Firms and Capital

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Theory:

- Standard complete markets model (e.g. Lucas, 1978)
- Differences in employment size among firms facing the same output production technology f(.) reflect differences in their management ability, θ
- Employment and Capital stock determined by first-order conditions

$$\boxed{\begin{aligned} f_L(\theta, K^*, L^*) &= w \\ f_K(\theta, K^*, L^*) &= r \end{aligned}}$$

Implications:

1) Firms small because have low ability.
2) For any given θ, constraints to capital reduce firm size given ability
   a) perhaps especially so for high-ability entrepreneurs.

Ability and capital

Why (or when) might credit constraints bind more tightly for high-ability owners?

Not always: With perfect capital and insurance markets, interest rates are constant across entrepreneurs, and each borrows to the point that $f_k = r$

If either capital or insurance markets are imperfect, this may not be the case. For example, if:

- Borrowing limits are fixed, or credit limited by collateral;
- External capital is limited to debt and owners are risk averse.

Then higher ability owners, who in equilibrium would employ more capital, will be more constrained if internal / external capital (e.g., savings and loans) availability is not closely correlated with ability.

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A very simple model

From De Mel et al. 2008, a very simple model that allows for imperfect credit and insurance markets.

Entrepreneurs choose capital stock to maximise utility:

$$\max_{K,B,A_k,I_k} EU(c) \tag{1}$$

subject to various constraints:

$$c = \epsilon f(K,\theta) - rK + f(A - A_k) + (nw - I_k) \tag{2}$$

$$K \leq A_k + I_k + B \tag{3}$$

$$B \leq \overline{B} \tag{4}$$

$$A_k \leq A \tag{5}$$

$$I_k \leq nw \tag{6}$$

Capital and insurance markets

With perfect markets (and ignoring labour for simplicity),

$$f'(K,\theta) = r \tag{7}$$

More generally:

$$f'(K,\theta) = \frac{1}{1 + \frac{CovU'(c),\epsilon}{EU'(c)}} \left[r + \frac{\lambda}{EU'(c)} \right] \tag{8}$$

where λ is the shadow value of capital from equation 3

Capital and insurance markets

Ignoring risk but allowing imperfect credit markets, Eq 8 simplifies to

$$f'(K, \theta) = r + \lambda \tag{9}$$

where λ is the shadow value of capital given the entrepreneur's liquidity constraints given by Equations 4, 5 and 6.

But perfect credit markets are not enough. With missing insurance markets, Equation 9 becomes

$$f'(K, \theta)(CovU'(c), \epsilon) = [r - f'(K, \theta)]EU'(c) \tag{10}$$

With reasonable assumptions, this implies that

$$r < lf'(K, \theta)$$

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Evidence on returns

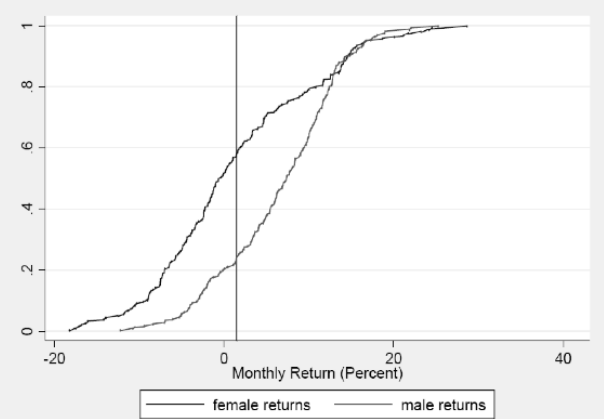
A few (non-randomly selected) examples of returns from grants:

1. de Mel et al. 2008, 2012: RCT with microenterprises in Sri Lanka; grants of USD100 - 200 to firms with less than in capital.
   - Returns of around 6% per month, on average
2. Fafchamps et al. 2014; RCT with similar sized businesses.
   - Returns for cash similar to SL, in kind 25% per month
3. Banerjee et al. 2015; Loans in Hyderabad. Fairly noise zero on average returns, but evidence of high returns among those with enterprises before the loans.

   These papers all show quite heterogenous returns to capital shocks across entrepreneurs.

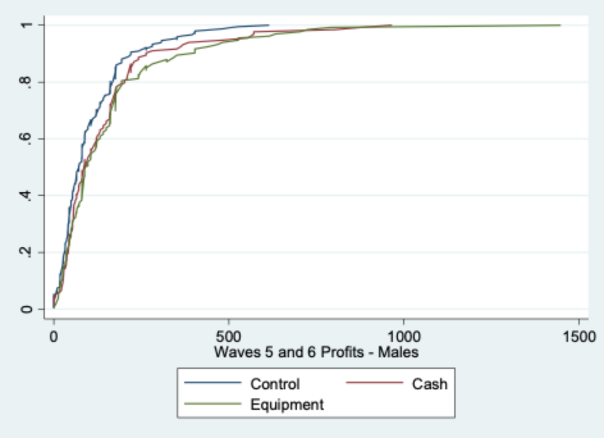
Heterogeneity in Sri Lanka

Returns are heterogenous: Predicted returns, Sri Lanka



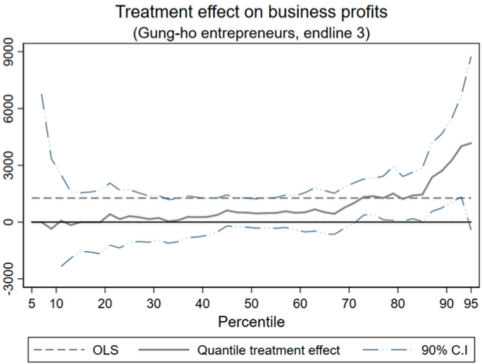
Heterogeneity ain Ghana

CDF by treatment Fafchamps et al. (Ghana, males)



Heterogeneity in India

Quartile regression on the subsample of pre-existing entrepreneurs (Banerjee et al. 2020)



(A) Gung-ho Entrepreneurs

Selecting on θ

Heterogeneity has long been a hallmark of the microenterprise sector (Peattie 1987). Similarly, VC firms make all their returns on a few superstar performers. //

One of the most consistent results (where reported) is that the effects are concentrated at the top of the distribution. The growth response of capital has a very long right-hand tail.

An obvious challenge: sample size may need to be very large to have a sufficient number of ''superstar'' enterprises. (See, e.g., de Mel et al 2013.)

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Heterogeneity and selection

In addition to research challenges, heterogeneity in returns raises (at least) two questions:

1. Do entrepreneurs self-select into sources of capital?
2. Can we identify those with higher returns, and if so, how?

On the first question, the literature on standard credit contracts is somewhat mixed. (See Cai et al.'s VoxDev Lit for a current review of the microcredit literature.)

- Meager 2019 uses Baysian hierarchical analysis to combine results from several microcredit RCTs, and finds only weak effects.
- However, loans to larger firms show higher returns:
  - Banerjee and Duflo (2014) use bank lending policy changes in India, finding that credit generates annual returns of 100% for firms with capital stock in the range of $150K - 700k.
  - Cai and Szeidl...

Self-selection on θ

Cai and Szeidl (2022) carry out a very interesting RCT with a banking partner in China, offering slightly favourable loans to retailers clustered at the market level.

Their goal is ask: What happens to a firm's sales when a competitor receives credit?

- They work with retailer/wholesalers clients in 78 markets in one city.
- Loans of up to \$80k are offered to 80%, 50%, or 0% of the firms in a given market.
- Returns to the borrowing firm are large and positive (ITT sales increase by 10 log points, with 28% takeup), but almost equal negative effects on competitors.

Ex ante / ex-post intentional selection

Bryan, Karlan and Osman (2022) work with the Alexandria(Egypt) Business Association to offer loans 4X in size to larger than previous limits.

They find modest average effects of the larger loans, but interesting patterns in heterogeneity.

Ex ante / ex-post intentional selection

They start with a sample of previous borrowers selected by loan officers for their potential (local knowledge).

Within this subset, can loan officers predict those who will succeed? (...No)

- No positive correlation between borrower performance with a standard loan and with a 4X loan.
- The top performers are predicted with psychometric and cognitive data; the ABA (as with most lenders) does not collect these data.

Instead, the type of firms doing the best with loans are among the worst performers in the control group, suggesting that past performance (which loan officers observe) is a poor predictor.

- Why? They say that all entrepreneurs are optimists, but some are excessively optimistic. This over-optimism pays with small investments, but the strategy blows up with larger investments.

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Ex post selection

The key to the exercise is ML predictions of treatment effects, using:

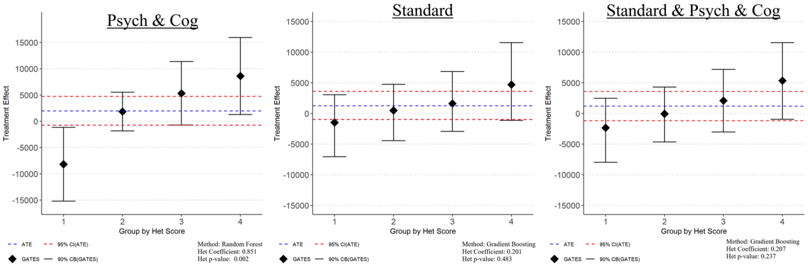
1. Psychometric and cognitive data
2. Standard lender data
3. Both of the above

Using 50/50 splits for training and testing data, the results are summarised on this graph:

Heterogeneity of treatment

Heterogeneity of treatment effects using ML on differing data.

Figure 2. Heterogenous Treatment Effects for Profits



Intentional selection

Bryon et al. (2022) is part of a rapidly growing literature searching for systematic methods of intentional selection. In their case, psychometrics and ML provide the novelty.

A lot of other very interesting work in this area, using differing sources of information:

- Hussam et al. (2022) show that community members can predict returns to capital among microenterprise owners in India.
- Selection from business plan competitions (Mckenzie 2017; Fafchamps and Woodruff 2017)

Risk rationing: Credit with flexibility

Business fortunes vary significantly across time.

So in the absence of the ability to ensure against this variance, is a rigid debt contract optimal?

Field et al. (2013) started a discussion of flexibility in repayment. (See also Fischer 2013.)
Some examples on this (all RCTs):

- Field et al. (2013): No payments for the first 2 months of the loan (grace period); 2nd-time borrowers, group, India.
- Barboni and Agarwal (2020), India: flexibility to delay for three months *at any point* during the payment cycle, individual loans, experienced borrowers.
- Battaglia et al. (2021), Bangladesh, flexibility to defer payment twice during a 12-month cycle, individual loans, experienced borrrowers.
- Bruhn et al. (2022); First-time borrowers, Colombia, individual loans, 3 months interest-only payment.

Outcomes with of flexibility

Field et al. compare a standard MFI contract (with immediate repayment flows) with the grace period contract. They find that the grace period group:

- Invests (6%) more of the loan in the business.
- has 57% higher profits (11% monthly return, compounded)
- Capital in the business 82% higher after a year
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Flexibility

What have we learned from these innovations?

1. Higher risk, higher return investments (Field et al.; Battaglia et al.). Or, ability to meet demand surges (Barboni and Agarwal). Or, no improvement (Bruhn et al.)
2. Higher default (Field et al.) or not (Barboni and Agarwal; Battaglia et al.).

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Risk rationing: Explicit risk sharing

This work suggests that risk is constraining how loans are invested.

Is more explicit risk sharing feasible? The ultimate innovation here would be a microequity contract.

De Mel et al (2020) describe a failed experiment attempting to make the full leap to microequity contracts.

- Investment of US$ 5000, with royalty-based revenue sharing in lieu of fixed interest
- principal paid partly through the royalty rate
- The failure came mainly from nonpayment rather than (just) under-reported sales
    - Among many lessons from the exercise, the Sri Lankan legal institutions did not recognise the contract as collateralizable.

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Risk sharing

De Mel et al. (2020) was perhaps a leap too far, but perhaps points in the direction we should be pushing.

Some recent more manageable (and more successful) steps in this direction:

- Bari et al. (2021): Rental contract for larger, lumpy assets
- Cordara et al: Credit to purchase a fixed asset, payments linked to (measurable) sales

Some concluding thoughts

First, two takeaways:

1. A lot of interesting work on scraping information to aid targeting and selection. Much more to do here.
2. Debt is almost certainly not the first-best external credit instrument, but moving the equity-like instruments is challenging.

In both cases, would do well to look at what VCs do and ask "How can we do that with smaller firms."

Not enough time! This was too focused no small firms and debt to to justice to the full agenda here. Need more on angel / VC finance, and investment readiness among the potential high-flyers.

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