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

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Abstract

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 a lower bound for the discount rate that is implicit in the occupational choice of urban own-account workers in Brazil. We find that at least 65% of those workers appear to discount the future at rates superior to those available in the credit market, which suggests constrained occupational choice. Finally, we show that the estimated time preference lower bound is positively associated with food, clothing, and housing deprivation.

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

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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 non-rich countries, and often face important labor income penalties relative to wage workers within their labor markets (International Labour Organization 2020; Gindling, Mossaad, and Newhouse 2016). These recurring patterns motivate two fundamental questions about labor markets in developing countries: Why are some individuals working for a firm while other, observationally similar people, are working 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 paper builds on the idea that own-account workers, by definition, do not need to match with a firm to start working. The relevant occupational choice could thus be summarized as a choice between two alternative return flows: own-account work paying less but starting sooner, versus wage employment 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 potential position in a firm, even when the second option offers them a relatively higher income in each future period after a job is found. Our proposed channel hence complements the other explanations proposed in the literature, which often rely on individual heterogeneity in skills or tastes, or on market segmentation, as we review in section 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 behavior parameter to the worker's optimization problem, as we are simply presenting a refined interpretation to the subjective discount rate that is already present in any intertemporal framework. The formalization of this mechanism is presented in section 3, where we describe the occupational choice issue using the canonical job search framework augmented by the possibility of working on your own.

Second, an empirical counterpart of this model can inform us about the subjective discount rates that are relevant for own-account workers in the labor market. To be concrete, the subjective discount rate of any own-account worker can be inferred as a function of the gap between her current labor income and the wage she could reasonably expect to receive as an employee, given the local market conditions — and the larger the gap, the larger the minimum time discount rate required to make own-account work the preferred option. In section 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 5 we discuss the estimation of the key components that make up the value of a counterfactual wage job: the minimum wage I would be willing to accept; how long I would take to find one; how much I could expect to earn after finding one; and how long it would last.

Third, our approach suggests a new criterion to discuss the issue of constrained own-account work. Because we can infer the minimum discount rate implied by their revealed choice, it is possible to identify the individuals whose decision suggests a subjective time discount rate strictly above the discount rate available in the credit market. In the context of our model, own-account work is revealed to be preferable in such cases because finding a wage job would take too long, present consumption is a pressing need, and it is not possible to finance it at the market's rate, which we propose as a characterization of a constrained occupational choice. Under the baseline specification, we find that this is the case for at least 65% of own-account workers in Brazil, as discussed in section 6.

This paper assumes that the workers' relative preference for 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 inaugural definition of this concept.[1] 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 in any way, it does change the implications of our findings. In section 7, we show that the own-account workers who report financial comfort and access to credit also have a lower estimate of the lower bounder of their discount rate; while the opposite is true for those facing housing, clothing, and food deprivation. While these results cannot be interpreted as causal, they are aligned with our proposed mechanism and suggest an important development point for future research.

These are consequential questions because different mechanisms behind the occupational choice will 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 gains by reducing the dependence on readily available (but lower 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 met their short-run consumption needs while searching.

2 Related Literature

The intertemporal tradeoff approach presented in this paper 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

[1] "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).

to subsistence, and 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 preference 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 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 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 5) is remarkably consistent with their results.

In this sense, our estimation strategy also adds to a broader literature on the identification of time preference parameters. 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 paper is one of the few that proposes to learn about an individual's time preference from their choices in the labor market.

In particular, our findings suggest that preference for the present and liquidity constraints are reasons why rational individuals in developing countries fail to make profitable investments, a result that has been documented in the context of the adoption of fertilizer 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 job search is also an investment, and how similar underinvestment mechanisms could take place.

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 builds 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, Karlan, and Zinman (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 a 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. In particular, Mullainathan and Shafir (2013) argue that 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.

3 Theory

The 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). 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 have some degree of preference for the present and any future flow of income is discounted by 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 simplicity, individuals do not look for a job if they are already working.[2] Furthermore, we abstract from the details of the matching mechanism or any strategic behavior from firms when setting wages and adopt an optimal stopping rule, in the tradition of McCall (1970), 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 the discounted flow of monetary returns, although we return to the implications of this assumption below.[3] 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.

3.1 Value of wage employment

The present discounted value of any wage job $W(w)$ depends on the wage w 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. Hence, one can derive the usual flow value expression for employment as:

$$\rho\ W(w) = w + \delta\ \left[U - W(w)\right] \tag{1}$$

3.2 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 $F(w)$.

$$\rho\ U = b + \lambda\ \int_{w_r}^{\infty} \left[W(w) - U\right]\ dF(w) \tag{2}$$

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

[2] 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 unemployed. This condition seems implausible because it would become trivially preferable for any agent to become an own-account worker as a strategy to find good jobs faster, and unemployment would nearly disappear (except for exceptionally high values for unemployment-specific income). If employees were to receive more (or better) offers while working, omitting on-the-job search would lead 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 potentially lead to even higher discount rates for those who decide to be own-account workers instead of investing their time into finding a wage job that would open new doors — in which case the lower bound we discuss remains a valid lower bound.

[3] 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."

indifferent between unemployment and wage employment. Therefore, any wage offer between 0 and w_r is refused and the individual remains unemployed.

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 (1) and equation (2), one can express the reservation wage implicitly as:

$$w_r = b + \frac{\lambda}{\rho + \delta} \int_{w_r}^{\infty} \left(w - w_r \right) \, dF(w) \tag{3}$$

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 the 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.[4]

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.

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:

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[4] Note that 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 that occurs 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.

$$OAW(y) = \left(\frac{1}{1+\rho\ dt}\right)\ \left[y dt + \max\left(U, OAW(y)\right)\right] \tag{4}$$

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 $\max\left(U, OAW(y)\right) = OAW(y)$ in all subsequent periods. For this reason, we have that:

$$OAW(y) = \left(\frac{1}{1+\rho\ dt}\right)\ \left[y\ dt + OAW(y)\right] \tag{5}$$

or

$$\rho\ OAW(y) = y \tag{6}$$

3.5 The occupational choice

The usual job search framework assumes that, once the decision to enter the labor market is taken, individuals are either 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 the results from equation (3) and equation (6), this decision can be expressed as:

$$y \geq b + \frac{\lambda}{\rho+\delta} \cdot \int_{w_r}^{\infty} \left(w - w_r\right)\ dF(w) \tag{7}$$

Notice that 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,

$$\mathbb{P}\left(y \geq b + \frac{\lambda}{\rho+\delta} \cdot \int_{w_r}^{\infty} \left(w - w_r\right)\ dF(w)\right) = \text{share of OAW in the workforce} \tag{8}$$

This expression suggests that 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 an insurance) decreases the value of the unemployment state.

3. *The arrival rate of offers is low enough.* When individuals expects to wait a long time to receive offers, they will be more likely to choose own-account work.

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.

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

Having established that equation (7) can describe the occupational decision, we reorganize the terms to express this choice as a condition on the discount rate:

$$\rho \geq \frac{\lambda}{y - b} \cdot \int_{w_r}^{\infty} \left(w - w_r \right) \, dF(w) - \delta \tag{9}$$

Fundamentally, equation (9) shows that there can always be a level of subjective preference for the present 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 preference for own-account work.

Note that we can reinterpret equation (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 preference for own account work, all else equal, can be formalized as 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 (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.

3.7 Outline of the empirical estimation protocol

To assess how relevant the potential heterogeneity in discount rates can be to actual occupational decisions, we propose a translation of the theoretical inequality established in equation (9) into its empirical counterpart. For this purpose, we just reexpress the integral from this expression as:

$$\rho \geq \frac{\lambda}{y-b} \cdot \left[\mathbb{E}(w \mid w > w_r) - w_r \cdot \bar{F}(w_r)\right] - \delta \tag{10}$$

and map this inequality into:

$$\rho_i \geq \frac{\mathbb{E}(\lambda \mid X_i)}{y_i - \mathbb{E}(b \mid X_i)} \cdot \left[\mathbb{E}(w \mid w > w_r, X_i) - \mathbb{E}(w_r \mid X_i) \cdot \mathbb{P}(w \geq w_r)\right] - \mathbb{E}(\delta \mid X_i) \tag{11}$$

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.

We proceed empirically as follows:

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

3. $\mathbb{E}(b \mid X_i)$: 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.

The interpretation of the right-hand side of equation (10) as a lower bound for the subjective discount rate ρ_i will be valid as long as equation (10) captures the relevant components of the occupational decision, to a first-order approximation, and equation (11) is an unbiased counterpart of it. In short, we assume our estimated expected values (in the statistical sense) to be a translation of the values expected by the individual (in the conceptual sense). From a technical perspective, we assume the error components of the estimations (1) to (6) to be uncorrelated. Under these conditions, revealed preference provides identification of the relevant boundary.

In other words, we take the econometric results to approximate the perception of the individuals when asking themselves “how much people like me can make in a wage job?”, “how many months is it going to take me to find one?” and “how long is this job likely to last?”. We fit an answer to those questions to uncover a parameter that is harder to observe: “given how long I might have to wait, is it worth it for me to forego current labor income in exchange for future labor income?”

An important limitation of our approach is that we explicitly neglect non-earnings dimensions of own-account and wage jobs. This assumption is adopted in the interest of model parsimony, but also due to data limitations, and the impact of its omission can be seen as affecting the y or w terms. Without further information about individual preferences, however, we are unable to sign what the potential net bias might be. In particular, if an individual appreciates own-account work for reasons not related to income (e.g. flexibility or autonomy), the value of monthly pay alone would underestimate the utility derived from this occupation, and we would be overestimating the associated discount rate lower bound.[5] Conversely, if wage positions are valued for reasons not related to income (e.g. 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.

4 Data

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, while 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 making use of a second dataset, the National Household Survey (“Pesquisa

[5] 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.

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.

The use of those two sources in tandem is possible because they aim to 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.[6] Moreover, both surveys compile the basic socioeconomic attributes of the household members (i.e. family position, ethnicity, gender, age, schooling) using the same definitions, and both allow us to infer the general structure of the household similarly. For transparency, table 1 compares the summary statistics using those two sources, and it is reassuring that the first moments of the key variables are very close, even if the very large sample size of the PNAD data 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 in appendix D.

4.2 The population of interest

One of the simple reasons why own-account workers can have a low average income as a group is because this is a frequent status for rural workers, who in turn are likely to have lower productivity than urban workers. Industrial composition, land-related constraints, and the social organization of labor are indeed very distinct in rural and urban areas, in ways that could confound the distribution of occupations and the monetary returns to labor. To keep the discussion clean of those considerations, and to stress that there is a meaningful income penalty for own-account workers even when one looks only to the urban context, we discard observations from rural strata (about 15% of the total population). We also restrict the population of interest to those between 14 and 64 years of age to focus on those who are most likely to be economically active (thus removing about 28% of the urban individuals).

[6] 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.

Table 1: Overview of the population of interest, according to our data sources.

	POF (2017/2018) Urban areas, working age pop.		PNAD (2017Q1-2018Q4) Urban areas, working age pop.		Difference between surveys	
	A	**std. err.**	**B**	**std. err.**	**A - B**	**p-value**
Gender and ethnicity (in %)						
Female	52.31	(0.16)	52.26	(0.06)	0.05	0.759
Nonwhite	54.74	(0.43)	55.12	(0.22)	-0.38	0.430
Education level (in %)						
Less than prim. school	28.08	(0.32)	27.35	(0.16)	0.74	0.039
Primary school	19.19	(0.22)	18.81	(0.09)	0.38	0.115
High school	37.10	(0.28)	38.00	(0.13)	-0.90	0.004
College or above	15.63	(0.37)	15.85	(0.20)	-0.21	0.608
Age group (in %)						
Age 14-24	24.03	(0.21)	24.04	(0.09)	-0.01	0.957
Age 25-34	20.87	(0.22)	21.19	(0.09)	-0.32	0.184
Age 35-44	21.03	(0.22)	21.73	(0.09)	-0.70	0.003
Age 45-54	18.82	(0.20)	18.41	(0.08)	0.40	0.058
Age 55-64	15.26	(0.21)	14.63	(0.09)	0.63	0.005
Survey structure						
Strata	373	·	373	·	·	·
Primary Sampling Units	4 597	·	13 907	·	·	·
Unique households	41 002	·	325 711	·	·	·
Unique individuals	96 175	·	828 925	·	·	·
Observations	96 175	·	2 311 201	·	·	·

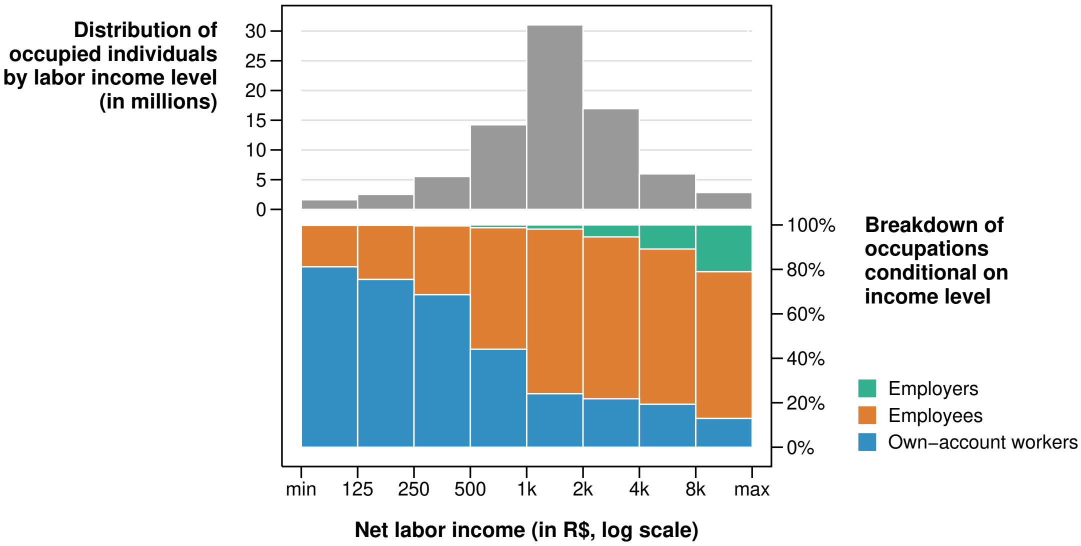
Notes: [1] Individual observations are weighted by the inverse of their sampling probability, following the survey design, in order to render the coefficients meaningfull for the population the sample represents. The standard errors around the point estimates are calculated via linearization, accounting 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 make use of 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.

In summary, the population of interest represents 125 million urban, working-age individuals (or 60% of all Brazilians) in 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.

4.3 Who are the own-account workers

Based on the POF survey, we estimate that about 81 million urban, working-age individuals received at least some form of labor income the previous 12 months. For 30 million of them, the monthly amount, net of taxes, was between R$ 1 000 and R$ 2 000 (or US$ 312 to US$ 624), as shown at the top of figure 1. In general terms, the earnings distribution is approximately log-normal, with some excess mass at the right side due to the presence of a minimal wage (R$ 954) that is binding for formal employees.

Figure 1: Occupations and labor income level (POF 2017-18)



Notes: Calculations based on urban, working-age (14-64) individuals with non-zero labor income. Breakdown based on the worker's primary occupation. Monetary values in R$, at prices of January 2018.

A more interesting picture emerges as we break down the composition of workers within each labor income level, as shown at the bottom of figure 1. First, it appears that own-account workers can be found across all the income range, reiterating that this is a heterogeneous category that includes from small service providers to specialized professionals — nevertheless, they are disproportionately concentrated at the bottom of the distribution. In this sense, there is a strong contrast with the group of employers, who are negligible under R$ 2 000 but make up an increasing share of the active population as we move up the income ladder. From an empirical point of view, this is a reminder that there is a substantive income polarization between own-account workers and employers that can be lost if one adopts "self-employment" as the category of analysis, and this is a key reason why we insist that the present discussion refers to own-account workers only. From a theoretical point of view, employers need to find their employees, and are more likely to require significant capital investments, but they are outside the scope of our model.

Second, own-account workers are a large group, accounting for 32% of all those who are occupied in the population of interest, as detailed in table 2. 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.[7] 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.

Table 2: Descriptive statistics for employees and own-account workers in Brazil.

	Household Budget Survey (POF) 2017-18					
	Urban areas, working age individuals (14-64 years)					
	All		Employees		Own-Account Workers	
	stat.	std. err.	stat.	std. err.	stat.	std. err.
Subpopulation size (in millions)						
Total subpopulation	124.9	(1.06)	51.8	(0.59)	26.0	(0.34)
Gender and ethnicity (in %)						
Female	52.3	(0.16)	44.4	(0.30)	52.4	(0.46)
Nonwhite	54.7	(0.43)	53.3	(0.51)	58.0	(0.62)
Education level (in %)						
Less than primary school	28.1	(0.32)	17.2	(0.33)	37.1	(0.57)
Primary school	19.2	(0.22)	14.8	(0.30)	18.7	(0.42)
High school	37.1	(0.28)	44.3	(0.43)	33.8	(0.53)
College or above	15.6	(0.37)	23.8	(0.55)	10.5	(0.53)
Age group (in %)						
Age 14-24	24.0	(0.21)	18.8	(0.31)	9.4	(0.30)
Age 25-34	20.9	(0.22)	27.9	(0.39)	19.9	(0.40)
Age 35-44	21.0	(0.22)	25.5	(0.37)	26.5	(0.46)
Age 45-54	18.8	(0.20)	18.4	(0.31)	26.3	(0.47)
Age 55-64	15.3	(0.21)	9.4	(0.24)	17.9	(0.42)
Income from main occupation (in R$)						
Average net work income	·	·	2 284.8	(31.81)	1 443.5	(25.35)

Notes: [1] The labor market position here is defined as someone's primary occupation. For completeness: the 124.9 million individuals in the population of interest can be broken down into 51.8 million employees, 26 million own-account workers, 2.9 million employers, and 44.2 million inactives (in the sense that they had no labor income in the reference period of 12 months). [2] The group of own-account workers include 6.2 million domestic workers (equivalent to 7% of all occupied individuals), who by default are classified as employees in the official figures from the Brazilian statistical office. This methodological decision is adopted throughout this paper. An overview of the results under the default classification is available in the appendix. [3] Monetary values are presented in R$, at prices of January 2018. [4] Work income is winsorized at the 1st and at the 99th percentiles.

Finally, we note that Brazilian own-account workers are indeed systematically different from those observed in wage employment: they are comprised of a higher share of female or nonwhite workers, they are generally less educated, and older. These patterns suggest that the 37% gap between the average net labor income of both groups (and, more generally,

[7] We examine the alternative hypothesis, grouping domestic workers with employees, in appendix C.

the earnings distribution pattern we described earlier in this section) could be simply due to heterogeneity in the jobs for which different people are eligible, combined with heterogeneity in how easily they can access those positions, two mechanisms that have been documented by the literature. In the next section, we account for such observable heterogeneity by estimating the labor market conditions that each own-account worker in the sample could reasonably expect to face so that we can investigate the role played by heterogeneity in their time preferences.

5 Estimation results

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.

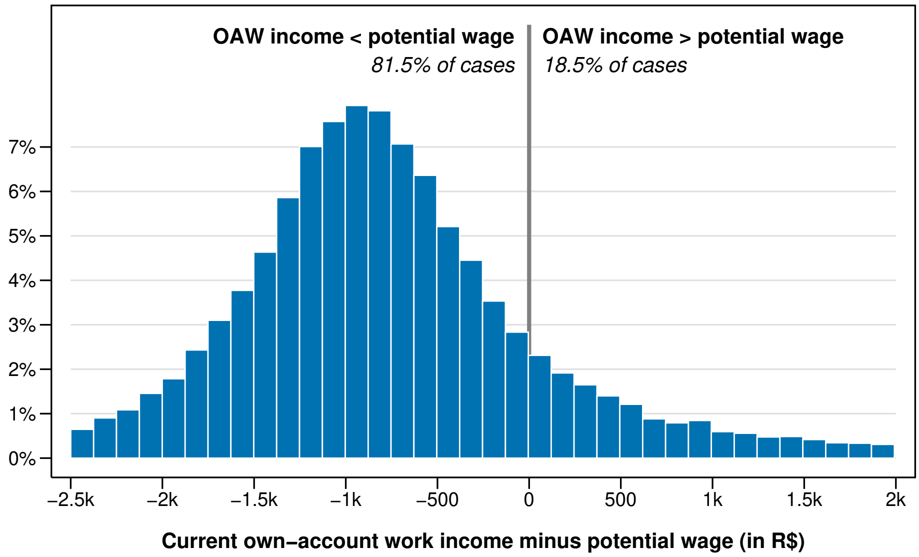
To purge the potential selection bias in the estimates of the marginal contribution of someone's attributes to their potential wage, the wage regression includes a control function, as suggested by Heckman (1979). Current school attendance and variation in household composition are added as exclusion restrictions in the model of selection into the status of wage employee.

The coefficients for the main equation and the selection equation are reported in table 3 in the appendix. As 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%).

In light of those results, we can argue that 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 81.5% of Brazilian own-account workers report a net labor income inferior to their potential wage,[8] even after accounting for individual heterogeneity, as shown in figure 2.

[8] 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

Figure 2: Distribution of the estimated gap between the labor income received by own-account workers and the wage they could expected to receive as employees



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, specially in developing countries.[9] 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.

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.[10] To examine the sensitivity of the results to different cutoffs, we replicate the estimation with 5th and 15th percentiles in appendix B.

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 expect to see in the

from log into R$ levels, we adopt the "smearing" technique from Duan (1983), which has been shown to perform well in large samples like ours.

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

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

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 4 provides the results if 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 wage, while here they affect the expected wage at the 10th percentile of the wage distribution.

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.[11] 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 E 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 5, 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.

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

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

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, i.e.

$$h = \lambda \cdot \mathbb{P}\left(w > w_r\right) \tag{12}$$

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

$$h = \lambda \cdot \left[1 - \Phi\left(\frac{\log\left(w_r\right) - \log\left(w\right)}{\sigma}\right)\right] \tag{13}$$

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, $\mathbb{P}\left(w > w_r\right) \approx 1$ for most individuals — and thus $\lambda \approx h$ in general.[12]

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. This result is of interest for it suggests that own-account workers are not discouraged to look for wage employment because they do not pay enough, but rather because they are too hard to come by.

5.5 The expected value of unemployment income

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

This is because unemployment insurance requires unjustified layoff from formal wage employment, plus 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 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.[13]

[12] 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.

[13] 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 the time preference in itself. Anticipating the findings

For those 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.

6 The discount rate lower bound and constrained own-account workers

The main results of this paper follow from the individual-specific lower bound discount rates inferred for a sample of nationally representative 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 (11), based on the full set of results shown in section 6 and using microsimulation for the sample of individuals in the POF. We find that this lower bound has a median of 9.7% 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.

To make sense of these estimates, we compare them against the typical interest rate levels adopted in retail credit operations to finance household consumption. According to the Central Bank, the average rate in consumer credit in the period 2017-18, weighted by total loan volume, was equivalent to 3.8% per month. Those 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 such 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 3, tells us that such financial constraint is binding for at least 2/3 of the urban own-account workers in Brazil.

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 lead us to classify those as *unconstrained cases.* Importantly, this share is higher than the 18% who are simply earning more than they could expect to earn as employees (see figure 2) since that comparison is missing the intertemporal dimension. Note also that 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.

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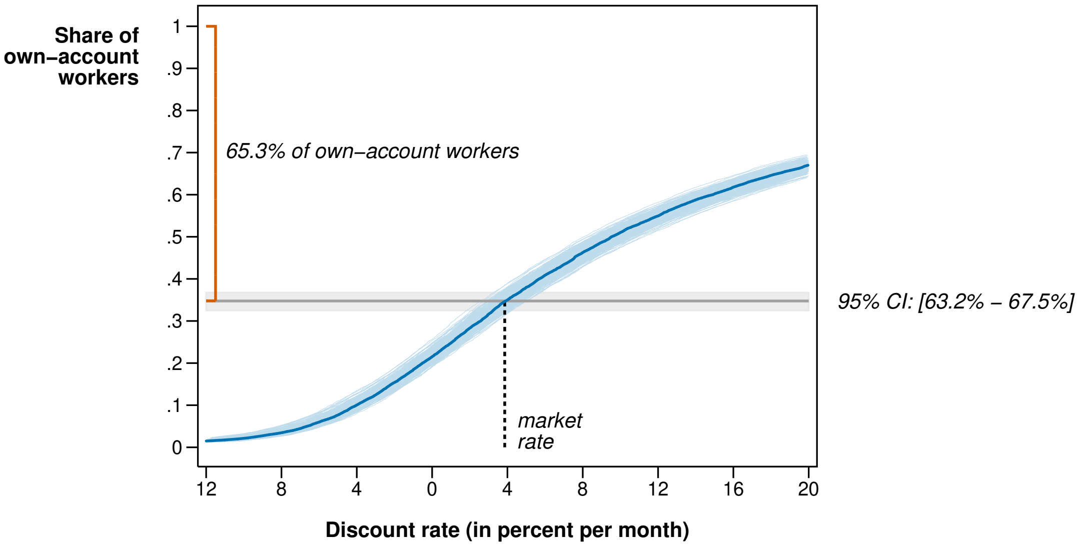
to be discussed in section 6, there is suggestive evidence that own-account workers who can count on transfers have a lower implicit urgency in their occupation decision because transfer income helps alleviate material deprivation.

Figure 3: Empirical cumulative density of the estimated discount rate lower bound



Notes: The dark blue curve shows the CDF at the baseline specification, and the light blue 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.

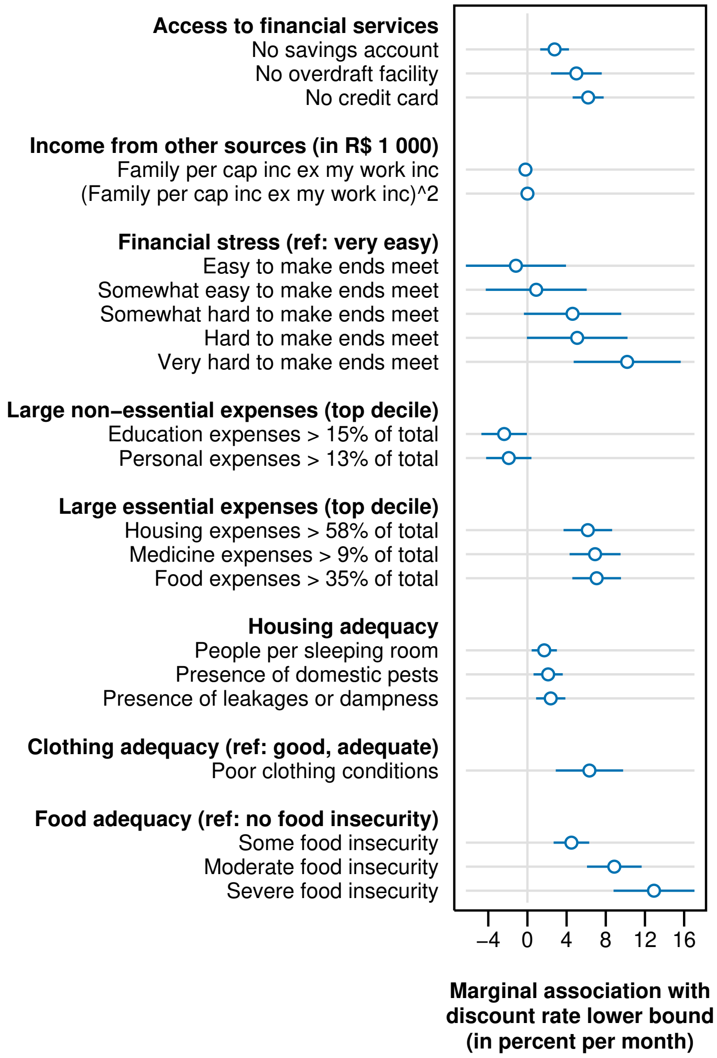
In contrast, the occupational choice of the remaining own-account workers is their best *constrained* option: it is still the one with the highest present value, but only because they assign strong relative importance to income in the near-term and cannot discount the future using the market rates, but 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.

6.1 The discount rate lower bound 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 non-causal 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 4 and the regression output under different specifications are available in table 6.

Figure 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.

The lack of access to financial services such as savings account, overdraft facilities, and credit card are all associated with relatively higher subjective time discounts (+2.7 percent points to +6.2 percent 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 6). 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 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 actual housing, clothing, and food inadequacy, and the estimated lower bound discount rate. All else constant, members of families facing hunger have a large consumption urgency are also more likely to take own-account work positions, and the association is monotonically increasing with the degree of food insecurity. This is a meaningful reminder of the empirical content of the otherwise abstract idea of "urgency" we refer to in this paper. We also note that this result is coherent with a body of research that has consistently documented a negative association between socioeconomic status and time preference 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).

Even though these marginal associations are consistent with the consumption urgency hypothesis, we must take this evidence with caution. In the absence of exogenous variation in living conditions in the present setting, it is not clear how much of it 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. It is reasonable to expect that both are in effect at the same time, characterizing a form of low-income occupational trap.

7 Concluding remarks

In this paper, 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 a frequent confusion of low-end self-employment and 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) reiterates 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 at 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.

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A Estimation Output Tables

Table 3: Estimation of potential wages with adjustment for selection.

	Main equation Log wage		Selection equation P(state = employee)	
	coef.	**s.e.**	**coef.**	**s.e.**
Ethnicity and gender (ref: 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 (ref: 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 (ref: Not currently studying)				
Attending school	·	·	-0.584^{***}	(0.033)
Attending college or above	·	·	0.114^{***}	(0.022)

Table 3: Estimation of potential wages with adjustment for selection. ***[continued]***

	Main equation Log wage		Selection equation P(state = employee)	
	coef.	**s.e.**	**coef.**	**s.e.**
Household position (ref: Head, with partner, no kids)				
Head, with partner, with kids	·	·	0.037	(0.028)
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 selection 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, in order 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. [4] The stars next to the coefficients denote statistical significance at 5% (*), 1% (**), and 0.1% (***).

Table 4: 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 (ref: 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 (ref: 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 (ref: 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)

Table 4: 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.**
Household position (ref: 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)
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, in order 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. [4] The stars next to the coefficients denote statistical significance at 5% (*), 1% (**), and 0.1% (***).

Table 5: 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 (ref: Nonwhite female)				
White female	1.062**	(0.022)	1.127**	(0.045)
Nonwhite male	0.976	(0.017)	1.873***	(0.059)
White male	0.965	(0.021)	1.652***	(0.066)
Age and education (ref: 14-24, less than prim. school)				
14-24, primary school	0.742***	(0.030)	1.042	(0.068)
14-24, high school	0.456***	(0.020)	0.986	(0.065)
14-24, college or above	0.274***	(0.025)	1.397**	(0.149)
25-34, less than primary school	0.757***	(0.032)	1.104	(0.094)
25-34, primary school	0.551***	(0.024)	1.170	(0.100)
25-34, high school	0.346***	(0.015)	1.100	(0.078)
25-34, college or above	0.222***	(0.011)	1.107	(0.100)
35-44, less than primary school	0.678***	(0.029)	0.920	(0.072)
35-44, primary school	0.489***	(0.025)	0.957	(0.087)
35-44, high school	0.323***	(0.014)	0.969	(0.073)
35-44, college or above	0.192***	(0.010)	1.001	(0.101)
45-54, less than primary school	0.637***	(0.027)	0.813*	(0.072)
45-54, primary school	0.473***	(0.026)	0.798*	(0.088)
45-54, high school	0.347***	(0.017)	0.790*	(0.080)
45-54, college or above	0.207***	(0.011)	0.754*	(0.108)
55-64, less than primary school	0.726***	(0.033)	0.586***	(0.063)
55-64, primary school	0.581***	(0.033)	0.453***	(0.081)
55-64, high school	0.456***	(0.024)	0.500***	(0.080)
55-64, college or above	0.353***	(0.019)	0.333***	(0.077)
Current schooling status (ref: Not currently studying)				
Attending school	1.411***	(0.047)	0.765***	(0.043)
Attending college or above	0.926**	(0.024)	1.294***	(0.053)

Table 5: Employment and unemployment duration models. ***[continued]***

	Out of wage work transition hazard		Unemp. into wage work transition hazard	
	haz. ratio	**s.e.**	**haz. ratio**	**s.e.**
Household position (ref: Head, with partner, no kids)				
Head, with partner, with kids	0.899***	(0.027)	0.963	(0.068)
Head, no partner, no kids	1.042	(0.036)	0.852*	(0.063)
Head, no partner, with kids	0.975	(0.033)	0.882	(0.078)
Partner, no kids	1.037	(0.036)	0.925	(0.074)
Partner, with kids	0.971	(0.029)	0.946	(0.063)
Child	1.257***	(0.039)	0.674***	(0.047)
Other young hh member	1.263***	(0.074)	0.800*	(0.077)
Other adult hh member	1.132**	(0.048)	0.845*	(0.067)
Number of household members by age				
N. kids (less than 15 years old)	1.064***	(0.008)	1.039**	(0.014)
N. young members (15-21)	1.077***	(0.010)	1.002	(0.019)
N. adult members (22-64)	1.014	(0.008)	0.993	(0.014)
N. elderly members (65+)	1.017	(0.016)	0.927*	(0.030)
Ancillary mixture parameters				
Hazard ratio for high type	6.186***	(0.248)	3.325***	(0.096)
Share of high type	0.418***	(0.012)	0.662***	(0.021)

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, in order 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. [6] The stars next to the coefficients denote statistical significance at 5% (*), 1% (**), and 0.1% (***).

Table 6: Association between the estimated discount lower bound of own-account workers in Brazil (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.**
Access to financial services								
No savings account	3.63***	(0.75)	·	·	·	·	2.77***	(0.75)
No overdraft facility	6.89***	(1.32)	·	·	·	·	5.00***	(1.32)
No credit card	8.23***	(0.81)	·	·	·	·	6.20***	(0.81)
Income from other sources (in R$ 1 000)								
Family per cap inc ex my work inc	−1.13***	(0.27)	·	·	·	·	−0.20	(0.27)
(Family per cap inc ex my work inc)^2	0.02***	(0.00)	·	·	·	·	0.00	(0.01)
Financial stress (ref: very easy)								
Easy to make ends meet	·	·	−0.99	(2.58)	·	·	−1.18	(2.61)
Somewhat easy to make ends meet	·	·	1.74	(2.59)	·	·	0.90	(2.63)
Somewhat hard to make ends meet	·	·	7.93**	(2.50)	·	·	4.61	(2.53)
Hard to make ends meet	·	·	10.98***	(2.60)	·	·	5.08	(2.62)
Very hard to make ends meet	·	·	19.73***	(2.70)	·	·	10.19***	(2.79)
Large non-essential expenses (top decile)								
Education expenses > 15% of total	·	·	−2.79*	(1.18)	·	·	−2.38*	(1.19)
Personal expenses > 13% of total	·	·	−0.95	(1.17)	·	·	−1.90	(1.18)
Large essential expenses (top decile)								
Housing expenses > 58% of total	·	·	7.53***	(1.27)	·	·	6.17***	(1.27)
Medicine expenses > 9% of total	·	·	8.21***	(1.35)	·	·	6.91***	(1.33)
Food expenses > 35% of total	·	·	8.38***	(1.28)	·	·	7.07***	(1.27)

Table 6: Association between the estimated discount lower bound of own-account workers in Brazil (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 adequacy								
People per sleeping room	·	·	·	·	2.40***	(0.68)	1.72**	(0.66)
Presence of domestic pests	·	·	·	·	2.41**	(0.77)	2.11**	(0.76)
Presence of leakages or dampness	·	·	·	·	3.01***	(0.76)	2.38**	(0.76)
Clothing adequacy (ref: good, adequate)								
Poor clothing conditions	·	·	·	·	7.95***	(1.76)	6.33***	(1.75)
Food adequacy (ref: no food insecurity)								
Some food insecurity	·	·	·	·	7.65***	(0.91)	4.49***	(0.93)
Moderate food insecurity	·	·	·	·	13.87***	(1.37)	8.87***	(1.42)
Severe food insecurity	·	·	·	·	19.10***	(2.00)	12.92***	(2.11)
Model statistics								
Adjused R^2	0.135		0.148		0.148		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, in order to render the coefficients meaningful for the population this sample represents, and the errors are clustered the the level of their Primary Sampling Unit. [3] All models include also controls for ethnicity, gender, age, education, position of the worker in the family, family composition, and geographic region. [4] The stars next to the coefficients denote statistical significance at 5% (*), 1% (**), and 0.1% (***).

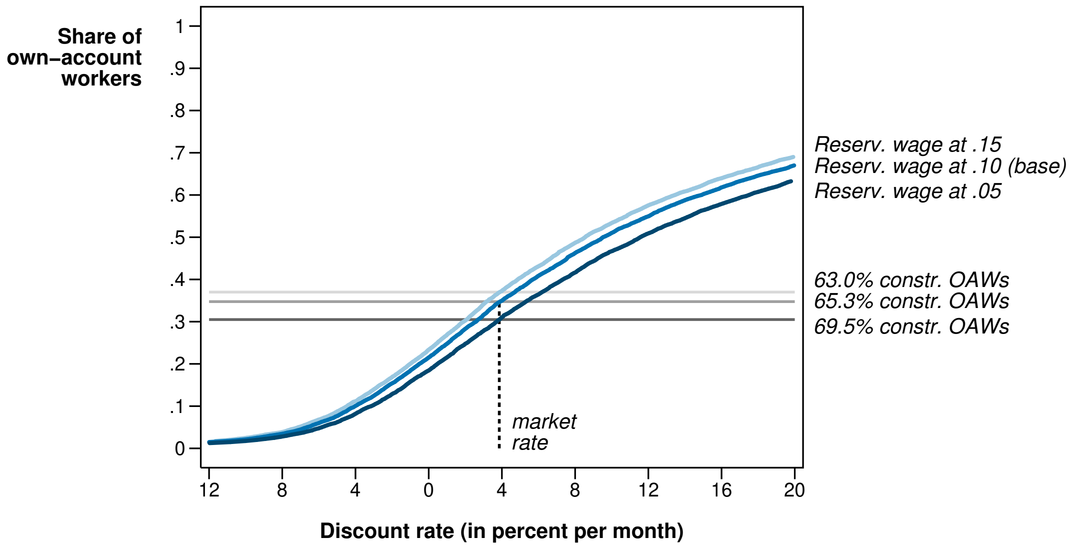
B Alternative Thresholds for the Reservation Wage

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 5). 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 5: Empirical CDF of the estimated discount rate lower bound under three alternative proxies for the concept of reservation wage



C Alternative Specifications: Domestic Workers as Employees

In the baseline case, we favor the interpretation that domestic workers are own-account workers, as discussed in section 4. For contrast and completeness, here we present how the main results change if we were to classify them as employees instead, as the national statistics office does.

This classification matters because domestic workers constitute a large and relatively homogeneous group: there are 6.2 million domestic workers out of 80.7 million occupied individuals in the population of interest; 95% are females; 66% are nonwhites; 48% have less than primary school; and 73% are above 35 years old.

Without domestic workers, the proportion of females among own-account workers falls from 52.4% (the same share found in the general population) to 38.9% (pointing to a majority of men in this occupation). This comparison illustrates how the discussion about gender and self-employment in Brazil depends on how one understands the group of domestic workers.

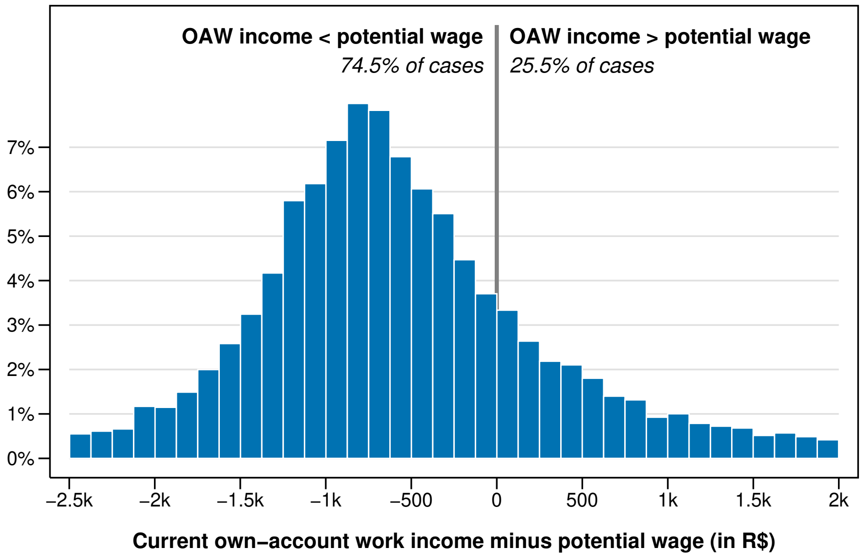
Table 7: Descriptive statistics for employees and own-account workers in Brazil, with domestic workers included among employees (IBGE's default classification).

	Household Budget Survey (POF) 2017-18					
	Urban areas, working age individuals (14-64 years)					
	Domestic Workers		Employees (Incl. Dom. Workers)		Own-Account Workers	
	statistic	std. err.	statistic	std. err.	statistic	std. err.
Subpopulation size (in millions)						
Total subpopulation	6.2	(0.15)	58.0	(0.64)	19.8	(0.28)
Gender and ethnicity (in %)						
Female	95.3	(0.42)	49.9	(0.28)	38.9	(0.53)
Nonwhite	65.7	(1.06)	54.7	(0.50)	55.5	(0.69)
Education level (in %)						
Less than primary school	48.4	(1.01)	20.5	(0.34)	33.5	(0.63)
Primary school	21.8	(0.87)	15.6	(0.29)	17.7	(0.46)
High school	28.8	(0.99)	42.6	(0.40)	35.3	(0.61)
College or above	1.0	(0.19)	21.3	(0.51)	13.4	(0.66)
Age group (in %)						
Age 14-24	9.2	(0.52)	17.8	(0.28)	9.5	(0.36)
Age 25-34	17.6	(0.77)	26.8	(0.36)	20.6	(0.47)
Age 35-44	28.5	(0.88)	25.8	(0.35)	25.8	(0.52)
Age 45-54	28.5	(0.96)	19.5	(0.30)	25.6	(0.52)
Age 55-64	16.2	(0.81)	10.2	(0.23)	18.5	(0.47)
Income from main occupation (in R$)						
Average net work income	832.5	(14.62)	2 129.1	(29.43)	1 635.7	(31.61)

Notes: [1] Throughout this research, we classify domestic workers as own-account workers, in constrast with the Brazilian statistical office (IBGE), who counts them as employees by default. In this table, we present the summary statistics for both employees and own-account workers under IBGE's standard definition, as well as for for domestic workers alone. [2] Monetary values are calculated at constant January 2018 purchase power. [3] Work income is winsorized at the 1st and at the 99th percentiles.

Furthermore, the removal of this subgroup increases the average for the group of own-account workers from R$ 1 443 to R$ 1 635, and narrows the gap relative to employees from 37% to 23%. For similar reasons, when we estimate a counterfactual wage for own-account workers using the default classification, we find that 74.5% of them could plausibly expect a higher net work income, which contrasts to the 82% found at baseline (see figure 2).

Figure 6: Distribution of the estimated gap between the labor income received by own-account workers and the wage they could expected to receive as employees (with domestic workers included among employees)



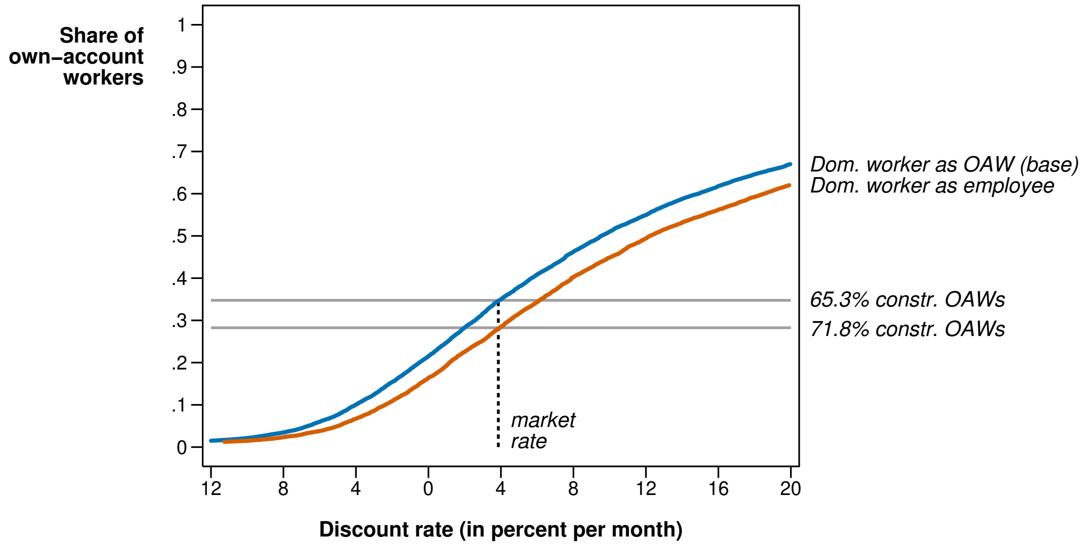
If we were to look at monthly pay only, we would conclude that this alternative classification implies a lower share of constrained own-account workers than the baseline. Interestingly, accounting for expected unemployment time reverses this conclusion.

Under our preferred 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 and she is no longer "at risk", as the survival jargon puts it. In contrast, under the alternative classification, the same observation is now considered a transition (since domestic work is wage employment in this case). 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 resulting distribution of the implicit discount rate under the alternative specification stochastically dominates the baseline curve (see figure 7).

In other words, if one views domestic work as one possible 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 time more than offset the losses in wage for those who are affected.

All in all, this exercise stresses the key role played by the expected search timing in the valuation of an occupation, and reiterates that our baseline result of 65% offers a conservative estimate of the share of constrained own-account workers.

Figure 7: Empirical CDF of the estimated discount rate lower bound taking domestic workers as OAWs (baseline) and as employees



D Alternative Specifications: Reweighted PNAD

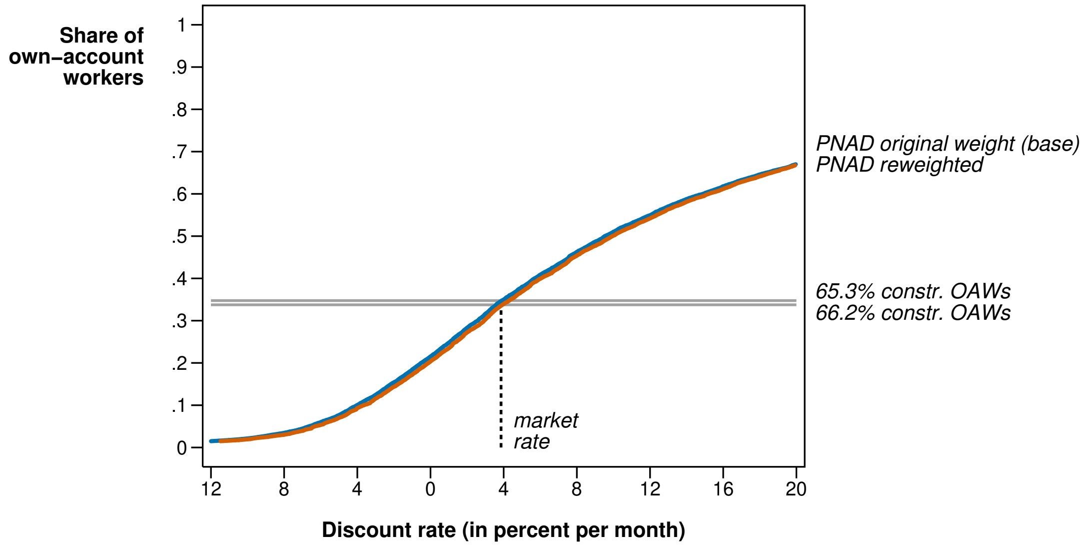
The baseline estimation adopts the original survey weights from both POF and PNAD, given that the surveys are meant to represent the same population, as discussed in section 4. The descriptive statistics presented in table 1 reinforce that the population of interest indeed has very similar attributes, 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 according to POF, relative to 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 21.03% in POF and 21.73% 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.

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.[14] 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 8). This compatibility can be seen as evidence that supports the baseline (non-reweighted) findings.

[14] 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-`.

Figure 8: Empirical CDF of the estimated discount rate lower bound adopting original survey weights (baseline) and reweighted PNAD survey



E 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 chap. 17-18 from 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 using a maximum likelihood approach.

As discussed in section 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.[15] 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 coefficients of the model, 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.

Even though the statistical model could allow for an arbitrary parametric baseline hazard, here we constrain the estimation to the exponential case to impose a hazard that is constant over the spell, mirroring the stationarity conditions assumed in the theoretical framework.

[15] Namely, 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.