SMALL FIRM INVESTMENT UNDER UNCERTAINTY: THE ROLE OF EQUITY FINANCE

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MOTIVATION: THE MICROFINANCE PUZZLE

Hundreds of millions of small firms operate in developing countries, and finance is often cited as critical for **growth**.

Yet, strikingly, a large wave of experimental evaluations identified **zero average impacts** of the classic microcredit product on business profits (Banerjee et al., 2015).

This poses a **puzzle** to the finance and development literature, considering:

1. **Macro-**level associations: financial access and growth (Beck et al., 2007);
2. **Micro-**level evidence: high returns to capital (McKenzie and Woodruff, 2008; De Mel et al., 2008, 2012; Fafchamps et al., 2014; Hussam et al., 2017).

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HYPOTHESIS: CONTRACT STRUCTURE CONSTRAINS INVESTMENT

The classic microcredit contract has many theoretically appealing features (Besley and Coate, 1995; Ghatak and Guinnane, 1999).

Repayment rigidity instills discipline, but it could discourage investment for the many small firms with **high but volatile returns**, and especially for the most **risk-averse** business owners (Fischer, 2013; De Mel et al., 2019).

Repayment **flexibility** can encourage higher-risk, higher-return investments (Field, Pande, Papp, Rigol, 2013; Barboni and Agarwal, 2023; Battaglia et al., 2023).

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EQUITY-LIKE CONTRACTS MAY BETTER STIMULATE INVESTMENT

I explore a different form of flexibility — equity-like contractual innovations through **performance-contingent** repayments — which were sub-optimal in many settings due to **costly state verification** (Townsend, 1979; Udry, 1990, 1994).

Finance is at an inflection point with **digitization** (Breza, 2024; Duflo, 2024). **Fintech** advancements alleviate supply-side frictions to **tailoring** (Suri, 2017; Higgins, 2022).

Key challenges for the literature (Banerjee, Karlan, & Zinman, 2015):

1. **Contractual innovations** to improve take-up & effectiveness;
2. **Non-credit** features;
3. Evidence on **growth-oriented** small firms.

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PREVIEW OF RESULTS

I conduct 'artefactual field experiments' (Harrison & List, 2004) with a sample of growth-oriented small firms drawn from two broader field experiments.

I first establish that equity-like contracts lead to **more profitable investment choices** than debt (Fischer, 2013).

Using **risk preference** measures from approximately 30,000 incentivized choices, I demonstrate the important but **nuanced role of risk preferences**: individuals who are risk- and loss-averse prefer and perform better under equity contracts.

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I illustrate a **demand-side friction** to implementing equity, drawing upon insights from **behavioral finance** that mostly focus on loss aversion and on high-income countries (Exceptions: Kremer, Rao, Schilbach, 2019; Carney et al., 2022; Jack et al., 2023).

Firm owners characterised by **non-linear probability weighting** dislike equity.

Results provide a novel **counterpoint** to the idea that such individuals desire **skewness** (Dimmock et al., 2021) & **overvalue** out-of-the-money options (Spalt 2013).

I argue that individuals with a propensity to overweight low-probability, high-profit scenarios would also be **averse to 'selling skewness'**.

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I also validate model predictions **‘outside of the lab’**.

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Selection and 'Naturalness' of decision-making environment (List, 2020): a policy-relevant sample of growth-oriented firms at a critical business juncture.

Pakistan: graduated borrowers offered $2,000 for asset financing (Bari et al., 2024).

Kenya: micro-distributors in a large multinational's route-to-market programme, offered financing for transportation asset (Cordaro et al., 2024).

Summary statistics

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1. Four domain-specific questions on self-reported risk attitudes in: financial matters, occupation, faith in others, and in general (Dohmen et al., 2011).
2. 30 incentivized choices between binary lotteries with $p_g \in \{0.25, 0.50, 0.75\}$ and a gradually increasing certain payment (Vieider et al., 2015).
3. 10 incentivized choices between certain payment and binary lottery with one payoff in the loss domain, with the loss gradually increasing (Bartling et al., 2015).

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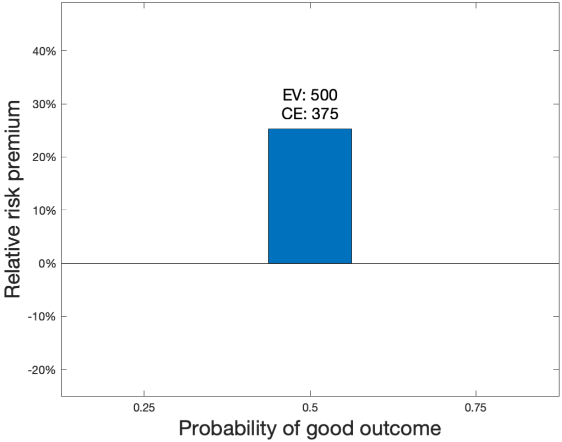

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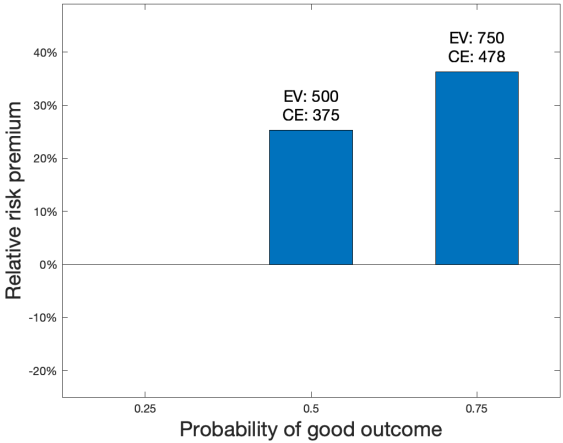

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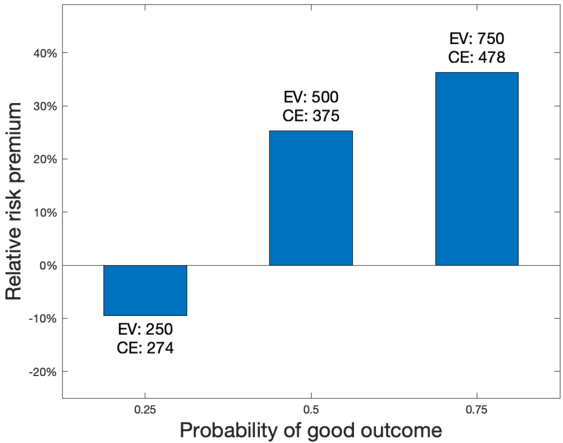

Further elicitation results

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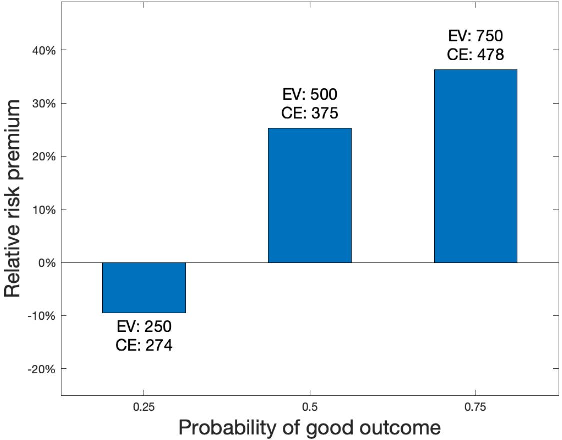

Further elicitation results

INVESTMENT GAME

Designed to mimic financial constraint to accessing higher-return investments.

Option	Cost	Low Payoff	High Payoff	Expected Profit
1	0	0	100	50
2	100	0	400	100
3	200	0	700	150
4	300	0	1000	200
5	400	0	1300	250

1. **Control** $\Omega = 200$;
2. **Debt** $\Omega = 200 + 500$ loan
3. **Equity** $\Omega = 200 + 500$ as equity (sharing ratio $\theta \in \{0.25, 0.50\}$)

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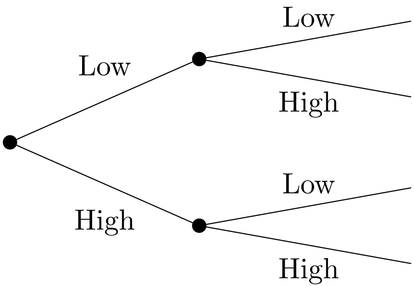

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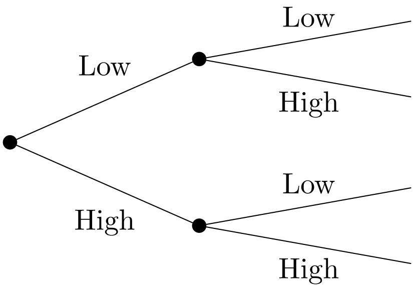

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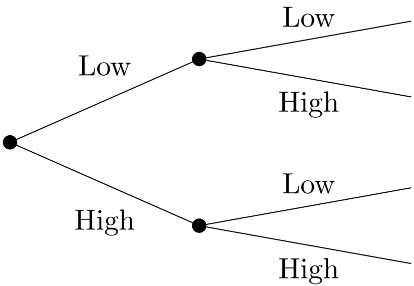

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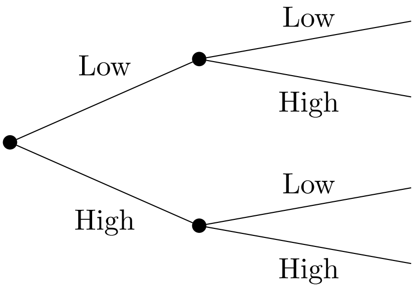

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EQUITY LEADS TO MORE PROFITABLE INVESTMENT CHOICES

	(1) Expected return	(2) Expected return	(3) Expected return
Debt			
Equity			
Observations	3,060		
Unique individuals	765		
Country	Pooled	Pakistan	Kenya
Control mean			
R-squared			
Test: Debt = Equity			
Effect size (%)			
Effect size (standard deviations)			

https://www.socialscienceregistry.org/trials/2224

Round 2 investments Round 3 investments 25% and 50% equity sharing ratios

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	(1) Expected return	(2) Expected return	(3) Expected return
Debt			
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Unique individuals	765		
Country	Pooled	Pakistan	Kenya
Control mean	111.21		
R-squared			
Test: Debt = Equity			
Effect size (%)			
Effect size (standard deviations)			

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Round 2 investments | Round 3 investments | 25% and 50% equity sharing ratios

EQUITY LEADS TO MORE PROFITABLE INVESTMENT CHOICES

	(1) Expected return	(2) Expected return	(3) Expected return
Debt	63.79***		
	(2.24)		
Equity			
Observations	3,060		
Unique individuals	765		
Country	Pooled	Pakistan	Kenya
Control mean	111.21		
R-squared			
Test: Debt = Equity			
Effect size (%)			
Effect size (standard deviations)			

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Debt	63.79***		
	(2.24)		
Equity	74.58***		
	(1.90)		
Observations	3,060		
Unique individuals	765		
Country	Pooled	Pakistan	Kenya
Control mean	111.21		
R-squared	0.267		
Test: Debt = Equity			
Effect size (%)			
Effect size (standard deviations)			

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Observations	3,060		
Unique individuals	765		
Country	Pooled	Pakistan	Kenya
Control mean	111.21		
R-squared	0.267		
Test: Debt = Equity	0.000		
Effect size (%)	6.2		
Effect size (standard deviations)	0.35		

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Debt	63.79***	66.89***	
	(2.24)	(2.55)	
Equity	74.58***	76.71***	
	(1.90)	(2.17)	
Observations	3,060	2,392	
Unique individuals	765	598	
Country	Pooled	Pakistan	Kenya
Control mean	111.21	109.36	
R-squared	0.267	0.283	
Test: Debt = Equity	0.000	0.000	
Effect size (%)	6.2	5.6	
Effect size (standard deviations)	0.35	0.35	

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	(1) Expected return	(2) Expected return	(3) Expected return
Debt	63.79***	66.89***	52.69***
	(2.24)	(2.55)	(4.66)
Equity	74.58***	76.71***	66.92***
	(1.90)	(2.17)	(3.93)
Observations	3,060	2,392	668
Unique individuals	765	598	167
Country	Pooled	Pakistan	Kenya
Control mean	111.21	109.36	101.20
R-squared	0.267	0.283	0.183
Test: Debt = Equity	0.000	0.000	0.001
Effect size (%)	6.2	5.6	9.2
Effect size (standard deviations)	0.35	0.35	0.37

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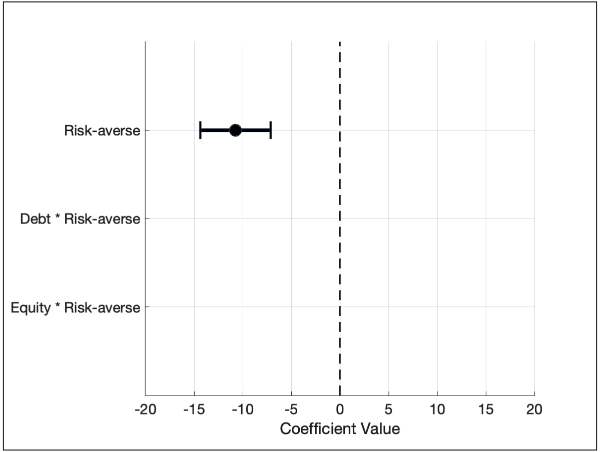
	(2.24)	(2.55)	(4.66)
Equity	74.58***	76.71***	66.92***
	(1.90)	(2.17)	(3.93)
Observations	3,060	2,392	668
Unique individuals	765	598	167
Country	Pooled	Pakistan	Kenya
Control mean	111.21	109.36	101.20
R-squared	0.267	0.283	0.183
Test: Debt = Equity	0.000	0.000	0.001
Effect size (%)	6.2	5.6	9.2
Effect size (standard deviations)	0.35	0.35	0.37

Round 2 investments Round 3 investments 25% and 50% equity sharing ratios

EQUITY IS MORE IMPACTFUL FOR RISK-AVERSE FIRM OWNERS

$$y_i = \beta_0 + \beta_1 Debt_i + \beta_2 Equity_i + \beta_3 Risk\text{-}averse_i + \beta_4 Debt_i \cdot Risk\text{-}averse_i + \beta_5 Equity_i \cdot Risk\text{-}averse_i + \epsilon_i$$



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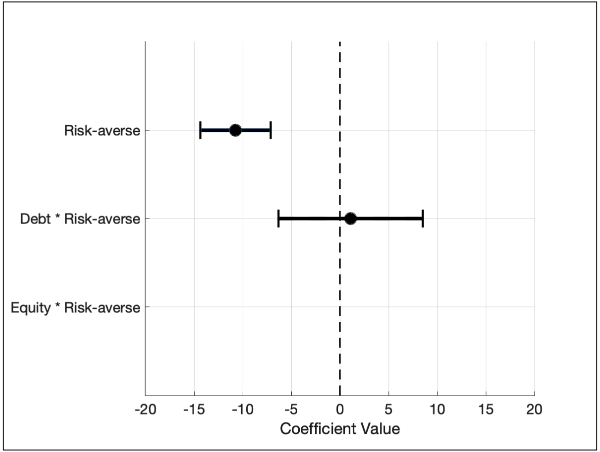

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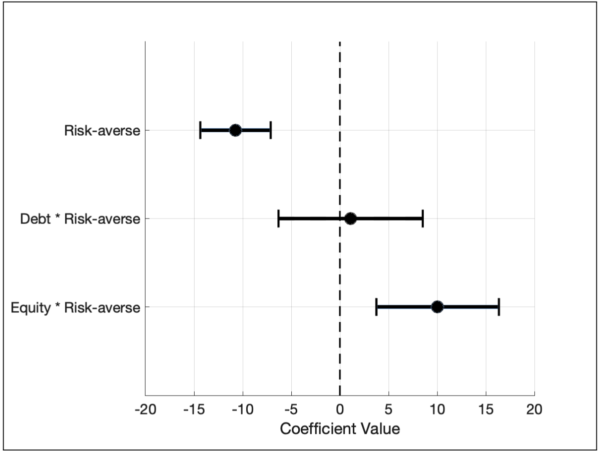

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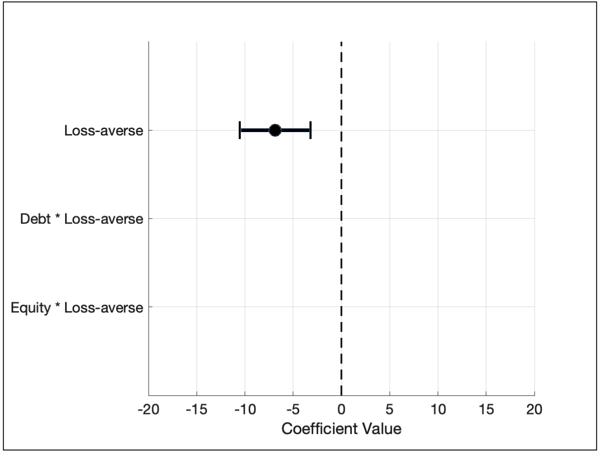

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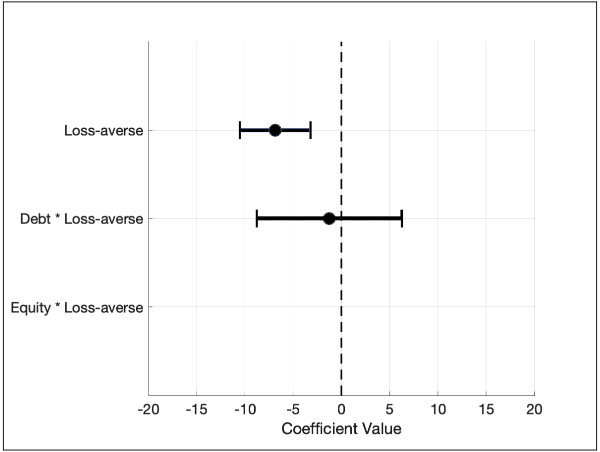

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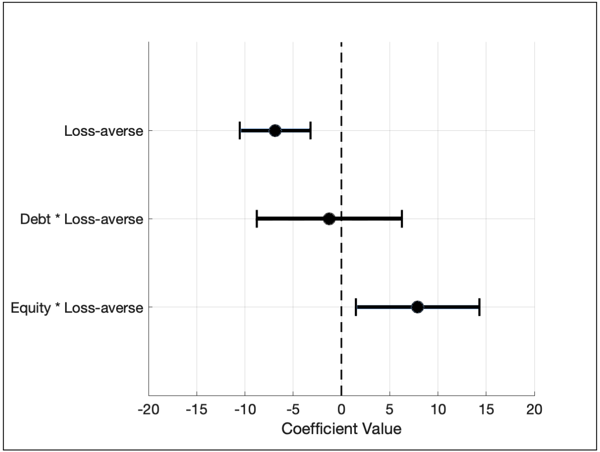

Jointly controlling for risk aversion and loss aversion

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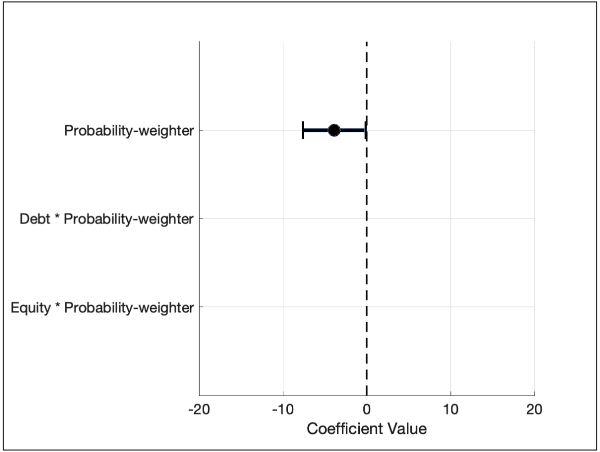

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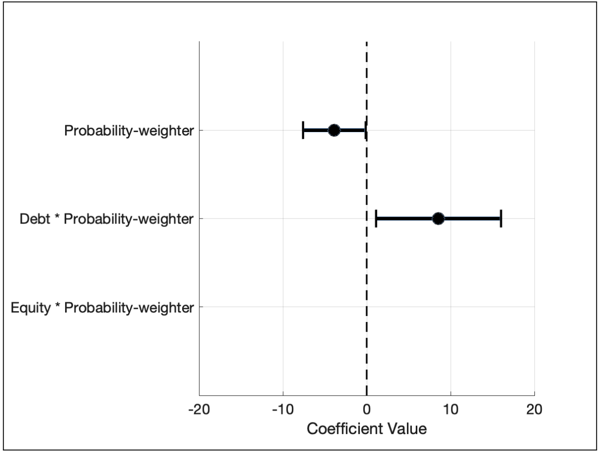

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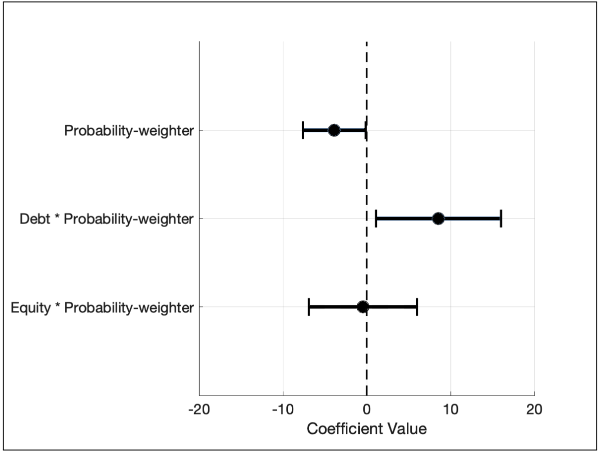

Robustness

- Order effects. →
- Trichotomized measure for each of the three risk preference variables. →
- Three alternative methods for constructing the probability weighting index. →
- Heterogeneity is not driven by business owner education. →
- Results on probability weighting reflect actual distortions rather than potential over-optimism of business owners. →

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MODELING DECISION MAKING

$$PU_i = \sum_{k=1}^{n} \underbrace{\pi(p_k)}_{\text{Decision weight}} \cdot \underbrace{U(x_k)}_{\text{Value function}}$$

EUT

$$\pi(p_k) = p_k$$

EUT

$$U(x) = x^r$$

PT

$$\pi_k = \omega(p_k + \cdots + p_n) - \omega(p_{k+1} + \cdots + p_n)$$

$$w(p) = \frac{p^\gamma}{(p^\gamma + (1-p)^\gamma)^{1/\gamma}}$$

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$$U(x) = \begin{cases} x^\alpha & \text{if } x \geq 0 \\ -\lambda(-x^\alpha) & \text{if } x < 0 \end{cases}$$

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MIXTURE MODEL

EUT: For a candidate r, the index of latent preferences $\nabla EUT = EUT_1 - EUT_2$ is linked to observed choices using a logistic or standard normal CDF $\Phi(\nabla EUT)$.

PT: For candidate α, λ, γ, link $\nabla PU = PU_1 - PU_2$ and choices using $\Phi(\nabla PT)$.

$$\ln L(r, \alpha, \lambda, \gamma; y, X) = \sum_i \ln[(\pi^{\mathrm{EUT}} \times L_i^{\mathrm{EUT}}) + (\pi^{\mathrm{PT}} \times L_i^{\mathrm{PT}})]$$

Result: **87% of observations better characterized by PT**, and 13% by EUT.

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ESTIMATED RISK PREFERENCE PARAMETERS

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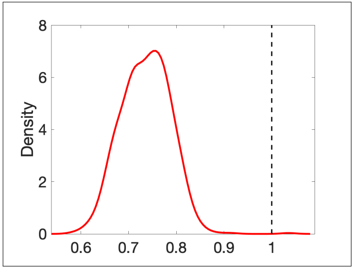

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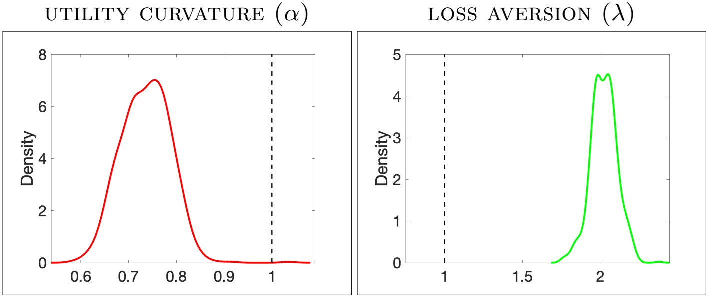

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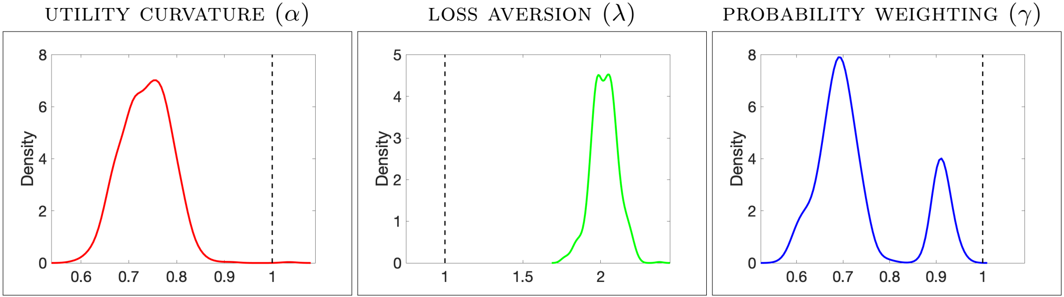

Generalizability of parameter estimates: λ and γ consistent with literature (DellaVigna, 2018; Kremer et al., 2019; Dimmock et al., 2021).

Structural noise parameter Joint distribution Implications of γ

MODELING SELECTION INTO CONTRACTS

I use a static framework to focus on exploring heterogeneity in risk preferences (Cohen & Einav, 2007; Barberis & Huang, 2008). I assume business returns X are drawn from the same stochastic distribution, fitted on 'real-world' profits. Distribution fit

A business owner evaluates different financing contracts based on prospect-theoretic preferences over final wealth $\widetilde{W} = W_0 + X - C - RP$.

$$C = \begin{cases} X \cdot \theta, & \text{if Equity,} \\ \min(K \cdot (1+r), W_0 + X), & \text{if Debt.} \end{cases}$$

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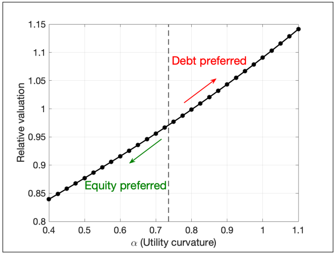

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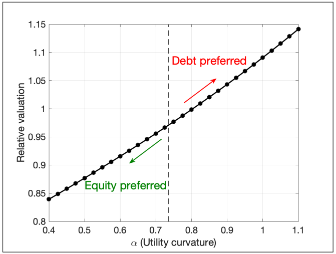
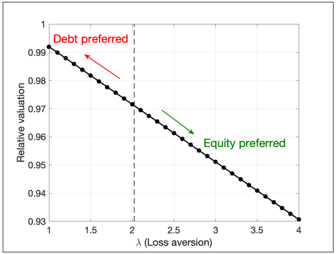


LOSS AVERSION (λ)



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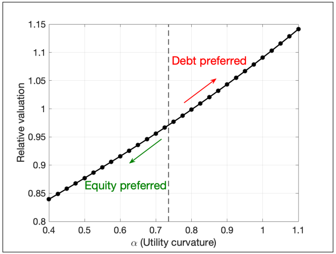

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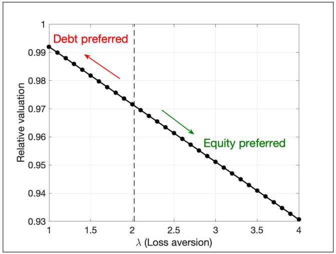
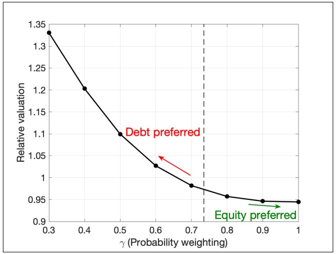


PROBABILITY WEIGHTING (γ)



PROBABILITY WEIGHTING AND RETURN SKEWNESS

Positively skewed distribution: individuals with inverse-S-shaped function:

1. **Overweight** the small probability of very high profits;
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Such business owners **dislike equity**.

Strikingly, result disappears when shape parameter $\sigma \to 0^+$ (Barberis & Huang 2008)

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A HYBRID CONTRACT INCREASES TAKE-UP

I show that a simple **contractual modification** can help individuals who benefit from equity contracts but select out of them due to overweighting of small probabilities.

A **'hybrid'** contract provides the same performance-contingent payment structure and risk-sharing benefits as equity, but with a (debt-like) capped upside.

While novel in this context, they share features with certain arrangements in **venture capital** (equity clawbacks, performance ratchets), and are increasingly being used by payment Fintechs. **Financial institutions** with more linear probability weighting functions can profitably offer such contracts.

Distribution of post-contract returns

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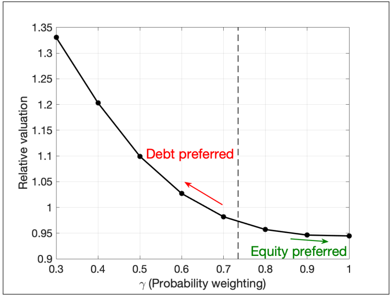
WITHOUT HYBRID



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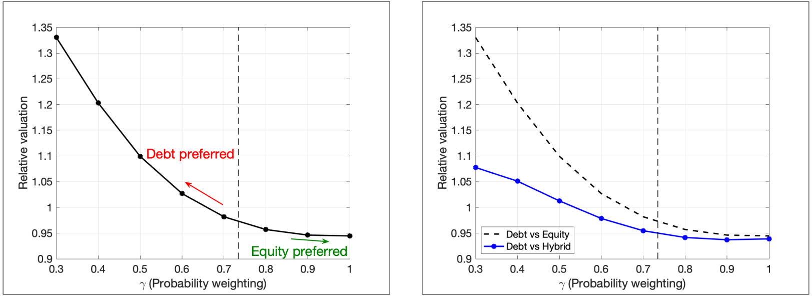

QUANTIFYING THE VALUE OF INTRODUCING THE NEW CONTRACT

I calculate a compensating-variation welfare measure using numerical optimization:

$$PU_i^{\text{hybrid}} = \int v(\widetilde{W}^{\text{hybrid}})\, dw(P(\widetilde{W})) = \int v(\widetilde{W}^{\text{debt}} + T)\, dw(P(\widetilde{W})) = PU_i^{\text{debt}}$$

I solve for individual-specific valuations of hybrid (T) accounting for each business owner's estimated σ, λ, and γ, and selection into their preferred contract.

Averaging across the sample and including the increase in MFI profits, the total surplus is 6% to 11% of disbursed capital.

QUANTIFYING THE VALUE OF INTRODUCING THE NEW CONTRACT

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Despite higher average profits for the financial institution from addressing the behavioral demand-side constraint, some supply-side challenges remain (Rigol & Roth, 2021; Choudhary & Limodio, 2022; Russel, Shi, & Clarke, 2023). Distribution of MFI profits

OUTLINE

1. Setting and design
2. Artefactual field experiment: reduced-form results
3. Structural parameter estimation and counterfactual analysis
4. Testing model fit

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2. Artefactual field experiment: reduced-form results
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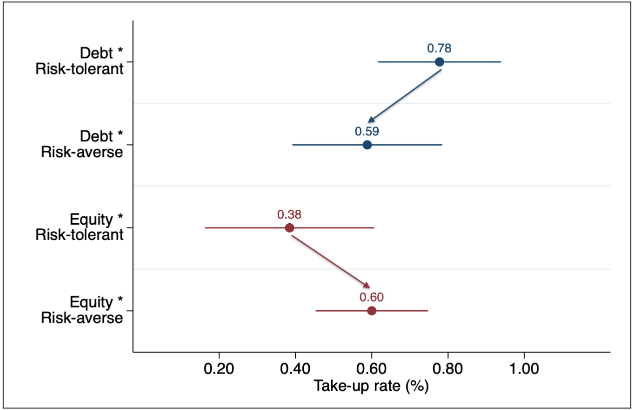
TESTING MODEL FIT: 'INSIDE THE LAB'

Incentivized take-up in the lab is consistent with previous results →

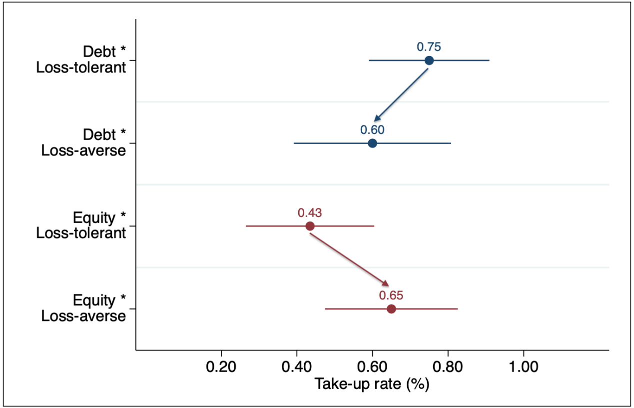
EXTERNAL VALIDITY: TESTING MODEL FIT 'OUTSIDE THE LAB'

TAKE-UP HETEROGENEITY: RISK AVERSION



EXTERNAL VALIDITY: TESTING MODEL FIT 'OUTSIDE THE LAB'

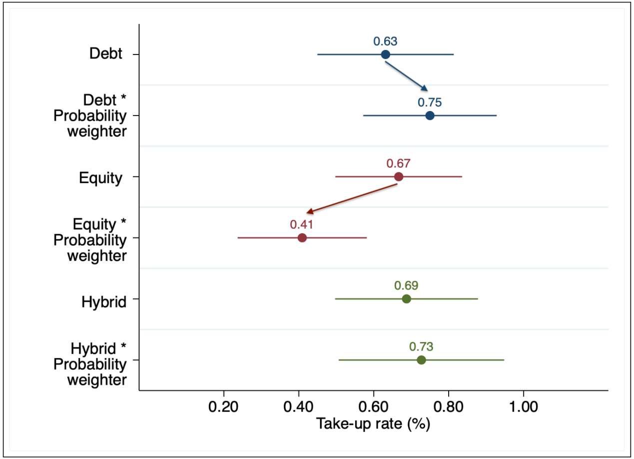
TAKE-UP HETEROGENEITY: LOSS AVERSION



Take-up: Pakistan

EXTERNAL VALIDITY: TESTING MODEL FIT 'OUTSIDE THE LAB'

TAKE-UP HETEROGENEITY: PROBABILITY WEIGHTING



CONCLUSION

I show that **equity-like** contracts lead to more profitable investment, and are particularly beneficial for the most risk- and **loss-averse** small firm owners.

However, individuals who **over-weight small probabilities** prefer debt contracts, especially in the presence of a **skewed** profits distribution.

Contractual innovations incorporating these behavioral insights can improve the feasibility of contracts that better encourage small firm investment and growth.

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Contractual innovations incorporating these behavioral insights can improve the feasibility of contracts that better encourage small firm investment and growth.

SMALL FIRM INVESTMENT UNDER UNCERTAINTY: THE ROLE OF EQUITY FINANCE

Muhammad Meki

American Finance Association
2025 ASSA
San Francisco

BASELINE SUMMARY STATISTICS

	Mean	Standard deviation	P10	P25	Median	P75	P90
Age	36	10	25	29	35	42	50
Years of education	7	4	2	4	8	10	12
Business experience	9	8	1	3	6	12	20
Business profits	231	177	50	100	200	300	500
Household size	6	3	2	4	5	7	9
Household savings	499	1,063	0	5	100	500	1,500
Household expenditure	209	118	95	130	185	250	342

Back

MEASURING RISK PREFERENCES: ELICITATION RESULTS

Self-reported measure of risk attitudes: I aggregate the scores across four questions, leading to an index of self-reported risk aversion that ranges from 0 to 40, with a mean of 21.2 and standard deviation of 8.3. I also find a strong and significant positive correlation of 0.30 between the risk aversion measures derived from the more general self-reported questions and those from incentivized games.

Incentivized activity: index of risk aversion that ranges from 0 to 30, with a mean of 20.3 and standard deviation of 9.4.

MEASURING RISK PREFERENCES: ELICITATION RESULTS

Non-parametric measure of probability weighting: For the $p_g = 0.25$ prospect, I find a mean risk premium of *negative* 23.6 (indicating a mean certainty equivalent of 273.6 that was actually higher than the 250 expected value of the risky prospect), and a standard deviation of 308.5. For the $p_g = 0.50$ prospect, I find a mean risk premium of 126.4 (reflecting a mean certainty equivalent of 374.6, compared to the expected value of 500), with a standard deviation of 336.2. For the $p_g = 0.75$ prospect, I find a mean risk premium of 272.0 (reflecting a mean certainty equivalent of 478.0 – much lower than the expected value of 750), with a standard deviation of 356.5.

Loss aversion: I construct a variable representing each individual's switching point, which is the mid-point between the x loss that they would tolerate (to accept the risky prospect) and the smallest x for which they would reject the prospect. The mean switching point is 601, with a standard deviation of 278. Back

(EQUITY LEADS TO MORE PROFITABLE INVESTMENT CHOICES

	(1) Round 1: Pakistan	(2) Round 1: Kenya	(3) Round 1: Pooled	(4) Round 2: Pooled	(5) Round 3: Pooled	(6) Round 1: Pooled	(7) Round 2: Pooled	(8) Round 3: Pooled
Debt	66.89***	52.69***	63.79***	64.18***	22.22***	63.79***	64.18***	22.22***
	(2.55)	(4.66)	(2.24)	(2.03)	(2.20)	(2.24)	(2.03)	(2.20)
Equity	76.71***	66.92***	74.58***	76.96***	30.82***			
	(2.17)	(3.93)	(1.90)	(1.77)	(1.91)			
Equity (25% sharing)						74.18***	76.60***	31.90***
						(2.10)	(2.01)	(2.09)
Equity (50% sharing)						74.97***	77.32***	29.74***
						(2.06)	(1.86)	(2.06)
Observations	2,392	668	3,060	3,060	3,060	3,060	3,060	3,060
Unique individuals	598	167	765	765	765	765	765	765
Control mean	109.36	101.20	111.21	78.79	178.12	107.58	77.97	176.47
R-squared	0.283	0.183	0.267	0.340	0.047	0.255	0.339	0.044
Country control			✓	✓	✓	✓	✓	✓
Test: Debt = Equity	0.000	0.001	0.000	0.000	0.000			
Effect size (%)	5.6	9.2	6.2	8.9	4.3			
Effect size (standard deviations)	0.35	0.37	0.35	0.49	0.15			
Test: Equity (25%) = Equity (50%)						0.640	0.650	0.178

Back

ROBUSTNESS: ORDER EFFECTS

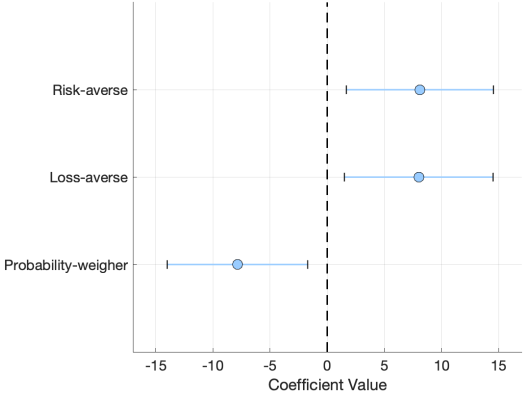
Outcome:	(1) Order 1	(2) Order 2	(3) Combined
Equity	75.64***	73.47***	73.47***
	(2.65)	(2.74)	(2.73)
Debt	67.91***	59.55***	59.55***
	(3.18)	(3.16)	(3.16)
Control	106.96***	108.22***	108.22***
	(1.58)	(1.57)	(1.57)
Equity * Order 1			2.17
			(3.81)
Debt * Order 1			8.36*
			(4.48)
Order 1			-1.26
			(2.23)
Observations	1,552	1,508	3,060
R-squared	0.27	0.24	0.26
Treat Effect (%)	4.4	8.3	
Treat Effect (Stdev)	0.25	0.45	
Test: Equity = Debt	0.005	0.000	

HETEROGENEITY: CONTROLLING FOR RISK AVERSION **and** LOSS AVERSION

	(1)	(2)	(3)	(4)
Risk-averse	-10.74***		-9.52***	
	(2.20)		(2.30)	
Loss-averse		-6.87***	-3.69	
		(2.23)	(2.31)	
Probability-weigher				-3.86*
				(2.27)
Debt * Risk-averse	1.10		1.70	
	(4.51)		(4.72)	
Debt * Loss-averse		-1.25	-1.82	
		(4.57)	(4.78)	
Debt * Probability-weigher				8.57*
				(4.53)
Equity * Risk-averse	10.05***		8.36**	
	(3.83)		(4.00)	
Equity * Loss-averse		7.90**	5.11	
		(3.89)	(4.05)	
Equity * Probability-weigher				-0.46
				(3.92)
Debt	63.19***	64.50***	63.89***	60.14***
	(3.33)	(3.52)	(3.92)	(2.96)
Equity	69.06***	70.09***	67.09***	74.77***
	(2.90)	(3.06)	(3.41)	(2.38)
Number of observations	3,060	3,060	3,060	3,060
Unique individuals	765	765	765	765
Control mean	107.35	107.35	107.35	107.35
Test (Risk aversion): Debt = Equity	0.015		0.091	
Test (Loss aversion): Debt = Equity		0.013	0.079	
Test (Probability weighting): Debt = Equity				0.014

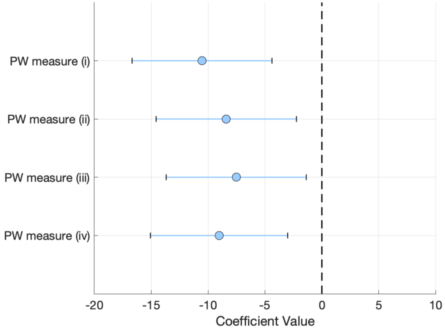
Back

ROBUSTNESS: TRICHOTOMIZED RISK PREFERENCE MEASURES



Back

robustness: Probability Weighting measure



Back

ROBUSTNESS: EDUCATION LEVELS

	(1)	(2)	(3)
Risk-averse	-10.75***		
	(2.20)		
Loss-averse		-7.01***	
		(2.23)	
Probability-weigher			-2.74
			(2.25)
Education	-3.16	-3.39	-3.46
	(2.21)	(2.23)	(2.24)
Debt * Risk-averse	1.09		
	(4.51)		
Debt * Loss-averse		-1.36	
		(4.57)	
Debt * Probability-weigher			7.17
			(4.58)
Debt * Education	-2.58	-2.63	-1.69
	(4.51)	(4.51)	(4.59)
Equity * Risk-averse	10.04***		
	(3.83)		
Equity * Loss-averse		7.86**	
		(3.89)	
Equity * Probability-weigher			-3.94
			(3.91)
Equity * Education	-1.38	-1.12	-1.91
	(3.82)	(3.83)	(3.90)
Debt	64.41***	65.81***	61.33***
	(3.88)	(4.06)	(3.92)
Equity	69.72***	70.64***	77.27***
	(3.22)	(3.46)	(3.16)
Control	114.98***	113.16***	110.47***
	(1.90)	(1.92)	(1.80)
Number of observations	3,060	3,060	3,060
Test (Risk aversion): Debt = Equity	0.015		
Test (Loss aversion): Debt = Equity		0.012	
Test (Probability weighting): Debt = Equity			0.003

Back

ROBUSTNESS: OPTIMISM

	(1) Alpha	(2) Lambda	(3) Gamma
Risk-averse	-10.36***		
	(-4.69)		
Loss-averse		-8.070***	
		(-3.60)	
Probability-weigher			-2.495
			(-1.10)
Optimistic	2.982	3.226	2.095
	(1.35)	(1.44)	(0.93)
Debt * Risk-averse	1.563		
	(0.34)		
Debt * Loss-averse		-1.319	
		(-0.28)	
Debt * Probability-weigher			7.224
			(1.59)
Debt * Optimistic	3.680	3.883	4.821
	(0.80)	(0.84)	(1.06)
Equity * Risk-averse	9.639*		
	(2.48)		
Equity * Loss-averse		8.337*	
		(2.10)	
Equity * Probability-weigher			-4.109
			(-1.06)
Equity * Optimistic	1.389	1.083	1.268
	(0.36)	(0.28)	(0.33)
Debt	61.79***	63.29***	58.70***
	(15.45)	(15.38)	(14.93)
Equity	69.09***	69.77***	76.33***
	(19.62)	(19.28)	(23.43)
Constant	111.8***	110.6***	107.8***
	(55.41)	(55.76)	(53.82)
Number of observations	2,988	2,988	2,988
Test (Risk aversion): Debt = Equity	0.032		
Test (Loss aversion): Debt = Equity		0.010	
Test (Probability weighting): Debt = Equity			0.002

Back

ESTIMATING THE EUT MODEL

I assume a simple constant relative risk aversion (CRRA) utility function $U(x) = x^r$, where r is the risk aversion parameter to be estimated, and x is wealth after the realization of outcomes for the prospect under consideration.

The expected utility for a prospect i is simply the probability-weighted utility of each possible outcome k in the prospect, using the experimentally induced probabilities that all business owners were made aware of through detailed explanations and tests of probabilistic understanding: $EUT_i = \sum_k p_k \cdot U(x_k)$.

The expected utility for each pair of prospects is calculated for a candidate estimate of r, and the difference $\nabla EUT = EUT_1 - EUT_2$ forms an index that is then used to define the cumulative probability of the observed choice using the logistic function

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ESTIMATING THE EUT MODEL

The likelihood, conditional on the EUT model being true, depends on the estimates of r and the observed choices:

$$\ln L^{\text{EUT}}(r; y, X) = \sum_i \ln l_i^{\text{EUT}} = \sum_i [y_i \ln G(\nabla EUT) + (1 - y_i) \ln(1 - G(\nabla EUT))]$$

where y_i is a binary variable denoting whether the business owner chose the first or the second of the two prospects on offer in each of the 40 questions, and X is a vector of individual characteristics measured in the baseline survey: age, gender, country, monthly business profits, total household savings, and highest level of education.

Estimation is via maximum likelihood.

ESTIMATING THE PT MODEL

Introduce the possibility of reference-dependent preferences and non-linear probability weighting in the decision making process.

The 40 risk preference elicitation questions induced variation in payoffs, including some in the loss domain, as well as probabilities.

Estimation proceeds in a similar manner to the EUT model, with each decision modelled as a binary choice between two prospects, and an index of latent preferences calculated as the difference in their prospective utility: $PU = PU_1 - PU_2$.

ESTIMATING THE PT MODEL

The utility of prospect i is the probability-weighted utility of each of the prospect's outcomes:

$$PU_i = \sum_{k=1}^{n} W(p_k) \cdot U(x_k),$$

$$\pi_k = \omega(p_k + \cdots + p_n) - \omega(p_{k+1} + \cdots + p_n)$$

for $k = 1, ..., n-1$, and

$$\pi_k = \omega(p_k)$$

for $k = n$, where x are the monetary outcomes, of which there are n possible outcomes for each prospect (with subscript k ranking outcomes from worst to best).

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ESTIMATING THE PT MODEL

$$PU_i = \sum_{k=1}^{n} W(p_k) \cdot U(x_k),$$

$$\pi_k = \omega(p_k + \cdots + p_n) - \omega(p_{k+1} + \cdots + p_n)$$

$\pi(\cdot)$ is now the decision weight, and $w(\cdot)$ is a probability weighting function that is defined over the cumulative distribution and transforms the experimentally induced probabilities

Distinction between $w(\cdot)$ and $\pi(\cdot)$: $w(\cdot)$ models the distortion of probability, and $\pi(\cdot)$ multiplies the value of each outcome.

ESTIMATING THE PT MODEL

I use a popular probability weighting function (Tversky and Kahneman, 1992):

$$w(p) = \frac{p^\gamma}{(p^\gamma + (1-p)^\gamma)^{1/\gamma}},$$

Where γ controls the shape of the probability weighting function (and $\gamma = 1$ charaterises linear probability weighting, as in the EUT model).

One-parameter weighting functions have been found in several studies to provide an excellent fit to the data, almost as well as the two-parameter, linear-in-log-odds weighting functions (Wu & Gonzalez, 1996).

ESTIMATING THE PT MODEL

I again use a simple CRRA power utility functional form, but now defined separately over gains and losses:

$$U(x) = \begin{cases} x^{\alpha} & \text{if } x \geq 0 \\ -\lambda(-x^{\alpha}) & \text{if } x < 0, \end{cases}$$

where α controls the curvature of the utility function and λ allows for the possibility of reference-dependent preferences, where the reference point being set at zero represents their initial starting point before undertaking the activities.

Identification of the loss aversion parameter λ comes from decisions comprising payoffs in the loss domain, and identification of the probability weighting parameter γ comes from variation of the probability of the good outcome $p_g \in \{0.25, 0.50, 0.75\}$ in the risky prospects on offer.

ESTIMATING THE PT MODEL

Estimation proceeds in the same manner as for the EUT model, using maximum likelihood. I calculate the utility of each prospect under consideration in the 40 decisions made by business owners, based on candidate values of the parameters α, λ, and γ.

I then link the latent index $\nabla PU = PU_1 - PU_2$ to the observed choices in the experiment using the logistic cumulative distribution function $G(\nabla PU)$. The conditional log-likelihood is:

$$\ln L^{PT}(\alpha, \lambda, \gamma; y, X) = \sum_i \ln l_i^{PT} = \sum_i \left[y_i \ln G(\nabla PU) + (1 - y_i) \ln(1 - G(\nabla PU)) \right].$$

ESTIMATING THE MIXTURE MODEL

To estimate the mixture model, let π^{EUT} denote the probability that the EU model is correct, and $\pi^{\mathrm{PT}} = (1 - \pi^{\mathrm{EUT}})$ as the probability that the PT model is correct. The grand likelihood can be written as the probability weighted average of the conditional likelihoods:

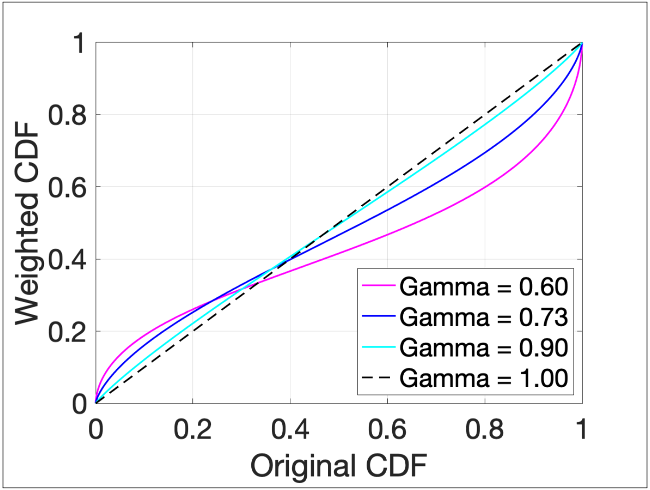
$$\ln L(r, \alpha, \lambda, \gamma, y'; y, X) = \sum_i \ln[(\pi^{\mathrm{EUT}} \times l_i^{\mathrm{EU}}) + (\pi^{\mathrm{PT}} \times l_i^{\mathrm{PT}})].$$

I then directly estimate the log-likelihood.

	Coefficient	Std. err.	$P > \lvert z \rvert$	95% confidence interval
π^{EUT}	0.127	0.015	0.000	[0.097 , 0.156]
π^{PT}	0.873	0.015	0.000	[0.844 , 0.903]

Back

IMPLICATIONS OF γ



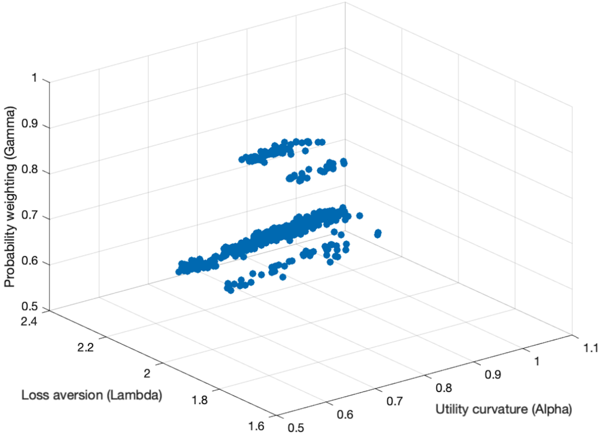
Back

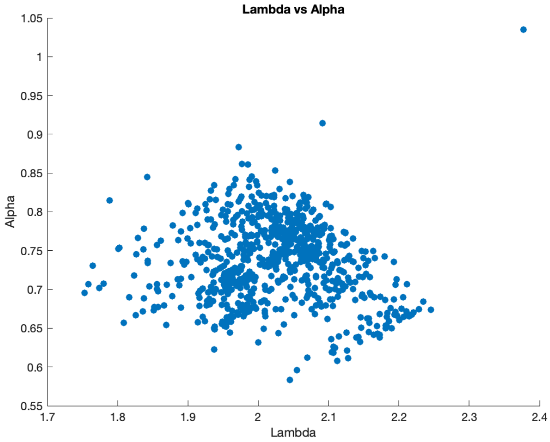
STRUCTURAL ESTIMATION WITH STOCHASTIC ERRORS

	Coefficient	Std. err.	$P > \|z\|$	95% confidence interval
α	1.032	0.020	0.000	[0.993, 1.072]
λ	2.504552	0.044	0.000	[2.418, 2.592]
γ	.6109845	0.011	0.000	[0.590, 0.632]
μ	2.342888	0.117	0.000	[2.113, 2.573]

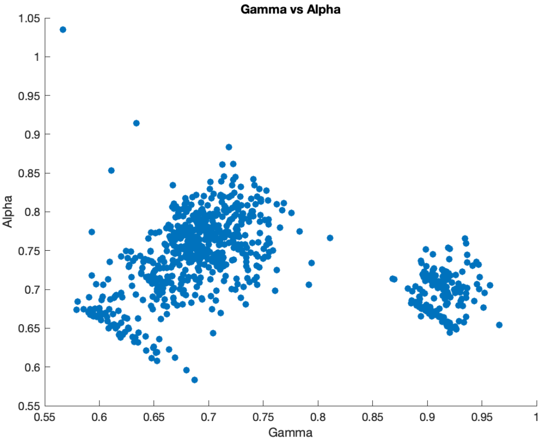
Back

JOINT DISTRIBUTION



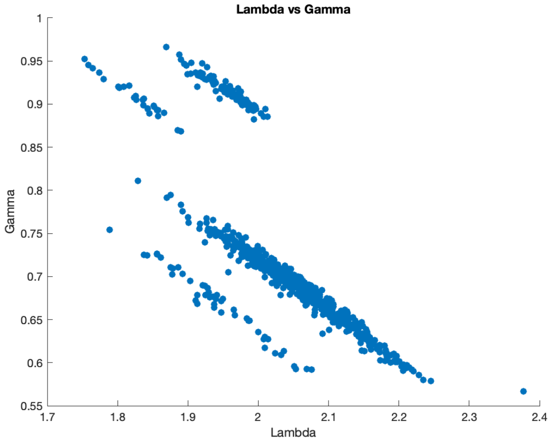

Lambda vs Alpha
1.05
1
0.95
0.9
0.85
0.8
0.75
0.7
0.65
0.6
0.55
Alpha
1.7
1.8
1.9
2
2.1
2.2
2.3
2.4
Lambda

Back



Gamma vs Alpha
Alpha
Gamma
1.05
1
0.95
0.9
0.85
0.8
0.75
0.7
0.65
0.6
0.55
0.55
0.6
0.65
0.7
0.75
0.8
0.85
0.9
0.95
1

Back


Lambda vs Gamma
Gamma
Lambda
1
0.95
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0.55
1.7
1.8
1.9
2
2.1
2.2
2.3
2.4

CORRELATES OF ESTIMATED RISK PREFERENCE PARAMETERS

Table: CORRELATION OF ESTIMATED RISK PREFERENCE PARAMETERS

	α	λ	γ
α	1.000		
λ	-0.125***	1.000	
γ	-0.174***	-0.731***	1.000

CORRELATES OF ESTIMATED RISK PREFERENCE PARAMETERS

Table: Estimated risk preference parameters: correlation with covariates

	Dependent Variable		
Covariates	α	λ	γ
Household savings (per $100)	-0.000	0.005**	-0.002***
	(0.000)	(0.002)	(0.000)
Business profits (per $100)	0.005**	-0.010	0.002
	(0.002)	(0.010)	(0.004)
Education	0.011***	-0.017***	0.011***
	(0.001)	(0.006)	(0.002)
Household head	0.030**	0.000	-0.016
	(0.012)	(0.049)	(0.018)
Female	0.022	-0.223***	0.004
	(0.018)	(0.068)	(0.028)
Age	-0.002***	-0.003	0.002**
	(0.001)	(0.002)	(0.001)
Kenya	-0.037**	-0.228***	0.287***
	(0.015)	(0.059)	(0.023)
Constant	0.712***	2.330***	0.545***
	(0.025)	(0.102)	(0.041)
Observations	29,880	29,880	29,880

CORRELATES OF ESTIMATED RISK PREFERENCE PARAMETERS

Table: CORRELATION BETWEEN RISK PARAMETERS AND OPTIMISM

	(1)	(2)	(3)	(4)	(5)	(6)
	α	α	λ	λ	γ	γ
Optimism: return to capital	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)
Constant	0.74***	0.71***	2.02***	2.33***	0.73***	0.55***
	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)
Observations	747	747	747	747	747	747
Controls		✓		✓		✓

Back

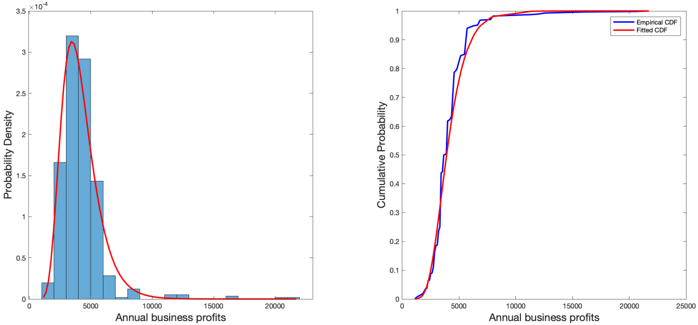
SELECTING DISTRIBUTION OF BUSINESS RETURNS FOR COUNTERFACTUAL ANALYSIS

Table: Distributional fit

Distribution	Sum of Squares Error (SSE)
Lognormal	0.078
Birnbaum-Saunders	0.093
Gamma	0.131
Normal	0.385
Weibull	0.412
Rayleigh	0.523
Poisson	1.658
Generalized Pareto	1.840
Exponential	2.146

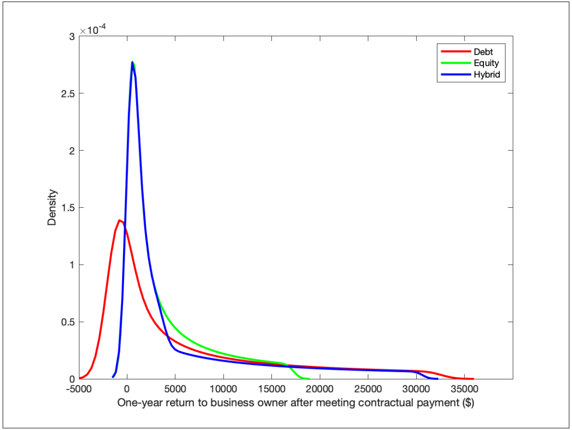
SELECTING DISTRIBUTION OF BUSINESS RETURNS FOR COUNTERFACTUAL ANALYSIS

Figure: VISUAL ASSESSMENT OF DISTRIBUTIONAL FIT



Back

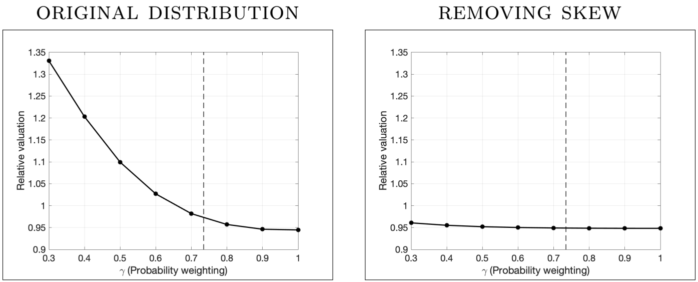
Figure: MODEL-BASED DISTRIBUTION OF RETURNS UNDER EACH FINANCING CONTRACT



Back

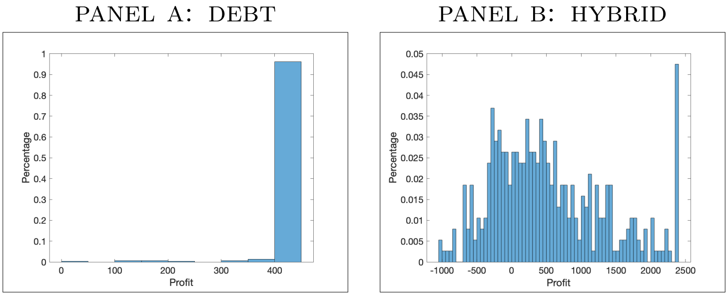
REMOVING SKEW FROM THE RETURNS DISTRIBUTION

Figure: EFFECT OF REMOVING SKEW FROM DISTRIBUTION



Back

HYBRID CONTRACTS AND COUNTERFACTUAL MFI PROFITS



Traditional lenders may struggle to provide riskier products (Choudhary & Limodio, 2022)

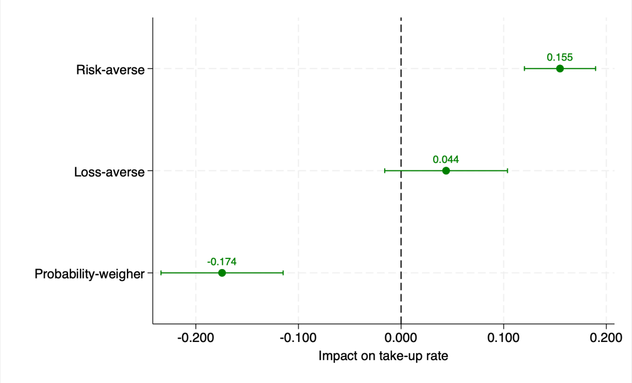
The incentive structures within MFIs may be a constraint, and may inhibit graduation to more sophisticated products (Rigol & Roth, 2021).

Back

TESTING MODEL FIT: INSIDE THE LAB

Overall take-up: 54% debt, 46% equity

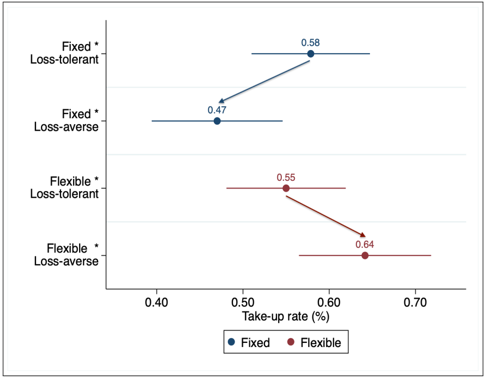
TAKE-UP HETEROGENEITY BY RISK PREFERENCE PARAMETER



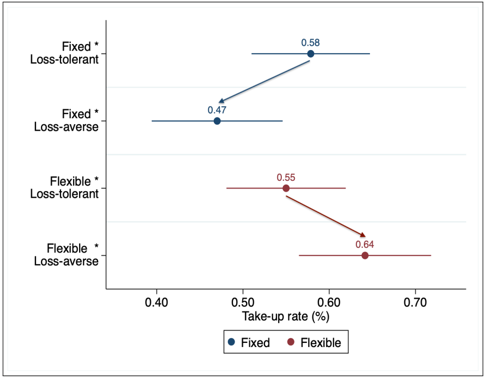
Back

FURTHER TAKE-UP RESULTS 'OUTSIDE OF THE LAB'

PANEL A: RISK AVERSION



PANEL B: LOSS AVERSION



Back