	.	.	.
Head, with partner, with kids	.	.	0.037	(0.028)

Table 2.5. Estimation of potential wages with adjustment for selection *(continued)*

	Main equation log wage		Selection equation P(status = employee)	
	coef.	s.e.	coef.	s.e.
Head, no partner, no kids	.	.	-0.044	(0.031)
Head, no partner, with kids	.	.	-0.075	(0.031)
Partner, no kids	.	.	-0.231	(0.031)
Partner, with kids	.	.	-0.249	(0.028)
Child	.	.	-0.491	(0.029)
Other young hh member	.	.	-0.489	(0.046)
Other adult hh member	.	.	-0.344	(0.033)
Number of household members by age				
N. kids (less than 15 years old)	.	.	-0.034	(0.007)
N. young members (15-21)	.	.	-0.011	(0.008)
N. adult members (22-64)	.	.	0.013	(0.007)
N. elderly members (65+)	.	.	-0.044	(0.015)
Heckman model ancillary parameters				
Errors correlation	-0.815	(0.009)	.	.
Standard deviation of errors	0.751	(0.009)	.	.

Notes: [1] The selection equation is estimated on 96,175 working-age individuals (14-64) living in urban areas in Brazil, and the main wage equation is estimated on the 37,582 of them whose primary occupation is wage employment, using data from the POF 2017-18 survey. [2] Individual observations are weighted by the inverse of their sampling probability, following the survey design, to render the coefficients meaningful for the population this sample represents. [3] All models include controls for region, defined as (i) the State capital; (ii) the metropolitan area outside the capital (in the States where such region is defined); or (iii) non-metropolitan urban areas, at each one of the 26 Brazilian States and the Federal District, making up a total of 77 geographic areas.

Table 2.6. Estimation of reservation wages: quantile regressions at 5th, 10th (baseline) and 15th centiles

	Quantile 0.05 log wage		Quantile 0.10 log wage		Quantile 0.15 log wage	
	coef.	s.e.	coef.	s.e.	coef.	s.e.
Ethnicity and gender						
Nonwhite female	.	.	.	.	.	.
White female	0.071	(0.018)	0.066	(0.011)	0.050	(0.009)
Nonwhite male	0.221	(0.018)	0.216	(0.010)	0.184	(0.009)
White male	0.296	(0.019)	0.300	(0.010)	0.256	(0.010)
Age and education						
14-24, less than prim. school	.	.	.	.	.	.
14-24, primary school	0.393	(0.156)	0.333	(0.043)	0.414	(0.081)
14-24, high school	0.763	(0.150)	0.617	(0.021)	0.551	(0.080)
14-24, college or above	0.880	(0.264)	0.895	(0.092)	0.899	(0.087)
25-34, less than primary school	0.666	(0.162)	0.528	(0.074)	0.457	(0.088)
25-34, primary school	0.836	(0.155)	0.741	(0.024)	0.691	(0.081)
25-34, high school	1.121	(0.150)	0.895	(0.023)	0.809	(0.080)
25-34, college or above	1.365	(0.152)	1.164	(0.024)	1.118	(0.082)
35-44, less than primary school	0.611	(0.151)	0.578	(0.103)	0.577	(0.082)
35-44, primary school	0.788	(0.170)	0.801	(0.030)	0.727	(0.083)
35-44, high school	1.240	(0.150)	0.959	(0.023)	0.882	(0.080)
35-44, college or above	1.592	(0.151)	1.373	(0.028)	1.310	(0.081)
45-54, less than primary school	0.681	(0.151)	0.670	(0.031)	0.628	(0.081)
45-54, primary school	1.030	(0.154)	0.835	(0.028)	0.751	(0.081)
45-54, high school	1.202	(0.150)	0.961	(0.024)	0.872	(0.080)
45-54, college or above	1.570	(0.152)	1.397	(0.031)	1.378	(0.081)
55-64, less than primary school	0.599	(0.179)	0.518	(0.065)	0.520	(0.099)
55-64, primary school	0.938	(0.157)	0.696	(0.037)	0.659	(0.083)
55-64, high school	1.099	(0.150)	0.893	(0.026)	0.838	(0.080)
55-64, college or above	1.436	(0.152)	1.351	(0.058)	1.270	(0.081)
Current schooling status						
Not currently studying	.	.	.	.	.	.
Attending school	-0.408	(0.116)	-0.401	(0.105)	-0.458	(0.039)
Attending college or above	-0.125	(0.019)	-0.061	(0.010)	-0.066	(0.010)
Household position						
Head, with partner, no kids	.	.	.	.	.	.
Head, with partner, with kids	0.049	(0.025)	0.060	(0.014)	0.019	(0.014)
Head, no partner, no kids	-0.065	(0.025)	-0.065	(0.020)	-0.093	(0.017)
Head, no partner, with kids	-0.045	(0.024)	0.007	(0.013)	-0.058	(0.016)

Table 2.6. Estimation of reservation wages: quantile regressions at 5th, 10th (baseline) and 15th centiles *(continued)*

	Quantile 0.05 log wage		Quantile 0.10 log wage		Quantile 0.15 log wage	
	coef.	s.e.	coef.	s.e.	coef.	s.e.
Partner, no kids	-0.104	(0.027)	-0.068	(0.018)	-0.089	(0.022)
Partner, with kids	-0.049	(0.023)	-0.040	(0.028)	-0.078	(0.015)
Child	-0.324	(0.029)	-0.334	(0.013)	-0.356	(0.020)
Other young hh member	-0.400	(0.046)	-0.405	(0.031)	-0.410	(0.023)
Other adult hh member	-0.184	(0.020)	-0.165	(0.016)	-0.214	(0.015)
Number of household members by age	.	.	.	.	.	.
N. kids (less than 15 years old)	-0.052	(0.007)	-0.033	(0.004)	-0.025	(0.005)
N. young members (15-21)	-0.060	(0.010)	-0.045	(0.005)	-0.039	(0.005)
N. adult members (22-64)	-0.001	(0.006)	0.001	(0.005)	-0.000	(0.004)
N. elderly members (65+)	-0.086	(0.015)	-0.045	(0.013)	-0.052	(0.007)

Notes: [1] All models are estimated on 37,582 working-age individuals (14-64), living in urban areas in Brazil, whose primary occupation is wage employment, using data from the POF 2017-18 survey. [2] Individual observations are weighted by the inverse of their sampling probability, following the survey design, to render the coefficients meaningful for the population this sample represents. [3] All models include controls for region, defined as (i) the State capital; (ii) the metropolitan area outside the capital (in the States where such region is defined); or (iii) non-metropolitan urban areas, at each one of the 26 Brazilian States and the Federal District, making up a total of 77 geographic areas.

Table 2.7. Estimation of employment and unemployment duration using an exponential transition model with two-types mixture for unobservable components

	Out of wage work transition hazard		Unemp. into wage work transition hazard	
	haz. ratio	s. e.	haz. ratio	s. e.
Ethnicity and gender				
Nonwhite female	.	.	.	.
White female	1.061	(0.022)	1.138	(0.047)
Nonwhite male	0.953	(0.018)	1.898	(0.058)
White male	0.946	(0.020)	1.671	(0.066)
Age and education				
14-24, less than prim. school	.	.	.	.
14-24, primary school	0.734	(0.029)	1.040	(0.069)
14-24, high school	0.460	(0.019)	0.990	(0.059)
14-24, college or above	0.282	(0.026)	1.418	(0.146)
25-34, less than primary school	0.744	(0.031)	1.112	(0.084)
25-34, primary school	0.543	(0.023)	1.155	(0.090)
25-34, high school	0.346	(0.014)	1.101	(0.072)
25-34, college or above	0.222	(0.012)	1.092	(0.093)
35-44, less than primary school	0.676	(0.030)	0.920	(0.072)
35-44, primary school	0.490	(0.026)	0.946	(0.086)
35-44, high school	0.325	(0.014)	0.967	(0.074)
35-44, college or above	0.192	(0.010)	0.996	(0.100)
45-54, less than primary school	0.632	(0.027)	0.802	(0.072)
45-54, primary school	0.475	(0.026)	0.791	(0.091)
45-54, high school	0.347	(0.017)	0.783	(0.072)
45-54, college or above	0.206	(0.012)	0.743	(0.097)
55-64, less than primary school	0.730	(0.035)	0.581	(0.068)
55-64, primary school	0.581	(0.036)	0.479	(0.088)
55-64, high school	0.457	(0.024)	0.500	(0.079)
55-64, college or above	0.358	(0.020)	0.336	(0.071)
Current schooling status				
Not currently studying	.	.	.	.
Attending school	1.424	(0.045)	0.771	(0.044)
Attending college or above	0.925	(0.025)	1.288	(0.052)
Household position				
Head, with partner, no kids	.	.	.	.
Head, with partner, with kids	0.905	(0.026)	0.940	(0.064)
Head, no partner, no kids	1.030	(0.035)	0.837	(0.062)
Head, no partner, with kids	0.969	(0.034)	0.865	(0.070)

Table 2.7. Estimation of employment and unemployment duration using an exponential transition model with two-types mixture for unobservable components *(continued)*

	Out of wage work transition hazard		Unemp. into wage work transition hazard	
	haz. ratio	s. e.	haz. ratio	s. e.
Partner, no kids	1.036	(0.038)	0.890	(0.075)
Partner, with kids	0.992	(0.028)	0.923	(0.057)
Child	1.295	(0.040)	0.650	(0.045)
Other young hh member	1.268	(0.071)	0.778	(0.077)
Other adult hh member	1.143	(0.047)	0.831	(0.065)
Number of household members by age				
N. kids (less than 15 years old)	1.067	(0.008)	1.038	(0.014)
N. young members (15-21)	1.074	(0.011)	1.000	(0.020)
N. adult members (22-64)	1.010	(0.008)	0.993	(0.014)
N. elderly members (65+)	1.015	(0.017)	0.927	(0.030)
Ancillary mixture parameters				
Hazard ratio for high type	6.210	(0.249)	3.311	(0.098)
Share of high type	0.409	(0.011)	0.671	(0.022)

Notes: [1] The employment (resp. unemployment) duration model is estimated on 259 262 (50 065) working-age individuals, living in urban areas in Brazil, who reported wage employment (unemployment) status in at least one interview, before transition or censoring, over the 8 quarters of 2017 and 2018, using data from the PNAD survey. [2] Individual observations are weighted by the inverse of their sampling probability, following the survey design, to render the coefficients meaningful for the population this sample represents. [3] Individual identifiers for PNAD are assigned using the advanced methodology from ribas_2008, as implemented in Stata statacorp_2015 by the user-written program `-datazoom_pnadcontinua-` from the Economics Department of PUC-Rio University. [4] All models include controls for region, defined as (i) the State capital; (ii) the metropolitan area outside the capital (in the States where such region is defined); or (iii) non-metropolitan urban areas, at each one of the 26 Brazilian States and the Federal District, making up a total of 77 geographic areas. [5] The reported coefficients and standard errors were bootstrapped over 400 replications, with Primary Sampling Units being resampled with replacement independently at each one of the 77 geographic areas.

Table 2.8. Association between the estimated discount lower bound of own-account workers (in percent per month) and the material conditions of their household

	Model A		Model B		Model C		Model D	
	other inc. sources		budget conditions		living conditions		full specification	
	coef.	s.e.	coef.	s.e.	coef.	s.e.	coef.	s.e.
Lack of access to financial services								
No savings account	3.60	(0.75)	·	·	·	·	2.75	(0.75)
No overdraft facility	6.92	(1.32)	·	·	·	·	5.04	(1.32)
No credit card	8.24	(0.81)	·	·	·	·	6.21	(0.81)
Income from other sources (in R$ 1,000)								
Family per cap inc ex my work inc	-1.12	(0.27)	·	·	·	·	-0.19	(0.28)
(Family per cap inc ex my work inc)^2	0.02	(0.00)	·	·	·	·	0.00	(0.01)
Making ends meet (ref: very easy)								
Easy to make ends meet	·	·	-1.08	(2.57)	·	·	-1.28	(2.60)
Somewhat easy to make ends meet	·	·	1.64	(2.58)	·	·	0.79	(2.62)
Somewhat hard to make ends meet	·	·	7.80	(2.49)	·	·	4.48	(2.53)
Hard to make ends meet	·	·	10.84	(2.60)	·	·	4.95	(2.61)
Very hard to make ends meet	·	·	19.59	(2.69)	·	·	10.08	(2.78)
Has large non-essential expenses (top decile)								
Education expenses > 15% of total	·	·	-2.82	(1.17)	·	·	-2.41	(1.17)
Personal expenses > 13% of total	·	·	-0.93	(1.17)	·	·	-1.88	(1.18)
Has large essential expenses (top decile)								
Housing expenses > 58% of total	·	·	7.51	(1.27)	·	·	6.14	(1.26)
Medicine expenses > 9% of total	·	·	8.13	(1.34)	·	·	6.83	(1.32)
Food expenses > 35% of total	·	·	8.41	(1.28)	·	·	7.09	(1.27)

Table 2.8. Association between the estimated discount lower bound of own-account workers (in percent per month) and the material conditions of their household *(continued)*

	Model A		Model B		Model C		Model D	
	other inc. sources		budget conditions		living conditions		full specification	
	coef.	s.e.	coef.	s.e.	coef.	s.e.	coef.	s.e.
Housing precarity								
People per sleeping room	·	·	·	·	2.39	(0.68)	1.71	(0.66)
Presence of domestic pests	·	·	·	·	2.45	(0.77)	2.15	(0.76)
Presence of leakages or dampness	·	·	·	·	3.01	(0.76)	2.38	(0.76)
Clothing precarity (ref: good, adequate)								
Poor clothing conditions	·	·	·	·	7.91	(1.75)	6.29	(1.75)
Food insecurity (ref: no insecurity)								
Some food insecurity	·	·	·	·	7.61	(0.91)	4.46	(0.93)
Moderate food insecurity	·	·	·	·	13.80	(1.37)	8.81	(1.42)
Severe food insecurity	·	·	·	·	19.07	(1.99)	12.89	(2.10)
Model statistics								
Adjusted R^2	0.134	·	0.147	·	0.147	·	0.166	·
Number of observations	20,424	·	20,424	·	20,424	·	20,424	·

Notes: [1] All models are estimated on 20 424 working-age own-account workers, living in urban areas in Brazil, using data from the POF 2017-18 survey and our estimation of the lower bound of their subjective time discount rate. [2] Individual observations are weighted by the inverse of their sampling probability, following the survey design, to render the coefficients meaningful for the population this sample represents, and the errors are clustered at the level of their Primary Sampling Unit. [3] All models include controls for ethnicity, gender, age, education, position of the worker in the family, family composition, and geographic region.

A.2 Alternative specifications for the own-account workers

This chapter argues that the economic activities performed by domestic workers fall within the proposed definition of own-account workers, as discussed in section 2.4. For completeness, this section describes this group in more detail and presents how the main results change if we were to classify them as employees instead, as the Brazilian national statistics office does.

This classification matters because this is a large and relatively homogeneous group: in any given quarter, there are 5.2 million people occupied as domestic workers among the urban, working-age Brazilians. Among them, there are 95% are women; 66% are nonwhites; 48% have less than primary education; and 61% are between 35 and 54 years old, as shown in table 2.9.

Without domestic workers, the proportion of nonwhite females among own-account workers falls from 29.6% to 19.9%, and men become a clear majority (from 49.4% to 62.4%). This comparison shows that the discussion about gender, ethnicity, and self-employment in Brazil depends on how one understands the group of domestic workers.

If we replicate the estimation of potential wages for own-account workers from section 2.5.1, now using the statistics office's classification, we find that 75% of them could plausibly expect a higher net work income working for a firm (figure 2.6). This share is smaller than the 82% found at baseline (figure 2.2) because the inclusion of domestic workers decreases the average gains from wage employment.

Looking at monthly wages only, this smaller gap would imply a lower share of constrained own-account workers. Yet, accounting for expected unemployment duration reverses this conclusion. Under the baseline classification, if an unemployed individual becomes a domestic worker, the unemployment spell is censored — we cannot see how long it would take her to find wage employment because something else happened before. In contrast, under the alternative classification, the same observation is now considered a transition to wage employment. Because of this distinction, the estimated average time to an offer falls to 5.9 months, about seven weeks less than the baseline. After integrating the individual-specific expected wage, expected unemployment time, and expected employment duration time, the distribution of the implicit discount rate under the alternative specification stochastically dominates the baseline curve (see figure 2.7).

In other words, if one views domestic work as wage employment, the resulting expectation about the monetary return of a wage job decreases, but it also becomes easier to find a job, on average. This result does not affect everybody the same way (because the conditional expectations are still individual-specific, black females are the most affected by this change in the definition), but the aggregate result suggests that the gains in transition time more than offset the losses in wage for those who are affected. Because the average discounted value of a wage job increases, the implicit discount rate of those who have preferred to work on their own also increases, and the estimated share of constrained own-account workers rises from 65% to 72%.

Table 2.9. Descriptive statistics by labor market status

	Domestic Workers	Own-Account Workers	Employees
Subpopulation size (in millions)	5.1	17.5	50.9
Ethnicity and gender (in %)			
Nonwhite female	62.8	19.6	21.0
White female	31.6	17.2	21.7
Nonwhite male	3.7	36.2	31.7
White male	2.0	26.9	25.7
Education level (in %)			
Less than prim. school	47.3	30.1	15.1
Primary school	22.3	17.2	13.8
High school	29.3	37.8	46.2
College or above	1.2	15.0	24.9
Age group (in %)			
Age 14-24	8.2	8.7	18.4
Age 25-34	17.4	24.0	31.0
Age 35-44	30.6	27.0	25.9
Age 45-54	28.8	24.1	17.1
Age 55-64	15.0	16.1	7.6
Formal work status (in %)	29.9	22.3	64.3
Usual workplace (in %)			
Dedicated store, office	0.0	33.9	83.2
Place chosen by client, employer	0.0	27.9	7.0
Client's, employer's home	100.0	3.6	0.3
Worker's home (dedicated area)	0.0	6.2	0.1
Worker's home (shared area)	0.0	9.3	0.2
Worker's vehicle	0.0	7.5	3.8
Public space	0.0	7.3	0.9
Other places	0.0	4.3	4.5

Notes: [1] These summary statistics were calculated using the National Household Survey (PNAD) and refer to all working-age individuals (14-64 years old), living in Brazil's urban areas, who reported being occupied as either own-account workers or wage employees. [2] The results represent the average over the 8 quarters of 2017-18, with the exception of the workplace information, which is only available for the 4 quarters of 2018. [3] Employment status, formality status, workplace, and occupation all refer to an individual's main employment. [4] A worker is assigned a formal work status by having a register either as worker ("carteira assinada") or as a small business ("CNPJ").

Table 2.10. Most frequent occupations by labor market status (in %)

	Domestic Workers	Own-Account Workers	Employees
1st	Domestic Cleaners, Helpers: 76.5	Bricklayers: (10.6)	Office Clerks: (6.3)
2nd	Child Care Workers: 9.9	Shopkeepers: (9.0)	Shop Sales Assistants: (6.2)
3rd	Home-based Personal Care Workers: 9.2	Door-to-door Salespersons: (6.0)	Cleaners, Helpers in Offices, Stores: (4.2)
4th	Cooks: 1.8	Hairdressers: (4.6)	Security Guards: (2.3)
5th	Tree and Shrub Crop Growers: 1.6	Beauticians: (4.3)	Primary School Teachers: (2.3)
6th	Car, Taxi and Van Drivers: 0.7	Car, Taxi and Van Drivers: (4.1)	Heavy Truck Drivers: (2.3)
7th	Domestic Housekeepers: 0.2	Building Construction Labourers: (2.7)	Cashiers and Ticket Clerks: (1.9)
8th	Security Guards: 0.1	Painters: (2.5)	Building Construction Labourers: (1.7)
9th	Kitchen Helpers: 0.0	Street Vendors (excluding Food): (2.3)	Nursing Associate Professionals: (1.7)
10th	Animal Care Workers: 0.0	Lawyers: (2.1)	Receptionists: (1.6)

Notes: The reported occupations are the most granular category (level 4) in the International Standard Classification of Occupations (ISCO). See also the notes for table 2.9.

Figure 2.6. Distribution of the estimated gap between the labor income received by own-account workers and the wage they could expect to receive as employees (with domestic workers included among employees)

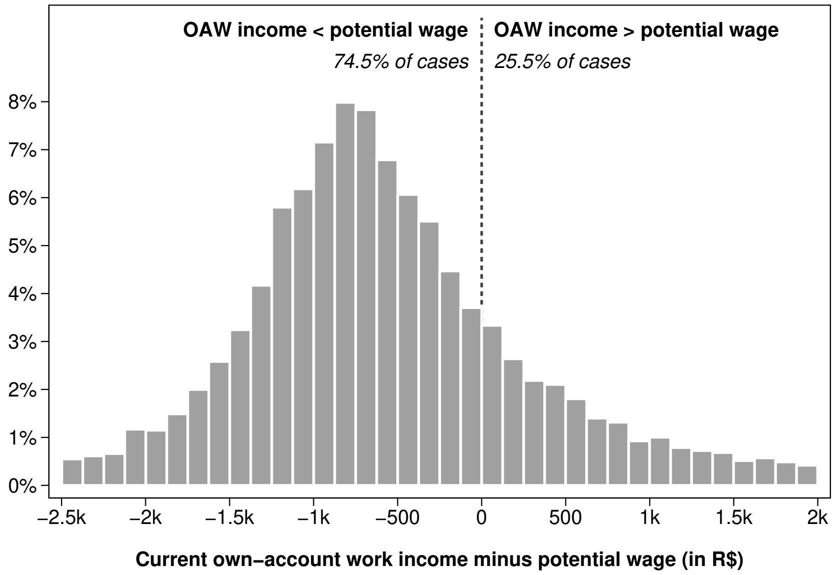
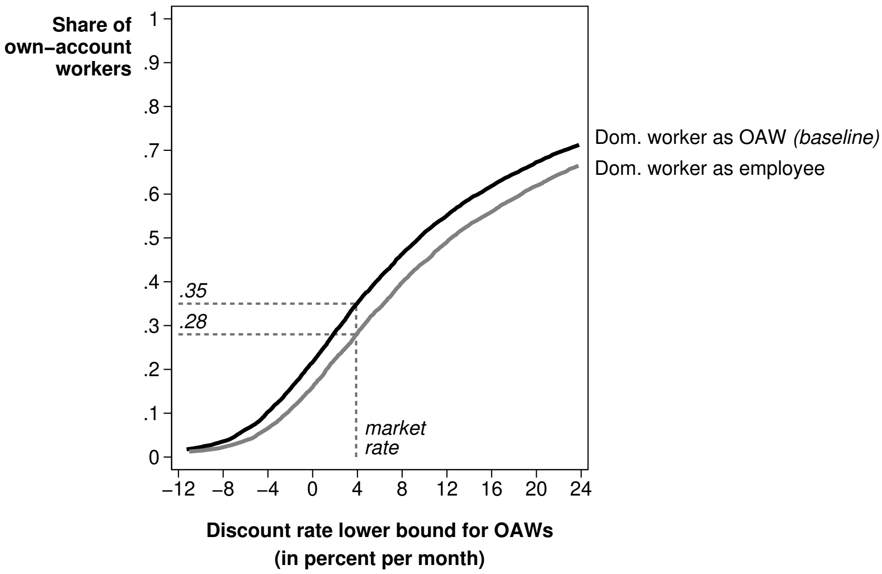


Figure 2.7. Empirical CDF of the estimated discount rate lower bound taking domestic workers as OAWs (baseline) and as employees



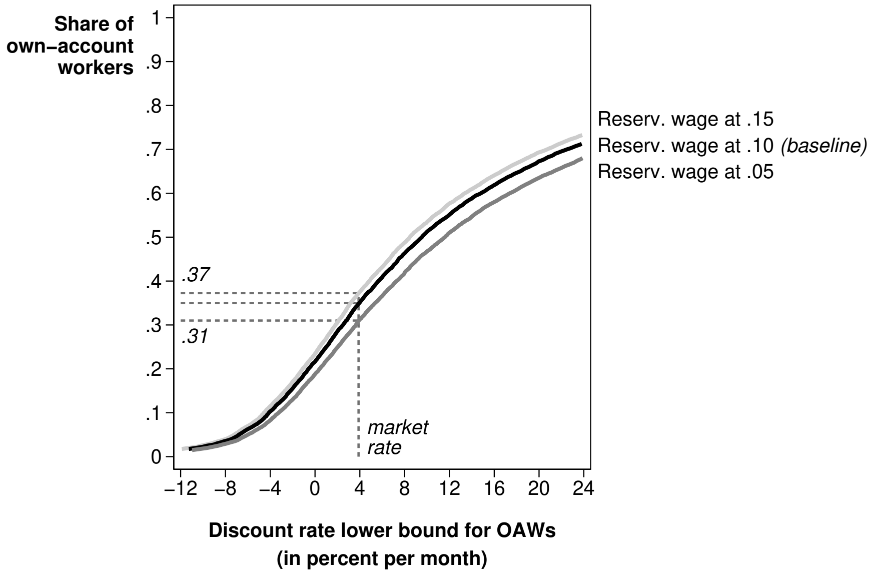
A.3 Alternative specifications for the reservation wage

In the baseline estimation, we adopted the conditional 10th percentile of the wage distribution as a proxy for the concept of reservation wage. As a robustness exercise, in this section we briefly examine how the main result changes under different conditional quantiles.

Within the framework adopted here, a lower reservation wage generally implies a higher discount rate. As a consequence, we can expect the discount rate lower bound calculated with reservation wage at the 5th conditional quantile to stochastically dominate the baseline model, which in turn should dominate the specification at the 15th centile.

Indeed, we find that the alternative definitions affect the results in the expected direction (see figure 2.8). Under the 5th percentile proxy, the estimation suggests 70% of own-account workers would have a subjective lower bound discount rate above the market rate, or 5 percentage points more than the baseline result. Under the 15th percentile proxy, the share would be 63%. We thus conclude that, under a reasonable range of reservation wages, there are between 6 and 7 constrained cases for every 10 own-account workers in Brazil.

Figure 2.8. Empirical CDF of the estimated discount rate lower bound under alternative proxies for the concept of reservation wage

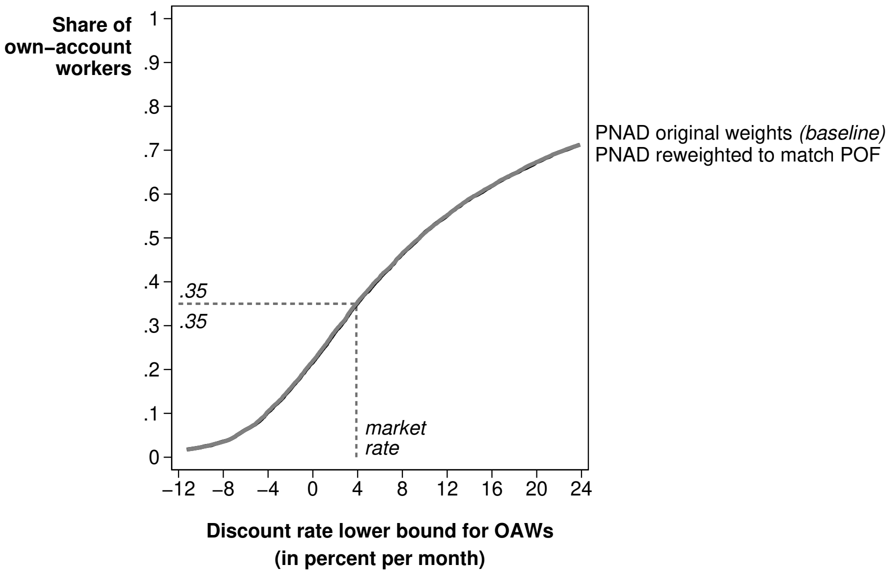


A.4 Alternative specification for the survey weights

The baseline estimation adopts the original survey weights from both POF and PNAD, given that the surveys are meant to represent the same population, as discussed in section 2.4. The descriptive statistics presented in table 2.1 reinforce that the population of interest indeed has very similar attributes, be it using POF's or PNAD's data. However, at a 5% confidence level, we cannot rule out that the population of interest is slightly less educated and a bit older in the POF, relative to the PNAD. A meaningful difference in the populations could compromise the strategy of using the hazard coefficients estimated with PNAD to fit conditional employment and unemployment durations on POF data.

In all cases, the differences are very small in magnitude. For instance, the share of people in the age interval 35-44 is 21.0% in POF and 21.7% in PNAD, but given the large size of both samples, this gap falls outside the confidence interval. It is not clear whether this is a false positive or a true small difference, and for robustness we run the estimation also using a reweighted version of PNAD.

Figure 2.9. Empirical CDF of the estimated discount rate lower bound adopting original survey weights (baseline) and reweighted PNAD survey



The covariate balancing protocol aims to adjust the original survey weights to ensure that the first and the second moments of the basic socioeconomic variables in PNAD (ethnicity, gender, age, and education) coincide exactly with the ones we calculate for POF, for each quarter and in each region.[24] Since the data sources are very similar to begin with, the algorithm converges quickly, leads to small adjustments, and the estimation results are nearly indistinguishable (see figure 2.9). This compatibility can be seen as evidence that supports the baseline (non-reweighted) findings.

24. In practice, we adopt an entropy balancing technique that finds the set of unit weights that satisfies the imposed moment constraints, as proposed by Hainmueller (2012) and implemented in Stata (StataCorp 2015) by the program `-ebalance-`.

A.5 Maximum likelihood estimation of the duration models

To the best of our knowledge, no statistical software to date offers a built-in semi-parametric estimation of transition hazards that, at the same time, accommodates the possibility of stock sampling, interval observation, and a potential mixture of unobserved components, despite an established framework about how it could be done (see Cameron and Trivedi 2005). To bridge this gap, we write a statistical model that is flexible enough to use the information available in all the different cases recorded in our data, and estimate it with a maximum likelihood approach. Even though the statistical model could allow for an arbitrary parametric baseline hazard, we constrain the estimation to the exponential case to impose a constant hazard over the spell, mirroring the stationarity conditions assumed in the theoretical framework.

As discussed in section 2.4, PNAD follows households during 5 quarters. When an individual enters the sample, she might be already employed (resp. unemployed) for a given known duration, which amounts to stock sampling. It is well understood that failing to account for it would bias the estimation, as people who tend to stay longer in a state would be more likely to be sampled. Furthermore, when there is a state transition, we can only see that it took place somewhere between the last interview and the current interview: hence, transitions are known to happen within an interval. While this is the case for most labor market surveys, empirical applications tend to overlook the issue and assume a transition at the midpoint, which may be a tolerable approximation when using monthly or weekly data. Since we have quarterly intervals, this imprecision would be more consequential.

The final component is related to unobservables. In linear regression models, omitted covariates that are independent of the observed ones are absorbed into the constant term and do not bias the estimation. This is generally not the case with the estimation of conditional hazard functions, and even independent unobservables could affect the estimation. To minimize this bias, we allow the population to be composed of a mixture of high and low types, as suggested by Heckman and Singer (1984). The likelihood model then becomes a weighted average with two types, allowing them to have different intercepts while sharing the remaining coefficients.

In practice, we can interpret it as some share of the population transitioning faster than the rest due to unobserved factors. Technically, both the share of the types and the gap between the different intercepts enter as additional parameters in the function to be minimized, subject to convenient regularity conditions: both shares are constrained to be in the interval $[0, 1]$, must sum up to one, and the intercept gap is constrained to be positive to ensure a single solution, without loss of generality. In this sense, the estimation is more flexible: an exponential distribution is assumed for the hazard, but the mixture of the unobserved term itself is just an average from two arbitrary mass points.

The introduction of a mixture reduces the bias in the model's coefficients, but we cannot identify the type of a given individual. Therefore, to predict a conditional duration, we adopt a weighted average that combines the linear index of the individual attributes and the model coefficients for high and low types, using the weights fitted by the model.

Chapter 3

Workers' Preferences over Payment Schedules: Evidence from Ridesharing Drivers

by Thiago Scarelli

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

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

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

3.1 Introduction

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

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

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

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

This chapter addresses this challenge by exploring the setting of the ridesharing drivers using a survey experiment in the field. The choice to focus on

1. See Gindling and Newhouse (2014), Bandiera, Elsayed, Heil, 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).

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

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

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

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

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

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

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

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

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

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

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

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

The remainder of this chapter is organized as follows. Section 3.2 describes the operation of the ridesharing activities in Brazil, focusing on the rules that determine the drivers' payout. Section 3.3 describes the survey design, the preference elicitation method, and the experimental manipulation, and provides an overview of the sample. Section 3.4 reports descriptive results from my survey, including a profile of the ridesharing drivers and their work routine. The same section also presents a text analysis of the qualitative responses from the drivers. Section 3.5 reports the experimental results, investigates heterogeneity in the effects for those who drive as a primary or a secondary occupation, discusses the evidence on a potential mechanism, and performs robustness checks. Section 3.7 concludes with a discussion of the implications of the results and directions for further research.

3.2 Context

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

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

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

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

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

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

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

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

3.3 Experimental design

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

The sample includes all individuals who agreed to participate and were assigned to a treatment or a control group. In practice, it means they answered at least the question regarding the subnational region where they usually work, which is the information required to perform the stratified randomization. The sample excludes (a) 35 cases flagged by the survey software as potentially repeated responses by the same individual and (b) 7 observations coming from the two strata with less than 20 observations. Unfortunately, it is not possible to report the precise response rate to the recruitment because the number of drivers registered with the company is confidential information. For a broad reference of magnitude, there were about 1.27 million active drivers in that period (Callil and Picanço 2023). This figure implies we collected data on about 1.1 percent of the universe. Section 3.4.1 provides further discussion on how the sample compares to the relevant reference groups in terms of demographics.

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

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

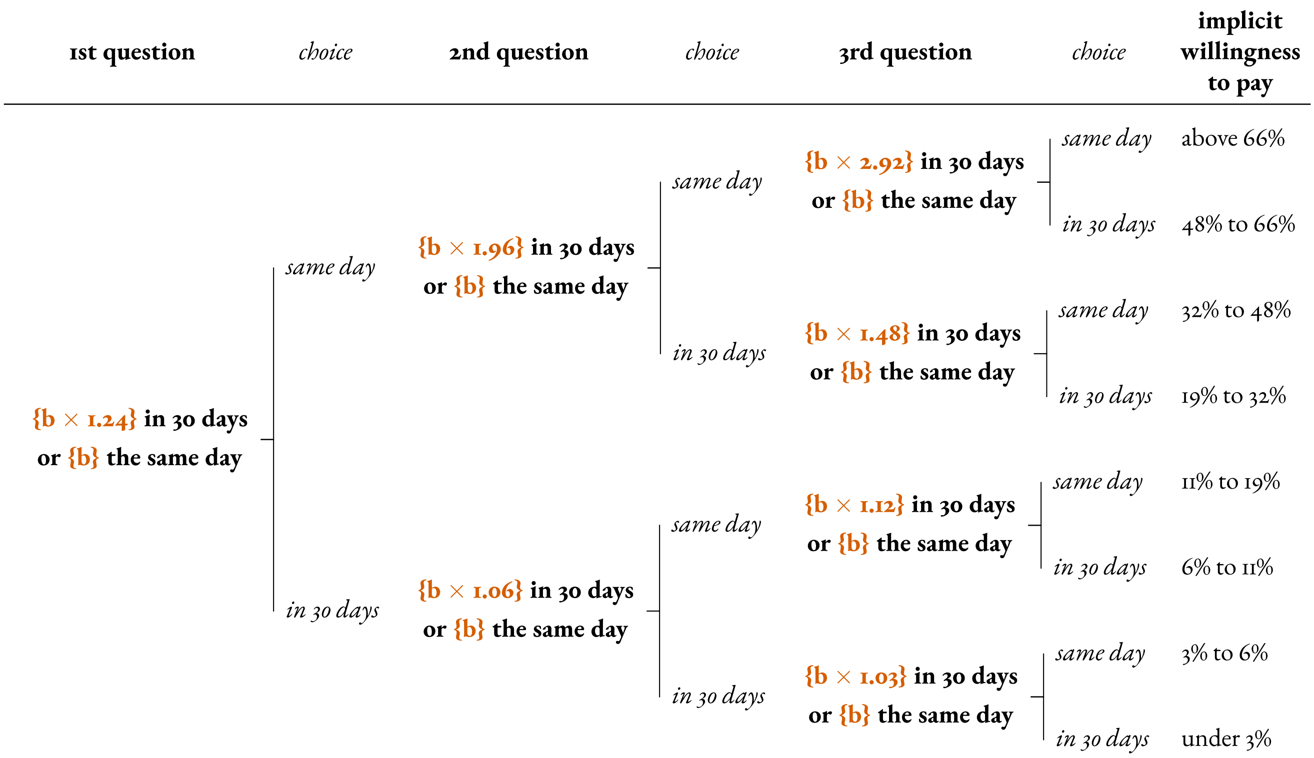
3.3.1 Preference elicitation protocol

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

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

The bracketed values were calculated dynamically according to the geographical region of the driver, such that the baseline rate b for the same-day option matches the actual kilometer rate that the respondent is familiar with. The 30 days rate is calculated using a multiplier m to the baseline rate b (1.24 in the first question; 1.06 or 1.96 for the second question; and 1.03, 1.12, 1.48 or 2.92 for the third question, as detailed in figure 3.1). 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 3.1. Sequences of possible contract choices and the corresponding rates



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

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

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

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

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

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

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

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

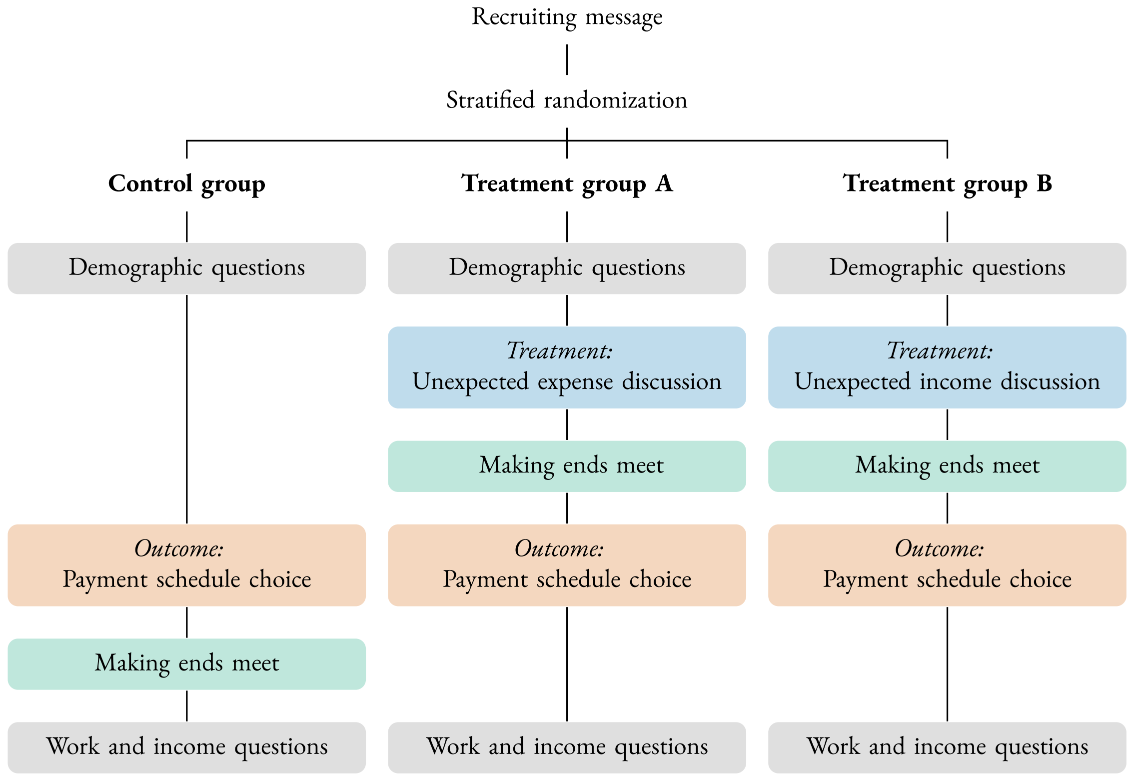
3.3.2 Experimental manipulation

To measure how the salience of one's financial conditions may affect one's preferences for rapid payment timing, the implementation of the survey splits the respondents into three groups, as shown in figure 3.2.

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.

Figure 3.2. Sequence of the survey blocks according to the assignment groups



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.

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

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

Or the following *unexpected income* scenario:

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

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

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

3.4 Descriptive results

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

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

3.4.1 Who are the ridesharing drivers?

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

What is more remarkable, the drivers in this study also reflect the general diversity of the urban, adult, working population in Brazil in terms of ethnicity, age, education, and household composition, as documented in table 3.1. While it would be excessive to claim that the participants of this study are representative workers in a broad sense, this tabulation shows that they are not a particularly eccentric group.

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

For completeness, table 3.8 in the appendix replicates the descriptive statistics from table 3.1 but keeps only men in both the drivers' sample and in the general workforce. In this case, after removing the women from the comparison, the share of workers with college decreases, while the average work hours and work income increase for all subgroups.

The drivers report an average net income from ridesharing of R$ 2,267 per month, after regular working expenses, which is equivalent to about US$ 900, adjusting for purchase power parity (see figure 3.3 for the distribution of monthly earnings from ridesharing). This average value represents 1.7 times the national minimum wage for a full-time formal employment position in Brazil. On the other hand, it is about 20% below the average monthly earnings reported by the general workforce in the same period (or 26% less, if we compare only male drivers with the male working population), as measured by the national household survey.

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

Table 3.1. Characteristics of the drivers in the survey and corresponding summaries for urban adult workers in Brazil

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

Table 3.1. Characteristics of the drivers in the survey and corresponding summaries for urban adult workers in Brazil *(continued)*

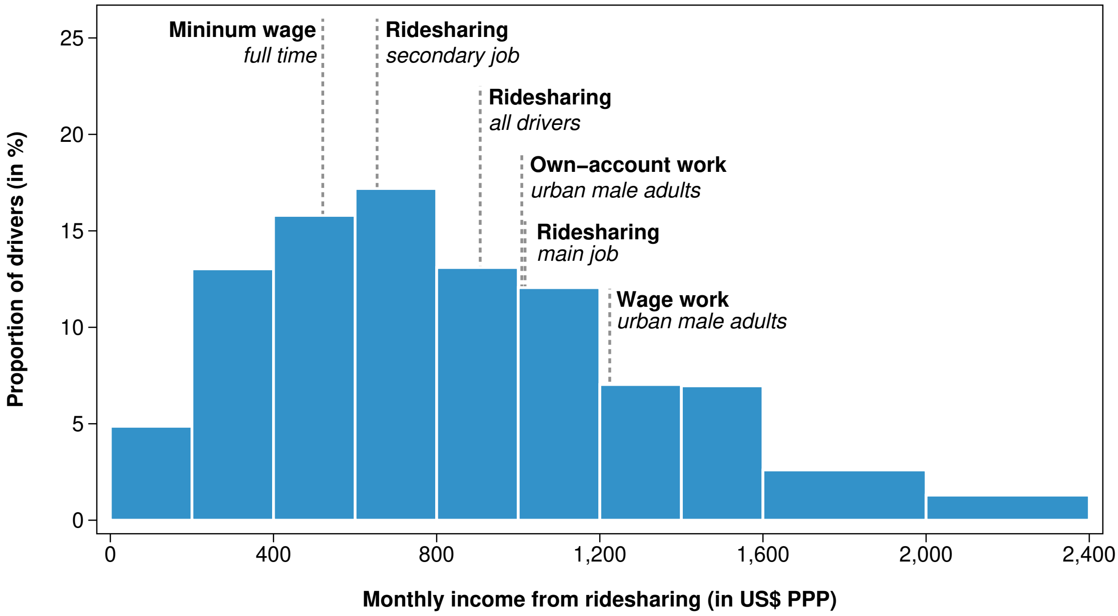
	Ridesharing Drivers Survey						*National Household Survey (PNADC)*					
	All drivers		*Driver as main job*		*Driver as secondary job*		*Adult urban workforce*		*Adult urban own-account workers*		*Adult urban employees*	
	stat.	*s. e.*	*stat.*	*s. e.*	*stat.*	*s. e.*	*stat.*	*s. e.*	*stat.*	*s. e.*	*stat.*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

Table 3.1. Characteristics of the drivers in the survey and corresponding summaries for urban adult workers in Brazil *(continued)*

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

Notes: [1] The drivers' survey was conducted by the author between the 24th and the 31st of January 2023 and its underlying population is all drivers working with a leading ridesharing company in Brazil. [2] The figures regarding to the general workforce are calculated using the microdata from Brazil's official labor survey, refer to the full year of 2022, and are weighted to be representative of the active population above 18 years old and living in urban areas. In particular, I use the data collected by PNADC's 5th interview with the sampled households, which records household income from all sources. [3] For all variables and all subpopulations, the statistics are calculated using the available responses required for that specific item, and therefore the number of observations may vary for different attributes. The sample size for all drivers represents to the number of unique individuals who participated in the survey, while the combined number primary job drivers and secondary job drivers refer to the respondents for whom there is sufficient information for this breakdown. [4] Monetary values from PNADC are reported in January 2023 equivalent terms. [5] Work-related statistics (such as *work income*, *work hours* and *how long in this job*) are specific to the occupation indicated in the column. [6] The *household income per capita* is composed of all income sources from all 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.

Figure 3.3. Distribution of monthly earnings for the ridesharing activity and the average work earnings for selected reference groups



Notes: The dashed lines mark the average work earnings for the different reference groups. The underlying values can be found at table 3.8 in the appendix.

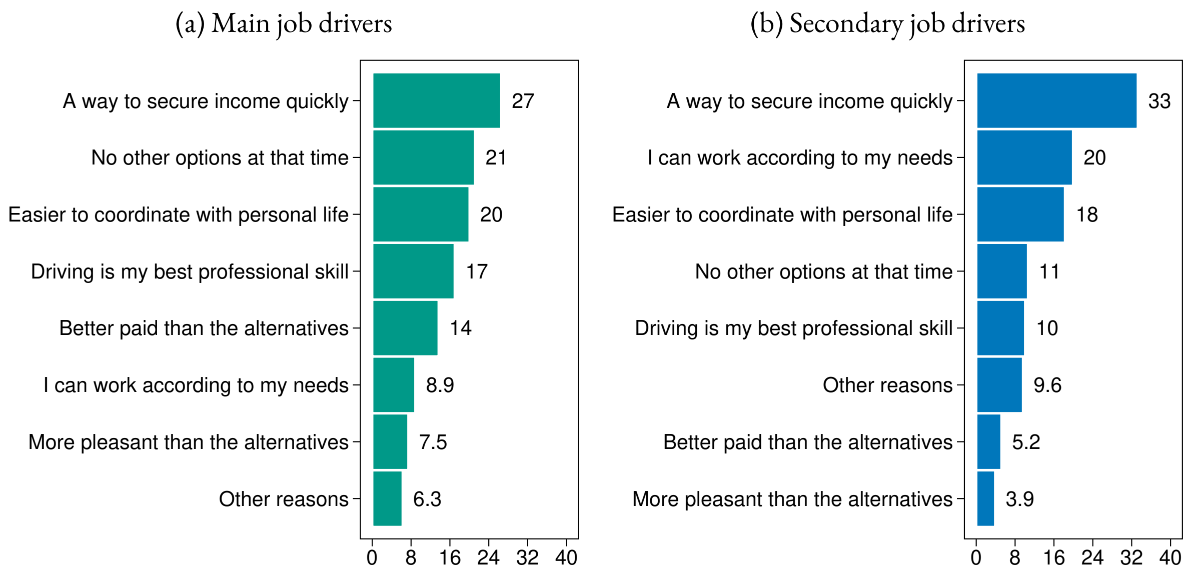
Going beyond the general average, it is possible to identify two very distinct profiles in this population: 3/4 of the drivers engage in ridesharing as their sole or main occupation (in the sense that it represents their main income source), while 1/4 use it as a supplementary activity. Primary job drivers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

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

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

The polarization between those two types of drivers is also reflected in other dimensions, as primary job drivers are systematically younger, less educated, live in poorer households, and are less likely to contribute to a pension system. Yet, these two groups have a major feature in common: *both appreciate the fact that this activity offered them a way to secure some income quickly*. Indeed, this is the single most frequent reason mentioned by the respondents when asked about what motivated them to take up ridesharing, considering the other paid activities they could do, as detailed in figure 3.4.

Figure 3.4. Most important reasons for taking up ridesharing, by driver type



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

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.

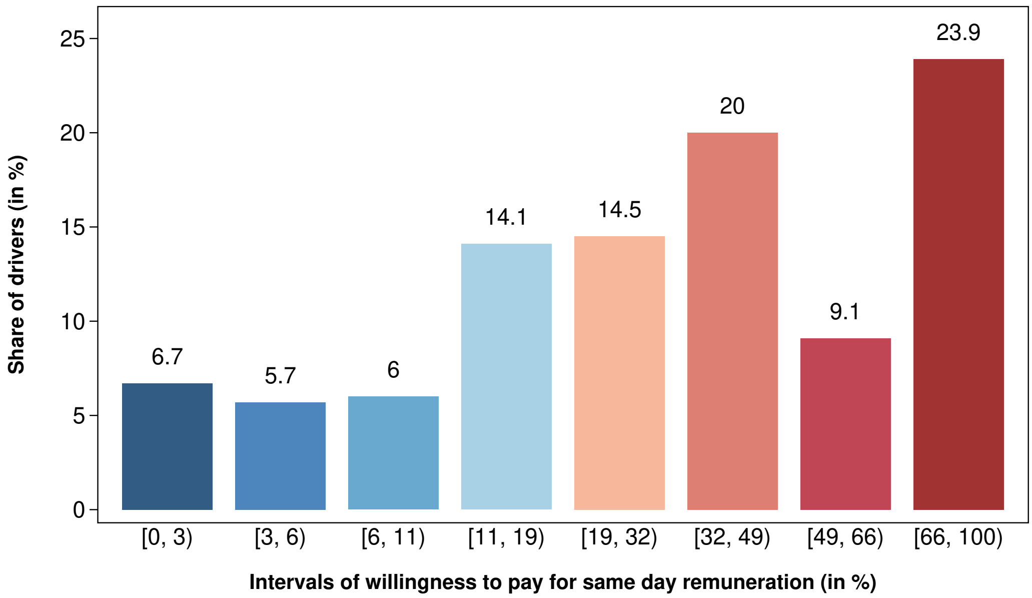
The caveat about these results is that the wording "a way to secure income quickly" can potentially cover two distinct senses for "quick": (a) the low entry barrier that allows people to start working faster relative to the counterfactual of searching for a match with a company and (b) the short time 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 section, we take this investigation a step further with the results from the WTP protocol, which have the double benefit of eliminating ambiguity (by isolating the value of the payment timing only) while being more precise regarding its importance (by measuring it in terms of forgone earnings).

3.4.2 How much do drivers value same-day remuneration?

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

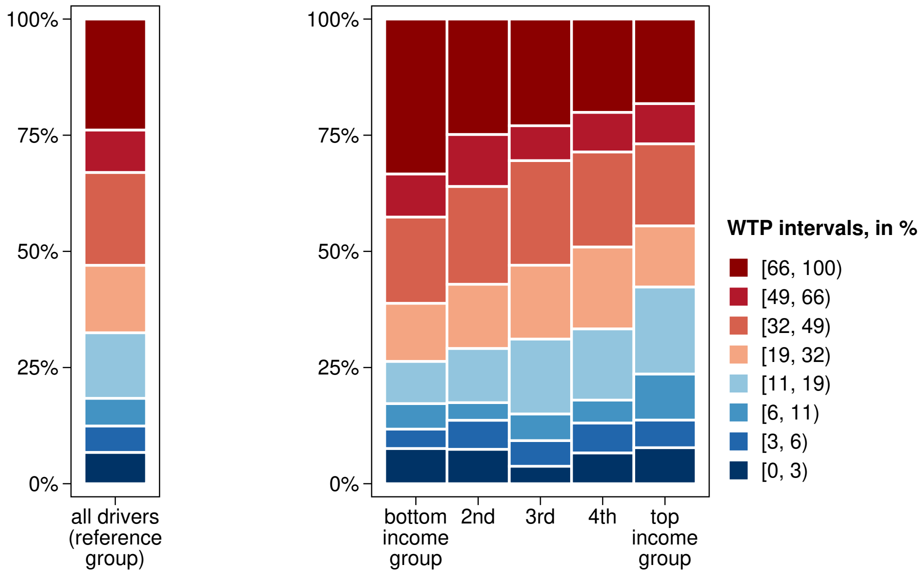
Figure 3.5. Distribution of preferences for same-day remuneration



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

Instead, these extreme preferences appear to partly reflect a context of structural resource scarcity and missing financial instruments, which makes one's labor a source of both domestic solvency *and* liquidity. This view is supported by the monotonic association between contract choices and poverty: the lower the total household income per capita, the more valuable the option to access one's earnings the same day, as summarized in figure 3.6.

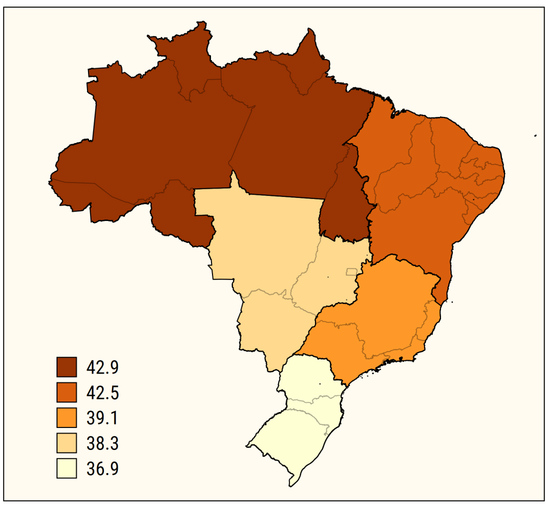
Figure 3.6. Distribution of preferences for same-day remuneration by quintile of household income per capita



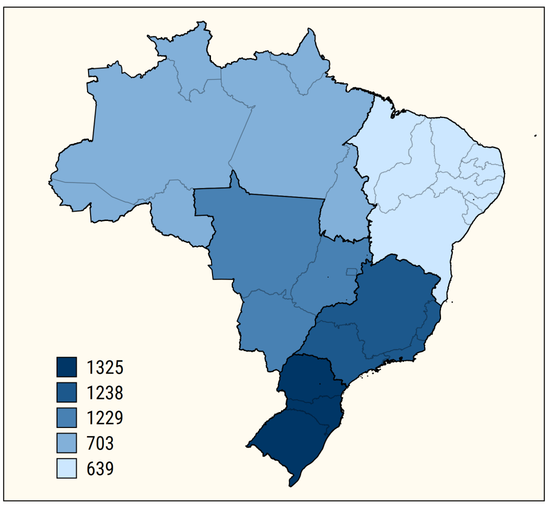
A similar correlation emerges at the geographical level. There is a known gradient in the median regional income (and in other poverty indicators derived from the surveys of the national statistics office) going from the Northern (poorest) to the Southern (richest) regions of the country. Since I collect data from drivers in all regions, I can document that a similar gradient holds for the WTP for same-day remuneration but in the opposite direction, as depicted in figure 3.7. Under the mild assumption that the potential association between the outcome and the response rates is not region-specific, the results suggest that drivers in the poorest regions are the ones who favor quick payment the most.

Figure 3.7. Payment preferences and median income level by 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 application process for a position in a call center in the United States, Mas and Pallais (2017) find that the applicants were willing to forgo 20% of their wages to avoid a schedule set by an employer on short notice, and 8% for the option to work from home. Using a panel of Danish respondents, Eriksson and Kristensen (2014) estimate a 13% WTP for high job flexibility, 8% for 5 days of training, and 7% for a large health package. With a sample of undergraduate students from the New York University (NYU), Wiswall and Zafar (2018) document that female students report a WTP of 4% for a percentage point lower chance of being fired, and a WTP of 7% for the option of working part-time. Looking at how much the workers in India are averse to accepting tasks that do not align with their own identity, Oh (2023) finds that 43% are willing to forgo at least 10 times their daily wage to avoid a type of work that is associated with other castes.

Part of the dislike of being paid later may also come from a concern that the company might fail to honor its payment commitments at some point, willingly or not. This factor is unlikely to play a large role in the results because most drivers already have a track record of many months working with this firm, which contributes to building trust in its payment capacity. As suggestive evidence of this, I find that those who have just started the activity tend to have the highest WTP, as depicted in figure 3.14. However, this result should be taken with a grain of salt, given that newcomers could plausibly be the most liquidity-constrained. In any case, there is little systematic association between seniority and WTP beyond the very first month of experience. Furthermore, according to Brazilian commercial law, the workers, service providers, and contractors have priority in the event of a business liquidation. Hence, the risk of non-payment due to the company quitting the market should not explain the magnitude of results I find, and much less so for a short 30-day interval.

There could also be some habit formation regarding payment rules, in the sense that people tend to lean towards the schemes they are already familiar with. If this is true in this setting, drivers who were previously wage employees (and, thus, subject to a form of deferred payment) could show less resistance to the 30-day interval relative to drivers who had other occupations. Yet, if we break down the preferred contract choices by the previous state, we find little difference between those coming wage-employment or self-employment. Instead, the major contrast in this dimension comes from those with or without any form of paid activity, with the inactive and the unemployed showing the highest willingness to pay for same-day remuneration, as per figure 3.14.

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

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

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

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

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

3.5 Experimental results

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

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

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

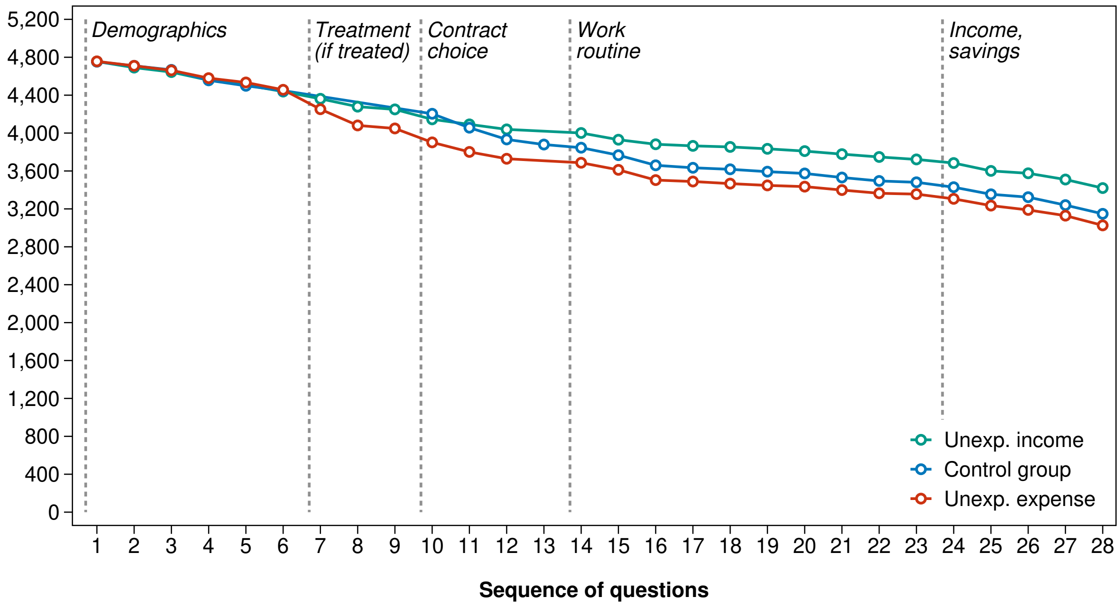
3.5.1 Working sample and treatment randomization balance

Given the nature of the data collection, it is reasonable to expect a gradual attrition throughout the questionnaire. The drivers may receive an offer to pick up someone or may want to check an incoming message on their mobile phone, among many other reasons, leading them to drop out at some point. With that in mind, the survey was designed to be concise, and achieved a relatively high completion rate. Of the 14,265 individuals who responded to the first question, about two-thirds finished it.

From the perspective of the treatment effect estimation, the main concern is that attrition affects the randomization balance between the different arms.

As the first step to address this issue, figure 3.8 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 a hypothetical scenario with a surprise income were less likely to drop out (in green), in comparison to the control group (in blue).

Figure 3.8. 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 3.2 suggest that, while people in the expense treatment condition were marginally more likely to drop out, this attrition was not driven by a particular profile of respondents. Formally, we can reject that the set of attributes we observe are jointly significant to distinguish those who completed the survey within this treatment arm. However, that is not the case for the income treatment. The excess of responses recorded in this group is particularly linked with full-time drivers (and, by extension, those who were previously unemployed, work more hours, and do not contribute to social security).

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 3.2.

Table 3.2. Summary statistics and randomization balance

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

Table 3.2. Summary statistics and randomization balance *(continued)*

	Control group (n = 2,672)	*Treatment group A: unexpected expense (n = 2,597)*		*Treatment group B: unexpected income (n = 2,873)*	
	mean (1)	*mean (2)*	*p-value (1) = (2)*	*mean (3)*	*p-value (1) = (3)*
Own car, fully paid	0.19	0.20	.	0.19	.
How long in this job					
Less than 1 month	0.02	0.03	0.469	0.02	0.543
1 to 3 months	0.10	0.09	.	0.09	.
3 to 6 months	0.10	0.10	.	0.10	.
6 months to 1 year	0.12	0.11	.	0.13	.
1 to 2 years	0.16	0.15	.	0.17	.
2 to 4 years	0.30	0.29	.	0.30	.
More than 4 years	0.20	0.22	.	0.20	.
Share of work income usually saved					
Less than 10%	0.73	0.69	0.002	0.74	0.376
Between 10% and 25%	0.18	0.21	.	0.18	.
More than 25%	0.09	0.10	.	0.08	.
Social security					
Not currently contributing	0.52	0.52	0.686	0.57	0.002
Public system (as individual)	0.22	0.23	.	0.21	.
Public system (as employee)	0.16	0.16	.	0.15	.
Private system	0.03	0.02	.	0.02	.
Does not know	0.07	0.07	.	0.05	.
Country region					
North	0.08	0.08	0.986	0.08	0.998
Northeast	0.20	0.20	.	0.20	.
Southeast	0.47	0.47	.	0.47	.
South	0.13	0.13	.	0.14	.
Central-West	0.11	0.11	.	0.11	.
Mobile phone					
Android 8 or below	0.03	0.04	0.171	0.04	0.565
Android 9	0.05	0.05	.	0.05	.
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.

3.5.2 Text analysis

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

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

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

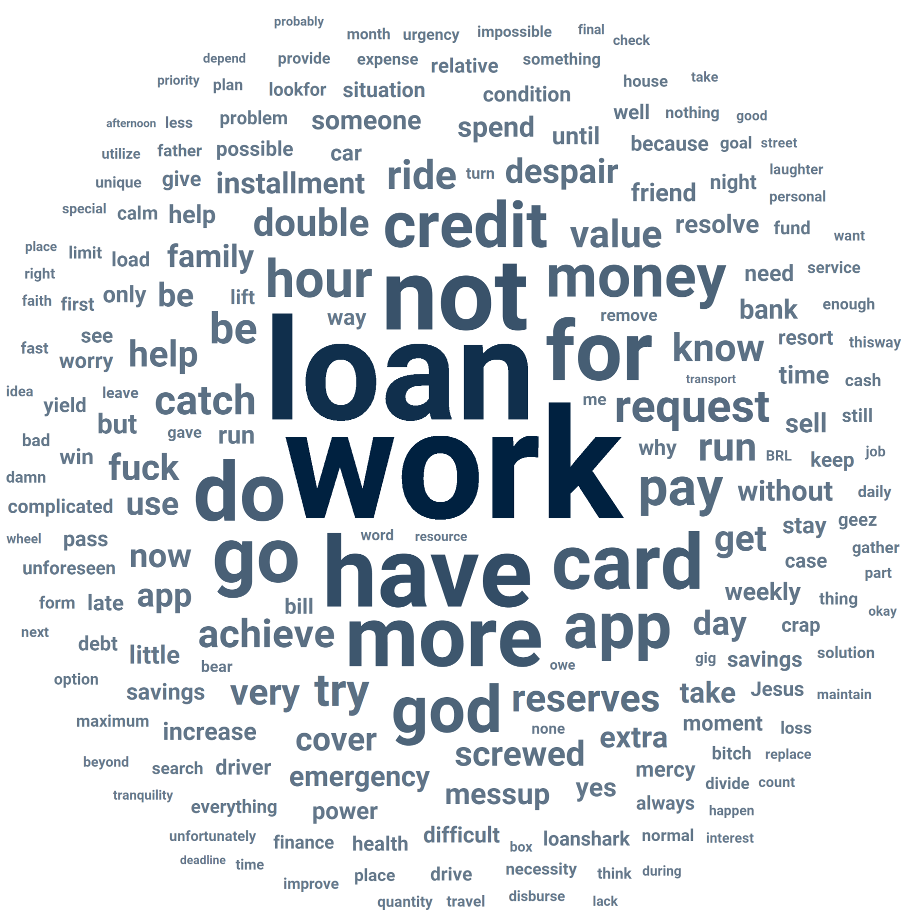
In the present case, individual response is defined as the combination of their answers to both questions that make up the treatment (that is, *what is the first word that comes to mind?* and *what would you do?*). In total, 8,507 individuals typed at least one word in their answers, with over 7,000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

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

After this cleaning protocol, we recover two distinct matrices, one for each alternative treatment. The first matrix comprises 1,017 unique terms used by 4,157 drivers when describing their reactions to the hypothetical financial emergency. The top 200 terms in this set are summarized in figure 3.9, in which size and color intensity are proportional to how often the drivers mention them.

Two concepts stand out in this graphical representation of total frequency: "work" and "loan". This pattern suggests that (a) precautionary savings are often

Figure 3.9. Most frequent terms mentioned by drivers when discussing how they would cover an unexpected expense



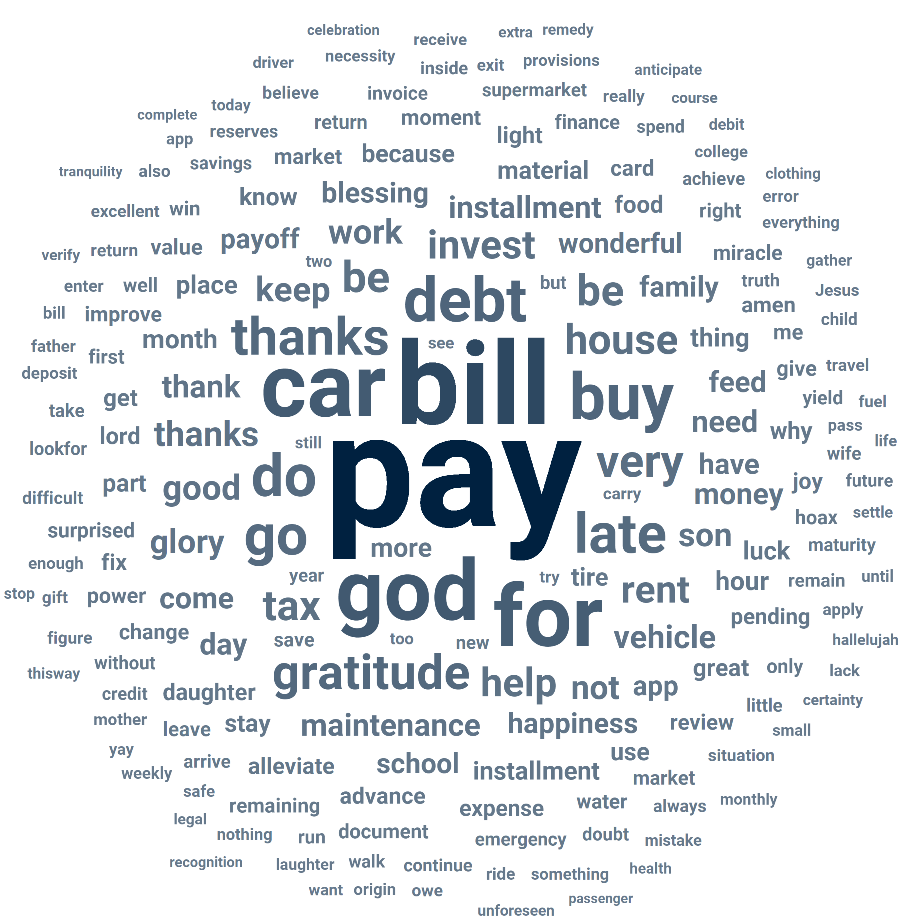
Notes: The word cloud depicts the 200 most frequent terms used by the ridesharing drivers who were invited to consider a situation where they would need to disburse R$ 1,400 (US$ 560 PPP) more than expected that week. The size and color intensity are proportional to the incidence of the term. The same representation using the original terms in Portuguese is available in figure 3.15 in the appendix.

modest or missing among this population and (b) work intensity is a primary margin of adjustment in reaction to negative liquidity shocks. If that is the case, it means that the possibility to choose your hours and quickly cash them can serve as an insurance mechanism.

Taking their responses seriously, how much extra work do people have in mind? A simple extrapolation using the net earnings from section 3.4 implies that the average driver would need about 130 working hours to make up the R$ 1,400 proposed in the scenario (about 2 or 3 working weeks).

Looking at the mirror image of this problem, the second set of answers includes 1,244 unique terms used by 4,350 drivers to discuss what they would do with an unexpected cash windfall. The word cloud shown in figure 3.10 is dominated by a single term: "pay". In this context, the most common reaction appears to be guided by concerns with recurring household bills and outstanding debts.

Figure 3.10. 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.

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

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

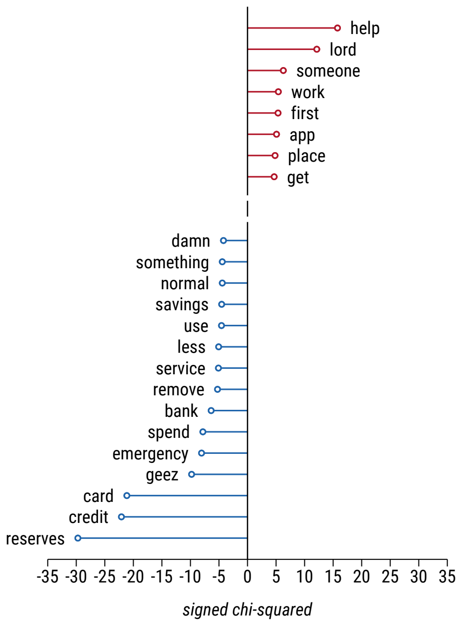
For simplicity, I divide the drivers into two groups: the top third of the distribution (those who claim to prefer same-day payment over 2 or 3 times larger rates) and the rest. The keyword analysis, in this case, is analogous to a chi-square test for a contingency table, in which we study whether a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

The results show that the people who rely on family members and on their own labor to help them fix a financial emergency are more likely to prioritize fast payment, as summarized in figure 3.11. On the other end, drivers who already have credit cards and precautionary funds available are the ones favoring larger earnings.

Similarly, the terms describing potential uses of the unexpected income reflect a strong polarization between circumstances of pressing needs (drivers claiming they would spend their cash windfall procuring food for their household tend to have the strongest preferences for same-day payment) and precautionary behavior (drivers who would save the money for the future also favor contracts with larger, deferred payments), as shown in figure 3.12.

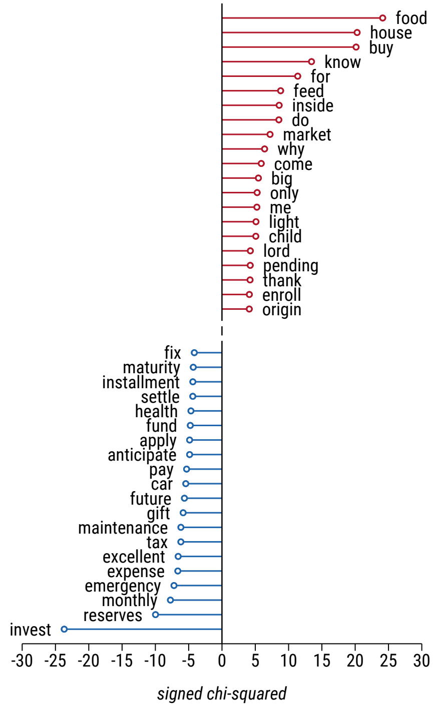
A critique to this type of analysis is that words lose much of their meaning outside a sentence. While this remains an important caveat in this chapter, the concern is partially mitigated by the constraints imposed by the text collection strategy. We have the benefit of recording responses that are not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

Figure 3.11. 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 3.12. 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.

3.5.3 Average treatment effects

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

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

$$Y_i = \alpha + \beta_{exp}\ \textit{Expense Discussion}_i + \beta_{inc}\ \textit{Income Discussion}_i + \gamma X_i + {}_i \quad (3.1)$$

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 3.2. The standard errors are clustered at the regional level adopted in the stratified randomization (defined as capital and non-capital areas, for each state).

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

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

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

The main experimental results are summarized in table 3.3. 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 (3.1), introducing the controls. Finally, the third column is an interval regression estimated using maximum likelihood, a specification that is more general because it formally incorporates the fact that the outcome is always observed between two boundaries.

Table 3.3. Effects of budget salience on the WTP for same-day remuneration

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

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

The main experimental result is that both the unexpected expenses and the unexpected income discussions led to a small decrease in the importance of same-day compensation, as reported in table 3.3. The preferred specifications (columns 2 and 3) suggest that the average WTP for same-day remuneration is at least 1.5 percentage points lower for treated drivers, relative to those in the reference group. Still looking at the specifications that include controls, we cannot reject that the effect is statistically the same in both treatments.

Notably, we also find that the effect is not homogeneous over the underlying distribution of preferences for payment timing. To investigate who is driving this result, I look at each threshold separately. Under the assumption that the ranking of preferences is stable, it is possible to stack the indifference intervals.

That is, if 24% of the respondents have a WTP above 66%, and 9% have a WTP between 49% and 66%, then 33% have a WTP above 49%. This approach has the advantage of using the frontiers of the intervals as it was elicited, with no need for extra assumptions for their midpoints.

Using each possible threshold in turn, I study the level at which the effects take place, as reported at table 3.4. One pattern stands out: the treatments have small effects, if any, on the share of people with WTP above 6%, 11%, or 19%, but there is evidence that both treatments reduce the share of people choosing same-day remuneration against very large multipliers (1.5, 2 or 3 times) within 30 days.

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

Table 3.4. 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.

3.5.4 Potential mechanisms

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

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

Another piece of evidence that supports this interpretation is their response time, which is precisely recorded by the survey instrument. While it is not possible to claim that individuals in both treatment groups were thinking *harder* about the trade-off, they did think *longer* than individuals in the control group. This result is consistent with treated individuals perceiving the question as a harder one, or being more careful in their choices, given the richer set of information that was made salient to them. Table 3.5 reports how the response time differed between treatment arms. The specification follows the baseline equation (3.1) closely, including the controls, except that the outcome here is the number of seconds spent on each of the three questions that make up the elicitation protocol. On average, drivers exposed to the expense discussion took 5 more seconds to complete the whole protocol, and those in the income discussion treatment took 3 seconds longer, out of an average of about 90 seconds for the control group. In both cases, the increase is most clearly identified in the third question.

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

As a caveat, I cannot rule out that the treatments led to a modest decrease in the reported WTP each for a different reason. For instance, the mental

Table 3.5. Effect of budget salience on the time to choose a contract

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

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

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

3.6 Robustness analysis

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

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

As summarized in table 3.6, the doubly robust estimates reinforce the finding that the increased salience of the household financial conditions induced by the expense and income questions led to a small marginal decrease in the average willingness to pay for same-day compensation. The point estimates for the doubly robust estimations are between -1.4 and -1.5 percentage points, qualitatively similar to the baseline results.

Table 3.6. Doubly robust estimation of the effect of budget salience on the time to choose a contract

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

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

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

Finally, table 3.7 reports the doubly robust estimates on the probability of assigning a value to the early payment option superior to each of the reference thresholds defined in the elicitation method. The same conclusion from the baseline estimation holds: the bulk of the effects come from a reduction in the share of drivers who would prefer same-day payment even against very high multipliers (that is, paying 2 or 3 times as much).

Table 3.7. 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.

3.7 Concluding remarks

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

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

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

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

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

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

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

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

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Appendix for Chapter 3

A.1 Figures and tables

Figure 3.13. Preferences for same-day remuneration by demographics

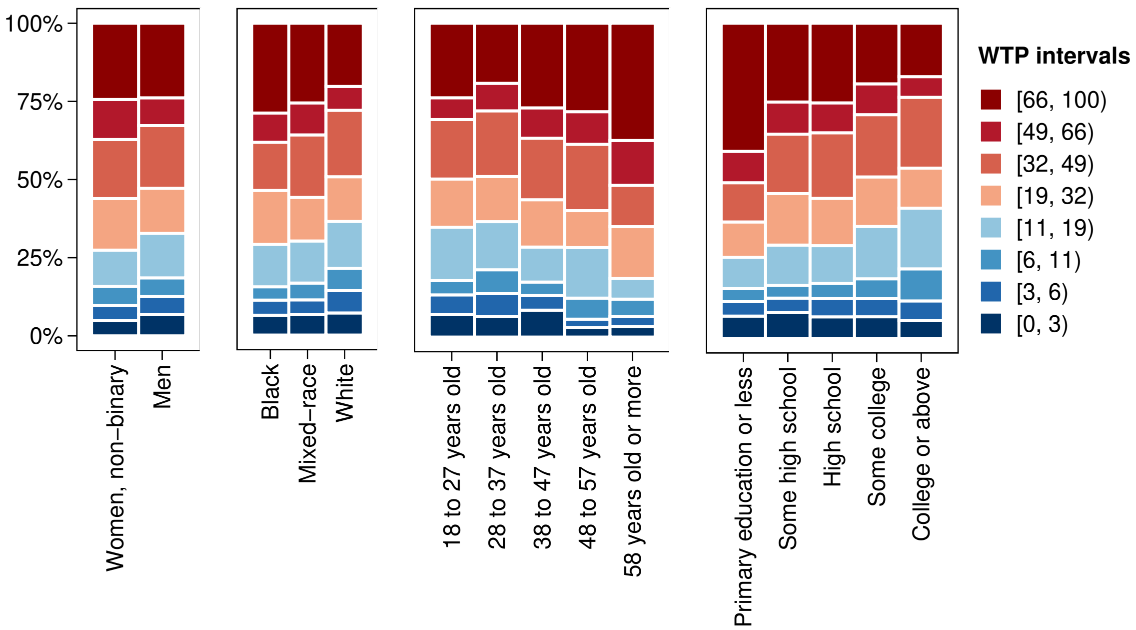


Figure 3.14. Preferences for same-day remuneration by work profile

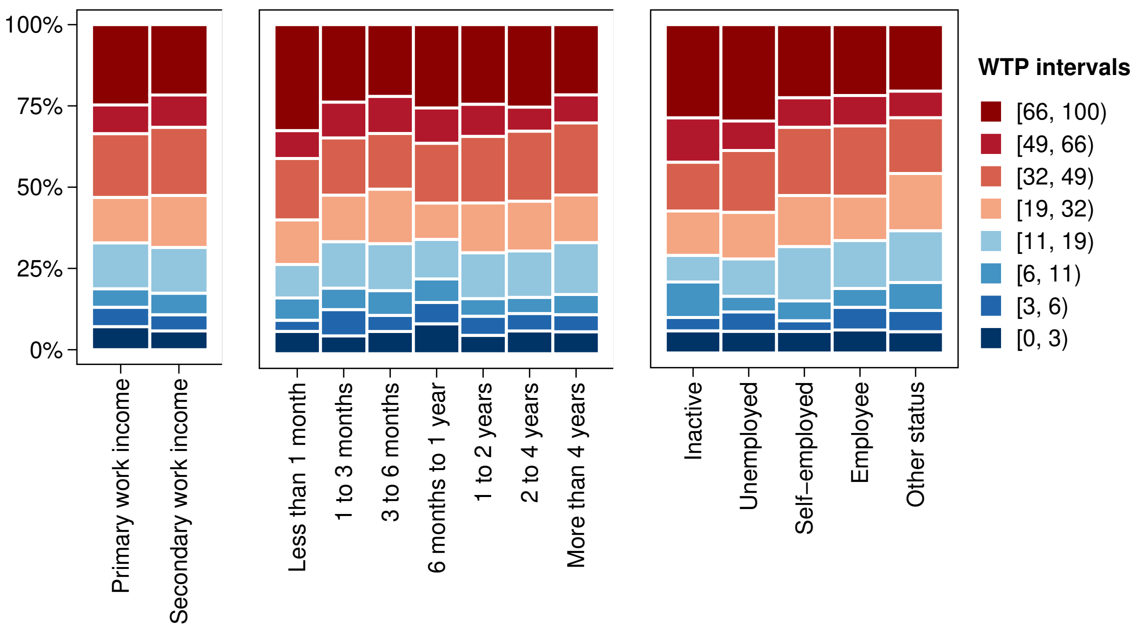
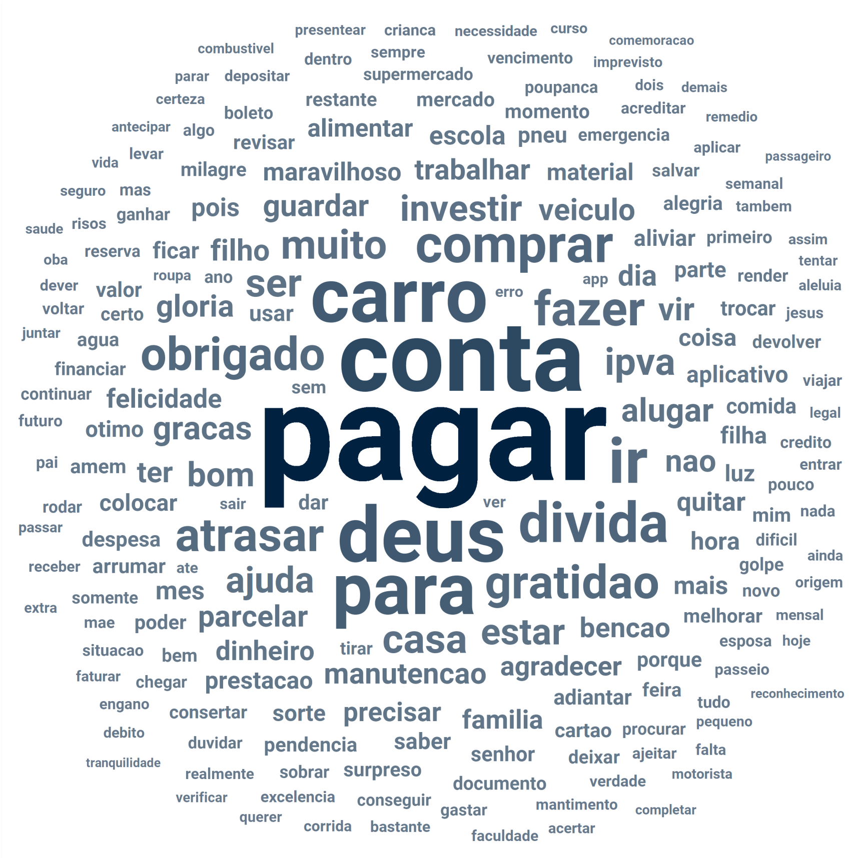


Figure 3.15. Most frequent terms mentioned by drivers when discussing how they would cover an unexpected expense (in Portuguese)

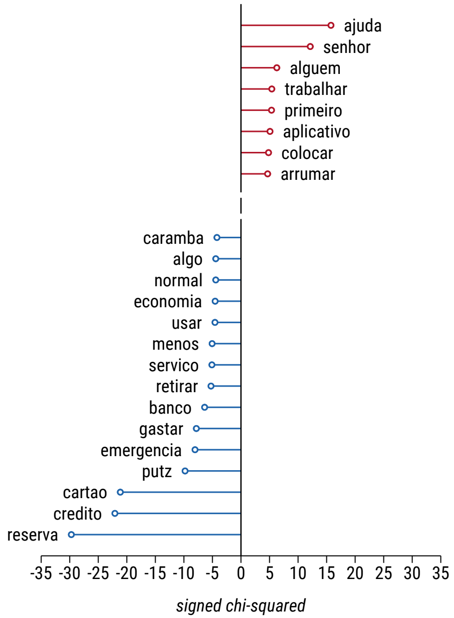
Notes: The word cloud depicts the 200 most frequent terms used by the ridesharing drivers who were invited to consider a situation where they would need to disburse R$ 1,400 (US$ 560 PPP) more than expected that week. The size and color intensity are proportional to the incidence of the term.

Figure 3.16. Most frequent terms mentioned by drivers when discussing what they would do with an unexpected income (in Portuguese)



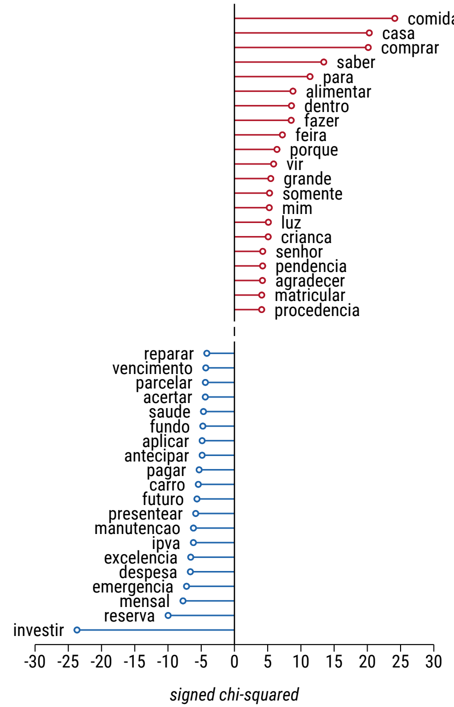
Notes: The word cloud depicts the 200 most frequent terms used by the ridesharing drivers who were invited to consider a situation where they would receive an unexpected deposit of R$ 1,400 (US$ 560 PPP) that week. The size and color intensity are proportional to the incidence of the term.

Figure 3.17. 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 3.18. 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.

Table 3.8. Characteristics of the male ridesharing drivers in the survey and corresponding summaries for male urban adult workers

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

Table 3.8. 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.*
N. of kids (age < 18)	1.1	(0.01)	1.1	(0.01)	1.1	(0.02)	0.7	(0.01)	0.7	(0.01)	0.8	(0.01)
Work routine												
Work hours per week	53.5	(0.25)	60.7	(0.27)	33.3	(0.40)	41.6	(0.06)	40.6	(0.14)	41.7	(0.06)
Monthly income (in R$)												
Average work income	2,305	(15)	2,542	(18)	1,635	(24)	3,128	(35)	2,522	(41)	3,061	(36)
Average household inc. per capita	1,384	(12)	1,335	(14)	1,520	(26)	2,106	(24)	1,922	(31)	2,149	(27)
How long in this job (share in %)												
Less than 3 months	11.8	(0.31)	9.9	(0.35)	16.0	(0.73)	10.6	(0.18)	8.6	(0.29)	12.1	(0.23)
3 to 6 months	9.7	(0.29)	8.9	(0.34)	12.2	(0.65)	6.0	(0.15)	4.1	(0.29)	7.3	(0.18)
6 months to 1 year	11.5	(0.31)	11.4	(0.38)	11.9	(0.64)	5.8	(0.13)	3.9	(0.20)	7.0	(0.17)
1 to 2 years	16.6	(0.36)	16.0	(0.43)	17.9	(0.76)	10.3	(0.17)	7.1	(0.26)	12.2	(0.23)
2 to 4 years	29.8	(0.44)	31.0	(0.55)	26.7	(0.88)	21.8	(0.22)	21.4	(0.40)	22.4	(0.28)
More than 4 years	20.5	(0.39)	22.8	(0.50)	15.3	(0.72)	45.5	(0.29)	54.9	(0.51)	39.0	(0.35)
Social indicators (share in %)												
Contributes to a pension system	43.4	(0.55)	31.5	(0.61)	76.3	(0.93)	66.9	(0.29)	32.7	(0.50)	81.6	(0.28)
Household inc. per cap. < USD 5.5/day	11.0	(0.33)	12.0	(0.40)	8.4	(0.57)	8.4	(0.16)	9.0	(0.29)	4.9	(0.14)

Table 3.8. 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.*
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 individuals in a given household.

Table 3.9. Descriptive statistics when ridesharing is their main or secondary job

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

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

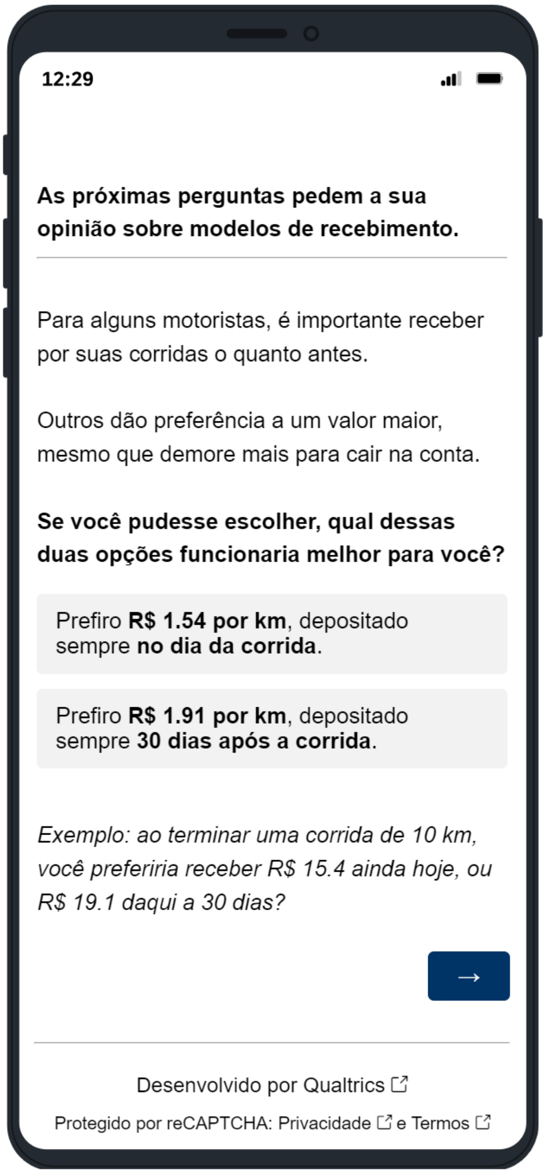
Notes: [1] The drivers' survey was conducted by the author between the 24th and the 31st of January 2023 and its underlying population is all drivers working with a leading ridesharing company in Brazil. [2] The figures regarding to the general workforce are calculated using the microdata from Brazil's 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.

Table 3.10. Doubly robust estimation of the effects of budget salience on the time to choose a contract

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

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

Figure 3.19. Interface of the survey instrument



A.2 Survey questionnaire (in English)

Sequence of question blocks by group

if group = {reference group}

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

if group = {discuss income sources}

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

if group = {discuss income uses}

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

Block 1: Geo Region

1.1. state

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

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

1.2. capital

In the capital or in other areas?

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

Block 2: Demographics

2.1. gender

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

2.2. race

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

2.3. age

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

2.4. schooling

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

2.5. hh_adults

How many adults (18 years or older) live in your household, including you?
[ ] 1 adult (just me)
[ ] 2 adults
[ ] 3 adults
[ ] 4 adults
[ ] 5 adults
[ ] 6 adults or more

2.6. hh_kids

How many children and teenagers (up to 18 years old) live in your household?
[ ] no children / teenager
[ ] 1 children / teenager
[ ] 2 childrens / teenagers
[ ] 3 childrens / teenagers
[ ] 4 childrens / teenagers
[ ] 5 childrens / teenagers
[ ] 6 childrens / teenagers or more

Block 3: Contract Choice

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

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

3.1. s_or_l

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

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

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

3.2. sas_or_las

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

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

if s_or_l == {30 days after the ride}

3.3. sal_or_lal

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

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

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

3.4. sass_or_lass

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

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

if sas_or_las == {30 days after the ride}

3.5. sasl_or_lasl

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

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

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

3.6. sals_or_lals

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

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

if sal_or_lal == {30 days after the ride}

3.7. sall_or_lall

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

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

Block 4: Making Ends Meet

4.1. making_ends_meet

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

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

Block 5: Work and Income

5.1. how_long_app

How long have you been working as an app driver?

If you have stopped this activity for over 3 months, consider only the period since you resumed it.

[ ] Less than a month
[ ] Between one and 3 months
[ ] Between 3 and 6 months
[ ] Between 6 months and one year
[ ] Between one and 2 years
[ ] Between 2 and 4 years
[ ] More than 4 years

5.2. previous_state

What was your situation the month before you started (or resumed) working with ridesharing apps?

[ ] Student
[ ] Unemployed
[ ] Self-employed worker
[ ] Full-time employee
[ ] Part-time employee
[ ] On leave due to long illness or other incapacity
[ ] Taking care of the household full-time
[ ] Retired
[ ] Other

if previous_state == {Unemployed}

5.3. previous_state_unemp

In the month before you started (or resumed) working with ridesharing apps, were you looking for a job?

[ ] Yes
[ ] No

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

5.4. previous_state_emp

In the month before you started (or resumed) working with ridesharing apps, were you a formal employee?

[ ] Yes
[ ] No

if previous_state == {Self-employed worker}

5.5. previous_state_oaw

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

5.6. main_reasons

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

5.7. how_many_apps

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

5.8. working_vehicle

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

5.9. work_days_per_week

How many days a week do you usually work as a driver, on average?
[ ] Less than 1 day per week
[ ] 1 day per week
[ ] 2 days per week
[ ] 3 days per week
[ ] 4 days per week
[ ] 5 days per week
[ ] 6 days per week
[ ] 7 days per week

5.10. work_hours_per_day

How many hours do you usually drive during a work day, on average?
[ ] Less than 1 hour
[ ] 1 hours
[ ] 2 hours
[ ] 3 hours
...
[ ] 22 hours
[ ] 23 hours
[ ] 24 hours

5.11. other_jobs

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

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

5.12. other_jobs_oaw

In this other activity, do you have a formal registration as a self-employed worker?
[ ] Yes
[ ] No

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

5.13. other_jobs_emp

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

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

5.14. main_or_second_inc

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

5.15. looking_for_a_job

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

5.16. driver_income

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

5.17. hh_income

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

5.18. savings

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

if savings ¿ 10%

5.19. savings_destination

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

5.20. pension

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

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

5.21. why_no_pension

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

Block 6: Open Feedback

6.1. feedback

Thank you very much for your attention!

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

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

Block 7: Discuss Income Sources

Now, let's consider a hypothetical situation.

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

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

7.1. priming_income_sources_word

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

7.2. priming_income_sources_descr

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

Block 8: Discuss Income Uses

Now, let's consider a hypothetical situation.

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

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

8.1. priming_income_uses_word

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

8.2. priming_income_uses_descr

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

A.3 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 {capital correspondente} e arredores
[ ] Em outra cidade de {estado}

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 parcial}

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.
[____________________________]

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