Life-cycle, Self-employment, and Credit Constraints

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1 Introduction

A high self-employment rate is a prominent feature of developing economies. In India, 51.4% of the total employed population was self-employed during 2011-2012 (ILO, 2018). Whereas for the U.S., this figure was 6.8% (OECD, 2018).[1] The difference in self-employment prevalence is a consequence of poor labor market conditions that induce a lack of choice for people in developing economies (Margolis, 2014).

On the other hand, credit constraints impose difficulties for entry and growth of the self-employed who face steep credit prices (Fields, 2019). For the case of Brazil, in de Sousa and Ottaviano (2018), the authors find that loans made by the Brazilian Development Bank (BNDES) help financially constrained small firms match the outcomes of unconstrained firms. In the Indian case, evidence supports that affordable microcredits help self-employed women engage in more profitable investments and alleviate poverty (Aruna and Jyothirmayi, 2011; Ghosh, 2012).

While potentially crucial, there are currently few discussions on the transition to self-employment in the presence of credit constraints. However, the discussion could be relevant in developing economies. As we will show in the descriptive statistics, paid employees earn more on average than the self-employed in India, and self-employment might serve as a temporary defense against household financial shock such as a new consumption debt and an unstable monthly payment stream. Therefore, if households can access affordable consumption loans, they might resort less to self-employment when

[1] This includes only non-incorporated self-employment for the US, but for other high-income countries like Germany and France, the percentage of self-employed workers is no greater than 12%.

they face negative financial shocks. In addition, being self-employed might be associated with riskier future income. More affordable credit means households can smooth consumption more easily. On the other hand, workers facing unstable working conditions could switch to self-employment if they gain access to credit to initially fund investments. The interaction between self-employment and credit constraints in developing economies is potentially ambiguous. In this proposal, we will use Indian data to scrutinize the relationship between self-employment and credit constraints and propose a model to understand better how credit access affects the decision to enter or exit self-employment.

Two strands of literature relate closely to our work. The first strand of literature studies self-employment: who selects self-employment, why, and the consequences of doing so. A couple of stylized facts introduced in this literature are that (1) self-employment is riskier and worse paid compared to paid employment (Hamilton, 2000), (2) Self-employment is different from entrepreneurship and lumping them together yields the conclusion that self-employment is worse paid, (3) Credit constraints limit entry into self-employment (Levine and Rubinstein, 2018; Humphries, 2017; Block and Sandner, 2009). The evidence that supports these findings is constructed using data from developed economies. Literature studying the phenomenon of developing economies has reached different conclusions. In recent work, Borchhardt and Sorenson (2022) proposed that in India, self-employment provides a more stable income flow than paid employment. In this case, workers facing low and unstable income in paid employment could recur to self-employment. In Oyenubi et al. (2019), the author finds in the case of Ghana that the average self-employed have higher earnings than the paid employed counterparts but that the top of the earnings distribution drives this difference.

The second strand of literature related to our work studies how access to credit affects developing economies. In this field, two of the most important works are Kaboski and Townsend (2011) and Banerjee and Duflo (2014). Both of them use quasi-experimental data. In the first paper, the authors find that a program to facilitate access to microcredit increases households' consumption at the one-to-one ratio and that the effect on investment is unclear. To further decompose the effects, they use a model of credit-constrained households with indivisible investments that match the data. With these results, the authors can uncover that access to credit allows constrained households to invest in high-yield projects and for other households to supplement consumption or pay other high-cost loans. In the second paper, the authors study how firms changed after accessing a targeted lending program. They conclude that many firms faced strong credit constraints and high marginal return to capital. In the presence of the program, they used access to credit to increase production by investing in capital.

In the rest of this proposal, we will describe the data set we will use in section two. Then, section three provides evidence of the connection between credit and self-employment, both in participation and performance. In section four, we will introduce the model we propose for estimation. Finally, in Section Five, we will provide a roadmap for the paper's completion and potential problems we might face.

2 Data

To implement this idea, we use the Consumer Pyramids Household Survey (CPHS), a household panel survey carried out by the Centre for Monitoring the Indian Economy (CMIE). The survey reports income, expenditure, working conditions, and household characteristics. The sample of CPHS is representative nationally, by state, and by a grouping of districts created by CMIE named homogeneous regions. The survey is conducted through three yearly waves per household, with around 160000 households per wave. We use data starting in 2017 and 2021.

We use only individuals who participate in the labor force at some point during their presence on the survey.[2] The final sample includes 364,326 individuals in 176,115 households with an average presence in 21 waves.

CPHS has high-quality records of both income and expenditure. Households report in each wave the monthly income of the household and each member, both total and from various sources *e.g.* wages, business profits. On the other hand, households report

[2]That implies that individuals who are students, housemakers, or retirees throughout the survey are excluded

monthly and weekly expenses on each wave. The weekly expenses focus on consumption goods and services that are usually purchased with higher frequency. In contrast, the monthly expenses are detailed in over 100 categories, including food, apparel, utilities, transportation, education, health, and Equated Monthly Installments (EMIS).

CPHS also has a detailed panel of occupational information. On each wave, the participants report their employment status, duration of the status, nature of employment (salaried permanent, temporary, or self-employment), and occupation industry. This allows us to identify unemployment spells and occupation transition, especially self-employment status. Finally, the survey includes a set of variables that describe the asset-holding position of the household. These variables are dummies that record whether a household has debt, the source of the debt, the purpose (consumption, business expenses, purchasing appliances, etc), and information about asset holding.

We use another dataset, the latest waves (2013,2019) of the All India Debt and Investment Survey (AIDIS), to supplement the CPHS dataset. The National Statistical Office (NSO) conducts the survey as part of the National Sample Survey (NSS report No. 588). It is a nationally representative household survey. The 2019 wave includes 69455 rural households across 5940 villages and 47006 urban households across 3995 blocks. Before the 2019 survey, four AIDIS surveys were conducted: 1971-72, 1981-82, 1992, 2003, and 2013. Different waves sample different cross-sections of households. To the best of our knowledge, AIDIS is the only public comprehensive survey in India with granular information about household demographics and detailed records of households' financial instruments. Unlike CPHS, the survey provides a detailed description of all the outstanding financial instruments households hold. It provides household-instrument level information such as the credit agency, original amount, paid amount, annualized interest rate, etc. We expect to identify various credit sources' credit limits and costs from this dataset.

3 Descriptive statistics

In Table 1, we present a set of descriptive statistics dividing our sample into five groups: daily wage workers, out of the market, salaried permanent, salaried temporary, and self-employed.[3] We see 31.11% of self-employed individuals, the largest group among the labor force. The self-employed have a similar composition to salaried temporary workers in terms of caste, education, religion, and gender. Self-employed individuals are more educated than daily wage workers but less than salaried permanent workers. Income is larger for salaried permanent workers and lowest for self-employed workers. The largest proportion of individuals who have debt is the daily wage workers, which supports the conjecture that access to credit helps employees in poor labor conditions to smooth out consumption. Table 2 presents the transition matrix for the same five groups. While the persistence of each group is large, we see the most transition going from daily wage and salaried temporary workers to self-employed. This aligns with the idea that workers in poor labor conditions are switching to self-employment.

We explore how income has changed over time for self-employees compared to paid workers in Figure 1. An average paid worker earned more money than a self-employee. In addition, the average income of self-employees is more unstable over time, except in the period corresponding to the COVID-19 lockdowns, where the paid employees experienced a larger decrease in average income. In Figure 2, we explore the proportion of self-employed who use debt compared to the proportion of paid employees. Paid employees consistently use more credit than self-employed workers. This would support the conjecture that households with access to credit can smooth their consumption and not switch to self-employment.

[3]Out of market includes all individuals who are not currently in the labor force, e.g., students or homemakers

Table 1: Descriptive statistics by employment arrangement

	Daily wage worker		Out of market		Salaried permanent		Salaried temporary		Self-employed	
	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd
Age	39.503	12.768	41.329	17.357	41.145	11.288	35.909	11.944	42.630	12.521
Caste										
Intermediate	0.048	0.214	0.103	0.304	0.125	0.331	0.077	0.267	0.116	0.320
Not stated	0.012	0.108	0.013	0.112	0.024	0.153	0.010	0.100	0.012	0.107
Other backwards	0.388	0.487	0.386	0.487	0.314	0.464	0.388	0.487	0.413	0.492
Scheduled tribes	0.361	0.480	0.221	0.415	0.175	0.380	0.257	0.437	0.147	0.354
Upper	0.100	0.300	0.219	0.413	0.325	0.468	0.221	0.415	0.259	0.438
Education										
No education	0.048	0.213	0.037	0.189	0.010	0.099	0.023	0.150	0.025	0.155
Incomplete high school	0.832	0.374	0.607	0.488	0.308	0.462	0.594	0.491	0.643	0.479
High school	0.069	0.254	0.160	0.366	0.159	0.366	0.170	0.376	0.157	0.363
College	0.024	0.154	0.120	0.325	0.282	0.450	0.136	0.343	0.110	0.312
Graduate	0.026	0.161	0.076	0.265	0.241	0.428	0.077	0.267	0.066	0.249
Debt	0.466	0.499	0.402	0.490	0.359	0.480	0.436	0.496	0.410	0.492
Log of Income	7.672	3.323	2.253	3.975	8.788	3.414	7.706	3.512	5.619	4.586
Male	0.845	0.362	0.541	0.498	0.876	0.329	0.841	0.365	0.908	0.289
Religion										
Buddhist	0.009	0.095	0.008	0.088	0.007	0.084	0.012	0.109	0.004	0.062
Cristian	0.019	0.136	0.018	0.134	0.025	0.155	0.020	0.139	0.013	0.111
Hindu	0.836	0.370	0.854	0.353	0.871	0.335	0.850	0.357	0.837	0.369
Muslim	0.113	0.316	0.093	0.291	0.056	0.230	0.101	0.302	0.106	0.308
Sikh	0.001	0.037	0.003	0.057	0.004	0.061	0.003	0.051	0.005	0.069
Other	0.022	0.147	0.024	0.152	0.037	0.189	0.014	0.118	0.036	0.186
N	2219896		4215407		1436157		1083996		4043388	
	17.08%		32.43%		11.05%		8.34%		31.11%	

Table 2: Transition matrix for employment status

	Daily wage worker	Out of market	Salaried permanent	Salaried temporary	Self-employed
Daily wage worker	92.819	2.449	0.334	0.782	3.616
Out of market	1.635	95.168	0.445	0.597	2.156
Salaried - permanent	1.113	1.870	92.696	1.288	3.033
Salaried - temporary	2.416	2.686	1.706	89.478	3.713
Self-employed	2.133	2.142	0.612	0.613	94.499

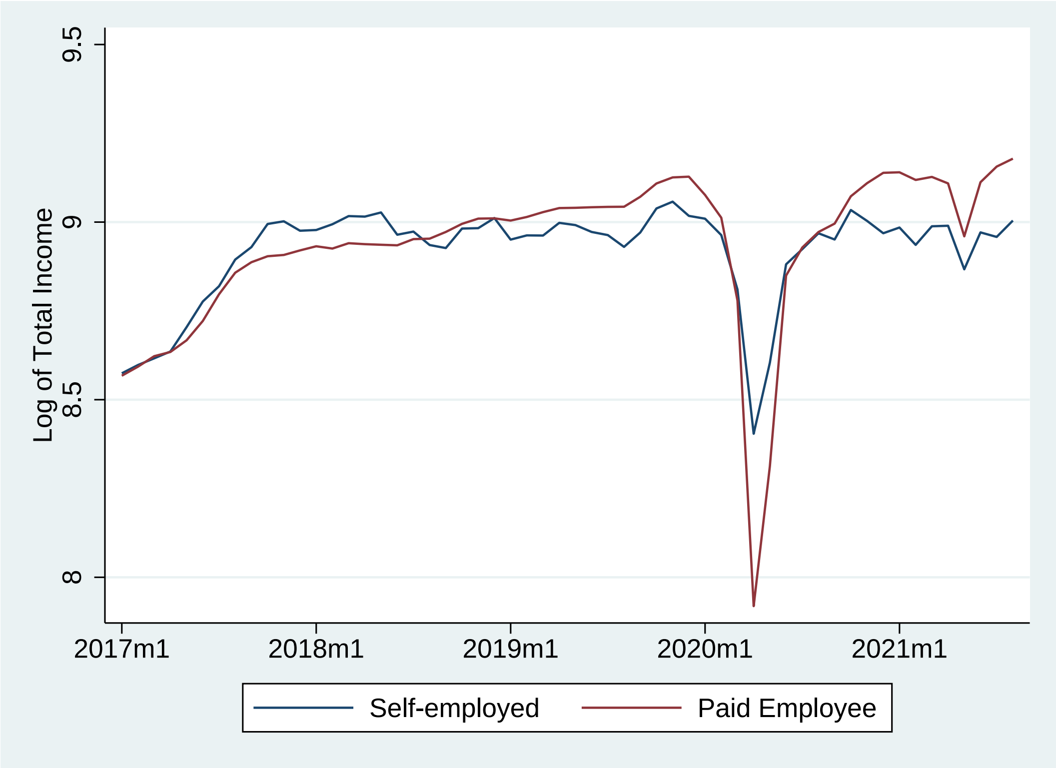

Figure 1: Income: Paid employees vs. Self-employed

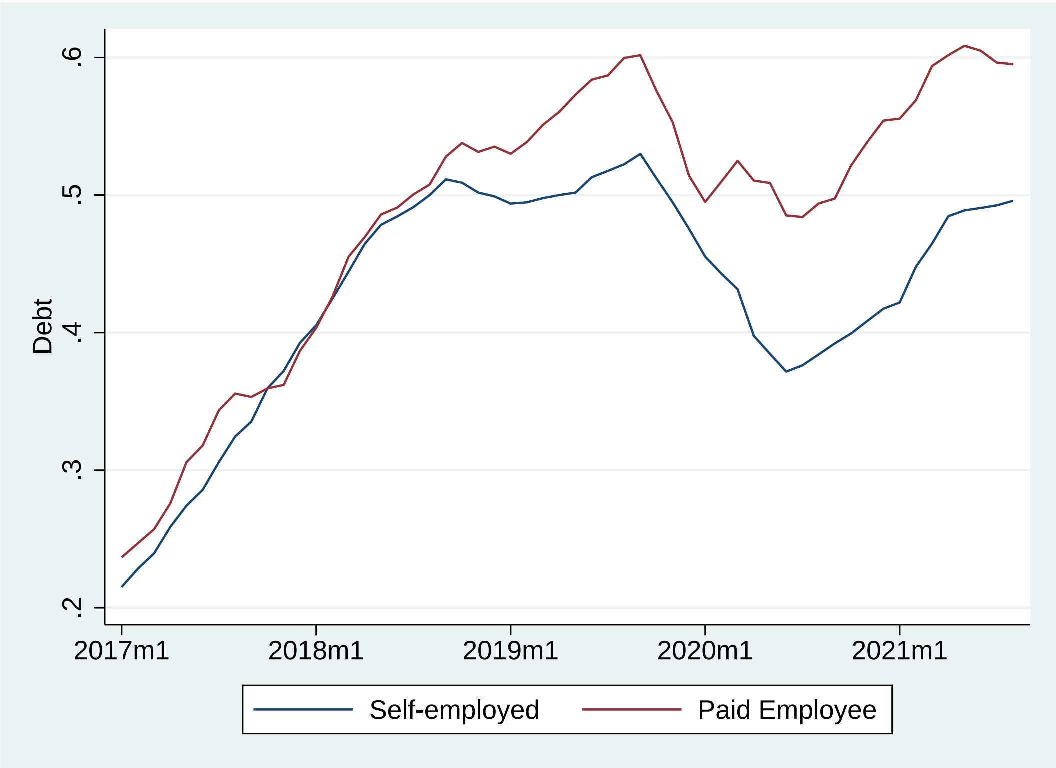

Figure 2: Credit utilization: Paid employees vs. Self-employed

The last descriptive statistics we show aims to provide correlations between debt and switching in and out of self-employment. To do so, we estimate two sets of logit regressions where the dependent variable is a dummy that takes value one if the person switches into or out of self-employment. On the right-hand side, we use several variables that identify if the household has debt, new debt, incumbent debt, finished paying debt, ever had debt, or the logarithm of the amount paid in monthly installments. We control for income, expenditure, size of the household, age, education, employment status, gender if the household lives in a rural area and industry, and month-year fixed effects.

Table 3 presents the results of these regressions for switching to self-employment. In column (1), we see that debt correlates with a higher probability of switching to self-employment. This supports the conjecture that accessing credit helps households switch to self-employment. In column (2), we decompose having debt and see a positive and significant coefficient associating new debt and finishing paying debt with switching to self-employment. This is not the case for incumbent debt in columns. Additionally, we find that having debt at any point in the past and the logarithm of EMIs also correlates with a higher probability of switching to self-employment.

We present the results for exiting self-employment in Table 4. The patterns in this case are very similar to those in Table 3. The results in Tables 3 and 4 suggest a connection between access to credit and entering or exiting self-employment. This can happen because of a causal relationship between accessing credit and self-employment, which can also reflect endogeneity. In this proposal, we have not yet worked on a solution to this potential problem, but we recognize the limitations of these results.

These results suggest a strong relationship between the choice of self-employment and access to credit. We then want to take the data to a model that mixes selection into self-employment with life-cycle and credit constraints. We want to be able to perform counterfactual analysis since the policy debate is not clear on what policies work better to help self-employed people grow. In particular, we want to learn how the selection into self-employment as well as the income of the self-employed change with two policies. The central policy we would introduce is subsidized credit for self-employed, but other policies would also interest us, e.g., subsidizing paid labor or training for self-employed transition into paid labor.

Table 3: Logit regression of switching into self-employment

	(1)	(2)	(3)	(4)
Has debt	0.00920*			
	(0.00546)			
Has new debt		1.43520***		
		(0.01046)		
Has incumbent debt		-0.62249***		
		(0.00674)		
Finished paying debt		1.44240***		
		(0.01203)		
Debt in the past			0.03318***	
			(0.00588)	
Ln(EMIs)				0.00955***
				(0.00103)
Observations	12,998,850	12,998,850	12,998,850	12,998,850

Clustered at household level errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 4: Logit regression of switching out of self-employment

	(1)	(2)	(3)	(4)
Has debt	0.04120***			
	(0.00584)			
Has new debt		1.59557***		
		(0.01013)		
Has incumbent debt		-0.46256***		
		(0.00702)		
Finished paying debt		1.47196***		
		(0.01211)		
Debt in the past			0.16796***	
			(0.00667)	
Ln(EMIs)				0.00376***
				(0.00117)
Observations	11,995,465	11,995,465	11,995,465	11,995,465

Clustered at the household level errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 5: Logit regression of switching into self-employment by employment status

	(1)	(2)	(3)	(4)
Has debt	-0.00842			
	(0.01012)			
Has debt ×	0.00464			
Out of the market	(0.01332)			
Has debt ×	0.02293			
Salaried permanent	(0.01797)			
Has debt ×	-0.02492			
Salaried temporary	(0.01872)			
Has new debt		1.62830***		
		(0.01783)		
Has new debt ×		-0.04863**		
Out of the market		(0.02376)		
Has new debt ×		0.14214***		
Salaried permanent		(0.03107)		
Has new debt ×		0.09679***		
Salaried temporary		(0.03360)		
Has incumbent debt		-0.47958***		
		(0.01194)		
Has incumbent debt ×		-0.07192***		
Out of the market		(0.01623)		
Has incumbent debt ×		-0.06577***		
Salaried permanent		(0.02239)		
Has incumbent debt ×		-0.01111		
Salaried temporary		(0.02264)		
Finished paying debt		1.59297***		
		(0.02158)		
Finished paying debt ×		-0.17924***		
Out of the market		(0.02803)		
Finished paying debt ×		0.03543		
Salaried permanent		(0.03728)		
Finished paying debt ×		0.10520***		
Salaried temporary		(0.03932)		
Debt in the past			0.26246***	
			(0.01247)	
Debt in the past ×			-0.26652***	
Out of the market			(0.01530)	
Debt in the past ×			-0.03528*	
Salaried permanent			(0.01973)	
Debt in the past ×			-0.03970*	
Salaried temporary			(0.02170)	
Ln(EMIs)				0.00635***
				(0.00204)
Ln(EMIs) ×				-0.00872***
Out of the market				(0.00261)
Ln(EMIs) ×				-0.00453
Salaried permanent				(0.00311)
Ln(EMIs) ×				-0.01080***
Salaried temporary				(0.00365)
Out of the market	-0.16986***	-0.14482***	0.02952**	-0.15989***
	(0.01014)	(0.01023)	(0.01368)	(0.00871)
Salaried permanent	-0.24938***	-0.26193***	-0.19710***	-0.23650***
	(0.01291)	(0.01305)	(0.01748)	(0.01143)
Salaried temporary	-0.03492***	-0.05309***	-0.00833	-0.03464***
	(0.01307)	(0.01329)	(0.01904)	(0.01115)
Observations	8,267,580	8,267,580	8,267,580	8,267,580

Clustered at household level errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 6: Logit regression of switching out of self-employment by employment status

	(1)	(2)	(3)	(4)
Has debt	-0.00842			
	(0.01012)			
Has debt ×	0.00464			
Out of the market	(0.01332)			
Has debt ×	0.02293			
Salaried permanent	(0.01797)			
Has debt ×	-0.02492			
Salaried temporary	(0.01872)			
Has new debt		1.62830***		
		(0.01783)		
Has new debt ×		-0.04863**		
Out of the market		(0.02376)		
Has debt ×		0.14214***		
Salaried permanent		(0.03107)		
Has debt ×		0.09679***		
Salaried temporary		(0.03360)		
Has incumbent debt		-0.47958***		
		(0.01194)		
Has incumbent debt ×		-0.07192***		
Out of the market		(0.01623)		
Has incumbent debt ×		-0.06577***		
Salaried permanent		(0.02239)		
Has incumbent debt ×		-0.01111		
Salaried temporary		(0.02264)		
Finished paying debt		1.59297***		
		(0.02158)		
Finished paying debt ×		-0.17924***		
Out of the market		(0.02803)		
Finished paying debt ×		0.03543		
Salaried permanent		(0.03728)		
Finished paying debt ×		0.10520***		
Salaried temporary		(0.03932)		
Debt in the past			0.26246***	
			(0.01247)	
Debt in the past ×			-0.26652***	
Out of the market			(0.01530)	
Debt in the past ×			-0.03528*	
Salaried permanent			(0.01973)	
Debt in the past ×			-0.03970*	
Salaried temporary			(0.02170)	
Ln(EMIs)				0.00635***
				(0.00204)
Ln(EMIs) ×				-0.00872***
Out of the market				(0.00261)
Ln(EMIs) ×				-0.00453
Salaried permanent				(0.00311)
Ln(EMIs) ×				-0.01080***
Salaried temporary				(0.00365)
Out of the market	-0.16986***	-0.14482***	0.02952**	-0.15989***
	(0.01014)	(0.01023)	(0.01368)	(0.00871)
Salaried permanent	-0.24938***	-0.26193***	-0.19710***	-0.23650***
	(0.01291)	(0.01305)	(0.01748)	(0.01143)
Salaried temporary	-0.03492***	-0.05309***	-0.00833	-0.03464***
	(0.01307)	(0.01329)	(0.01904)	(0.01115)
Observations	8,267,580	8,267,580	8,267,580	8,267,580

Clustered at household level errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

4 Model

Consider a representative household i, characterized by a set of socioeconomic characteristics X_i. It has one decision-maker, the household head. We interchangeably use the words "household head" and "household." Denote each period as t.[4]

The household head chooses at the beginning of each period $a_{it} = (C_{it}, O_{it}, D_{it})$ where C_{it} is consumption; O_{it} is vector of indicator variables that take value one depending on the occupation choice with options: wage labor, self-employment, or out-of-market activities; D_{it} is household new debt.

The state variables are:

$$\Omega_{it} = (a_{t-1}, X_{it}, E_t, \epsilon_{it}, A_{it}, S_{it-1}). \tag{1}$$

Where X_{it} represents households' socioeconomic characteristics, E_t observable environmental characteristics, a_{it-1} the lagged control variables, ϵ_{it} the unobserved household idiosyncratic income shock, A_{it} and S_{it} the stock of debt and savings respectively.

The household problem is a life-cycle total utility maximization problem, parameterized by Θ. We omit the subscript i from now on for simplicity.

$$\begin{aligned} V_t(\Omega_t, \Theta) &= \max_{a_t} \left[U(a_t, \Omega_t; \Theta) + \rho \int V_{t+1}(\Omega_{t+1}; \Theta)\, dF(\Omega_{t+1} \mid \Omega_t) \right] \\ \text{s.t. } & C_t + m(\Omega_t, a_t; \Theta) + H(\Omega_t, a_t; \Theta) = w(\Omega_t, a_t; \Theta) \end{aligned}$$

$$\begin{aligned} \text{where: } & \Omega_{t+1} = F(\Omega_t) \\ & a_{it} = (C_{it}, O_{it}, D_{it}) \end{aligned}$$

In the above budget constraint, $H(.)$ denotes the cost function associated with acquiring and paying off debt. And $w(.)$ denotes the disposable income function. $F(.)$ denotes the transition functions of the states. $m(.)$ is the cost of changing the current occupation.

[4]Unless mentioned, the variables below are one dimensional for each household in each period.

The instantaneous utility that consumers derive in each period is

$$U\left(a_t, \Omega_t; \eta\right) = \frac{\left(c_t/n_t\right)^{\eta}}{\eta} \tag{2}$$

The function $w(.)$ describes income from the household. We include an idiosyncratic unobserved productivity shock that depends on the occupational choice of the household. A flexible function form of the socioeconomic characteristics. D_t and S_{t-1} that describe the amount of debt that the household acquires in period t and the savings that the household hold in period $t-1$ respectively. r_t^s the interest rate for savings. Finally, macroeconomic and idiosyncratic shocks E_t and $_t$ respectively.

$$w_t(\Omega_t, a_t; \Theta) = \theta O_t + f(X_t) + D_t + (1 + r_t^s)S_{t-1} + E_t + \epsilon_t \tag{3}$$

The $H(.)$ function describes the costs associated with debt:

$$H\left(A_t; \phi, \bar{D}_t\right) = (r_t^D + \phi)A_t + \infty 1_{D_t > \bar{D}_t} \tag{4}$$

Transition function $F(.)$ entails the following processes

$$A_{t+1} = (1 - \phi)A_t + D_t, \tag{5}$$

$$S_{t+1} = w(\Omega_t, a_t; \Theta) - H(\Omega_t, a_t; \Theta) - C_t \tag{6}$$

$$\bar{D}_{t+1}|X_t \sim \textit{Truncated Normal}\ (\mu, \sigma) \tag{7}$$

The rest of the transition functions of the states can be flexibly estimated.

Timing and information The information each household i gets within a period t and the resulted timing of the events are listed below

1. At the start of the period t, Ω_t is known to the households.

2. Households receive wage $wage(.)$ that is heterogeneous by X_t, E_t, and occupation O_t. Additionally they get interest payment from savings $S_{t-1}(1 + r_t^s)$

3. After solving their maximization problem, the household chooses occupation O_t. If the occupation is different they face cost $m(.)$.

4. Based on the draw of $\bar{D}_t$ and the maximization problem solution, households choose whether to get new debt or not.

5. After solving the problem then households have a_t that results in utility $\frac{(c_t/n_t)^\eta}{\eta}$.

6. The state variables are updated according to equations 5-7.

7. Period t ends

4.1 Sending the model to the data

The measurement for each variable above is straightforward from our previous discussion. We hence list the assumptions needed:

- We need to assume that the difference between observed income and expenditure proxies for D_t. We do not observe $\bar{D}_t$. Is it plausible to estimate it in the context of a Tobit estimation where the left truncation responds to denied credit and the right truncation responds to debt limits?

- We observe equated monthly installments for households with debt. Most of the debt households take is paid within the sample period. This means that we have a proxy for the loan amount, maturity, and interest rate.

Let's say we can observe all X_t and E_t. We can discuss some details later (e.g. whether we need to find interest rate data for r_t^s, r_t^d.).

5 Challenges

The original idea for this project involved using information from different credit sources. Utilization of each and the demographics of those who choose to use them can show the cost associated with each credit source. For the present document, we stay away from this idea because we are unsure how to estimate it if included in the model. In our current setting, we can estimate the CCP (conditional choice probability) or the policy functions in reduced form and use a two-step approach for indirect inference.

We have one first-order condition for the static optimization of consumption and two Euler equations for making decisions of O_t, S_t, and D_t. The core structural parameters function $m(.)$, ϕ, and $\bar{D}$ can be identified by sending these corresponding moments to the AIDS data. We can estimate the heterogeneity of households using rich CPHS demographics by forming micro-moments (e.g., the consumption choice among households having income lower than 5000 rupees a month with self-employed status).

Two periods might be easier to work with at the start. Given the very complex information structure, we find it hard to completely spill out the first-order condition and its Euler functions. We are not strict enough when discussing the unobservables. We need to explicitly flesh out what we will use from our dataset for specific observables and what we will leave as unobservables.

In the current model, the choice of occupation is trivial; pick the one with the highest wage (from that wage schedule) given an individual list of state variables. We want it to be linked to credit, maybe using an indivisible investment for self-employment similar to Kaboski and Townsend (2011). This allows us to learn about what happens in terms of investment in self-employment when households gain access to affordable credit.

References

Aruna, M. and M. R. Jyothirmayi (2011). The role of microfinance in women empowerment: A study on the shg bank linkage program in hyderabad (andhra pradesh). *Indian Journal of Commerce & Management Studies ISSN 2229*, 5674.

Banerjee, A. V. and E. Duflo (2014). Do firms want to borrow more? testing credit constraints using a directed lending program. *Review of Economic Studies 81*(2), 572–607.

Block, J. and P. Sandner (2009). Necessity and opportunity entrepreneurs and their duration in self-employment: evidence from german micro data. *Journal of Industry, Competition and Trade 9*(2), 117–137.

Borchhardt, G. and O. Sorenson (2022). Entrepreneurship as the safe option: Evidence from india.

de Sousa, F. L. and G. I. Ottaviano (2018). Relaxing credit constraints in emerging economies: The impact of public loans on the productivity of brazilian manufacturers. *International economics 154*, 23–47.

Fields, G. S. (2019). Self-employment and poverty in developing countries. *IZA world of labor*.

Ghosh, M. (2012). Micro-finance and rural poverty in india shg-bank linkage programme. *Journal of Rural Development 31*(3), 347–363.

Hamilton, B. H. (2000). Does entrepreneurship pay? an empirical analysis of the returns to self-employment. *Journal of Political economy 108*(3), 604–631.

Humphries, J. E. (2017). *The causes and consequences of self-employment over the life cycle*. The University of Chicago.

ILO (2018). India wage report: Wage policies for decent work and inclusive growth. Technical report, International Labour Organization.

Kaboski, J. P. and R. M. Townsend (2011). A structural evaluation of a large-scale quasi-experimental microfinance initiative. *Econometrica 79*(5), 1357–1406.

Levine, R. and Y. Rubinstein (2018). Selection into entrepreneurship and self-employment. Technical report, National Bureau of Economic Research.

Margolis, D. N. (2014). By choice and by necessity: Entrepreneurship and self-employment in the developing world. *The European Journal of Development Research 26*(4), 419–436.

OECD, P. (2018). *OECD labour force statistics 2017*. OECD Paris.

Oyenubi, A. et al. (2019). Who benefits from being self-employed in urban ghana. Technical report.