# 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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The current version of this research is available here

**Abstract**

This paper explores a fundamental trade-off imposed by imperfect labor markets: individuals may work on their own at any time, but they can only take a potentially better-paid wage job after spending some time looking for it. First, we formalize this intuition using the standard tools of the job search framework, and we show that a sufficiently high subjective discount rate can rationalize the preference for own-account work even when it pays less than wage work. Next, we use the structure established by the theoretical model to estimate the minimum discount rate that would be consistent with the observed occupational choice of own-account workers in Brazil, given the labor market opportunities they face. In the baseline specification, we find that 60 percent of them must discount future consumption at rates strictly superior to the average market rates. This result suggests that (1) intertemporal considerations appear to play a relevant role in occupational choices in this context, and (2) if own-account work is only preferable under such high discount rates, we can classify their occupational choice as a financially constrained one. Finally, we find that the estimated discount rate lower bound is negatively associated with access to credit and positively associated with measures of food deprivation, an evidence that supports the hypothesized channel between current living conditions, time preferences, and labor market decisions.

**JEL Classification:** J22, J24, J31, J64.

**Keywords:** Self-Employment, Own-Account Work, Imperfect Labor Markets, Job Search, Developing Countries, Financial Constraints, Time Discounting.

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## 1 Introduction

The International Labor Organization (ILO) estimates that about one in every three occupied individuals worldwide is an own-account worker, and this share increases to one in every two if we look only to developing countries. Despite such magnitude, people working outside the employer-employee framework are still underrepresented in labor economics. Moreover, in the rare cases when economists use the concept of own-account work, they often reduce it to a proxy for entrepreneurship or informality.

The entrepreneurship view emphasizes the risk-taking component and the satisfaction of being one's own boss (as if each own-account worker were a potential CEO in the making) but this perspective fails to explain why poor regions have such a disproportionate share of "entrepreneurs", while in rich ones they are typically less than 10% of the employed population. In contrast, development economics often understands own-account work as an informal and parallel labor market, one with lower productivity and lower regulation compared to wage employment. Such a view overlooks that a share of own-account workers would remain so even if they had instant access to all possible wage jobs.

This paper aims to complement those views by looking at own-account work as an occupation that could offer a high or a low income, depending on one's productivity, but whose defining attribute is simply to preclude the need to search and match with a firm. We show that this trade-off between own-account work now versus a potentially better wage work a few months in the future is enough to sort otherwise identical workers over those two occupations based solely on their time preference. This result offers a new rationale for the coexistence of poorly paid own-account workers and observationally similar employees.

By linking the occupational decision to intertemporal optimization, this framework also proposes an alternative definition for the concept of constrained own-account workers, namely: those whose preference for this occupation can only be rationalized by discount rates above the ongoing market rates. The idea is that those workers would be better off financing their job search, as they would later benefit from a relatively larger monetary gain from employment. If, by contrast, they are observed working on their own, their choice reveals an impossibility of doing so — in other words, a financial constraint.

In the second half of this research, we use an empirical counterpart of this model to study the discount rates of own-account workers in Brazil. In a nutshell, the strategy consists of comparing the current work income of autonomous workers to the potential wages they could expect to earn if they were to postulate for a job, accounting for how long they would need to search until finding one. This set of counterfactual values are estimated off the observable attributes of employees, under the assumption that this statistical method can mimic the agents' perceptions about their chances on the labor market. The observed choice for own-account work thus informs that this occupation must provide the highest value for the agent, therefore identifying the lowest discount rate that rationalizes their decision, by revealed preference. Under the assumptions of the baseline specification, we find that about 60% of the Brazilian own-account workers have an implicit time discount above the consumer's credit rate, which we interpret as evidence of a financially constrained occupational choice.

The hypothesis is that the high discount rates suggested here are, to some extent, reflecting a pressing urgency to consume, in tandem with the impossibility to finance such consumption with future income. Indeed, in the final part of this research, we find suggestive evidence that the implicit discount rate lower bound tends to be higher for own-account workers that have experienced recent hunger episodes and lower for those who have a savings account.

Those insights are relevant for policy because they suggest a new reason in favor of programs that support present consumption during income shocks. Absent such smoothing, agents facing frictional labor markets and imperfect financial markets could rationally shift into relatively unproductive own-account work and get permanently stuck in a low-consumption equilibrium. According to our estimates, this is not a marginal possibility — it can be a major driver for the majority of own-account workers in a developing country.

Our study also suggests that there is wide heterogeneity in the time discount rate used by individuals to make occupational decisions. This is relevant because there is scarce empirical evidence on the distribution of subjective discount rates, notably so in the developing world. Furthermore, from a methodological perspective, our findings warn against the usual practice in labor economics of assuming a homogenous rate at the financial market level for all agents.

The remainder of the study is organized as follows. Section 2 discusses the importance of understanding own-account work as one particular subcategory of self-employment and describes its typical features across countries and within Brazil. Section 4 presents PNAD and POF, the two Brazilian nationwide surveys that we explore in tandem in the estimations. At the core of the paper, Section 3 introduces our novel model for occupational choice, based on a simple reinterpretation of the ingredients from the job search literature. Section 5 details the protocol for the piecewise empirical estimation of the structural model, discusses the assumptions required for the identification of a worker's discount rate lower bound, and examines the properties of the distribution obtained using our baseline specification. Section 6 looks at associations between the estimated discount rate lower bound and socioeconomic attributes outside the estimation process to examine drivers of a potentially endogenous time preference parameter. Finally, section 8 summarizes the limitations of the paper and concludes.

## 2 Key concepts and some stylized facts

The subject matter of this research is the *own-account workers*, defined as the workers who are the sole responsible for their economic activity. This concept embeds two important consequences. First, there are no internal coordination issues: own-account workers have neither employers nor employees and organize the production according to their will. Second: they are entitled to all the revenue derived from it, in contrast with the employee's wage (generally defined by an agreement between the employee and the firm) and with the employer's profit (the residual term after the remuneration of all other production inputs).[1]

We insist on the contrast between *own-account workers* and *employers* because this crucial distinction is often lost behind the broad category of "self-employment". This conflation explains part of the mixed views present on the literature, where self-employment is taken as a proxy for the normatively desired entrepreneurs,[2] but also to denote the normatively undesired informal, marginal or secondary labor market.[3] Indeed, while relying on this imprecise terminology, economists and sociologists have long acknowledged there is heterogeneity among the so-called self-employed by choice and those driven by necessity, but there is yet no consensus on how to distinguish them.[4] Our proposition here is simply to look at own-account workers as a category in itself and try to investigate it based on one of its most fundamental attributes, and not as a proxy for another concept.

1. The International Classification of Status in Employment (ICSE-93), which is the current reference for the ILO, states that "[o]wn-account workers are those workers who, working on their own account or with one or more partners, hold the type of job defined as a 'self-employment job' (...), and have not engaged on a continuous basis any 'employees' (...) to work for them during the reference period. It should be noted that during the reference period the members of this group may have engaged 'employees', provided that this is on a non-continuous basis." (Hoffmann, 2003).

2. This is the case in Evans and Leighton (1989), Evans and Jovanovic (1989), Lindh and Ohlsson (1996), Magnac and Robin (1996), Blanchflower and Oswald (1998) and Lazear (2005). All of these studies investigate the conditions — be it liquidity, personality traits, risk preferences, or skills — that could foster the choice for self-employment understood as entrepreneurship.

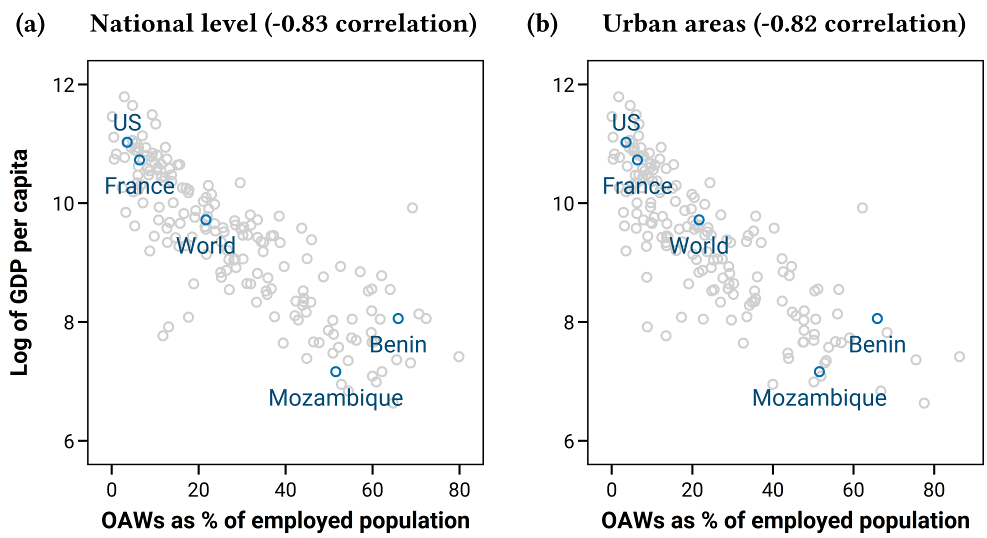
3. Examples include Tokman (2007), Albrecht, Navarro, and Vroman (2009), and the literature on segmented market in developing countries more generally, as reviewed in Fields (2009).

4. Some alternative measurements of success or motivation have been proposed. Gindling and Newhouse (2014) emphasize the own-account work versus employer distinction as a measure of success in itself, alongside the question of whether the self-employed lives in a noon-poor household; Global Entrepreneurship Monitor (2017) surveys people about their motivation, and Fairlie and Fossen (2018) defines necessity entrepreneurs as those who go into self-employed from unemployment. For a review of this general discussion, refer to Margolis (2014).

To support this motivation, we start by documenting a set of remarkable empirical regularities. First: the presence of own-account workers in a given region is inversely proportional to the average income in that region. For concreteness, ILO figures for 2018 show that most of the employed population in poor countries are own-account workers (such as 72% in Benin and 62% in Mozambique), in comparison to a small minority in the high-income group (such as 7.1% in France and 3.7% in the United States), as shown in figure 1a.

Second: while it is true that activities typical of rural areas are strongly associated with own-account work, and poor regions have a higher share of their workers living in rural areas, the strong negative relationship between own-account work and income remains if we look only to urban areas, as depicted in figure 1b. To emphasize this point, we will restrict the analysis to urban own-account work in all that follows, avoiding urban/rural composition effects.

**Figure 1: Share of own-account work and income by country (2018)**




*Notes: Occupation data comes from the ILO; income data comes from the International Monetary Fund World Economic Outlook (IMF WEO).*

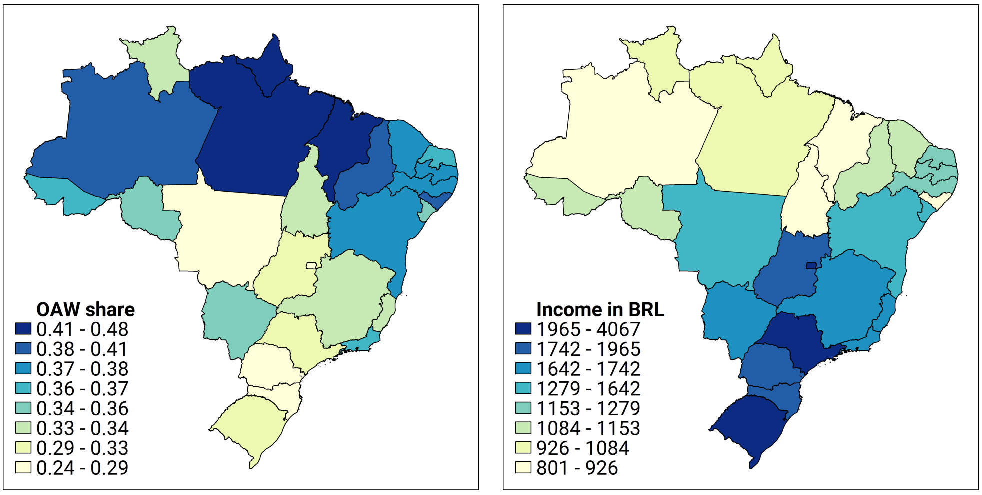
Third: the same relationship also holds at a national scale, as exemplified by the contrast between different regions within Brazil. At the national level, own-account workers make up 33% of the employed urban population.[5] However, the poorer states in

5. Our figure is above the 25% proportion calculated by the Brazilian statistics office (and adopted by the ILO) because we add domestic workers to the own-account workers, while the standard classifications do not. We favor this classification because domestic workers sell their autonomously produced domestic services to the final consumer. The perception of the hiring family as bosses instead of clients appears to be more related to the social construction of this activity than to its actual economic content. The jump in own-account workers (+8 percentage points) speaks about the size of this activity

the north of the country have a higher share, closer to that observed for lower-middle-income countries, while the opposite is true for the richer states in the south, as shown in figure 2.

**Figure 2: Share of own-account work and income in Brazil (2017-18)**

**(a) Share of own-account workers** **(b) Log of income per capita**

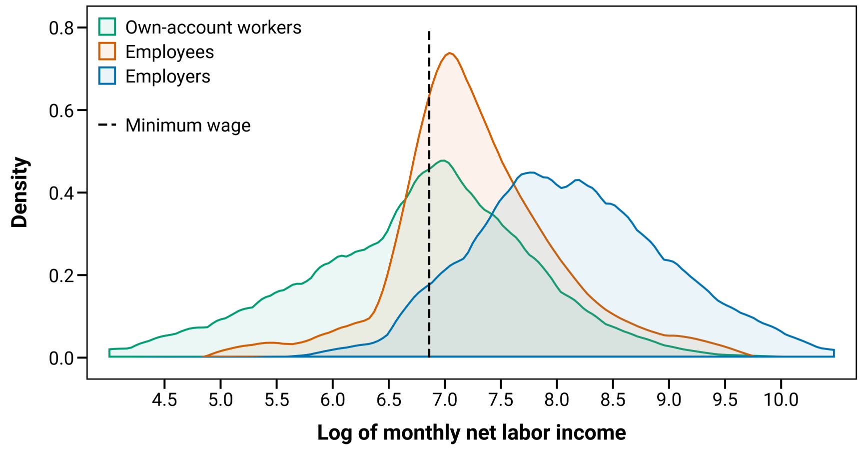



*Notes: All calculations refer to urban areas only. Occupation is defined as the lastest primary occupation within the previous year. Domestic workers are classified as own-account workers. Income is measured as per capita monthly income from all sources, net of taxes, from the 2017-18 POF survey.*

This pattern helps us to put in context the discussion about autonomous employment. From the developed world perspective, where most of the economic research is produced, employers are indeed a large share within the small group of the self-employed — large enough to be seen as representative. In contrast, in poor countries, own-account workers make the bulk of self-employment, and it is more likely to comprise a wide range of workers: from a few well-paid lawyers to street vendors not far from the subsistence level.

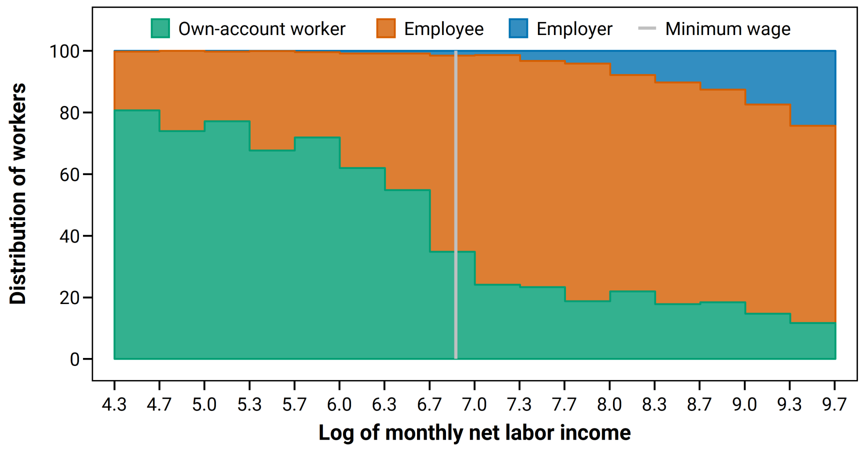
To see it, let's examine the full distribution of work income by employment category in Brazil, as depicted in figure 3 and figure 4. The distribution of employees has a strong focal point around the regulatory minimum wage (about 954 BRL, or 244 EUR) and a heavy right-tail. Employers have a much more symmetric distribution of income, with a center of mass at a higher level, in a pattern that could be explained by their particular managerial skills or the remuneration of the risk they bear. The pattern for own-account workers is more complex: some of them are making as much as the average employer or a well-off employee, but they are largely overrepresented at the lower end of the income distribution. The fourth stylized fact is that own-account workers are the majority of workers making less than the minimum wage.

**Figure 3: Work income distribution according to occupation**




*Notes: Income is measured as most recent monthly income received from work activity net of taxes, from the 2017-18 POF survey.*

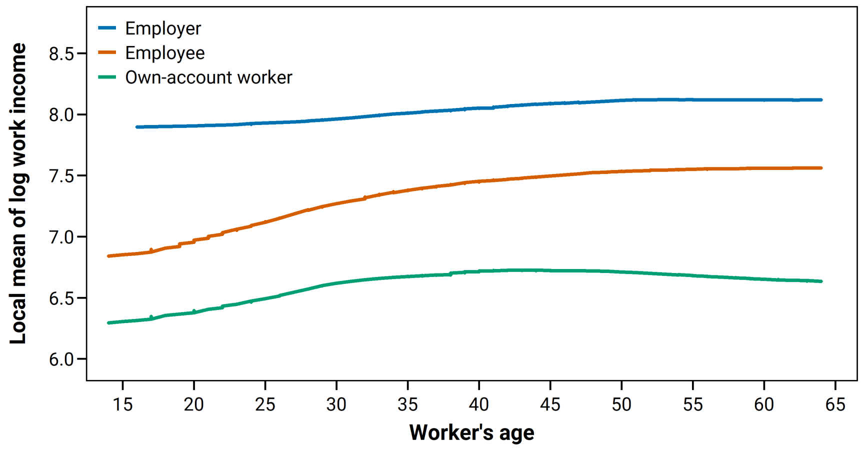
**Figure 4: Composition of work force by income level**




*Notes: Income is measured as most recent monthly income received from work activity net of taxes, from the 2017-18 POF survey.*

To conclude this section, we look at the work income schedule by age for those three occupation categories. Steeper returns to seniority could rationalize the low pay observed for young own-account workers that would then access higher income later in life, versus a flatter profile for employees. This hypothesis finds little support in the data: the earnings gap observed between own-account workers and employees around the 20s goes steady during the prime working-age and spreads further after the age of 45. Even though this graph is not following a single cohort, we interpret these results as evidence that there are no extraordinary returns for experienced own-account workers, while the average work income of employees increases continuously, even if at a slow pace. This pattern may reflect an accumulation of occupation-specific skills and is also consistent with the experience-earnings profile required to provide career incentives to paid employees, as suggested by Lazear (1979). If individuals can freely choose their occupation, the option for own-account work is puzzling at any given age — and even less rewarding in monetary terms as a life-long career.

**Figure 5: Work income by age, according to occupation**




*Notes: Income is measured as most recent monthly income received from work activity net of taxes, from the 2017-18 POF survey.*

All in all, this evidence supports the argument that own-account work is a particular employment category and constitutes a research object in itself. Furthermore, these stylized facts lead to the question of what features of the labor markets and the individual occupational choice protocol could contribute to such results. Finally, they point to the importance of assessing to what extent the own-account workers can be said to be in their first best occupation and what kind of constraints they could be facing in order this the best possible labor supply choice.

## 3 Theory: Own-account workers in a job search framework

The argument we formalize in this section is built around one fundamental intuition: individuals willing to supply their labor services must decide whether to work on their own or to look for a job position elsewhere. In the first case, people may enter their occupation immediately and will be entitled to all the income generated by their productivity. In the second case, the job-seeker needs to find a firm willing to hire them and their income will be the wage agreed upon between both parties. Since one doesn't know immediately which firm has a vacancy position, the search process requires some time in unemployment.

The model itself is a simple extension of the canonical job search framework in partial equilibrium. [6] We assume the agents have the relevant information about the labor market conditions: they know the exogenous distribution of wages one could expect to earn when working in a firm, how often one might get a job offer when looking for it, and how long those jobs usually last. The uncertainty lies in the fact that the characteristics of a particular vacancy (i.e. the wage per period attached to the future job) are known only at the arrival of an offer. To this set of standard assumptions, we add that that individuals know what would be their deterministic productivity if they were to work on their own.

The environment is stationary: in expectation, the potential jobs the unemployed could access tomorrow are similar to the ones they could access today. Technically, this condition suggests that the number of offers per interval follows a stochastic Poisson distribution (and, conversely, that the hazard rate of offer arrivals is exponential).

Agents have some degree of preference for the present, in the intuitive sense that $100 today is preferred to $100 tomorrow. For that reason, any future flow of income is discounted by a rate $\rho$ that converts it into a comparable present value. Importantly, individuals are allowed to be heterogeneous in the subjective rate they discount the future.

For simplicity, individuals do not look for a job if they are already working, translating the idea that job searching requires an amount of effort and time that cannot be reconciled with the ongoing occupation (a discussion on the implications of relaxing this assumption is provided at section 8). Furthermore, we abstract from the details of the matching mechanism and from any optimization behavior that may take place at the side of the firms when setting wages. In this sense, we apply the optimal stopping rule, in the tradition of McCall (1970), where individuals sample from a given distribution of wage offers and stop searching whenever they find an offer above their reservation threshold.

We purposefully assume away any taste parameter — the only determinant of utility is the occupation-specific monetary payoff per period. From a methodological perspective, our challenge is to justify the choice for own-account work without violating individual rationality and without relying on an arbitrary introduction of tastes.[7]

6. For an introduction to the ingredients we adopt in this paper, see chapter 5 of Cahuc, Carcillo, and Zylberberg (2014). Refer to Rogerson, Shimer, and Wright (2005) for a review of the properties, assumptions, and advantages of a broad family of search models.

7. In any case, it is not obvious that autonomous work offers a higher non-monetary utility than other forms of work. Hanglberger and Merz (2015) argue that some results that rely on reported satisfaction differentials overestimate the joy of the self-employed for omitting anticipation and adaption effects. As people tend to be strongly dissatisfied before changing jobs and disproportionately content in the initial periods of the new one, a honeymoon phenomenon can bias the comparison with wage jobs if recent self-employed are overrepresented. Accounting for those dynamics, they estimate that any gap in satisfaction vanishes. In some contexts, own-account workers might as well *dislike* their occupation.

### 3.1 Value of wage employment

The discounted value of any wage job $W(w)$ depends on the instantaneous wage it pays $w$ and accounts for the possibility that the job may end with an instantaneous rate $\delta$, in which case the worker would go back into unemployment, which has value $U$. Denoting a small time interval by $dt$, we can derive the usual flow value expression for employment as:

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

$$W(w) + \rho \cdot dt \cdot W(w) = w \cdot dt + \delta \cdot dt \cdot U + W(w) - \delta \cdot dt \cdot W(w) \tag{2}$$

$$\rho \cdot W(w) = w + \delta \cdot \big[U - W(w)\big] \tag{3}$$

### 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 instantaneous flow $b$, a component that summarizes 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 $\lambda$ the unemployed draws an offer from the known distribution $F(w)$. Hence:

$$\begin{aligned} U = \left(\frac{1}{1+\rho \cdot dt}\right) \cdot \Bigg[ & b \cdot dt \\ & + \lambda \cdot dt \cdot \int_0^{w_r} U \; dF(w) \\ & + \lambda \cdot dt \cdot \int_{w_r}^{\infty} W(w) \; dF(w) \\ & + \big(1 - \lambda \cdot dt\big) \cdot U \Bigg] \end{aligned} \tag{4}$$

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

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Banerjee and Duflo (2011) describe that the most common aspiration of poor parents around the world, many of them working on their own, is for their children to avoid the uncertainty and instead get a salaried job, preferably a stable position in a government office. Another way to frame our model is to say that none of the non-monetary components unambiguously offset the others, with a distribution of taste for own-account work centered at zero.

while offers above $w_r$ lead to a job with a continuation value $W(w)$. With probability $1 - \lambda \cdot dt$, the job-seeker receives no offer and continues to search.

Using the fact that $U = \int_0^\infty U \; dF(w)$, we have that:

$$\begin{aligned} \rho \cdot dt \cdot U = b \cdot dt & \\ & + \lambda \cdot dt \cdot \int_0^{w_r} U \; dF(w) \\ & + \lambda \cdot dt \cdot \int_{w_r}^\infty W(w) \; dF(w) \\ & - \lambda \cdot dt \cdot \int_0^\infty U \; dF(w) \end{aligned} \tag{5}$$

Because $\int_0^\infty U \; dF(w) = \int_0^{w_r} U \; dF(w) + \int_{w_r}^\infty U \; dF(w)$, we can write the unemployment valuation simply as:

$$\rho \cdot U = b + \lambda \cdot \int_{w_r}^\infty \big[W(w) - U\big] \; dF(w) \tag{6}$$

### 3.3 The reservation wage

By definition, a job that pays the reservation wage has the same value as the unemployment state. Hence:

$$\rho \cdot W(w_r) = \rho \cdot U \tag{7}$$

Using equation (3) and the definition of the reservation wage:

$$w_r + \delta \cdot \big[U - W(w_r)\big] = \rho \cdot U \tag{8}$$

$$w_r = \rho \cdot U \tag{9}$$

Using the flow value of unemployment defined in equation (6):

$$w_r = b + \lambda \cdot \int_{w_r}^\infty \big[W(w) - U\big] \; dF(w) \tag{10}$$

Let us go back to equation (3) in order to rewrite $\big[W(w) - U\big]$:

$$\rho \cdot W(w) = w + \delta \cdot \big[U - W(w)\big] \tag{11}$$

$$\rho \cdot W(w) - \rho \cdot U = w + \delta \cdot \big[U - W(w)\big] - \rho \cdot U \tag{12}$$

$$\big[\rho + \delta\big] \cdot \big[W(w) - U\big] = w - \rho \cdot U \tag{13}$$

$$\big[W(w) - U\big] = \frac{w - w_r}{\rho + \delta} \tag{14}$$

Finally, substituting it back into equation (10):

$$w_r = b + \lambda \cdot \int_{w_r}^{\infty} \frac{w - w_r}{\rho + \delta} \, dF(w) \tag{15}$$

### 3.4 The value of own-account work

So far, the valuation equations follow the canonical results. To add the possibility of own-account work, we make three fundamental 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* doing so, is already an own-account worker, which is fundamentally different from a job-seeker waiting for a call-back.

Second, *the income generated by the own-account activity is fully determined by someone's productivity* and 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. Should I offer myself to paint houses? Could I give private Math classes? Sell fruits at the exit of a Metro station? Collect recyclable materials on the street? — we interpret $y$ as the highest net return in that list, given someone's 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 income $y$.

Third, there is no exogenous destruction rate. To be precise, *the possibility of a destruction rate is immaterial for the valuation*, which is a logical consequence that follows from the two assumptions above. If own-account work is always available, even if the current task were to come to an end, in the subsequent period another one would be available. Because we take 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.

In intuitive terms, this assumption also translates the idea that one cannot be fired by himself. However, one can always decide to quit. In order to account for that possibility, we allow own-account workers to review their occupational decision at every period and pick the best option between looking for a job and working alone. Under those assumptions, we define the value of own-account work $OAW(y)$ as:

$$OAW(y) = \left(\frac{1}{1+\rho \cdot dt}\right) \cdot \Big[y \cdot dt + \max\big(U, OAW(y)\big)\Big] \tag{16}$$

At steady-state, this expression simplifies further. When the parameters of the labor market are stable, if own-account work is preferred to job searching *at any point in time*, it will be preferred *at all points in time*. Thus, for any own-account worker, it must be that $\max\big(U, OAW(y)\big) = OAW(y)$ in all subsequent periods.[8] For this reason, we have that:

$$OAW(y) = \left(\frac{1}{1+\rho \cdot dt}\right) \cdot \Big[y \cdot dt + OAW(y)\Big] \tag{17}$$

$$OAW(y) + \rho \cdot OAW(y) \cdot dt = y \cdot dt + OAW(y) \tag{18}$$

$$\rho \cdot OAW(y) = y \tag{19}$$

### 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 by themselves before looking for a job. Under this assumption, rational individuals will become own-account workers whenever the value of doing so is higher than the value of looking for a job:

$$OAW(y) \geq U \tag{20}$$

Equivalently, using the results from equation (15) and equation (19), this decision can be expressed as:

$$y \geq b + \frac{\lambda}{\rho+\delta} \cdot \int_{w_r}^{\infty} \big(w - w_r\big)\, dF(w) \tag{21}$$

The reader will notice that our discussion boils down to an expression analogous to the classic formulation for the participation decision, except that we assign a new interpretation to the outside option, that in our case is own-account work instead of

8. The reader may wonder why we bothered including the possibility of exiting own-account work if we are going to focus on the case where it never happens. We do it to stress that such permanence does not result from an a priori definition of own-account work as an absorbing state, but instead emerges naturally from the agent's sequential optimization.

inactivity. This interpretation is sufficient to motivate a set of implications for the prevalence of own-account work in the economy.

To see it, let us note that the share of autonomous workers in a given population is simply the proportion of individuals for whom the inequality above holds:

$$\mathbb{P}\left(y \geq b + \frac{\lambda}{\rho + \delta} \cdot \int_{w_r}^{\infty} (w - w_r)\, dF(w)\right) = \text{share of OAW in the workforce} \tag{22}$$

The intuition is that, given a sufficiently low reservation wage, even tasks with low productivity become attractive for many workers. To be precise, the comparative static analysis 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. This result shows that the classic explanation, according to which people choose the occupation they are more skilled at, is indeed a particular case of our model.

2. *The unemployment income is low enough.* Lack of an insurance system decreases the value of the unemployment state.

3. *The arrival rate of offers is low enough.* Working alone is preferred when offers are too scarce anyway.

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

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

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

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

Having established that equation (21) describes the occupational choice, we can take a step further and characterize it as a condition on the discount rate:

$$\rho \geq \frac{\lambda}{y - b} \cdot \int_{w_r}^{\infty} (w - w_r)\, dF(w) - \delta \tag{23}$$

To be clear, equation (23) is just an alternative expression for equation (21) that formalizes the minimum discount rate sufficient to make the value of own-account work higher than the value of unemployment, given the labor market parameters. This particular expression is of interest because it shows that, under realistic conditions, there can always be an arbitrarily high level of preference for the present that rationalizes the choice for own-account work.

The inequalities above are meaningful if $\lambda$ is non-negative and finite (there is some friction in the market); $\rho + \delta$ are strictly positive (some degree of preference for the present); expected wage and reservation wage are finite (otherwise no finite outside option would beat it); and $y$ is strictly above $b$ (otherwise unemployment is trivially a better option).

### 3.7 Some insights from the model

*A. If anyone can work on their own, why is there unemployment?*

The possibility of autonomous work does not make it necessarily a better choice than unemployment. The job search framework explicitly tells us that unemployment is a valuable state in itself because it creates the possibility of finding a job — we just explore this idea to compare the value of unemployment to that of autonomous work. In summary, it is optimal to be a job-seeker if the discounted future stream of a potential wage is greater than the discounted future stream of own-account work income.

*B. Why is own-account work more prevalent in poor regions?*

The comparative statics outlined in the previous section shows that the elements associated with a higher relative valuation of own-account work are also the elements commonly found in developing labor markets. To be precise, a high incidence of own-account work would be consistent with lack of social welfare policies (low $b$); scarcity of job vacancies (low $\lambda$); lack of long-lasting jobs (high $\delta$), and underdeveloped financial markets and high interest rates (high $\rho$).

*C. Why do people work on their own if there exist better-paid wage jobs?*

The usual explanation suggests that individuals may value non-monetary aspects of own-account work. As an alternative to this view, the model suggests that a scarcity of job positions combined with a strong preference for present consumption is sufficient to justify this decision. For concreteness, the argument is that a family head with no savings may discount the future very heavily if day-to-day expenses are not secured. In that case, low earnings today are preferred to the alternative of investing time on the possibility of a minimum wage in 6 months, especially if the worker cannot access the financial market to smooth her intertemporal consumption. Notably, if the labor market conditions are stationary, the individual will be stuck: at each moment she is allowed to choose and at each moment she chooses the alternative that provides low, immediate earnings.

*D. If individuals decide by themselves to work alone, how can we talk about "necessity" cases? In which sense can own-account workers be constrained?*

The hypothetical case discussed just above illustrates how an occupation that provides a lower instantaneous income can still be more valuable for rational agents whose utility is determined only by monetary returns. In itself, it requires no market failure. If all transactions take place at market prices, there is little room to argue that their decision is not optimal in a strictly economic sense. The view from the dismal science is that workers facing low demand for their skills are as constrained as tourists who face high prices for ice-cream.

However, it can be the case that an individual who would like to anticipate future income *at the prevailing interest rates* to smooth her intertemporal consumption during the unemployment interval may be unable to do so because of market failures, be it missing markets or information asymmetry. For this worker, the possibility to quickly receive some work income instead may become her best (constrained) option.

When we frame the problem this way, we can offer a more precise interpretation for the idea of constrained own-account workers as those for whom such an occupation is preferred to searching for wage employment due to their high preference for the present, although they would have opted for looking for a better-paid wage job if they were able to finance consumption at the prevailing market rates during the search period. This approach has the benefit of backing the "necessity" occupational decision with a particular market failure, providing an objective meaning to the constraint.

### 3.8 Empirical estimation strategy

Our strategy to bring the model to the data is simply to translate the theoretical inequality on discount rates we established in equation (23) into its empirical counterpart. For that purpose, it is useful to reexpress the integral that appears in that expression as follows:

$$\rho \geq \frac{\lambda}{y-b} \cdot \left[ \int_{w_r}^{\infty} \left(w - w_r\right) \cdot f(w)\, d(w) \right] - \delta \tag{24}$$

$$\rho \geq \frac{\lambda}{y-b} \cdot \left[ \int_{w_r}^{\infty} w \cdot f(w)\, d(w) - \int_{w_r}^{\infty} w_r \cdot f(w)\, d(w) \right] - \delta \tag{25}$$

$$\rho \geq \frac{\lambda}{y-b} \cdot \left[ \int_{w_r}^{\infty} w \cdot f(w)\, d(w) - w_r \cdot \left[1 - F(w_r)\right] \right] - \delta \tag{26}$$

$$\rho \geq \frac{\lambda}{y-b} \cdot \left[ \mathbb{E}(w \mid w > w_r) - w_r \cdot \overline{F}(w_r) \right] - \delta \tag{27}$$

In other words, the difference between the stochastic job wage and the reservation wage integrated over the support of the acceptable wage offers is equivalent to the mean value of the gains from acceptable wages.

After that, an empirical counterpart for equation (27) for a given own-account worker $i$, with a vector of attributes $X_i$, can be written as:

$$\hat{\rho}_i \geq \frac{\mathbb{E}\left(\lambda \mid X_i\right)}{y_i - \mathbb{E}\left(b \mid X_i\right)} \cdot \left[\mathbb{E}\left(w \mid w > w_r, X_i\right) - \mathbb{E}\left(w_r \mid X_i\right) \cdot \mathbb{P}(w \geq w_r)\right] - \mathbb{E}\left(\delta \mid X_i\right) \quad (28)$$

where the theoretical parameters are substituted by conditional expected values that can be estimated. We will discuss the details of each step in the next section, but the outline of the estimation plan is:

- $\mathbb{E}\left(w \mid w > w_r, X_i\right)$: The potential wage is estimated by fitting a regression on the observed wage of employees;
- $\mathbb{E}\left(w_r \mid X_i\right)$: The reservation wage is assumed to be the conditional bottom 10th percentile of the observed wage of employees;
- $\mathbb{E}\left(b \mid X_i\right)$: The unemployment income is assumed to be zero;
- $\mathbb{E}\left(\delta \mid X_i\right)$: The expected job destruction rate is estimated using an exponential model of employment duration;
- $\mathbb{E}\left(\lambda \mid X_i\right)$: The expected job offer arrival rate is estimated using an exponential model of unemployment duration, given the probability that an offer will be acceptable;
- $\mathbb{P}(w \geq w_r)$: the probability that an offer will be acceptable is calculated off the fitted $\hat{w}$ and $\hat{w}_r$;
- $y_i$: The income from own-account work is directly observed for the individuals currently in this employment category;
- $\hat{\rho}_i$: the discount rate threshold is implied by the structural combination of all the components above for own-account workers, for whom the inequality must hold.

The fundamental assumption we make to claim that equation (28) is a credible translation of equation (27) is that the estimation of those parameters is consistent with the agent's perception of the market conditions they face. In other words, we take the econometric results to measure the empirical content equivalent to "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?". At the core, we fit an answer to each of those questions to uncover a parameter that is harder to observe, namely: "at which rate am I willing to change future consumption for present consumption?".

## 4 Data

The empirical analysis is based on a combination of two data sources: the 2017-2018 edition of the Brazilian Household Budget Survey ("Pesquisa de Orçamentos Familiares" or POF), a cross-section survey focused on earnings and expenditure (IBGE, 2019), whose work income data we explore to estimate potential wages and reservation wages, and the Brazilian National Household Survey ("Pesquisa Nacional por Amostra de Domicílios" or PNAD), a short rotating panel compiled quarterly (IBGE, 2018) that is the basis for our estimation of employment and unemployment duration.

Both surveys are run by the same statistical office ("Instituto Brasileiro de Geografia e Estatística" or IBGE), which contributes to their coherence in terms of the sociodemographic concepts employed. In particular, both capture the basic socioeconomic attributes of the individuals (family position, race, gender, age, schooling) using the same criteria, while allowing us to infer the general structure of the household (how many senior family members are there or if the head of the household lives with a partner, for example). This alignment is important because it avoids potential noise from translating non-identical concepts between surveys.

Besides the coherence of their content, both surveys cover the same population. POF and PNAD are designed to be nationally representative, thanks to a common stratification scheme based on Brazil's 2010 national census. In summary, IBGE's master sample divides the Brazilian population into small groups of at least 60 neighbor households, which compose the Primary Sampling Units (or PSUs), and PSUs are organized within relatively homogeneous strata, according to their sociogeographical and statistical characteristics. In a given survey, to ensure that enough households are observed in each region of interest, the PSUs are then sampled within their stratum, and about 14 random households are interviewed from each one of the sampled PSUs. Such design allows for estimations that are representative both at rural and urban areas, at the State level, for metropolitan areas, and the State's capitals (or any higher aggregation of those). The key point for us is that the POF and each of the quarterly rounds of the PNAD can be broadly seen as particular draws from a common pool.

The distinction between the two sources is their recurrence and their focus. The POF survey interviewed 57 920 households (comprising 178 431 individuals) between July 2017 and July 2018, but each family was contacted once, given the depth of the data collection. From our perspective, the focus on the household budget offers three main advantages. First, data on individual income is detailed and makes it possible to calculate net disposable work income in a comprehensive sense (adding extra hours, performance bonuses, and work-related government transfers, while deducting taxes). Second, its granular questionnaire reduces mismeasurement relative to a single, generic question on income. Third, this particular edition of the survey is enriched by a set of questions about access to credit, living standards, and food security that are rarely found on nationally representative datasets. Given the quality of this data, POF is taken to be the reference source for most of the estimation in what follows — the main drawback is that we can't infer typical employment and unemployment duration with this data without strong simplifications.

This limitation is overcome with PNAD, since it follows sampled households for 5 consecutive quarters, in a rotating panel structure. 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. Overall, this PNAD sample includes 4.5 million observations (about 560 000 observations per quarter).

From the original POF and PNAD data described above, we discard all observations from rural strata (about 25% of the full sample in both cases, representing close to 15% of the Brazilian population, thanks to oversampling in such areas). By doing so, we aim to restrict the discussion to the context of urban labor markets. We share the understanding that the dynamics of own-account work in rural areas are heavily related to local agriculture practices, access to land, and social rules, questions that are outside the scope of this investigation.

After calculating the household-specific statistics (the total number of kids in a household, for instance), we also discard individuals below 14 or above 64 years old (about 28% of the remaining sample and of the Brazilian urban population it represents). To summarize, the final population of interest is composed of working-age individuals in urban areas in the period 2017-2018, as described in table 1. In particular, within this population, we will compare and contrast own-account workers and employees, who are defined as such according to their most recent primary occupation.[9]

9. Due to its focus on yearly income and consumption, "most recent" in the POF refers to a period of 12 months. Since it does not inform whether the most recent occupation is still being held currently and it does not ask if the individual is looking for a job, there is no obvious measure of unemployment: either the individual was at some point occupied or did not work at all for 12 months, a case that we classify as inactivity. The PNAD, as a traditional labor market survey, understands "most recent" as the past week and adopts the usual definition of unemployment: currently not working and looking for work. In the analysis of transitions between labor market states, where this concept is central, we make use of the PNAD data and its standard definition.

**Table 1: Overview of the population of interest, according to the two data sources used in this paper: the Brazilian Household Budget Survey (POF), a cross-section collected between mid-2017 and mid-2018, and the Brazilian National Household Survey (PNAD), a short rotating panel collected on a quartely basis.**

| | POF (2017-2018 edition) | | | PNAD (2017Q1 to 2018Q4) | | |
|---|---|---|---|---|---|---|
| | Urban, working age individuals | | | Urban, working age individuals | | |
| | All | Own-account workers | Employees | All | Own-account workers | Employees |
| *Labor market status (share per category)* | | | | | | |
| Own-account worker | .209 | 1 | 0 | .187 | 0 | 0 |
| Employee | .415 | 0 | 1 | .391 | 0 | 0 |
| Employer | .0237 | 0 | 0 | .0295 | 1 | 0 |
| Inactive | .352 | 0 | 0 | .301 | 0 | 1 |
| Unemployed | . | . | . | .0913 | 0 | 0 |
| *Ethnicity and gender (share per category)* | | | | | | |
| Nonwhite female | .281 | .308 | .220 | .281 | .291 | .208 |
| Nonwhite male | .265 | .271 | .312 | .265 | .281 | .306 |
| White female | .243 | .217 | .224 | .243 | .214 | .228 |
| White male | .211 | .204 | .243 | .211 | .214 | .257 |
| *Age groups (share per category)* | | | | | | |
| 14-24 | .241 | .0954 | .189 | .241 | .0797 | .179 |
| 25-34 | .209 | .198 | .279 | .209 | .197 | .283 |
| 35-44 | .210 | .264 | .254 | .210 | .272 | .259 |
| 45-54 | .188 | .262 | .183 | .188 | .271 | .188 |
| 55-64 | .153 | .180 | .0942 | .153 | .180 | .0897 |
| *Highest educational level (share per category)* | | | | | | |
| Primary education or less | .149 | .211 | .0873 | .149 | .207 | .0824 |
| Lower secondary education | .231 | .269 | .161 | .231 | .272 | .154 |
| Upper seconday education | .390 | .366 | .423 | .390 | .365 | .423 |
| College or above | .230 | .153 | .330 | .230 | .157 | .340 |
| *Work income per month (in constant BRL)* | | | | | | |

**Table 1: Summary statistics.** ***(continued)***

| | POF (2017-2018 edition) | | | PNAD (2017Q1 to 2018Q4) | | |
|---|---|---|---|---|---|---|
| | Urban, working age individuals | | | Urban, working age individuals | | |
| | All | Own-account workers | Employees | All | Own-account workers | Employees |
| Median work income | 1409.5 | 994.3 | 1539.1 | 1350.5 | 1000.0 | 1447.0 |
| Average work income | 2221.3 | 1477.1 | 2328.1 | 2185.8 | 1521.2 | 2260.8 |
| *Survey structure* | | | | | | |
| Sample size | 96456 | 20658 | 37754 | 2316703 | 418294 | 878402 |
| Sample size per quarter | . | . | . | 289588 | 52287 | 109800 |
| Primary Sampling Units | 4597 | 4597 | 4597 | 13965 | 13965 | 13964 |
| Strata | 373 | 373 | 373 | 419 | 419 | 418 |
| Target population (million) | 125 | 26 | 52 | . | . | . |
| Target pop. per quarter (million) | . | . | . | 125 | 23 | 49 |

Notes: Rural strata are discarded in both surveys. Individuals below 14 or above 64 years old are removed after household statistics are computed. For POF, the labor status is understood as the most recent occupation within the previous 12 months, if any, while PNAD captures the occupation within the reference week and asks whether the individual is looking for a job, hence identifying unemployment cases. In constrast to the default classification from IBGE, domestic workers here are considered as own-account workers and not as employees, which increases the share of own-account workers by about 5 percentage points (from 25% to 30%) with respect to usual official figures from the same source. The PNAD data was reweighted in order to match the first moments of the POF data (per quarter and per region) on a basic set of individual indicators: ethnicity and gender, age groups, and education. Monetary values are calculated at constant January 2018 purchase power. At each one of the paid occupational category (employees, own-account workers and employers), the distribution of work income is winsorized at the 1st and at the 99th percentiles. Individual identifiers for PNAD are assigned following the advanced methodology from Ribas and Soares (2008), as implemented in Stata (StataCorp, 2015) by the user-written program `-datazoom_pnadcontinua-` from the Economics Department of PUC-Rio University.

The important takeaway from the summary statistics: compared to all Brazilian working-age individuals and to those who are employees, Brazilian own-account workers show a higher share of nonwhite individuals (in particular, of nonwhite females), as well as a higher share of older (35+) and less educated (lower secondary education or less) individuals. In line with what we discussed in section 2, both their median work income and their average work income are about 35% smaller than what is observed for employees. These patterns suggest that part of the income gap can be explained by the differences in the human capital of people who self-select into each occupation (as described in a traditional Roy model of relative productivity), combined with potential ethnic and gender segregation in the positions one may postulate to (one mechanism emphasized by the market segmentation hypothesis). To acknowledge the role played by both channels, one needs to compare individuals who are similar along those dimensions to discuss residual gaps. Individuals with more years of education and more experience can expect a higher wage, everything else constant, while people in a market with fewer opportunities can expect to take longer to find a job. Our objective is to investigate the potential role of heterogeneity in time preference (which cannot be observed directly in any survey), after all those known differences in labor market access have been accounted for.

# 5 Estimation: The discount rate embedded in the worker's choice

## 5.1 Potential wages: How much could I earn as an employee?

The first step of the empirical analysis is to estimate the conditional average income a given individual could expect to earn from a wage job based on the work income of employees who are observationally similar to them. These results have a central role in the model because higher potential wages will make paid employment a more attractive option vis-à-vis own-account work, everything else constant.

The statistical specification here is a regression of log monthly net work income on a set of socioeconomic observables that inform about the agent's relevant labor market and their human capital. To clean the marginal contribution of someone's attributes from the potential confounding with the particular selection of those who are observed as employees, the wage regression includes a control function, as suggested by Heckman (1979), exploring differences in household composition as excluding restrictions that help the selection model to discriminate between employees and non-employees.

In choosing the covariates, our objective was to be flexible, yet parsimonious. In particular, we split employees into discrete ethnicity-gender and age-education levels, to capture arbitrarily non-linear effects on those dimensions. All estimations control for regional differences, with regions being defined as either capital, metropolitan area (if any), or other cities, for each one of the 27 federative States, in a total of 77 exhaustive, mutually exclusive, and relatively homogeneous areas.

The coefficients for the main equation and the selection equation are reported in table 2 in the appendix. As expected, we find an increasing premium for education, more clearly so for workers above 35 years old, with particularly high gains for college diploma: everything else constant, the average wage for a 40 years old college graduate is expected to be 127% higher than the average wage for a 20-years old with primary education or less. We also document a steep gradient for the interaction of gender and ethnicity, increasing from nonwhite females (the reference group), to nonwhite males (+7%), to white females (+11%), to white males (+30%). Those relationships are ultimately used to recover conditionally expected wages.Since the model is fit in log terms, the linear index composed by the estimated coefficients and the attributes of the individuals of interest will lead to a predicted log wage. To avoid a transformation bias when translating it back into BRL levels, we adopt the "smearing" technique from Duan (1983), which has been shown to perform well in large samples as ours.

Note that neither the estimated potential wages nor the estimated reservation wages are ex-ante constrained to be above the official minimum wage defined for formal full-time jobs. As presented in section 2, many employees do earn less than the minimum wage, be it because they work part-time or because they work in jobs where the minimum wage is not enforced. From our perspective, the distinction between formal and informal jobs is irrelevant in the sense that both require searching for an employer. If some agents are more likely to find low-wage informal jobs, conditional on their attributes, this will be captured by a lower estimated potential wage.

### 5.2 Reservation wages: What's the minimum work income usually accepted by people like me?

Given that household surveys do not pose a direct question about the lowest wage an individual would be willing to accept, it is necessary to estimate it. As a starting point, one could simply take the absolute lowest value observed at conditional cells defined by a set of individuals 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 attenuate 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. To examine the sensitivity of the results to different cutoffs, in the robustness analysis we replicate the estimation with 5th and 15th percentiles.

The most important difference in comparison to the previous estimation is that now we introduce family characteristics into the main equation. This econometric choice is motivated by the idea that living alone or having two kids should not affect the wage opportunities a worker expect to see in the market (after correcting for selection), but it can affect the minimum monthly income someone is willing to accept (which is on a channel that could motivate the selection itself).

The signal of the remaining coefficients is largely aligned with what we found in the previous section, although the margins there refer to the average wage, while here they change the expected wage at the 10th percentile rank.

### 5.3 Employment and unemployment duration: How long does it take to find a job? How long will it last?

We've estimated the wage someone expects to receive as a paid employee and the typical values that are found at the lower end of the distribution of accepted wages. However, paid jobs are not found instantaneously and do not last forever. To calculate the value of looking for a job, we also need to estimate how long people usually spend in unemployment and how long those jobs typically last.

Those questions have a direct empirical measurement with duration analysis.[10] Because our theoretical model assumes agents forming expectations at steady state, the consistent choice is to use a parametric duration model that fits the duration outcome using an exponential distribution and, by construction, estimates transition hazards that are independent of the history of the job search.

To operationalize the empirical content of entry into paid employment as closely as possible, all other transitions from unemployment (namely, into inactivity or self-employment) are treated as censoring — intuitively, those changes prevent us from observing a transition into a wage job, in the same way that the end of follow up does. In other words, we are interested in a risk-specific hazard. On the other hand, in the case of end of employment, we treat all transitions as an event of job destruction, since the present discounted valuation of the job is affected only by its expected duration, not by the subsequent state.

[Comment the results from the estimation.]

10. Here we follow a long tradition in applied labor economics that uses duration estimation techniques to model individual spells in different employment states, in the spirit of the classic works of Kiefer (1988) and Meyer (1990). For a comprehensive treatment of these techniques, see Kalbfleisch and Prentice (2002). For other applications of duration analysis in the Brazilian context, see Menezes-Filho and Picchetti (2000) and Margolis (2009).

### 5.4 A note about the job offer arrival rate

The parameter of interest $\lambda$ in the model is the *rate of arrival of job offers* and represents the frequency according to which new employment positions appear to the job-seeker. In principle, it does need to coincide with the object we've estimated in the previous section, the *rate of transition into a job* (let's denote it as $h$, for clarity), which accounts only for the opportunities that are sufficiently attractive to be accepted.

By its nature, the arrival of job offers is much harder to track and is usually not included in labor surveys. However, we can make use of the asymptotic distribution of the estimated potential wage for a given individual $\hat{w}$ and of the estimated reservation wage for the same individual $\hat{w}_r$ to recover their estimated job arrival rate $\hat{\lambda}$, based on the statistical relationship:

$$h = \lambda \cdot \mathbb{P}(w > w_r) \tag{29}$$

Denoting by $\hat{\sigma}_{\hat{w}}$ and $\hat{\sigma}_{\hat{w}_r}$ the standard error of the individual estimations for potential wage and reservation wage, respectively, and assuming independence:

$$\mathbb{P}(\hat{w} - \hat{w}_r > 0) = 1 - \Phi\left(\frac{\hat{w} - \hat{w}_r}{\sqrt{\hat{\sigma}_{\hat{w}} + \hat{\sigma}_{\hat{w}_r}}}\right) \tag{30}$$

In practice, this technical step has little influence on the results, as our calculations suggest that offers are nearly always acceptable, under our simplifying assumptions: $\mathbb{P}(\hat{w} - \hat{w}_r > 0) \approx 1$ for the large majority of individuals. This means that the estimated arrival rate of offers $\hat{\lambda}$ is ultimately very close to the estimated transition rate $\hat{h}$.[11]

### 5.5 The expected value of unemployment income

The theory reasonably anticipates that any consumption smoothing insurance providing income for people looking for a job would increase the value of doing so. In the case of Brazil, the information available at both surveys used here suggests that such form of income is in practice negligible: the vast majority of the job-seekers report receiving no government insurance at all.

A few factors contribute to the weak role of formal unemployment insurance in the Brazilian context. Notably, the benefit can be provided only in the case of unjustified layoff of formal employees — therefore, people looking for a job for the first time, those coming from informal positions or from a long unemployment spell are automatically unqualified. When it exists, it lasts for at most five months, less than the average unemployment duration, and is typically equivalent to the minimum wage, its regulatory floor.

11. Interestingly, this is a recurrent result in the estimation of similar structural models, as discussed also in Wolpin (1987), Devine (1989) and van Den Berg (1990).

Given the small presence of insured job-seekers, there is very little informational gain from trying to estimate the probability of receiving the official benefit or from modeling the expected value of the insurance, since the result — a few extra BRLs per month — do not reflect the bimodality of few receivers and many no-receivers.

Informal transfers from within the agent's social network can play a similar role, but those are hard to be clearly and systematically captured, even with the detailed data from the consumption survey we have. The key conceptual difficulty is that $b$ must be tied to the unemployment condition: a differential transfer that arrives only while looking for a job. Any other income that is nonsystematic (or independent from the labor market state) does not increase *per se* the relative value of a given state versus another.[12]

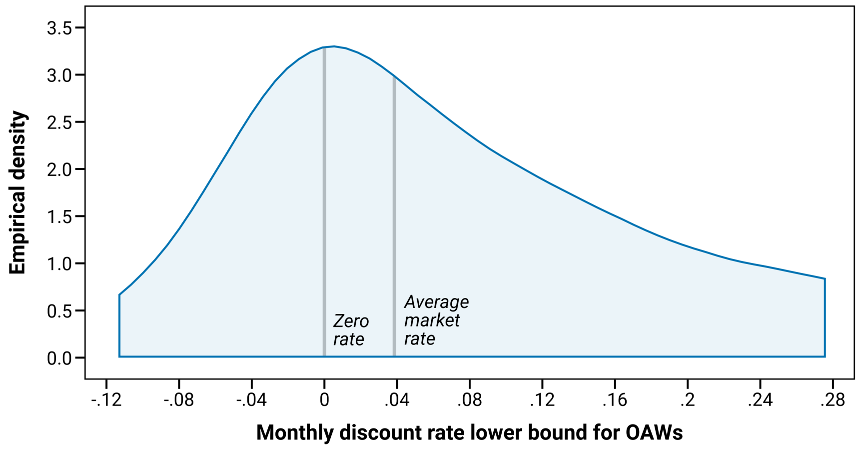
Hence, for tractability, we assume that workers do not account for any unemployment-related income when choosing their occupation. While acknowledging it is a limitation, we argue that this strategy has the appealing feature of being representative for the majority of the population.

### 5.6 Main results: the subjective discount rate lower bound

Now we have all the pieces to calculate the implicit time discount rate of the Brazilian own-account workers, as defined equation (28). The object we recover is a *lower bound for* $\rho$, in the sense that it is the minimum discount rate that makes the value of own-account work higher than the value of looking for a wage job, given the potential labor market conditions the workers are facing. Since this inequality must hold for every rational agent who has revealed their choice for working alone, we can calculate the individual $\rho$ lower bound and examine the distribution of such minima in the population of own-account workers, whose empirical density is plotted in figure 6.

12. To be precise, the availability of transfers can affect the value of different occupations in our framework *via* the discount rate, since agents within a family receiving earnings beyond their work income tend to have a lower consumption urgency and thus are less likely to take a poorly paid own-account work, as we find in section 6.

**Figure 6: Empirical density of the implicit discount rate lower bound for Brazilian own-account workers on 2017-2018**

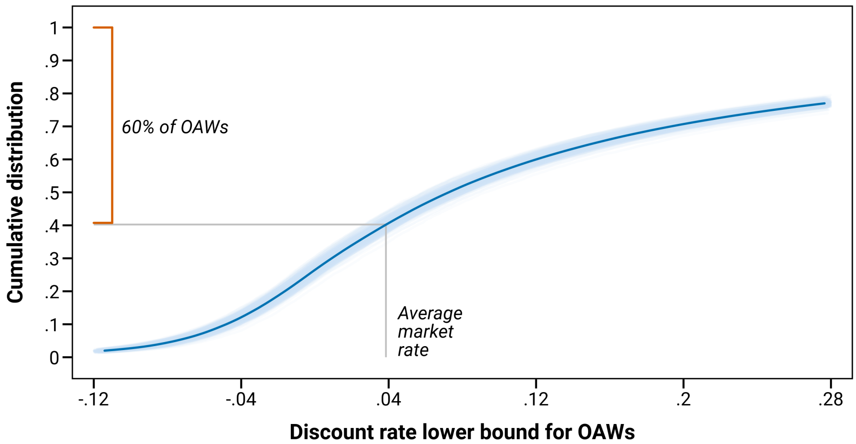



*Notes: The reference line marks the average consumer credit rate for individuals in 2017-2018, equivalent to 3.8% per month, according to the Brazilian Central Bank. Own calculation based on POF and PNAD surveys.*

To make sense of this distribution, it is useful to compare it to the interest rate observed in credit operations between banks and individual borrowers. For simplicity, we focus on new consumer loans, as reported by the Central Bank. During the analysis period (2017-2018), the average for such interest rate was 3.8% per month.

This value can serve as a threshold: when the lowest rate consistent with the observed occupational decision of the own-account worker is strictly above the average market rate for personal credit, we have some indirect evidence that the agent did not have access to such market, because had she been able to borrow at the prevailing rate, she would have chosen to search for wage work instead. The cumulative density of the lower bound of $\rho$, as plotted in figure 7, tells exactly how frequent this situation is.

**Figure 7: Empirical cumulative density of the implicit discount rate lower bound for Brazilian own-account workers on 2017-18**




*Notes: The dark blue curve shows the results from the baseline specification and the light blue curves represent each one of the 400 replications of such estimation, performed with clustered resampling of the data. The reference line marks the average consumer credit rate for individuals in 2017-2018, equivalent to 3.8% per month, according to the Brazilian Central Bank. Own calculation based on POF and PNAD surveys.*

At the lower end of the CDF, we find that 25% of the Brazilian own-account workers have an implicit minimum discount rate below zero. In the terms of the model, it suggests that their monthly pay is sufficiently above their potential wage job opportunities to ensure that their occupation would remain preferable regardless of any intertemporal consideration.

There is an intermediary group, comprising about 15% of the own-account workers, whose minimum implicit discount rate lies between zero and the market rate. In this case, their option for own-account work can be said to be driven by some degree of preference for the present but there's still no evidence of a constrained choice.

Finally, we find that 60% of the own-account workers in Brazil appear to be in this occupation due to a combination of labor market frictions and financial constraints, in the sense that the lowest time discount rate implied by their choice is strictly higher than the prevailing market rates. In those cases, the income they have in their occupation is so low (relative to potential labor market opportunities available for individuals similar to them) that rationalizing their decision requires a particularly high time discount rate.

These results imply that traditional models of comparative advantages, without frictions and without time, can explain only 25% of the own-account employment in Brazil. The other 75%, we argue, can only be rationalized with intertemporal considerations. Those individuals would be better off shifting to wage work if there were positions immediately available. Moreover, the majority of them would be better off even if they could finance the unemployment period at rates of 55% per year. It is in this sense that the possibility to bypass the job search process makes own-account work the best *constrained* option.

## 6 Who is more likely to have a higher discount rate lower bound?

What does it mean to have a high discount rate? Which workers are more likely to be at the high end of the curve?

Discuss the results of the regression of the estimated lower on individual attributes: (a) rho is decreasing in other income available in the household (everybody's income but mine); (b) rho is decreasing in measures of access to formal banking; (c) rho is increasing in bad home conditions, proxied by the number of people per sleeping room, and in bad food conditions, measured as "family member experiencing hunger in the past 90 days"; (d) rho is increasing in self-reported bad food, bad clothing, and bad health conditions. Compare different profiles using a linear combination of the parameters. Not causal evidence, risk of reverse causality, but is aligned with the plausible causal mechanism we put forward.

Note that the associations we find are not sufficient to determine how much of the discount rate could be predetermined as a fixed personality parameter and how much of it could be a function of specific environmental circumstances. While this question goes beyond the scope of this paper, the results from table 5 suggest a role for the contingent component.

## 7 Robustness exercises

### 7.1 Alternative quantiles in the estimation of the reservation wage

To estimate the reservation wage, we argued the conditional 10th centile is low enough to proxy the concept of lowest acceptable values and high enough to avoid the difficulties related to estimating extremes, such as the sensitivity to outliers and estimation instability. Still, it remains an arbitrary threshold. In this section, we briefly examine the results of the model using the 5th and 15th centiles.

Discuss the small variation found with the results. It is possible to bootstrap confidence intervals for the three curves, but computer-intensive.

## 8 Conclusion, caveats and possible extensions

This study considered how the interaction between labor market frictions and financial market failures can help to explain the higher presence of own-account work in developing countries. Absent frictions, workers can simply pick whatever occupation offers the highest income, but if job-seekers take time to find vacancies and cannot finance their present consumption, there is a trade-off between securing a small return quickly and waiting for higher income in the future. Using a simple extension of the job search model, we showed how a sufficiently high discount rate can make own-account work more valuable than unemployment.

In the empirical application, we used the counterpart of the model to infer how high such a discount rate needs to be for the particular case of own-account workers in Brazil. We find that 69% of them appear to be financially constrained, as their occupational choice suggests a discount rate that is strictly above the market rate. Additionally, our results highlight the importance of allowing for heterogeneity in time discounting, a parameter that is most often assumed homogeneous (and usually at the same level of the market rate) in theoretical and empirical research.

### 8.1 Consistency of the identification

Our empirical conclusions are valid conditional on two fundamental assumptions: (a) the model can capture the relevant components of the occupational decision, to a first-order approximation, and (b) our estimates of the labor market parameters are sufficiently close to how workers perceive their potential career opportunities. In a nutshell, we assume our expected values (in the statistical sense) to be a translation of the values expected by the individual (in a heuristic sense).

In the first case, we might have imposed an incorrect structure or omitted crucial elements in the agent's labor supply decision. This would be the case if social norms and peer effects are the major determinants, making workers less responsive to pure monetary returns. One could imagine, as an alternative hypothesis, that workers in poor regions are particularly averse to hierarchy and therefore more inclined to work on their own, regardless of their time discount. As it often happens with preferences, such a hypothesis could only be supported with a strong justification for why this particular taste would be more prevalent in some regions and for some particular subpopulations, which we do not have at this point.

In the second case, the agents could be systematically more (or less) confident on their chances of finding a job, or about the level of wages that firms are offering, compared to what our estimates suggest, and we would overestimate (or underestimate) their respective discount rate threshold. We cannot rule out that the agents are systematically mistaken about their opportunities, but this possibility would require some form of permanent limitation on their rationality.

### 8.2 Limitations and possible extension

Because the focus here is to discuss how intertemporal consumption can push agents into own-account work, we have focused on a parsimonious set of parameters, which imposes important simplifications. Notably, the model takes the range of jobs created by firms as given and assumes away any non-pecuniary attributes of a job. Moreover, since the environment is stationary in all parameters, this framework cannot be used to discuss dynamic processes, such as economic cycles (for the economy) or career trajectories (for individuals).

The perfect information assumption also means agents know ex-ante the range of wage offers they can expect to receive. In a richer model, agents could learn about their chances during unemployment and update their priors systematically. That could explain, for instance, why some individuals spend some time in unemployment before ultimately deciding for own-account work. In the model presented here, the optimal decision would have been to take own-account work immediately — but it is plausible to imagine that some agents could be overly optimistic at the start of their job search. The complement of this situation implies that some own-account workers (inefficiently) never bother to look for a job because they underestimate their chances. This imperfect information extension is left for future work.

The model also assumes away any issues related to physical or financial capital. As we described in section 4, the profile of the typical own-account worker suggests that such occupation does not require a large accumulation of capital. The decision to become an employer, by contrast, is likely more dependent on capital considerations. An interesting extension of this model would be to integrate the employers, whose return can be seen as a function of their productivity, as we did with own-account workers, combined with the productivity of their invested capital and their hired workers.

Furthermore, in the same way, we omitted preferences for a particular occupation, we also omitted any disutility of labor: in our model, the monthly income is sufficient to characterize the employment position. In practice, it means that a job that pays 1,000 for 40 hours is identical to a second one that pays 1,000 for 20 hours, and is preferable to a third one that pays 500 for 20 hours. We argue that this simplification is appropriate if individuals are mainly concerned with their monthly income in their labor supply decision. This view also makes a discussion about time discount rates more straightforward.

Note that extending this model to allow for on-the-job search would not change our conclusions, provided that the effectiveness of the search while occupied is strictly inferior to that of the search when unemployed. To be concrete, we are ruling out a situation where one finds a job more easily as an own-account worker than as an unemployed, in which case everyone would do so and unemployment would disappear. By contrast, allowing wage workers to receive offers (at any rate) would increase the present discounted value of the employee condition — and suggest even higher implicit discount rates for those who decide to be own-account workers instead of investing their time into finding a wage position. In any case, the estimated lower bound presented here remains a valid lower bound.

### 8.3 Policy implications

Our model adds a layer of complexity to the usual consensus in development economics according to which credit constraints *prevent people from working on their own*, since we claim that credit constraints *prevent people from finding a better job*. This apparent contradiction is due to the confusion over the empirical content of self-employment, as we discussed in section 2. If one has in mind that entrepreneurial activity requires capital (as in the case of a potential employer), then credit constraints hinder self-employment. In our model, by contrast, own-account work is valuable because it offers the possibility to bypass the job search period, thus the usual credit constraints will foster it.

That said, the immediate policy implication of our model is that it suggests a new reason in favor of programs that support present consumption during income shocks, be it privately or publicly organized. In absence of such smoothing, agents facing frictional labor markets and imperfect financial markets could rationally shift into relatively unproductive own-account work and get permanently stuck in a low-consumption equilibrium. According to our estimates, this is not a marginal possibility — it can be the main driver for the majority of own-account workers in a developing country.

We can claim that this would be welfare improving because the majority of own-account work in Brazil appears to be a misallocation of labor force driven by a combination of market failures. However, the most efficient way to address those market failures remains an open research question. It would be important to investigate whether a policy of unearmarked credit for the unemployed would be superior to the adoption of a comprehensive unemployment insurance rule, including those looking for a job for the first time, from the point of view of public finance, banking stability, credit risk, and social welfare — questions that the partial equilibrium model presented here cannot answer.

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# A Estimation output tables

**Table 2: Heckman selection model for potential wages.**

| | Main equation Log wage | | Selection equation P(state = wage worker) | |
|---|---|---|---|---|
| | coef. | s.e. | coef. | s.e. |
| Constant | 7.636* | (0.072) | -0.911* | (0.080) |
| *Gender and skin color (reference: nonwhite female)* | | | | |
| Nonwhite male | 0.072* | (0.013) | 0.475* | (0.016) |
| White female | 0.108* | (0.016) | 0.009 | (0.018) |
| White male | 0.262* | (0.015) | 0.267* | (0.019) |
| *Age and highest educ. level (reference: 14-24 years old, primary education or less)* | | | | |
| 14-24, lower secondary educ. | -0.022 | (0.062) | 0.010 | (0.069) |
| 14-24, upper secondary educ. | -0.091 | (0.059) | 0.529* | (0.068) |
| 14-24, college or above | 0.001 | (0.062) | 0.774* | (0.075) |
| 25-34, primary educ. or less | 0.214* | (0.071) | -0.014 | (0.081) |
| 25-34, lower secondary educ. | 0.113 | (0.061) | 0.279* | (0.071) |
| 25-34, upper secondary educ. | 0.194* | (0.058) | 0.578* | (0.067) |
| 25-34, college or above | 0.501* | (0.061) | 0.980* | (0.069) |
| 35-44, primary educ. or less | 0.251* | (0.062) | -0.158* | (0.070) |
| 35-44, lower secondary educ. | 0.257* | (0.060) | 0.119 | (0.068) |
| 35-44, upper secondary educ. | 0.384* | (0.059) | 0.414* | (0.067) |
| 35-44, college or above | 0.823* | (0.062) | 0.931* | (0.072) |
| 45-54, primary educ. or less | 0.387* | (0.062) | -0.271* | (0.071) |
| 45-54, lower secondary educ. | 0.435* | (0.061) | -0.150* | (0.071) |
| 45-54, upper secondary educ. | 0.575* | (0.060) | 0.159* | (0.069) |
| 45-54, college or above | 1.057* | (0.067) | 0.722* | (0.077) |
| 55-64, primary educ. or less | 0.495* | (0.062) | -0.602* | (0.071) |
| 55-64, lower secondary educ. | 0.589* | (0.065) | -0.502* | (0.076) |
| 55-64, upper secondary educ. | 0.763* | (0.067) | -0.223* | (0.075) |
| 55-64, college or above | 1.322* | (0.069) | 0.137 | (0.079) |
| *Currently studying (reference: not at school)* | | | | |
| Currently at public school | · | · | -0.641* | (0.028) |
| Currently at private school | · | · | -0.203* | (0.037) |
| Currently at public college | · | · | -0.279* | (0.052) |
| Currently at private college | · | · | -0.057 | (0.033) |
| *Family position (reference: child)* | | | | |
| Head, with partner, no kids | · | · | 0.487* | (0.029) |
| Head, with partner, with kids | · | · | 0.524* | (0.021) |

**Table 2: Heckman selection model for potential wages.** ***(continued)***

| | **Main equation Log wage** | | **Selection equation P(state = wage worker)** | |
|---|---|---|---|---|
| | coef. | s.e. | coef. | s.e. |
| Head, no partner, no kids | · | · | 0.456* | (0.030) |
| Head, no partner, with kids | · | · | 0.408* | (0.028) |
| Partner, no kids | · | · | 0.254* | (0.032) |
| Partner, with kids | · | · | 0.240* | (0.021) |
| Others | · | · | 0.099* | (0.021) |
| *Number of members in the family per age group* | | | | |
| N. kids (less than 15 years old) | · | · | -0.041* | (0.007) |
| N. young members (15-21) | · | · | -0.018* | (0.008) |
| N. adult members (22-64) | · | · | 0.019* | (0.007) |
| N. elderly members (65+) | · | · | -0.055* | (0.015) |
| *Local labor markets conditions* | | | | |
| 77 regional dummy indicators | Yes | · | Yes | · |
| *Heckman selection model ancillary parameters* | | | | |
| Errors correlation ($\rho$) | -0.809* | (0.010) | · | · |
| Standard deviation of errors ($\sigma$) | 0.749* | (0.009) | · | · |

Notes: Observations are weighted by the inverse of their sampling probability and standard errors are clustered, following the design of the data collection for the POF survey. A star (*) next to the coefficient signals its p-value is smaller than 0.05.

**Table 3: Models for estimation of reservation wages. Alternative specifications of quantile regressions for log wage as function of individual attributes at 5th, 10th (baseline) and 15th percentiles.**

| | Quantile 0.05 Log wage | | Quantile 0.10 Log wage | | Quantile 0.15 Log wage | |
|---|---|---|---|---|---|---|
| | coef. | s.e. | coef. | s.e. | coef. | s.e. |
| Constant | 5.830* | (0.068) | 5.826* | (0.224) | 6.129* | (0.085) |
| *Gender and skin color (reference: nonwhite female)* | | | | | | |
| Nonwhite male | 0.207* | (0.021) | 0.203* | (0.014) | 0.182* | (0.015) |
| White female | 0.070* | (0.027) | 0.073* | (0.016) | 0.064* | (0.018) |
| White male | 0.295* | (0.023) | 0.286* | (0.018) | 0.268* | (0.017) |
| *Age and highest educ. level (reference: 14-24 years old, primary education or less)* | | | | | | |
| 14-24, lower secondary educ. | -0.107* | (0.050) | 0.094 | (0.227) | 0.106 | (0.091) |
| 14-24, upper secondary educ. | 0.222* | (0.056) | 0.514* | (0.223) | 0.395* | (0.078) |
| 14-24, college or above | 0.481* | (0.065) | 0.646* | (0.225) | 0.557* | (0.094) |
| 25-34, primary educ. or less | 0.109 | (0.172) | 0.399 | (0.223) | 0.279* | (0.092) |
| 25-34, lower secondary educ. | 0.341* | (0.075) | 0.566* | (0.224) | 0.473* | (0.087) |
| 25-34, upper secondary educ. | 0.667* | (0.054) | 0.818* | (0.222) | 0.663* | (0.077) |
| 25-34, college or above | 0.897* | (0.056) | 1.036* | (0.222) | 0.914* | (0.081) |
| 35-44, primary educ. or less | 0.187* | (0.053) | 0.442 | (0.234) | 0.415* | (0.095) |
| 35-44, lower secondary educ. | 0.283* | (0.106) | 0.664* | (0.225) | 0.545* | (0.081) |
| 35-44, upper secondary educ. | 0.800* | (0.048) | 0.894* | (0.222) | 0.739* | (0.077) |
| 35-44, college or above | 1.072* | (0.055) | 1.249* | (0.224) | 1.111* | (0.081) |
| 45-54, primary educ. or less | 0.235* | (0.103) | 0.546* | (0.228) | 0.475* | (0.083) |
| 45-54, lower secondary educ. | 0.401* | (0.112) | 0.738* | (0.225) | 0.625* | (0.080) |
| 45-54, upper secondary educ. | 0.763* | (0.052) | 0.868* | (0.223) | 0.721* | (0.078) |
| 45-54, college or above | 1.079* | (0.064) | 1.271* | (0.225) | 1.181* | (0.091) |
| 55-64, primary educ. or less | 0.099 | (0.086) | 0.350 | (0.260) | 0.389* | (0.095) |
| 55-64, lower secondary educ. | 0.517* | (0.054) | 0.594* | (0.222) | 0.487* | (0.089) |
| 55-64, upper secondary educ. | 0.690* | (0.052) | 0.803* | (0.223) | 0.704* | (0.080) |
| 55-64, college or above | 0.979* | (0.055) | 1.194* | (0.226) | 1.105* | (0.087) |
| *Currently studying (reference: not at school)* | | | | | | |
| Currently at public school | -0.487* | (0.073) | -0.514* | (0.035) | -0.545* | (0.041) |
| Currently at private school | -0.179 | (0.133) | -0.177* | (0.083) | -0.125* | (0.024) |
| Currently at public college | -0.356* | (0.040) | -0.337* | (0.065) | -0.330* | (0.066) |
| Currently at private college | -0.175* | (0.054) | -0.153* | (0.022) | -0.153* | (0.036) |
| *Family position (reference: child)* | | | | | | |
| Head, with partner, no kids | 0.350* | (0.058) | 0.335* | (0.021) | 0.308* | (0.033) |
| Head, with partner, with kids | 0.385* | (0.030) | 0.360* | (0.020) | 0.356* | (0.020) |
| Head, no partner, no kids | 0.306* | (0.043) | 0.273* | (0.023) | 0.270* | (0.028) |
| Head, no partner, with kids | 0.311* | (0.043) | 0.307* | (0.026) | 0.283* | (0.025) |

**Table 3: Models for estimation of reservation wages.** ***(continued)***

| | **Quantile 0.05 Log wage** | | **Quantile 0.10 Log wage** | | **Quantile 0.15 Log wage** | |
|---|---|---|---|---|---|---|
| | coef. | s.e. | coef. | s.e. | coef. | s.e. |
| Partner, no kids | 0.259* | (0.047) | 0.271* | (0.028) | 0.262* | (0.026) |
| Partner, with kids | 0.281* | (0.032) | 0.261* | (0.021) | 0.268* | (0.021) |
| Others | 0.061 | (0.057) | 0.080* | (0.030) | 0.104* | (0.025) |
| *Number of members in the family per age group* | | | | | | |
| N. kids (less than 15 years old) | -0.037* | (0.006) | -0.035* | (0.006) | -0.027* | (0.007) |
| N. young members (15-21) | -0.049* | (0.010) | -0.042* | (0.008) | -0.048* | (0.007) |
| N. adult members (22-64) | 0.015 | (0.009) | 0.015* | (0.006) | 0.010 | (0.006) |
| N. elderly members (65+) | -0.062 | (0.035) | -0.070* | (0.016) | -0.051* | (0.016) |
| *Local labor markets conditions* | | | | | | |
| 77 regional dummy indicators | Yes | · | Yes | · | Yes | · |

Notes: Observations are weighted by the inverse of their sampling probability, according to the design of the data collection for the POF survey. A star (*) next to the coefficient signals its p-value is smaller than 0.05.

**Table 4: Employment and unemployment duration models. The first model estimates the hazard of transition out of wage work and the second one estimates the hazard of transition from unemployment into wage work. In both cases, the parametric estimation assumes constant hazard, incorporates all types of censoring and allows for a two-type mixture for unobserved heterogeneity.**

| | **Out of wage work transition hazard. Exponential model, 2 types mixture** | | **Unemp. into wage work transition hazard. Exponential model, 2 types mixture** | |
|---|---|---|---|---|
| | hazard ratio | s.e. | hazard ratio | s.e. |
| Constant | 0.059* | (0.005) | 0.035* | (0.005) |
| *Gender and skin color (reference: nonwhite female)* | | | | |
| Nonwhite male | 0.989 | (0.017) | 1.882* | (0.059) |
| White female | 1.031 | (0.022) | 1.101* | (0.047) |
| White male | 0.949* | (0.019) | 1.613* | (0.064) |
| *Age and highest educ. level (reference: 14-24 years old, primary education or less)* | | | | |
| 14-24, lower secondary educ. | 1.055 | (0.075) | 0.923 | (0.105) |
| 14-24, upper secondary educ. | 0.619* | (0.044) | 0.939 | (0.105) |
| 14-24, college or above | 0.439* | (0.038) | 1.144 | (0.141) |
| 25-34, primary educ. or less | 0.849 | (0.071) | 0.958 | (0.135) |
| 25-34, lower secondary educ. | 0.754* | (0.057) | 1.039 | (0.126) |
| 25-34, upper secondary educ. | 0.447* | (0.032) | 1.075 | (0.125) |
| 25-34, college or above | 0.297* | (0.023) | 1.098 | (0.134) |
| 35-44, primary educ. or less | 0.859* | (0.065) | 0.918 | (0.117) |
| 35-44, lower secondary educ. | 0.675* | (0.050) | 0.826 | (0.102) |
| 35-44, upper secondary educ. | 0.411* | (0.030) | 0.953 | (0.117) |
| 35-44, college or above | 0.252* | (0.020) | 0.992 | (0.133) |
| 45-54, primary educ. or less | 0.819* | (0.060) | 0.795 | (0.111) |
| 45-54, lower secondary educ. | 0.621* | (0.047) | 0.752* | (0.100) |
| 45-54, upper secondary educ. | 0.424* | (0.033) | 0.770* | (0.102) |
| 45-54, college or above | 0.286* | (0.022) | 0.773 | (0.119) |
| 55-64, primary educ. or less | 0.895 | (0.070) | 0.496* | (0.079) |
| 55-64, lower secondary educ. | 0.754* | (0.061) | 0.556* | (0.093) |
| 55-64, upper secondary educ. | 0.575* | (0.046) | 0.464* | (0.085) |
| 55-64, college or above | 0.472* | (0.036) | 0.433* | (0.105) |
| *Currently studying (reference: not at school)* | | | | |
| Currently at public school | 1.689* | (0.048) | 0.820* | (0.040) |
| Currently at private school | 1.106 | (0.059) | 1.291* | (0.111) |
| Currently at public college | 1.509* | (0.085) | 1.274* | (0.120) |
| Currently at private college | 0.990 | (0.045) | 1.170* | (0.072) |
| *Family position (reference: child)* | | | | |

**Table 4: Employment and unemployment duration models.** ***(continued)***

| | **Out of wage work transition hazard. Exponential model, 2 types mixture** | | **Unemp. into wage work transition hazard. Exponential model, 2 types mixture** | |
|---|---|---|---|---|
| | hazard ratio | s.e. | hazard ratio | s.e. |
| Head, with partner, no kids | 0.809* | (0.024) | 1.505* | (0.107) |
| Head, with partner, with kids | 0.716* | (0.016) | 1.417* | (0.073) |
| Head, no partner, no kids | 0.839* | (0.026) | 1.297* | (0.083) |
| Head, no partner, with kids | 0.787* | (0.025) | 1.307* | (0.096) |
| Partner, no kids | 0.850* | (0.028) | 1.381* | (0.095) |
| Partner, with kids | 0.782* | (0.019) | 1.410* | (0.073) |
| Others | 0.942* | (0.025) | 1.225* | (0.050) |
| *Number of members in the family per age group* | | | | |
| N. kids (less than 15 years old) | 1.068* | (0.009) | 1.040* | (0.014) |
| N. young members (15-21) | 1.086* | (0.011) | 0.997 | (0.019) |
| N. adult members (22-64) | 1.010 | (0.008) | 1.000 | (0.014) |
| N. elderly members (65+) | 1.024 | (0.017) | 0.929* | (0.029) |
| *Local labor markets conditions* | | | | |
| 77 regional dummy indicators | Yes | · | Yes | · |
| *Ancillary model parameters* | | | | |
| Hazard ratio for high type | 6.339* | (0.246) | 3.326* | (0.095) |
| Share of high type | 0.413* | (0.010) | 0.661* | (0.020) |

Notes: The reported coefficients and standard errors are bootstrapped over 200 replications, with PSUs being resampled with replacement independently at each one of the 77 geographical regions to account for potential error correlation. A star (*) next to the coefficient signals its p-value is smaller than 0.05.

**Table 5: Determinants of the estimated discount rate lower bound.**

| | Family structure | | Credit access | | Housing and food security | | Life conditions | |
|---|---|---|---|---|---|---|---|---|
| | coef. | s.e. | coef. | s.e. | coef. | s.e. | coef. | s.e. |
| Constant | 0.565* | (0.087) | 0.594* | (0.087) | 0.451* | (0.088) | 0.534* | (0.087) |
| *Family position (reference: child)* | | | | | | | | |
| Head, with partner, no kids | -0.134* | (0.030) | -0.110* | (0.030) | -0.126* | (0.031) | -0.113* | (0.030) |
| Head, with partner, with kids | -0.117* | (0.024) | -0.091* | (0.024) | -0.092* | (0.024) | -0.085* | (0.024) |
| Head, no partner, no kids | -0.090* | (0.032) | -0.076* | (0.031) | -0.087* | (0.032) | -0.080* | (0.031) |
| Head, no partner, with kids | -0.086* | (0.030) | -0.065* | (0.030) | -0.078* | (0.030) | -0.066* | (0.029) |
| Partner, no kids | -0.012 | (0.031) | -0.003 | (0.031) | -0.015 | (0.031) | -0.000 | (0.031) |
| Partner, with kids | -0.007 | (0.024) | 0.005 | (0.024) | 0.007 | (0.024) | 0.012 | (0.024) |
| Others | 0.026 | (0.028) | 0.031 | (0.028) | 0.028 | (0.028) | 0.032 | (0.028) |
| *Number of members in the family per age group* | | | | | | | | |
| N. kids (less than 15 years old) | 0.040* | (0.007) | 0.037* | (0.007) | 0.013 | (0.007) | 0.032* | (0.007) |
| N. young members (15-21) | -0.008 | (0.008) | -0.011 | (0.008) | -0.024* | (0.008) | -0.012 | (0.008) |
| N. adult members (22-64) | -0.032* | (0.008) | -0.031* | (0.008) | -0.035* | (0.008) | -0.030* | (0.008) |
| N. elderly members (65+) | -0.050* | (0.016) | -0.051* | (0.016) | -0.051* | (0.016) | -0.049* | (0.016) |
| *Income earned by other family members (in 1 000 BRL)* | | | | | | | | |
| Family per capita income ex self | -0.012* | (0.003) | -0.008* | (0.003) | -0.006 | (0.003) | -0.006* | (0.003) |
| *Access to financial products* | | | | | | | | |
| Has credit card | · | · | -0.085* | (0.015) | -0.071* | (0.015) | -0.080* | (0.015) |
| Has current account | · | · | -0.073* | (0.014) | -0.064* | (0.014) | -0.069* | (0.014) |
| Has savings account | · | · | -0.055* | (0.012) | -0.047* | (0.012) | -0.052* | (0.012) |
| *Housing conditions* | | | | | | | | |
| Own house | · | · | · | · | 0.017 | (0.013) | · | · |
| People per sleeping room | · | · | · | · | 0.026* | (0.009) | · | · |
| *Food security* | | | | | | | | |
| Worried about food shortage | · | · | · | · | 0.057* | (0.015) | · | · |
| Family member faced hunger | · | · | · | · | 0.155* | (0.017) | · | · |
| *General living standards (reference: good or satisfactory conditions)* | | | | | | | | |
| Bad food conditions | · | · | · | · | · | · | 0.120* | (0.025) |
| Bad clothing conditions | · | · | · | · | · | · | 0.161* | (0.023) |
| Bad health conditions | · | · | · | · | · | · | 0.051* | (0.014) |
| Bad leisure conditions | · | · | · | · | · | · | 0.009 | (0.013) |
| Bad housing conditions | · | · | · | · | · | · | -0.009 | (0.022) |
| Bad education conditions | · | · | · | · | · | · | -0.019 | (0.019) |
| *Ethnicity, gender, age, education and local markets conditions* | | | | | | | | |
| Include controls | Yes | · | Yes | · | Yes | · | Yes | · |

**Table 5: Determinants of the estimated discount rate lower bound. *(continued)***

| | Family structure | | Credit access | | Housing and food security | | Life conditions | |
|---|---|---|---|---|---|---|---|---|
| | coef. | s.e. | coef. | s.e. | coef. | s.e. | coef. | s.e. |
| *Model statistics* | | | | | | | | |
| R-Square | 0.065 | · | 0.071 | · | 0.080 | · | 0.078 | · |

Notes: Observations are weighted by the inverse of their sampling probability, according to the design of the data collection for the POF survey, as well as by the inverse of the variance of the estimated dependent variable, as to give more weight to individuals whose discount rate lower bound was estimated more precisely in the previous step. A star (*) next to the coefficient signals its p-value is smaller than 0.05.

## B Maximum Likelihood Estimation of the duration models

To the best of our knowledge, no statistical software to date offers a pre-programmed semi-parametric estimation of transition hazards that, at the same time, accommodates the possibility of stock sampling combined with interval censoring and a potential mixture of unobserved components, despite an established framework about how it could theoretically be built. To bridge this gap, we adopt a general maximum likelihood approach and write a statistical model that is flexible enough to use the information available in all the different cases recorded in our data.

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 period, 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 are oversampled.

Furthermore, when there is a state transition, we can only see that it took place somewhere between the previous and the current quarter: they are interval-censored. While this is generally the case for most labor market surveys, economists tend to overlook the issue and assume a transition in the midpoint, tolerating the approximation when using monthly data. Since we have quarterly intervals, the imprecision would be more relevant.

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, where they are allowed to have different intercepts while sharing the remaining coefficients. The share of high types and the gap between the two intercepts enter as additional parameters in the maximization process, subject to convenient regularity conditions, as the share needs to be in the interval $[0, 1]$ and the gap should be constrained to be positive (or negative) to ensure a single solution. It is in this sense that the estimation is semi-parametric: an exponential model is assumed for the hazard, but the mixture itself is just an average of two types.

The mixture model does not identify the type of a given individual, however. To predict a conditionally expected duration, we simply use a weighted average again to combine the linear index of the individual attributes and the model coefficients for high and low types, using the weights fitted by the model. The key advantage over a model with no mixture is not to fit on unobservables — which would be too ambitious — but to fit the observables on potentially less biased coefficients.

Even though the statistical model could allow for a monotonic hazard, here we constrain the estimation to the exponential case. This way, the hazard is constant over the spell, mirroring the stationarity conditions assumed in the theoretical framework.

Add the MLE equations