SMALL FIRM INVESTMENT UNDER UNCERTAINTY: THE ROLE OF EQUITY FINANCE*

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December 2025

ABSTRACT. Private enterprise development in low-income countries remains elusive, and the failure of microcredit to stimulate small firm growth poses a puzzle to the finance and development literature. Combining data from artefactual field experiments, two field experiments, and structural estimation, I show that equity-like contracts stimulate more profitable investments, and I find a novel and nuanced role for risk preferences. Loss-averse individuals prefer equity, but the substantial portion of individuals who overweight small probabilities prefers debt. I demonstrate that equity-like contractual innovations that incorporate these insights — and are increasingly feasible due to FinTech developments — can unlock small firm investment.

Keywords: Finance and development; Small firms; Investment choice; Behavioral finance; Contract design.

*I am grateful to the Society for Experimental Finance, which awarded this paper the Vernon L. Smith Young Talent Award. I thank audiences at the NBER Summer Institute (DEV), the BREAD Conference on Development at UCSD, CEPR-WEFIDEV workshop at Bocconi University, the American Finance Association / ASSA, European Finance Association, FIRS Conference Seoul, University of Chicago Development Workshop and Advances with Field Experiments Conference, Harvard University NEUDC, Northwestern University IPA financial inclusion workshop, HEC Paris Entrepreneurship Workshop, Research in Behavioral Finance Conference, Royal Economic Society Junior Symposium, Society for Experimental Finance, Symposium on Economic Experiments in Developing Countries, Nordic Conference in Development Economics, Centre for the Study of African Economies, and IGC Pakistan. I am also grateful to Johannes Abeler, Elena Asparouhova, Giorgia Barboni, Thorsten Beck, Pedro Bordalo, Peter Bossaerts, Emily Breza, Gharad Bryan, Rachel Cassidy, Emanuele Colonnelli, Kim Fe Cramer, Vincent Crawford, Christina Czura, Josh Dean, Stefan Dercon, Felix Fattinger, Ernst Fehr, Cary Frydman, Xavier Giné, Juanita González-Uribe, Rema Hanna, Glenn Harrison, Sean Higgins, Jessica Jeffers, Anett John, Dean Karlan, Asim Khwaja, Olivia Kim, Michael Kirchler, Michael Koelle, Michael Kremer, Pramila Krishnan, Greg Lane, Nicola Limodio, John List, Karen Macours, Colin Mayer, Craig McIntosh, Karlijn Morsink, Paul Niehaus, Stefan Palan, Amma Panin, Jacopo Ponticelli, Simon Quinn, S.K. Ritadhi, Gautam Rao, Ben Roth, Chris Roth, Simone Schaner, Frank Schilbach, Dimitri Vayanos, Eric Verhoogen, Chris Woodruff, Constantine Yannelis, and Jonathan Zinman, for their very helpful comments. Ahmad Ayub and Elizabeth Gatwiri provided excellent research assistance. A pre-analysis plan is available at https://www.socialscienceregistry.org/trials/2224. Ethics approval was obtained from the University of Oxford (R37860/RE001/2). I would like to thank the Economic and Social Research Council (ESRC) and the International Growth Centre (IGC) for funding.

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1 Introduction

Small firms employ the vast majority of workers in low- and middle-income countries, and credit constraints are often cited as a key barrier to their growth. Microfinance emerged to fill this gap, serving hundreds of millions of borrowers while maintaining high repayment rates. Yet a large wave of experiments finds little average impact of standard microcredit on small-firm profits. This poses a puzzle for the finance and development literature, given: (i) significant macro-level evidence linking financial development and growth, and (ii) consistent micro-level evidence of high returns to capital among small firms, on the order of 5–10 percent per month (Liu & Roth, 2022).

One potential explanation is contract structure, not just the quantity of credit. Standard debt contracts involve rigid repayment schedules, which help mitigate adverse selection and moral hazard in opaque lending markets, but may discourage the higher-risk, higher-return investments needed for growth. Equity-like contracts with performance-contingent payments can be better suited to financing investments with more volatile cash flows, especially for risk-averse owner-managers, but are rarely provided to small firms. The corporate finance literature recognizes the value of financial flexibility and optimal contract design under uncertainty, but much less is known for small, owner-managed firms, where owners' risk preferences map directly into business investments in a way that differs from larger, multi-layered firms.

In this paper, I explore how small-firm owners' risk preferences shape demand for debt versus equity-like contracts, and what this implies for contract design. I take the supply side as given: the analysis is conditional on a lender being able to offer performance-contingent contracts, abstracting from the institutional and enforcement frictions that traditionally limit the supply of equity-like finance. Those frictions remain important, but are becoming less binding in several sectors as digital payments, rich transaction data, and real-time monitoring via open banking APIs reduce monitoring and verification costs and enable novel financial products in emerging markets (Gertler, Green, & Wolfram, 2024). In India, for example, more than 12 billion digital transactions are now processed per month, with a value of over $240 billion (Alok, Ghosh, Kulkarni, & Puri, 2024), with similar growth in Brazil and other developing countries. Real-time transaction data are increasingly used by payment and e-commerce platforms to provide revenue-based finance to small firms (Russel, Shi, & Clarke, 2025). Two additional facts motivate a focus on demand. First, in one field experiment from which my sample is drawn, fewer firm owners chose an equity-like profit-sharing contract over standard debt, despite the risky business environment and their high risk aversion. Second, in a separate pilot, initial enthusiasm for profit-sharing contracts faded after some clients experienced rare, high payments, which loomed large in owners' perceptions and constrained demand even among those who recognized the insurance benefits of equity. Both patterns suggest that, conditional on the ability to offer such contracts, demand-side forces—particularly the way small-firm owners think about risk and rare events—can be an important additional constraint on the implementation of potentially beneficial equity-like contracts.

To organize the analysis, I use a simple model of small-firm investment under uncertainty in which heterogeneous risk preferences map into demand for different financing contracts. Returns in the model are simulated from a lognormal distribution calibrated to business profit data from one of the field experiments. Contracts differ only in their payment schedules: a standard fixed-repayment debt contract; an equity-like contract that shares a fixed fraction of profits; and a hybrid contract that shares profits up to a cap, after which the firm keeps all additional upside. The model allows for rich risk preferences that nest standard expected utility and prospect theory. In this framework, three preference parameters—utility curvature, loss aversion, and probability weighting—jointly determine small-firm owners' ranking of contracts.

I calibrate the model using artefactual field experiments with 765 growth-oriented small-firm owners in Kenya and Pakistan. Participants were recruited from two larger asset-finance experiments and were actively considering business expansion at the time of the study. During half-day baseline workshops, they completed 30,000 incentivized tasks that varied payoffs, probabilities, and the possibility of losses. I estimate a mixture model of expected utility and prospect-theoretic types, letting the data choose between them; the estimates strongly favor the prospect-theoretic component. The estimated preference distributions feature a moderate degree of risk aversion, loss aversion in the canonical range, and a bimodal distribution of the probability-weighting parameter with a large mass around an inverse-S shape that overweights small probabilities. These estimates are close to those obtained in household and investor samples in high-income countries (DellaVigna, 2018; Dimmock, Kouwenberg, Mitchell, & Peijnenburg, 2021), suggesting that the distribution of preferences among small-firm owners in my setting is not unusual.

I then use a simple incentivized investment game as a test of the model's comparative statics. Business owners chose between five stylized investment options that trade off expected return and risk, under financing contracts that mimic debt and equity. Contracts were implemented with real money, and the activities were embedded in the same workshops where participants were being surveyed for real asset financing. Results reveal that business owners choose significantly higher-expected-profit investments under the equity-like contract than under debt, with an effect size of about 0.35 standard deviations that is almost identical in both Kenya and Pakistan, supporting external validity. Exploring heterogeneity, I find that the gain from equity is largest for more risk-averse and loss-averse business owners, and smallest for those who overweight small probabilities. These patterns align with the model's predictions: equity is valuable in providing downside protection, but demand decreases for business owners who overweight the small chance of very high profits that must be shared under equity.

The structural model then allows me to explore several relevant counterfactuals. First, the extent to which probability weighting pushes a substantial subset to choose debt is intricately linked to the skewness of the returns distribution. In particular, this equity-aversion result vanishes when I replace the calibrated lognormal profit distribution with a symmetric normal distribution, which aligns with the findings of Barberis and Huang (2008) in developed financial markets. Second, under the calibrated skewed distribution, I show the value of introducing a hybrid contract that combines debt- and equity-like features: it shares profits with the lender but caps the upside, mitigating concerns about sharing very large profits for owners who overweight low-probability, high-return states. I compute a compensating-variation measure of the value of adding such a hybrid contract to a lender's product menu; introducing the hybrid contract generates sizeable welfare gains while also raising expected lender profits, since many small-firm owners value a contract with downside protection and capped upside sharing. The cap is akin to a deeply out-of-the-money option on the upper tail of profits that a lender with closer-to-linear probability weighting can profitably sell to firm owners who overvalue this optionality due to overweighting small probabilities.

Finally, I validate the model's predictions "outside the lab" using take-up decisions from a field experiment that supplied my sample. Findings from the field experiment confirm that risk-averse and loss-averse business owners are more likely to accept equity-like contracts than standard debt, while those who overweight small probabilities are less likely to do so. When the hybrid contract is offered, take-up is high even for those who overweight probabilities, consistent with model predictions. These results show that prospect-theoretic preferences, estimated from modest-stake elicitation tasks, meaningfully predict high-stakes financing choices for small firms in this environment.

My primary contribution is to use insights from behavioral finance to inform the design of financial contracts that encourage more profitable investment by small firms in developing economies. I build on the finance and development literature which finds that more flexible debt contracts can stimulate small-firm growth (Barboni & Agarwal, 2021), while taking a distinct approach that responds to Banerjee, Karlan, and Zinman (2015)'s call for work on contract innovations and non-credit product features, by studying equity-like contracts that were previously non-optimal due to costly state verification (Townsend, 1979), yet are increasingly feasible in modern digital ecosystems (Higgins, 2024). By allowing for a broader conception of risk preferences than is typical in the development economics literature, I also respond to calls for more research on "behavioral firms" in developing countries (Kremer, Rao, & Schilbach, 2019). I present, to my knowledge, the first evidence that loss-averse business firm owners may both prefer and choose more profitable investments under equity-like contracts than under debt, based on cleanly estimated risk preferences and real business decisions in the field.

My results provide a novel counterpoint to the behavioral finance literature, which finds that individuals who overweight low-probability events have a preference for skewness in investment returns (Dimmock et al., 2021) and that large firms can profit from this by implicitly selling deeply out-of-the-money stock options that such individuals overvalue (Spalt, 2013). In the small-firm context I study, business owners who overweight low-probability, high-profit states are equity-averse, because equity contracts require them to *sell* skewness and share a large fraction of the upside in precisely those states they overweight. A financial institution with a more linear probability-weighting function can unlock mutual gains from trade by offering contracts that cap upside sharing and effectively waive claims in these low-probability, high-profit states, echoing theoretical work on risk-sharing networks in which more risk-tolerant individuals absorb risk from more risk-averse individuals (Chiappori, Samphantharak, Schulhofer-Wohl, & Townsend, 2014) and connecting to classic work on risk-sharing (Ligon, 1998; Udry, 1990). While recent work has advanced our understanding of the cognitive foundations of preferences (Frydman & Jin, 2023), I instead document that small-firm owners' behavior in my setting is well captured by standard prospect-theoretic models and trace out the implications of these preferences for small-firm investment, without taking a stand on the underlying cognitive mechanisms. My results also relate to a behavioral corporate-finance literature on the importance of managerial traits for financial contract design, showing that overconfident managers prefer debt over equity (Landier & Thesmar, 2008; Malmendier, Tate, & Yan, 2007). Even after ruling out over-optimism as the mechanism, my evidence indicates that probability weighting—a related but distinct behavioral bias—can generate a similar preference for debt. Finally, in contrast to the prevailing security-design literature, which typically assumes a representative entrepreneur, my approach directly elicits heterogeneous risk preferences using incentivized tasks and links them to subsequent contract choices.

Methodologically, I adopt a structural approach that embeds the experimental variation in a model of contract choice, enabling counterfactual analysis and welfare evaluation of contract innovation (Whited, 2023), echoing recent work that explores the gains from introducing digitally enabled novel financing contracts in developing countries (Gertler, Green, Li, & Sraer, 2025). An artefactual field experiment combined with structural estimation provides a clean way to estimate risk preferences and the welfare effects of new financial contracts, allowing me to separate probability weighting from biased beliefs in a way that is difficult with field data alone. I address external validity using the framework of List (2020): the sample consists of growth-oriented firms actively seeking financing; the experimental choices are made in a natural setting at a critical business juncture; and the main patterns are consistent both with prospect-theoretic predictions from other studies and, within this paper, across two countries and actual contract take-up in the field. These features support the generalizability of the findings and offer guidance for future work on increasingly feasible equity-like contractual innovations.

Section 2 describes the institutional background, sample, and data. Section 3 presents the model of contract choice and estimation of risk-preference parameters. Section 4 presents the evidence from artefactual and field experiments. Section 5 concludes.

2 Institutional background and data

2.1 Sample

I conducted artefactual field experiments with 765 small-firm owners participating in two distinct field experiments in Kenya and Pakistan.[1] While both samples consist of growth-oriented small firms in key developing countries, they differ in some ways, which helps assess external validity. I implemented a series of incentivized investment tasks during a baseline workshop with business owners prior to the randomized offering of financing contracts in the broader field experiments, thereby increasing the naturalness of the setting (List, 2020). The activities took place on the same day, ensuring no attrition for the investment tasks.

The first experiment was implemented in Pakistan between 2017 and 2018. Pakistan provides an important setting to explore contracts with greater risk-sharing, which the IMF and World Bank highlight as a promising means of extending finance to hundreds of millions of financially excluded business owners (IMF, 2015; World Bank, 2012). As of 2019, Pakistan had 46 registered microfinance providers. They are categorized into two groups, which have quite different funding structures: microfinance banks (MFBs), and non-bank microfinance companies (NBFCs).[2] I worked with Akhuwat, an NBFC. As of 2019, Akhuwat was the largest microfinance provider in the whole of Pakistan in terms of both geographical spread as well as number of borrowers, with a market share of around 13%, comprising over 891,000 active borrowers across 811 branches, and an outstanding portfolio of PKR 16.4 billion (approximately US$106 million at prevailing market rates) (Pakistan Microfinance Network, 2020). Akhuwat is based in Lahore, and I sampled from small firms in and around Lahore that had passed a simple screening process of having graduated from repaying smaller business loans, and reaching the maximum borrowing amount of just under $500. Clients who expressed an interest in expanding their business with the purchase of a fixed asset (up to the value of approximately $2,000) were invited to the baseline workshop, where enumerators conducted a detailed household survey and incentivized behavioral tasks to elicit risk preferences.

Summary statistics are presented in Appendix A. The average age of participants in Pakistan was 38 years, with an average of eight years of formal education, and ten years of experience in their current business. The most popular business sector was rickshaw driving (20%), followed by clothing and footwear production (11%), food and drink sales (10%), and retail trade in the form of

[1] For impact evaluations of the asset finance product in these two experiments, see Bari, Malik, Meki, and Quinn (2024) and Cordaro et al. (2025).

[2] The key distinction concerns deposits: MFBs are permitted to accept deposits, whereas NBFCs are not. For this reason, MFBs are regulated by the central bank (whereas NBFCs are regulated by the securities commission). MFBs and NBFCs each serve around half of active borrowers. MFBs' primary source of funding is public deposits, with borrowing constituting less than 10% (borrowing is mostly from local banks and development finance institutions). About 75% of funds for NBFCs come from debt, provided mainly from the apex funding agency, the Pakistan Microfinance Investment Company, which provides subsidised loans to NBFCs (Malik et al., 2020).

fabric and garment sales (7%). Average monthly business profits were $257 (median $220), and average monthly household consumption expenditure was $209 (median $185), which puts the average household in the second quintile of the overall distribution for household consumption in Pakistan (Pakistan Bureau of Statistics, 2017).[3]

The second experiment was implemented in Kenya, also in 2017. Kenya represents a natural setting to leverage technological developments to test novel financial contracts, given its position as the mobile money capital of the region, which has led to a significant increase in digital financial literacy (Suri, 2017). I collaborated with one of the largest multinational food companies in the world, which I refer to pseudonymously as 'FoodCo'. FoodCo developed a route-to-market distribution program using self-employed distributors. The distribution system is built around small warehouses (called 'stockpoints'), which are located in both rural and urban areas. Stockpoints receive deliveries of FoodCo's product, which they sell alongside various other products. Micro-distributors purchase FoodCo's product (as well as other products) from stockpoints, before selling to customers (often on foot). They initially purchase the product from the stockpoints with an up-front discount to the market price, which must be paid in full. They additionally receive an end-of-month bonus via mobile money (M-Pesa). There is no obligation for distributors to sell FoodCo's product exclusively, but selling the company's product is relatively profitable, and they have a strong incentive to stay in the program. This setting is common to many route-to-market distribution programs run by multinational corporations around the world.

I worked with micro-distributors within FoodCo's supply chain who expressed an interest in purchasing a fixed asset for their business. The availability of administrative data on business performance permitted the implementation of performance-contingent financing contracts in the broader field experiment, which I utilize in Section 4.4 to assess the external validity of the elicited risk preference measures and model predictions outside the controlled setting of the artefactual field experiment. The average participant in the Kenyan sample was 31 years old, with monthly sales from all micro-distribution activities of $995, and mean profits of $143. Average monthly household consumption expenditure was similar to the Pakistani sample, at $189 per month. Given the average household size of 3.3, this places the average participant's consumption above the median per-capita monthly expenditure in Kenya in 2016, which was $31, and also above the mean of $44 (Kenya National Bureau of Statistics, 2020).

The artefactual field experiment followed identical procedures in both countries. During the half-day baseline workshop I conducted surveys, risk-preference elicitation, and the investment experiment; Section 4 describes the experimental design and results in more detail, and Section 4.4 reports contract take-up in the broader field experiments.

[3] Henceforth, I use $ to refer to US dollars, based on the actual Pakistani rupee (Re) and Kenyan shilling (Ks) amounts and the baseline US$-Re and US$-Ks exchange rates of 105 and 103, respectively.

2.1.1 Motivating an examination of the determinants of demand for equity-like contracts

In the Kenyan field experiment, the same micro-distributors described above were randomly offered different contracts to finance the actual asset in the broader project. When designing that project, described in further detail in Cordaro et al. (2025), qualitative work and pilot data demonstrated substantial month-to-month volatility in profits—an average per-person coefficient of variation of 0.79 and an AR(1) of 0.31, even after individual and month-of-year fixed effects—suggesting a large transitory component in earnings, and a potentially large benefit from performance-contingent financing contracts. Yet absolute take-up of the debt contract in the field experiment was significantly higher than that of the equity-like contract (68% versus 49%). Debt and equity-like contracts were then calibrated to be roughly payment-parity in expectation, so the take-up gap is unlikely to be driven mechanically by pricing, motivating a closer examination of factors relevant for small-firm demand for equity-like contracts.

An additional field-based motivation for focusing on demand comes from a pilot of equity-like financing contracts with the National Rural Support Programme (NRSP), one of Pakistan's largest rural finance providers, with a similar client profile and institutional and regulatory context to the other field experiment from which the remaining sample is drawn. The programme provided around 1,250 skilled but capital-constrained clients with asset financing under a simple profit-sharing rule in which clients were expected to share a fixed fraction of monthly profits with NRSP. Further details are provided in Appendix B. After implementation, I surveyed a stratified sample of 248 of these clients to understand how the contracts operated in practice. Early qualitative feedback suggested strong interest in the equity-like product, but the survey and focus-group discussions with managers and loan officers emphasized that more profitable clients in particular felt they were sharing too much in good months. Over time, these concerns contributed to a gradual shift away from performance-contingent payments toward a one-size-fits-all fixed instalment schedule, and the equity finance pilot unravelled. Results from this case study underscore how perceptions of high sharing payments in very profitable periods can erode otherwise strong demand for equity-like contracts, and further motivate the analysis that follows on how small-firm owners evaluate upside sharing under risk and different distributions of returns.

These field experiences motivate a focus on the demand side. In the sections that follow, I study selection into and valuation of equity-like finance, conditioning on a lender being able to offer such contracts. Supply-side frictions remain important, but are becoming less binding in environments with digital payments, granular transaction data, and real-time monitoring, where performance-contingent contracts are increasingly feasible in practice (Alok et al., 2024; Russel et al., 2025).

2.2 Measuring risk preferences

All participants answered 44 questions designed to assess their attitudes towards risk. These included 40 incentivized choices among lotteries that varied in payoffs and probabilities, and 4 domain-specific, self-reported measures of risk attitudes. This approach allows the creation of simple non-parametric measures of utility curvature, loss aversion, and probability weighting. Additionally, the variation in amounts, probabilities, and gain–loss domains allows structural estimation of risk-preference parameters under specific functional forms. All activities utilized real currency notes and business framing to aid comprehension, following best methodological practice (Lowes & Nunn, 2025). Average payment amounts were non-trivial, representing approximately three times median daily business profits for individuals in the sample.[4] For the self-reported measures of risk attitudes, each business owner was asked to rate, on a scale of 1 to 10, their willingness to take risks in financial matters, business decisions, trust in others, and their overall tendency to embrace or avoid risks. The questions were adapted from Dohmen et al. (2011), who find that they are strongly correlated with incentivized risk-taking, and are often preferred due to their simplicity and ease of field implementation. I also find a significant positive correlation of 0.30 between the risk aversion measures derived from the more general self-reported questions and those from incentivized tasks. I aggregate the scores across the 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 complement the self-reported measures of risk aversion with responses from a more narrowly defined incentivized activity. The activity built upon the work of Barr and Packard (2002) and Vieider et al. (2015), and involved a certainty-equivalent elicitation technique that provided the best trade-off between comprehension and quality of data for this population of small business owners, as discovered through extensive piloting. Respondents were posed a series of 30 questions, in which they were offered a risky 'prospect' with two possible outcomes: (i) zero; or (ii) 1,000 units of local currency.[5] The 30 questions were split into three sets of ten, with variation in the probability of a good outcome: $p_g \in \{0.25, 0.50, 0.75\}$. For each set of 10 questions, the choice was between accepting the risky prospect or rejecting it and taking a certain amount of money, which increased from zero (a test of comprehension, since all of the risky prospects had non-zero expected value), to 100, and then in increments of 100 up to 1,000. For each participant, I count how often they selected the certain cash payment over the risky prospect. This results in an index of risk aversion that ranges from 0 to 30, with a mean of 20.3 and standard deviation of 9.4.

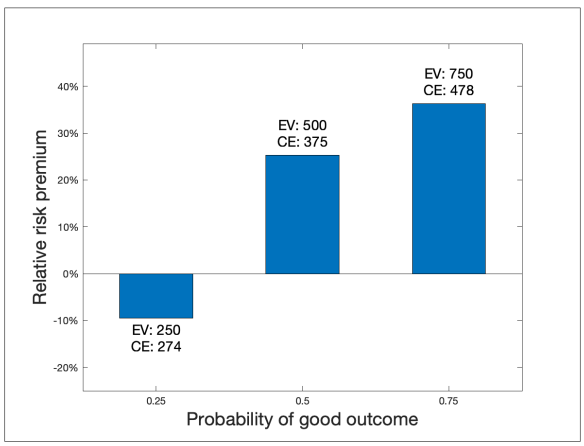
The variation in p_g also allows for a non-parametric measure of probability weighting. For each probability level $p_g \in \{0.25, 0.50, 0.75\}$, I compute the participant's certainty equivalent — the

[4] Further details of experimental protocols are provided in Appendix C.

[5] Henceforth, I use the more general term "prospect" rather than "lotteries" (Tversky & Kahneman, 1992; Wakker, Thaler, & Tversky, 1997).

midpoint between the highest sure payment they rejected and the lowest sure payment they accepted. The risk premium at each p_g is the gap between this certainty equivalent and the expected value of that specific 1,000/0 prospect: 250 for $p_g = 0.25$, 500 for $p_g = 0.50$, and 750 for $p_g = 0.75$. The use of 25%, 50%, and 75% probabilities, implemented through simple randomization devices, is a common practice in developing country settings to enhance participant comprehension (Humphrey & Verschoor, 2004a, 2004b). In the experimental literature, the switch from overweighting to underweighting probabilities typically occurs between 25% and 50%; I therefore follow Dimmock et al. (2021) in constructing a simple proxy for probability weighting as the average premium in the underweighting range ($p_g \in \{0.50, 0.75\}$) minus the premium in the overweighting range ($p_g = 0.25$). The benefit of the non-parametric approach is to avoid assuming a specific functional form for probability weighting.[6]

Figure 1: RISK PREMIA BY PROBABILITY OF A GOOD OUTCOME



Note: The bars illustrate the mean relative risk premium for a prospect that pays 1,000 with probability $p_g \in \{0.25, 0.50, 0.75\}$ and 0 otherwise, for the 765 small-firm owners. The relative risk premium is defined as $(\text{EV} - \text{CE})/\text{EV}$, where EV denotes the expected value of the prospect and CE its certainty equivalent.

Figure 1 displays the results. 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 125.4 (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.

Finally, to measure loss aversion, business owners were asked ten questions, based on the method

[6] Further, if individuals use narrow framing (i.e., not integrating outcomes with existing wealth) and utility curvature affects the responses, taking the difference between the premiums largely mitigates the influence of curvature, because curvature affects all premiums similarly (Dimmock et al., 2021). In Section 3, I do impose structure on the estimation in order to conduct counterfactual contract analysis with individual-level parameters.

used in Bartling, Fehr, and Herz (2014). In each question, business owners had to accept or reject an equal-probability binary-outcome prospect that either paid 1,000 or incurred a loss of x, with x beginning at 0 and gradually increasing to a loss of 1,000, in increments of 100. If a loss was incurred in the activity, then the amount would be taken from the participation fee of 1,000 that all business owners received for taking part in the broader survey and workshop for the field experiment i.e., it was a real loss. I then construct a variable representing each individual's switching point, which is the midpoint 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, suggesting that business owners in the sample are roughly twice as sensitive to losses as they are to gains.

I next use these elicitation choices to estimate preference parameters and embed them in a simple model of contract valuation and selection.

3 Structural estimation of risk preference parameters and counterfactual contract analysis

To organize the analysis, I use a simple model of contract choice under uncertainty in which heterogeneous risk preferences map into valuations of debt, equity-like, and hybrid contracts. The model nests standard expected utility and prospect theory through three parameters: utility curvature, loss aversion, and probability weighting. The framework links preference heterogeneity to contract selection and the welfare effects of expanding the menu beyond standard debt. In line with recent calls to integrate structural and empirical work in finance (Whited, 2023), I use the framework to move beyond reduced-form take-up and evaluate alternative contract designs.

3.1 Estimating risk preferences

Rather than presupposing the validity of prospect theory (PT) over expected utility theory (EUT), I estimate a mixture model that incorporates both theories and lets the risk-preference elicitation tasks in Section 2.2 determine which has more empirical support. I follow Harrison and Rutström (2009) in specifying separate likelihood functions for the EUT and PT models and combining them in a single mixture likelihood so that both theories can coexist in explaining the observed choices.

The 765 business owners were asked 40 incentivized questions, choosing between two prospects. To estimate the EUT model, I assume a simple constant relative risk aversion (CRRA) utility function $U(w) = w^r$, where r is the risk aversion parameter to be estimated, and w is wealth after the realization of outcomes for the prospect under consideration.[7] The expected utility for prospect i, which can yield n distinct outcomes (each denoted by x_k, where $k = 1, \ldots, n$), is given by $EUT_i = \sum_{k=1}^{n} p_k \cdot U(x_k)$, with p_k representing the experimentally induced probability of outcome x_k. These probabilities were explicitly communicated to the participants, and their understanding of the objective probabilities was verified before they made decisions between the two prospects. The prospects were visually presented as 'option 1' and 'option 2,' with real physical devices and currency used to illustrate payoffs and probabilities. The expected utility for each of the two options 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 $G(\nabla EUT) = exp(\nabla EUT)/[1 + exp(\nabla EUT)]$. The likelihood, conditional on the EUT model being true, depends on the estimates of r and the observed choices:

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

where i indexes decisions (of which there are approximately 30,000 in total, given 40 decisions from each of the 765 business owners), and y_i is a binary variable indicating whether the participant chose option 1 or option 2 for that particular decision. In the maximum likelihood estimation procedure, I also allow the risk preference parameters to vary by a vector X_i of individual characteristics, discussed further below.

To estimate the PT model, I introduce the possibility of reference-dependent preferences and distortions of probabilities in the decision making process. The 40 risk preference elicitation questions induced variation in payoffs, including scenarios in the loss domain, as well as varying probabilities. The PT model is estimated in a similar manner to the EUT model, with each decision modeled as a binary choice between two prospects, and an index of latent preferences calculated as the difference in their prospective utility: $PU = PU_1 - PU_2$. The utility of prospect i is the probability-weighted value of each of the prospect's outcomes:

$$PU_i = \sum_{k=1}^{n} \pi_k \cdot v(x_k), \tag{2}$$

where there are n possible outcomes for each prospect, with each ranked from worst (x_1) to best (x_n), π_k is the decision weight associated with each possible outcome x_k, and $v(\cdot)$ is the prospect-theoretic value function. The decision weight reflects the incremental contribution of the cumulative probability associated with each outcome, and is calculated as $\pi_k = w(p_k + \cdots + p_n) - w(p_{k+1} +$

[7] This includes the fee that business owners were paid at the end of the experimental session i.e., assuming 'perfect asset integration' between the endowment and the prospect payoff. CRRA is the most widely-used functional form in the literature, supported by extensive results from panel data (Barseghyan, Molinari, O'Donoghue, & Teitelbaum, 2013; Conte, Hey, & Moffatt, 2009; Fezzi, Menapace, & Raffaelli, 2021; Wakker, 2008).

$\cdots + p_n)$ for $k = 1, ..., n-1$, and $\pi_k = w(p_k)$ for $k = n$. For the probability weighting function $w(\cdot)$, which operates over the cumulative distribution $P(\cdot)$ to transform the experimentally induced probabilities, I adopt the widely used specification by Tversky and Kahneman (1992):

$$w(P) = \frac{P^\gamma}{(P^\gamma + (1-P)^\gamma)^{1/\gamma}}, \tag{3}$$

where γ controls the shape of the probability weighting function (and $\gamma = 1$ characterizes linear probability weighting, as in the EUT model). In the elicitation tasks, probabilities were objectively known and explicitly communicated to participants (with comprehension checks), so the estimated probability-weighting parameter γ captures distortions of known probabilities within the tasks rather than mistaken beliefs about the odds. 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).[8] To summarize, the probability weighting function $w(\cdot)$ is distinct from the decision weight π_k; the probability weighting function models the distortion of (cumulative) probabilities, and the decision weight is the term that multiplies the value of each outcome in the final utility function. To calculate the value of each outcome, I use a simple CRRA power utility functional form, defined separately over gains and losses:

$$v(x_k) = \begin{cases} x_k^\alpha & \text{if } x_k \geq 0 \\ -\lambda(-x_k)^\alpha & \text{if } x_k < 0, \end{cases} \tag{4}$$

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.[9]

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.

Identification via simulation. Following best practice, I validate identification by simulating from known parameter vectors and re-estimating the model on the resulting choices (DellaVigna, 2018). I vary one dimension at a time—(i) $\alpha < 1$ with $(\lambda, \gamma) = (1, 1)$, (ii) $\lambda > 1$ with $(\alpha, \gamma) = (1, 1)$, and (iii) $\gamma < 1$ with $(\alpha, \lambda) = (1, 1)$—simulate the 40 decisions with a small Fechner noise term, and re-estimate the full CPT model. Across scenarios, the estimates closely recover the generating

[8] Various probability weighting functions exist (Stott, 2006), including Prelec (1998)'s notable alternative.

[9] As discussed in Section 2.2, if a loss was incurred in the experimental activities, the amount would be taken from the participation fee that all business owners received for taking part in the broader survey and workshop for the field experiment i.e., it was a real loss.

values; Appendix G presents further details.

Estimation. 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:

$$\ln L^{PT}(\alpha,\lambda,\gamma;y,X) = \sum_i \ln l_i^{PT} = \sum_i \left[y_i \ln G(\nabla PU) + (1-y_i)\ln(1-G(\nabla PU))\right]. \tag{5}$$

where i again indexes decisions, and y_i is a binary variable indicating whether the participant chose option 1 or option 2 for that particular decision.

To estimate the mixture model, let π^{EUT} and $\pi^{\text{PT}} \equiv (1-\pi^{\text{EUT}})$ denote the probability that the EUT and PT models are correct, respectively.[10] The overall likelihood can be written as the probability weighted average of the conditional likelihoods:

$$\ln L(r,\alpha,\lambda,\gamma;y,X) = \sum_i \ln[(\pi^{\text{EUT}} \times l_i^{\text{EUT}}) + (\pi^{\text{PT}} \times l_i^{\text{PT}})]. \tag{6}$$

The mixture probabilities are constrained to be between 0 and 1. Finite mixture models guard against overfitting through their mixing weight mechanism: components that fail to improve the overall likelihood sufficiently are driven toward negligible weight during estimation, creating an effect analogous to the explicit complexity penalties in information criteria like BIC or AIC (Conte, Hey, & Moffatt, 2011).[11]

Estimation results are presented in Appendix E, and clearly favor the PT model. Specifically, 87.3% of observations are better characterized by the PT model, and 12.7% are characterized by EUT. Given the high proportion of choices explained by PT, and the reduced-form evidence suggesting the importance of loss aversion and probability weighting for investment decisions, I proceed with estimating the PT model and using the estimated parameters to assess the implications

[10] Note that the estimated mixture specification does not classify *individuals* as completely EUT or PT. Such a specification would be possible, but the present approach is more flexible as it allows the same individual to behave in accordance with EUT for some choices and with PT for others, which is consistent with experimental evidence that task domain can influence the strength of support for EUT (Harrison & Rutström, 2009).

[11] Harrison and Rutström (2009) show that, in practice, PT only "wins" those choices where it demonstrably outperforms EUT; if its extra parameters merely fit noise, the maximum-likelihood estimation drives its mixture weight toward zero. Bruhin, Fehr-Duda, and Epper (2010) show that, in their latent-class model, the richer PT specification does not absorb all observations, indicating that model complexity alone does not guarantee dominance.

of introducing alternative equity-like and hybrid contracts.[12] Standard errors are corrected for the possibility that the 40 responses are clustered for the same individual.

I allow the risk preference coefficient to differ depending on individual business owner characteristics as measured in the baseline survey: age, gender, if they are the primary decision maker in the household, country, monthly business profits, total household savings, and highest level of education. For example, for the EUT model with a single utility curvature parameter r to be estimated, the estimate $\hat{r}$ is:

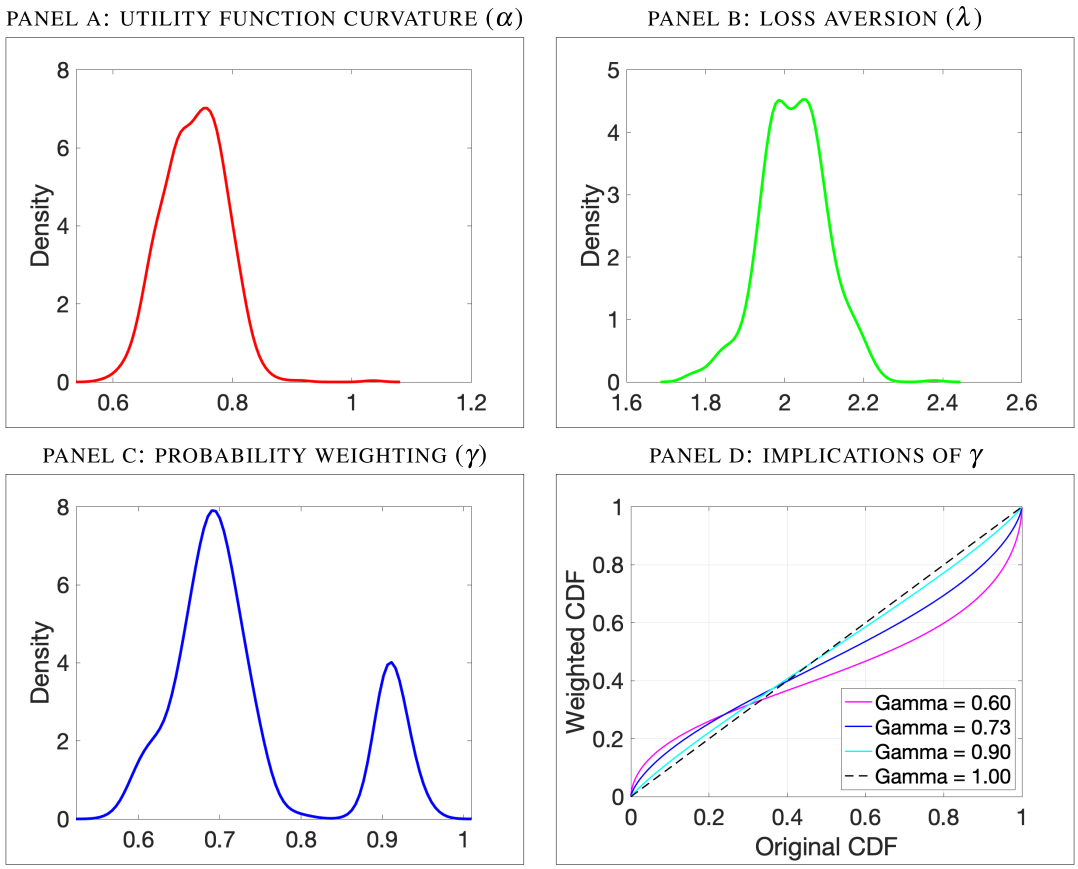
$$\hat{r} = \hat{r}_0 + \hat{r}_1 \cdot \text{Savings} + \hat{r}_2 \cdot \text{Profits} + \hat{r}_3 \cdot \text{Education} + \hat{r}_4 \cdot \text{DecisionMaker} + \hat{r}_5 \cdot \text{Female} + \hat{r}_6 \cdot \text{Age} + \hat{r}_7 \cdot \text{Kenya} \tag{7}$$

where $\hat{r}_0$ represents the estimated constant. If all individual characteristics were excluded, this would imply a single utility curvature parameter that characterizes all choices across subjects, meaning everyone would share the same risk preference parameter. Equation 7 thus provides a richer characterization of risk attitudes.

Figure 2 illustrates the results. I estimate a moderate amount of risk aversion, with a utility curvature parameter and bell-shaped curve around a mean of $\alpha = 0.74$ (where $\alpha = 1$ represents risk neutrality given the simple power utility specification). I estimate a loss aversion parameter with a mean of $\lambda = 2.04$, suggesting that business owners in the sample are approximately twice as sensitive to losses as they are to gains. This is consistent with the 'classic' range of λ between 2.00 and 2.25 that is estimated in much of the literature (Brown, Imai, Vieider, & Camerer, 2024; DellaVigna, 2018; Kremer et al., 2019). For probability weighting, I estimate a bimodal distribution, with a mean of $\gamma = 0.73$, a mass at almost-linear probability weighting ($\gamma \approx 1$), and a large mass with a non-linear probability weighting parameter of $\gamma \in [0.5, 0.8]$. This is also very consistent with estimates in the literature from high-income countries, where $\gamma = 0.7$ is typical (Comeig, Holt, & Jaramillo-Gutiérrez, 2022; Dimmock et al., 2021). The fourth panel of Figure 2 illustrates the implications of the mean value of $\gamma = 0.73$: overweighting of small probabilities and underweighting of large probabilities, generating the famous 'inverse-S' shape that has been documented in the majority of empirical studies of probability weighting.

[12] There also exist methods that do not require functional form assumptions for estimating individual-level risk parameters, but they require a 'chaining' method whereby the choices offered to a subject depend on their prior choices, which may introduce significant measurement error (Dimmock et al., 2021).

Figure 2: STRUCTURALLY ESTIMATED RISK PREFERENCE PARAMETERS



Note: Panel A shows the estimated distribution of the utility-curvature parameter α with mean 0.74 (risk neutrality corresponds to $\alpha = 1$). Panel B shows the distribution of loss aversion λ with mean 2.04. Panel C shows the distribution of the probability-weighting parameter γ with mean 0.73 and mass near both $\gamma \approx 1$ and $\gamma \in [0.5, 0.8]$. Panel D plots the implied weighting function for $\gamma = 0.73$, which overweights small probabilities and underweights large probabilities (inverse-S).

Note that an inverse-S-shaped weighting function does not imply that all small probabilities are overweighted; overweighting depends on the rank and salience of the associated outcome, with extreme payoffs typically receiving extra weight (Fehr-Duda & Epper, 2012; Quiggin, 1982). In my setting, probabilities in the elicitation activities were objective and explicitly stated, so the estimated weighting reflects distortions of known odds, not mistaken beliefs (Kahneman, 1979; Wu & Gonzalez, 1996).[13] In Appendix F, I repeat the estimation while allowing for errors in the decision-making process of business owners, using a structural noise parameter.[14] Results indicate even more pronounced loss aversion ($\lambda = 2.50$) and probability weighting ($\gamma = 0.61$), and much lower utility curvature ($\alpha \approx 1$).

[13] For a discussion of the broader empirical evidence on inverse-S probability weighting, see Appendix D.

[14] I employ the 'Fechner error' specification of Hey and Orme (1994) that posits the latent index $\nabla PU = \frac{(PU_1 - PU_2)}{\mu}$; as μ gets larger, the choice that individuals make between prospects essentially becomes random.

Appendix H illustrates how the estimated parameters vary with individual characteristics. In general, there is little correlation of the parameters α, λ, and γ with demographic variables, household wealth, or business profits — some coefficients are statistically significant, but the magnitudes are relatively small.[15] This is consistent with the findings from a low-income setting of Chiappori et al. (2014), who argue that there is little theoretical guidance on the relationship between risk preferences and observable variables. Since I am measuring relative risk aversion, it is also consistent with the finding of Chiappori and Paiella (2011) that the correlation between wealth and relative risk aversion — which they estimate from household portfolio structures in Italy — is very weak. Guiso and Paiella (2008) also find little correlation between household characteristics and risk aversion, which they argue are characterized by "massive unexplained heterogeneity".

3.2 Modeling selection into financial contracts

I next model how business owners evaluate different contracts to finance investment. I follow a similar approach to Barberis and Huang (2008), who use a one-period model with a fixed returns distribution to analyze how prospect-theoretic preference parameters influence stock market investors' pricing of securities. Here, I similarly use a one-period model and assume that business returns are drawn from a common stochastic distribution. By focusing on heterogeneity in risk preferences rather than in underlying risk, I also align with the finding of Cohen and Einav (2007) that unobserved heterogeneity in risk aversion is more significant—and has greater implications for pricing—than unobserved heterogeneity in risk. Consistent with standard security-design assumptions, I assume the lender knows the population distribution of risk-preference parameter types — but not individual types (Polo, Taburet, & Vo, 2025) — a distribution that, as discussed in Section 3.1, aligns closely with estimates in other studies. In focusing on risk preferences I deliberately abstract from the institutional and enforcement frictions that have traditionally constrained the supply of equity-like finance. These frictions remain important, but they are becoming less binding in several sectors as digital payments, rich transaction data and real-time monitoring via open banking APIs reduce monitoring and verification costs (Alok et al., 2024; Demirgüç-Kunt, Klapper, Singer, & Ansar, 2022), and e-commerce platforms are increasingly used to provide revenue-based finance to small firms (Russel et al., 2025).

I assume that a business owner evaluates different financing contracts based on prospect-theoretic preferences. Under this framework, each firm starts with wealth W_0, realizes a return X, and makes

[15] For example, as shown in Table A.6, there is a correlation between business profits and utility curvature, but the coefficient of $+0.005$ per \$100 of monthly business profits (indicating that more profitable business owners are less risk averse) is small in magnitude given that mean monthly profits in the sample are \$231.

a contract-specific payment C. Final wealth $\widetilde{W}$ is then evaluated relative to a reference point RP:

$$\widetilde{W} \;=\; W_0 \,+\, X \,-\, C \,-\, RP,$$

The payment C depends on the type of financing contract:

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

where the equity contract requires sharing a proportion θ of the drawn business return X, and the debt contract stipulates a fixed interest rate r applied to borrowed capital K, with a limited liability structure ensuring that the business owner's final wealth cannot fall below zero.

Utility under a given contract is computed as:

$$U = \int v(\widetilde{W})\, dw(P(\widetilde{W})),$$

which is equivalent to equation (2) used for estimating risk preference parameters in the discrete choice elicitation activities of Section 3.1, but modified to apply the weighting function $w(\cdot)$ to the continuous cumulative probability distribution of $\widetilde{W}$, $P(\cdot)$:

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

where γ represents the probability weighting parameter. Similarly, the value function is defined analogously to that used in Section 3.1:

$$v(\widetilde{W}) = \begin{cases} \widetilde{W}^\alpha, & \text{if} \quad \widetilde{W} \geq 0, \\ -\lambda(-\widetilde{W})^\alpha, & \text{if} \quad \widetilde{W} < 0, \end{cases}$$

where α captures the curvature of the utility function, and λ represents the degree of loss aversion. Gains ($\widetilde{W} \geq 0$) represent total net wealth $\big(W_0 + X - C\big)$ in excess of the reference point RP, while losses ($\widetilde{W} < 0$) correspond to total wealth below the reference point.

I assume a distribution of returns that is fitted to the actual distribution of business profits from the broader field experiment from which participants are drawn. I use a data-driven method to determine the best-fitting distribution, which turns out to be a lognormal distribution with parameters $\mu = 8.25$ and $\sigma = 0.43$.[16] Further details are provided in Appendix I. I model business owners as receiving \$1,500 in financing from the lender, which is comparable to the financing amount received

[16] This corresponds to an absolute annual mean profit of $e^{\mu+\frac{\sigma^2}{2}} = \$4,198$ and standard deviation of $\sqrt{(e^{\sigma^2}-1)e^{2\mu+\sigma^2}} = \$1,892$.

by many business owners in the broader field experiment.

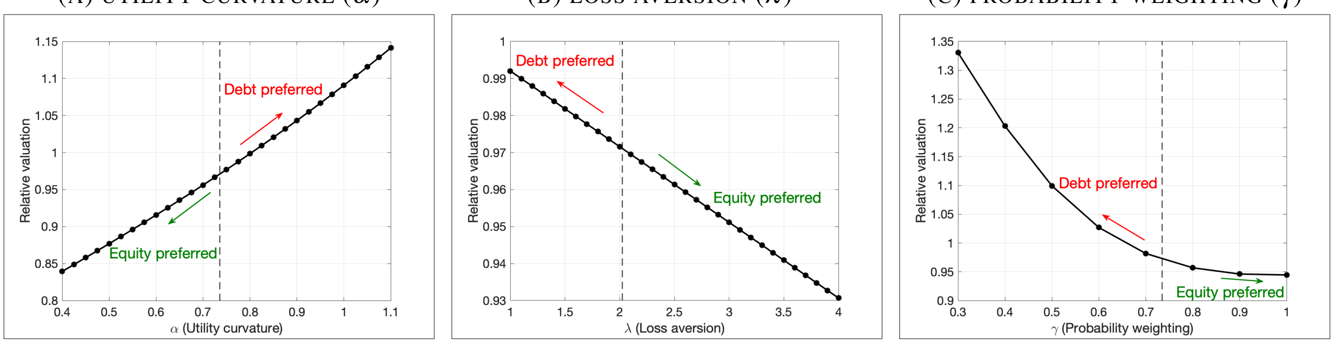
The contract parameters ($r = 0.27$ and $\theta = 0.5$) were chosen to equalize the expected average payments, making the contracts equally attractive to both the lender and its clients and to align them with local lending rates in this setting.[17] Given the similar *average* payments, the difference between contracts is reflected in the *distribution* of post-payment returns, as illustrated in Figure 5. The distribution of post-payment returns for the debt contract features more mass in the left-tail, where the fixed repayment requirement implies net losses in low-return states of the world. This is in comparison to the equity contract where low returns lead to lower required payments, in return for sharing more in high return states of the world, as reflected in less mass in the right tail of the distribution compared to debt.

3.3 How contract valuation varies with risk preference parameters

Figure 6 illustrates how variations in the three risk preference parameters influence the relative valuation of the debt and equity contracts. In each panel, a vertical dashed line marks the average value of the parameter as estimated in Section 3.1.

Figure 3: CONTRACT VALUATION AND RISK PREFERENCE PARAMETERS

(A) UTILITY CURVATURE (α) | (B) LOSS AVERSION (λ) | (C) PROBABILITY WEIGHTING (γ)



Note: Panels A, B, and C illustrate how variation in risk preference parameters (α, λ, and γ, respectively) influence the relative valuation of debt and equity contracts. The vertical dashed line indicates the average parameter value from the estimation results illustrated in Figure 2.

Panel A illustrates that lower values of α, corresponding to greater risk aversion, lead to relatively higher valuations of equity. This is consistent with the implicit insurance of equity contracts appealing to business owners with more concave utility functions. As α increases, indicating greater risk tolerance, the relative valuation of debt rises.

[17] The central bank of Pakistan reports an average microcredit interest rate of approximately 30% (Hussein & Khan, 2009). There is no data for equity sharing ratios as lending institutions do not typically offer such contracts; I therefore use 50% as it is a common sharing ratio used in agricultural output-sharing contracts (Burchardi, Gulesci, Lerva, & Sulaiman, 2017) (a 25% sharing ratio is also common — this could be incorporated in the current model with a two-year duration contract rather than a one-year 50% sharing contract). In piloting for the artefactual field experiment, I found significantly increased comprehension when using such round numbers for sharing ratios.

Panel B illustrates that as λ increases, indicating greater loss aversion, equity becomes more valued. This is consistent with business owners who are more sensitive to losses than gains valuing the downside protection offered by equity, and being more willing to share upside in return for that downside risk-sharing. In contrast, debt amplifies the risk of falling below their wealth reference point, to which they are particularly sensitive.

Panel C explores the relationship between contract preference and probability weighting. As γ decreases, indicating a more pronounced inverse-S-shaped probability weighting function with greater overweighting of small probabilities (and underweighting of large probabilities), debt is significantly preferred over equity. Recall that the model uses a profit distribution based on actual data from the field experiment, which follows a lognormal distribution with moderate skewness. For positively skewed returns, individuals with an inverse-S-shaped weighting function overweight the small probability of very high profits—scenarios where equity contracts require sharing significant returns with the capital provider. Conversely, they underestimate the higher probability of low profits, where equity contracts offer valuable loss-sharing benefits.

To illustrate the importance of skewness, in Appendix J I repeat the model analysis using a return distribution with zero skew by setting the shape parameter, which controls skew, from $\sigma = 0.43$ to $\sigma \to 0^+$ (essentially transforming the lognormal distribution to a normal distribution). Strikingly, the previous findings disappear: there is no longer any meaningful relationship between contract preference and probability weighting. This aligns with the findings of Barberis and Huang (2008), who show using data from a high-income setting that, under the assumption of normally distributed returns, the asset pricing implications of prospect theory are no different from those of expected utility — they only differ when introducing some assets with positively skewed investment returns.

4 Experimental evidence

4.1 Investment experiment

In this section, artefactual field experiments replicated in both Kenya and Pakistan provide a test of the model's predictions about contract choice. I conducted an investment task with the business owners that was designed to mimic key aspects of 'real-world' business investment decisions, specifically the challenges small business owners face in accessing higher-expected-return investments due to financial constraints. The use of real cash stakes and the inclusion of vignettes motivated by realistic business scenarios further enhance the naturalness of the decision-making environment (List, 2020; Lowes & Nunn, 2025), which took place at the baseline of two larger field experiments on asset-based financing.

The basic structure of the investment experiment involved each participant being given 200 units of local currency notes as initial capital. There were two decision rounds, and in each round participants had a choice of five binary-outcome investment options. The 'bad' outcome for each of the investment options was a payoff of $x_b = 0$, and there were five possible 'good' outcomes $x_g \in \{100, 400, 700, 1000, 1300\}$. Each of the five outcomes had an associated cost: $c \in \{0, 100, 200, 300, 400\}$. The five investment options, illustrated in Table 1, monotonically increase in expected return and risk. In each decision round, the participant was required to choose one of the investment options, conditional on it being affordable. Affordability for the first-round decision was determined by an initial amount of capital that was provided in the activity (the use of outside funds was not permitted). The second-round choice was a function of the first-round capital as well as the return from the realization of the investment option chosen in the first round (that is, first-round proceeds were carried forward to second-round decisions, after which the experiment ended).

Table 1: **INVESTMENT EXPERIMENT OPTIONS**

INVESTMENT OPTION	COST	PAYOFF: LOW	HIGH	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

Note: Business owners had a choice of five options in the investment experiment. All amounts are in local currency.

The experiment consisted of three types of treatment, with each business owner receiving each treatment (i.e., a within-subject design), and the order of treatments randomized:[18]

(i). **Control Treatment (CT):** Participants received an initial endowment of 200, limiting first-round investments to the first three options; options 4 and 5 became available in round two only after a high initial outcome in round one.

(ii). **Debt Treatment (DT):** In addition to the initial endowment of 200, participants received 500 as a zero-interest loan, to be repaid at the end of the two-round activity. This mimicked external debt capital that could be used to finance higher expected return but costlier investment options. The loan was collateralized by the 1,000 participation fee that every business owner received as part of the workshop; any loss due to default was deducted from this fee.

[18] Randomization of the order addresses the additional "causal transience" identification assumption required for within-subject experimental designs (List, 2025) — that treatment effects do not carry over from one period to the next.

(iii). **Equity Treatment (ET):** Like DT, the participant received an initial endowment of 200 and external financing of 500, which in this case is in the form of equity-like performance-contingent financing. Specifically, participants were required to share whatever wealth remained at the end of the second round, net of all gains and losses arising from the realization of the investment choices. This treatment was also implemented twice, once with a sharing ratio of 25%, and once with a sharing ratio of 50%.

When communicating with participants, the words 'debt' or 'equity' were not used; instead the more neutral words 'loan contract' and 'sharing contract' were used (in the local language).

The net payoff to participants at the end of the investment task is represented by $Y_T = W_T(1 - \theta \cdot ET) - DT \cdot K$, where DT and ET are treatment dummies for each corresponding contract, T is the number of investment decision rounds, Y_T is net payoff after settling contractual payments, W_T is wealth after the realization of investment outcomes, K is the amount of external financing provided in both DT and ET, and θ is the sharing ratio for ET. The experiment was designed using simple simulations of a utility-maximizing agent choosing investment options over multiple rounds to maximize terminal profits.

To summarize the pre-specified baseline predictions from these simulations, business owners were predicted to choose more profitable (and riskier) investments under the equity contract, with the effect greatest for more risk-averse and loss-averse individuals. When designing the experiment, simulations were also used to verify that the main predictions were not highly sensitive to a particular choice of initial capital level W_0, the amount of external capital k, or the number of rounds in the activity T. As described above, in the final design, $T = 2$, $k = 500$, and $\theta \in \{0.5, 0.25\}$. The final parameters were chosen after piloting with the aim of a simple design that would allow a clear comparison of contractual structures and the role of risk preferences.[19]

The design deliberately used simple binary equal-probability prospects to keep the contract comparison transparent and to target the pre-specified comparative statics for risk and loss aversion.[20]

[19] Piloting suggested that a two-round activity would capture the main conceptual elements, while mitigating the risk of overburdening the participants given the length of the workshop. Additionally, I used a strategy method to elicit second-round investment decisions, rather than taking first-round decisions and drawing balls from a bag to realize the outcomes. This mitigated the risk of participants making second-round decisions because they felt that a particular investment option had good or bad luck based on the first-round realization. Imas (2016) demonstrates the significant impact that prior outcome realizations can have on choice under uncertainty. The strategy method also permitted the elicitation of two data points: the second-round decision conditional on (i) a low outcome from the first-round investment choice; (ii) a high first-round outcome.

[20] See https://www.socialscienceregistry.org/trials/2224. The Kenyan experiment was a replication built into the wider field experiment (see https://www.socialscienceregistry.org/trials/4789). The investment task was not designed to provide sharp identification of the impact of probability weighting from within-task variation in probabilities or skewness. A simple prospect-theoretic model, developed ex ante, was used to simulate outcomes and choose the contract parameters for the artefactual field experiment and the pre-specified comparative statics for risk and loss aversion. The more nuanced role of skewness and non-linear probability weighting that I highlight in the paper emerged from ex post structural estimation using the risk-preference elicitation tasks and counterfactual analysis (Section 3), and from reconciling the model with take-up data from the field experiment (Section 4.4).

4.2 Experimental results

I now present results from the artefactual field experiments in Kenya and Pakistan, with the main pre-specified empirical specifications. The sample consists of 3,060 observations—one decision per treatment arm for each of the 765 respondents.[21] The panel is fully balanced, with each subject participating in all four treatment conditions, which satisfies one of the key additional identification assumptions for a within-subject design (List, 2025). In addition, while potential concerns regarding another key identification assumption — causal transience — were addressed by randomizing the order of the financing treatments, I also explicitly test for carryover effects in the Appendix.

Result 1: Equity leads to more profitable investment choices

Table 2 presents results from the following specification, estimated by OLS:

$$y_i = \beta_0 + \beta_1 \text{Debt}_i + \beta_2 \text{Equity}_i + \varepsilon_i, \tag{8}$$

where y_i is the expected profit of the investment option chosen by individual i, Debt_i is a dummy for assignment to debt financing and Equity_i is a dummy indicating assignment to equity financing (initially pooling the contracts with 25% and 50% sharing ratios, and then splitting them). Standard errors are clustered at the individual level. I adjust p-values for multiple hypothesis testing using the method of List, Shaikh, and Vayalinkal (2023), which builds on Romano and Wolf (2010), to control for the familywise error rate. β_0 represents the average expected return of investments chosen by individuals in the control group, while β_1 and β_2 represent the change in expected profit of investments chosen by debt-financed and equity-financed individuals relative to the control group, respectively.

In each column, the dependent variable is the expected profit of the chosen investment option in that particular round. Column 1 displays results for the Pakistani sample; equity-financed business owners selected investment options in the first round of the activity that had expected returns 0.35 standard deviations higher than those chosen by debt-financed individuals (with a multiple hypothesis-adjusted p-value from a cross-coefficient test of 0.002). Column 2 presents results for the Kenyan sample, showing a very similar effect size of 0.37 standard deviations ($p = 0.016$ for the difference between equity and debt). Column 3 pools the two samples, revealing a statistically significant and economically meaningful difference in investment choices under equity versus debt, with a pooled effect size of 0.35 standard deviations, representing a 9.7% increase in absolute expected return. The replication of results across the two countries increases confidence in the

[21] In Round 1, the sample consists of 3,060 observations—one decision per treatment arm for each of the 765 respondents; Round 2 analyses also use the same balanced 765 × 4 panel and are conducted separately for the two conditional (strategy-method) decisions.

external validity and generalizability of the findings. Moreover, a 0.35 standard deviation increase in expected profitability of investment choices in a one-shot, capped-stakes task is plausibly a lower bound for real-world impacts, where firms face repeated investment decisions and small profitability improvements can accumulate over time (abstracting from agency frictions involved in implementing equity contracts and focusing on the pure effect of contract structure on the profitability of investment choices). This is consistent with the longer-run effects of equity-like contracts documented in the broader Kenyan field experiment, described in Section 4.4, which led to substantial annual returns.

Table 2: OVERALL EFFECT OF CONTRACTS ON INVESTMENT CHOICE

	(1) Round 1: Pakistan	(2) Round 1: Kenya	(3) Round 1: Pooled	(4) Round 2: Pooled	(5) Round 2: Pooled
Debt	66.89	52.69	63.79	64.18	22.22
	(2.55)	(4.66)	(2.24)	(2.03)	(2.20)
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
	{0.00}	{0.00}	{0.00}	{0.00}	{0.00}
Equity	76.71	66.92	74.58	76.96	30.82
	(2.17)	(3.93)	(1.90)	(1.77)	(1.91)
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
	{0.00}	{0.00}	{0.00}	{0.00}	{0.00}
Observations	2,392	668	3,060	3,060	3,060
Unique business owners	598	167	765	765	765
Control mean	109.36	101.20	111.21	78.79	178.12
R-squared	0.283	0.183	0.267	0.340	0.047
Country control			✓	✓	✓
Test: Debt = Equity (adjusted $p-$value)	0.002	0.016	0.000	0.000	0.001
Effect size (%)	9.0	14.1	9.7	16.2	4.8
Effect size (standard deviations)	0.35	0.37	0.35	0.49	0.15

Note: The dependent variable is the expected profit of the chosen investment option in that round. *Debt* and *Equity* are dummies for assignment to the respective contracts; coefficients are relative to the control-group mean. Standard errors (in parentheses) are clustered at the business-owner level. Square and curly brackets report raw and multiple-hypothesis-adjusted p-values, respectively, using the procedure in List et al. (2023) building on Romano and Wolf (2010). The final three rows report: (i) the adjusted p-value for a test of equality between the *Debt* and *Equity* effects; (ii) the implied equity-versus-debt effect as a percentage of the control-group mean; and (iii) the same effect in standard deviations of the outcome in the control group.

Column 4 analyzes choices in the second round of the investment experiment, conditional on a low outcome in the first round, and reveals that equity-financed business owners chose investments that were 0.49 standard deviations higher in expected return than choices under debt ($p < 0.001$). Column 5 illustrates second-round decisions conditional on a *high* outcome in the first round, and reveals a smaller but still significantly positive effect size of 0.15 standard deviations ($p = 0.001$).

Appendix Table A.9 explores whether there is a differential impact between the 25% and 50% equity sharing ratios in each investment round. In all specifications, the coefficients on equity are very similar for the two sharing ratios, and the null hypothesis that there is no difference in effects cannot be rejected ($p = 0.640$, $p = 0.650$, and $p = 0.178$, respectively). In the heterogeneity analysis that follows, I pool the equity arms and focus on first-round investment decisions. In Appendix Table A.10, I demonstrate robustness of the results to controlling for order effects, given the within-subject experimental design that involved randomization of whether participants were first allocated to the debt or equity treatment arms.

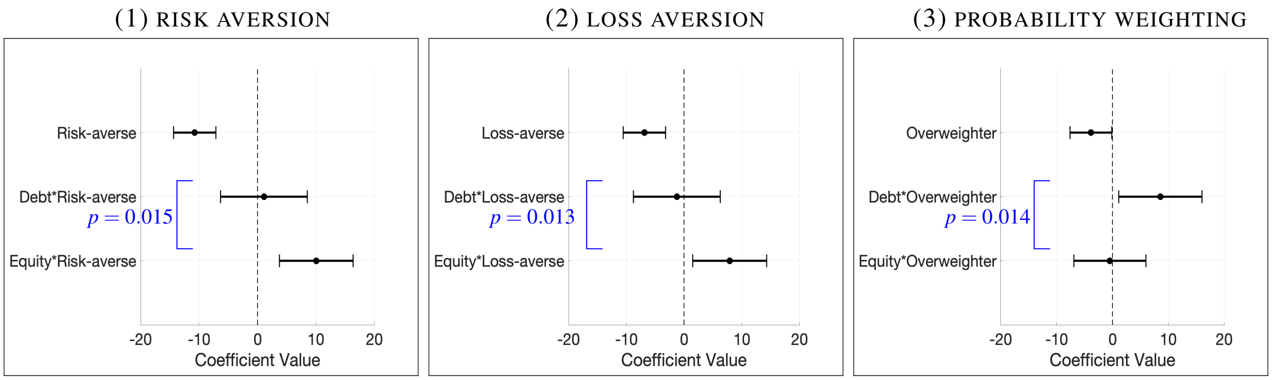
Result 2: Equity is most impactful for risk-averse and loss-averse business owners, and least impactful for those who overweight small probabilities

Risk-averse business owners may particularly benefit from the insurance-like features of equity, which provides greater risk sharing than fixed-repayment debt contracts. There may also be a distinct benefit for individuals with reference-dependent preferences, with loss-averse business owners valuing the downside protection of equity contracts: lower required payments after a negative business shock meaning lower risk of ending up below their utility reference point, compared to a fixed-repayment debt contract. In return for that downside protection, they may be willing to share in the upside, so equity contracts may be ideally designed for business owners who are more sensitive to losses than gains. In the investment experiment, a salient reference point is the participation fee that was promised to all participants at the end of the workshop, as is commonly used in the literature (Verschoor & DExelle, 2020). Figure 4 presents results from estimation of the following specification:

$$y_i = \beta_0 + \beta_1 \,\text{Debt}_i + \beta_2 \,\text{Equity}_i + \beta_3 \,\text{HighX}_i + \beta_4 \,\text{Debt}_i \cdot \text{HighX}_i + \beta_5 \,\text{Equity}_i \cdot \text{HighX}_i + \varepsilon_i, \quad (9)$$

where $HighX_i$ is a dummy for individuals with an above-median value of the heterogeneity variable X_i. $H_0 : \beta_4 = \beta_5$ tests whether individuals with higher values of X_i are differentially affected by the *Equity* and *Debt* treatments. The heterogeneity variables tested are indices that capture the three distinct dimensions of risk preferences that have been identified in the literature, as outlined in Section 2.2: (i) risk aversion (which is synonymous with utility curvature in expected utility models), (ii) loss aversion, and (iii) probability weighting. For (i), I aggregate the responses from the two sets of risk preference elicitation exercises (the domain-specific self-reported measures and the decisions in the certainty equivalent task). For (ii), I aggregate the number of decisions for which each individual rejected a prospect that contained an outcome in the loss domain. For (iii), I follow the methodology of Dimmock et al. (2021) in constructing a simple proxy for probability weighting as the average risk premium (inferred from the certainty equivalent elicitation questions) in the underweighting range ($p_g \in \{0.50, 0.75\}$) minus the premium in the overweighting range ($p_g = 0.25$). I then apply a median split to all indices, so that individuals with above-median values of X_i have: (i) higher risk aversion; (ii) higher loss aversion; (iii) more non-linear probability weighting (resulting in overweighting of small probabilities). In Appendices M and N, I repeat the analysis using trichotomized variables for the three risk preference measures (rather than a median split) and using three alternative methods for constructing the probability weighting index; results are robust to those alternative specifications.

Figure 4: INVESTMENT CHOICE: HETEROGENEITY BY RISK PREFERENCES



Note: Each panel reports coefficients from heterogeneous treatment–effect regressions based on 3,060 observations from 765 business owners generated from the within-design experimental setup. The dependent variable is the expected profit of the chosen investment option. The three panels correspond to the three dimensions of baseline risk preferences measured in incentivized tasks: (1) risk aversion; (2) loss aversion; and (3) probability weighting (overweighting of small probabilities). For each dimension, I split the sample at the median of the corresponding index and estimate how the effects of debt and equity differ for business owners above the median. *Equity * Risk-averse* is the incremental (differential) equity treatment effect for risk-averse business owners relative to risk-tolerant owners, with an analogous interpretation for the other interaction terms. The reported p-values test whether the incremental effect of equity for the above-median group equals the incremental effect of debt for that group (e.g., *Equity * Risk-averse* = *Debt * Risk-averse*). In Appendices M and N, I repeat the analysis using trichotomized variables for the three risk-preference measures (rather than a median split) and three alternative methods for constructing the probability-weighting index.

Panel 1 of Figure 4 shows that, in the control group, more risk-averse individuals chose investment options with a lower expected profit than more risk-tolerant individuals: a coefficient on $Risk-averse$ of -10.74 ($p < 0.001$), compared to the mean for risk-averse individuals in the control treatment of 107.35. The coefficient on $Debt \cdot Risk-averse$ of 1.10 ($p = 0.808$) indicates no differential impact of the debt contract on the investment of risk-averse individuals. In contrast, the coefficient on $Equity \cdot Risk-averse$ of 10.05 ($p = 0.009$) indicates that the most risk-averse individuals were significantly more likely to choose higher expected profit investments than the most risk-tolerant individuals under equity financing. This is confirmed using a cross-coefficient test of equality between $Debt \cdot Risk-averse$ and $Equity \cdot Risk-averse$ ($p = 0.015$). Notably, the magnitude of the coefficient on $Equity \cdot Risk-averse$ is nearly identical to, but of the opposite sign to, that on $Risk-averse$. This suggests that the equity contract effectively reverses the diminished investment associated with risk aversion.

Panel 2 addresses a similar question, exploring the role of loss aversion. The coefficient of -6.87

($p = 0.002$) on $Loss-averse$ indicates that more loss-averse individuals chose investment options with a lower expected return than more loss-tolerant individuals in the control group. As in the case of risk aversion, the coefficient of -1.25 ($p = 0.784$) on $Debt \cdot Loss-averse$ does not indicate a significant differential impact of the debt contract on the investment of loss-averse individuals, while the coefficient of 7.90 ($p = 0.042$) on $Equity \cdot Loss-averse$ indicates that the most loss-averse individuals were significantly more likely to choose higher expected profit investments under equity financing. This is confirmed by the cross-coefficient test of equality between $Debt \cdot Loss-averse$ and $Equity \cdot Loss-averse$ ($p = 0.013$). It is again notable that the magnitude of the coefficient on $Equity \cdot Loss-averse$ is nearly identical to that on $Loss-averse$, but it has the opposite sign.

Finally, panel 3 explores the impact of probability weighting. Notably, results are opposite to those found for risk aversion and loss aversion. Individuals who overweight small probabilities are *less* likely to make profitable investments under equity compared to debt. The coefficient on $Debt \cdot Overweighter$ is 8.57 ($p = 0.059$), while the coefficient on $Equity \cdot Overweighter$ is -0.46 ($p = 0.906$), with the cross-coefficient test indicating that business owners who overweight small probabilities make relatively more profitable investment choices under debt than under equity ($p = 0.014$).[22]

Robustness

In Appendix M, I show that the results from Figure 4 are robust to using a trichotomized measure for each of the three risk preference variables, rather than a median split. Appendix N demonstrates the stability of results to using three alternative methods for constructing the probability weighting index. In Appendices O, P, Q, R, and S, I replicate the analysis controlling for business owner education, owner age, and business age, revenue, and profits, respectively; these robustness checks confirm that the findings on risk aversion, loss aversion, and probability weighting are not driven by heterogeneity in these owner and business characteristics. Finally, concerns may arise that the results on probability weighting reflect potential over-optimism of business owners rather than distortion of probability weights. In Appendix T, I use a measure of optimism about personal returns to capital, elicited from business owners at baseline, validating that results hold when controlling for optimism and its interaction with the treatments (Additionally, in Appendix H, I show that the estimated probability weighting parameter is not correlated with business owner optimism.)

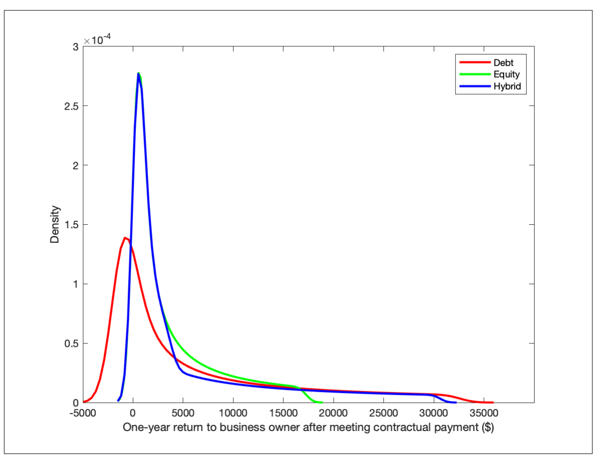
[22] The cross-coefficient test is based on the interaction contrast ($\beta_5 - \beta_4$) in equation (9). A negative estimate indicates that equity's incremental advantage over debt is attenuated for individuals who overweight small probabilities; it should not be interpreted as equity reducing expected-profit choices in levels for this group, because the overall average effect of equity on expected profits is positive and sizeable relative to debt.

4.3 Hybrid contracts

I next demonstrate that a simple contractual modification can benefit individuals who might otherwise reject equity contracts due to overweighting small probabilities. Specifically, I implement a "hybrid" contract that blends debt- and equity-like features. The contract provides a performance-contingent payment structure akin to an equity contract but caps the upside—once payments reach a predetermined maximum, the contract terminates. Such hybrid contracts are increasingly used by payment fintechs in high-income countries (Russel et al., 2025) and share features with venture capital arrangements (e.g., equity clawbacks, performance ratchets, and convertibles) that align investor and business owner interests through adaptable reward structures based on achieved targets (Feld & Mendelson, 2019; Jansen, Phalippou, & Noe, 2024; Kaplan & Strömberg, 2003).

In the model, I initially set the maximum payment at twice the amount due under the debt contract. This ensures that expected payments to the capital provider under the hybrid contract are equivalent to those under the debt and equity contracts. The post-payment distribution of returns under hybrid is contrasted with those under debt and equity in Figure 5. The hybrid contract assumes an intermediate shape between the debt and equity contracts. It reduces the business owner's exposure to potential losses associated with the fixed-repayment debt contract. Simultaneously, it caps the upside-sharing in a manner that still allows for a significantly larger right tail than the equity contract. Under the equity contract, large amounts of money must be shared in low-probability, high-profit states of the world, which are overweighted by a significant proportion of individuals.

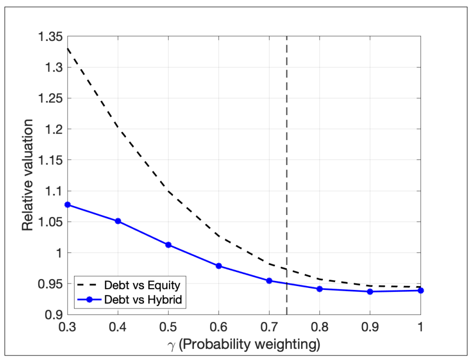
Figure 5: MODEL-BASED DISTRIBUTION OF RETURNS UNDER EACH FINANCING CONTRACT



Note: The figure plots kernel densities of post-payment annual returns to a business owner who receives $1,500 in financing under three contracts: a 27% fixed-interest debt contract, an equity contract that shares 50% of returns, and a hybrid contract that shares returns up to a payment cap equal to twice the debt payment. Returns are simulated from a lognormal distribution fitted to the observed profit distribution in the broader experiment (see Appendix I). Contracts are calibrated so that expected payments to the lender are equal across the three designs. All amounts are in US$.

Panel D of Figure 6 illustrates the impact of introducing the hybrid contract. The relative valuation of the hybrid contract compared to debt increases significantly for low values of γ, where equity contracts were previously significantly undervalued relative to debt. Hybrid contracts share features with certain arrangements in venture capital, such as equity clawbacks and performance ratchets, which incentivize performance while aligning the interests of investors and business owners through adaptable reward structures based on achieved targets. My results highlight the value of such features for the substantial proportion of small business owners who overweight small probabilities. Financial institutions with more linear probability weighting functions can profitably offer such contracts, as discussed in Section 4.5.

Figure 6: INTRODUCING THE HYBRID CONTRACT



Note: The dotted line illustrates how variation in γ influenced the relative valuation of debt and equity contracts before the introduction of the hybrid contract. The blue line illustrates the impact of introducing the hybrid contract.

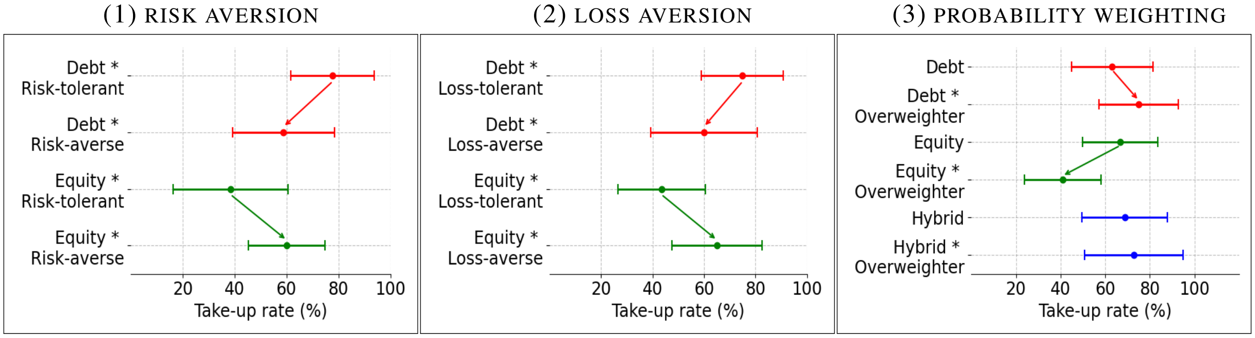
4.4 Testing model predictions: contract take-up "inside and outside the lab"

I test the model's main predictions using take-up decisions in two settings: (i) within the artefactual field experiment; and (ii) "outside the lab," in the broader field experiments from which participants are drawn. This allows for a test of both the external validity of the lab-elicited risk preference measures and the model's predictions. The focus is on evaluating relative predictions—the relationship between risk preferences and contract choice—rather than on comparing absolute take-up rates in the lab, model, and field, which differ in decision environments and the profile of investments on offer.

In the reduced-form results of Section 4.2, each business owner made investment decisions under both debt and equity contracts, using a within-subject design. In Appendix Figure A.6, I separately analyze their overall contract preference through an incentivized take-up question at the end of the artefactual field experiment. Each participant was asked which contract they would prefer if it were selected for payment, and this choice increased the probability of that contract being realized. I estimate a simple linear probability model, where the dependent variable is a dummy indicating whether the business owner chose to take an equity contract over debt; covariates are dummies indicating whether the business owner is more risk-averse (α below the median), more loss-averse (λ above the median), and more likely to overweight small probabilities (γ below the median), using the structurally estimated parameters. Results indicate that risk-averse business owners were 15.5 percentage points more likely to choose an equity contract ($p < 0.001$), compared to the overall equity take-up rate of 46%. The coefficient for loss aversion is also positive (4.4 percentage points), but not statistically significant at conventional levels ($p = 0.228$). The coefficient on probability weighting is very large and highly significant, indicating that individuals who overweight small probabilities are 17.4 percentage points *less* likely to choose equity compared to debt ($p < 0.001$).

In Figure 7, I analyze take-up decisions outside the lab. This provides a validation test for the predictive power of the lab-elicited measures of risk preferences, as well as a test of model predictions for take-up of different contracts among individuals with varying levels of risk aversion, loss aversion, and probability weighting. Specifically, I analyze asset finance take-up decisions from the broader Kenyan field experiment. In that experiment, business owners had the opportunity to finance an asset, and were randomly offered take-it-or-leave-it decisions for different types of contract. Acceptance of the offer meant that they proceeded to sign the contract with the financial institution, and subsequently have their asset delivered. As such, all decisions were incentivized, for a real business asset. The debt contract offered in the field experiment required a total repayment amount equal to the asset financing amount plus a 15% mark-up, spread evenly over 12 fixed monthly payments. The 'equity-like' contract was a 12-month contract that required clients to pay half of the fixed monthly payment of the debt contract (calculated in the equivalent way), as well as paying a 10% share of their monthly profits (calculated from administrative data, which I had access to; i.e., not relying on self-reported profits). The sharing ratio in this setting was calculated to equate the expected payoffs under debt and equity for the median business owner, very similar to the procedure used in the model in Section 3 to ensure no contract was clearly advantageous in terms of expected payments.

Figure 7: **TESTING MODEL FIT: CONTRACT TAKE-UP 'OUTSIDE THE LAB'**



Note: Figures (1) to (3) illustrate take-up results of the actual asset finance product in the broader Kenyan field experiment from which the sample is drawn. The dependent variable is a dummy indicating whether the business owner accepted the asset financing product that was offered to them, interacted with a dummy indicating whether they had above-median risk aversion, loss aversion, and probability weighting (overweighting). Three asset finance contracts were offered in the field experiment: a standard fixed-interest debt contract, an equity-like profit-sharing contract, and a hybrid contract featuring equity-like performance-contingent payments with a debt-like maximum amount to be repaid, similar to the repayment cap simulated in the model in Section 3.

The first panel of Figure 7 illustrates that the take-up rate of debt among the most risk-tolerant business owners was 78%, and decreases for the most risk-averse to 59%. The opposite is observed for equity: only 38% of the most risk-tolerant individuals take up equity, and this *increases* to 60% for the most risk-averse. A formal test confirms the significant difference-in-differences ($p = 0.070$). The second panel reveals very similar patterns for loss aversion. Take-up of debt for the most loss-tolerant business owners is 75%, and it decreases to 65% for the most loss-averse. The opposite pattern is again evident for equity: take-up for the most loss-tolerant is 43%, and increases to 65% for the most loss-averse (and $p = 0.094$ for the difference-in-differences test). Taken together, these results align closely with the model's comparative statics: more risk- and loss-averse individuals are significantly more likely to select contracts with performance-contingent or flexible repayment structures.

The third panel demonstrates the opposite result for probability weighting. Take-up rate of debt among business owners who have closer-to-linear probability weighting is 63%, and it *increases* for individuals who are more likely to overweight small probabilities, to 75%. The opposite effect is observed under equity: take-up of equity is 67% for business owners with more linear probability weighting, and *decreases* to 41% for those who overweight small probabilities. Finally, I test the model prediction that a hybrid contract would 'undo' the negative effects of probability weighting on the take-up of equity. In the Kenyan experiment, a hybrid contract was offered to business owners, with equity-like performance-contingent payments and a repayment cap set at the same total nominal amount due under the equivalent debt contract. Results in the third figure of Panel B reveal a take-up rate for the hybrid contract that does not vary depending on whether individuals have more linear or non-linear probability weighting (take-up rates of 69% and 73%, respectively). These patterns are also consistent with model predictions: equity take-up falls with greater probability weighting, while the hybrid contract neutralizes this effect.

Beyond take-up, contract assignment also affected real economic outcomes in the Kenyan field experiment. Business owners who were randomly offered the hybrid contract earned 170% higher monthly profits in intent-to-treat (ITT) terms compared to the control group, significantly outperforming the 59% increase observed under the standard debt contract. Those assigned the hybrid contract also demonstrated greater business effort – reporting substantially more intensive use of the asset, wider geographical reach, and improved business management practices. While repayment was incomplete across all arms, partly due to COVID-related limits on enforcement, repayment under the hybrid contract outperformed the standard debt contract, with an average repayment rate of 78% compared to 59%.[23]

In Appendix V, I present further evidence demonstrating the predictive power of the lab-elicited measures for take-up decisions of the asset financing product offered in the Pakistani experiment.[24]

4.5 Quantifying the value of introducing the new contract

I quantify the value of introducing hybrid contracts into the portfolio of products offered to small business owners using individual-level estimates of risk preference parameters from Section 3.1. For each of the 765 business owners, I calculate the benefit (or lack thereof) of offering hybrid contracts by solving for the compensating variation, the monetary amount required to make a debt-financed business owner indifferent between debt and hybrid contracts:

$$PU_i^{\text{hybrid}} = \int v\big(\widetilde{W}^{\text{hybrid}}\big)\, dw(P(\widetilde{W})) = \int v\big(\widetilde{W}^{\text{debt}} + T_i\big)\, dw(P(\widetilde{W})), \tag{10}$$

where T_i is the compensating transfer that makes business owner i indifferent between debt and the hybrid contract ($T_i = 0$ for owners who weakly prefer debt to hybrid), and contract-specific payments (C) and final wealth ($\widetilde{W} = W_0 + X - C - RP$) are defined as in Section 3.2. This approach provides a direct measure of the benefits of introducing hybrid contracts, accounting for each business owner's risk preferences and selection into their preferred contract. Consistent with

[23] For further details on post-contract outcomes from the Kenyan experiment, see the impact evaluation in Cordaro et al. (2025).

[24] The two financing contracts on offer in Pakistan featured either a fixed repayment schedule or a more equity-like flexible repayment schedule. The contractual variation is not as rich as in the Kenyan experiment, meaning that I cannot test the model predictions for take-up of a hybrid contract. Nevertheless, results do provide a helpful further validation of the elicited risk measures. Specifically, as described in further detail in Appendix V, the most risk-averse and loss-averse business owners had significantly higher take-up of the more equity-like flexible-repayment contract compared to the more debt-like fixed-repayment contract.

standard security-design assumptions, I assume the lender knows the population distribution of risk-preference parameters but not individual types.

Appendix U illustrates the resulting distribution of profits for the lender, after allowing business owners to select into their preferred contract. Mean profits under debt are \$400, with a standard deviation of \$38, which represents a net return to the lender of 27% on the \$1,500 capital provided. The distribution of profits for the lender from the debt contracts has most of the mass at \$400, and a few points below that for business owners who partially default (with the implicit default rate of 2% consistent with historically low default rates in microfinance (Cai et al., 2021). The distribution of profits for the lender from business owners that select into the hybrid contract has a higher mean of \$530, along with a higher standard deviation of \$816. Results therefore suggest that financial institutions can profitably offer such equity-like contracts in their portfolio of products for small business owners, and that they would be especially valued by loss-averse individuals and the significant portion of individuals with non-linear probability weighting functions. However, the implications for a more dispersed distribution of lender returns may be unacceptable to many conventional lenders, especially given their organizational structures and loan officer incentives, which I discuss further in the conclusion.[25]

The average value to business owners who take up the hybrid contract is \$21. Averaging that across the whole sample, and adding it to the increase in average lender profits from the introduction of hybrid contracts leads to a total surplus of \$91, which represents 6% of the average disbursed capital amount of \$1,500. The total surplus rises when incorporating results from the reduced-form analysis that equity-financed business owners chose investments that were more profitable than under debt.

5 Conclusion

An enduring puzzle in the finance and development literature lies in reconciling the high returns observed in studies providing capital grants to small firms with the modest average returns found with microcredit. In this paper, I focus on the repayment rigidity of traditional credit contracts as an impediment to investment and show that equity-like contracts with performance-contingent repayments can encourage more profitable investments, particularly among risk-averse and loss-averse small business owners. However, individuals who overweight small probabilities prefer debt contracts, especially in the context of positively skewed return distributions. Through counterfactual analysis, I demonstrate that simple contractual innovations can significantly enhance the feasibility

[25] In low-income countries, traditional lenders may find it particularly difficult to provide riskier products and financing for longer-term investments due to substantial liquidity risks stemming from their own unstable funding sources and volatile deposits (Choudhary & Limodio, 2022).

of equity-like contracts and unlock small-firm investment.

One of the paper's key contributions is highlighting the importance of behavioral finance theory for modeling small firm investment under uncertainty in an unexplored development setting, while providing a novel counterpoint. An artefactual field experiment combined with structural estimation offers an ideal method for estimating risk preferences and welfare effects of new financial contracts, addressing confounding factors in field data such as the challenge in separately identifying probability weighting from biased beliefs. The study also has several features that enhance its external validity. These include the selection of a policy-relevant sample of growth-oriented firms at a critical juncture of actively seeking financing; choice tasks that mimic financing constraints; similar overall treatment effects observed in Kenya and Pakistan; high alignment between the estimated prospect-theoretic preference parameters and findings from other studies; and the consistency of experimental results and model predictions with actual take-up in two broader field experiments.

In low- and middle-income countries, recent technological advancements have greatly enhanced the observability of income streams in increasingly varied contexts, such as online marketplaces or businesses accepting digital payments through point-of-sale systems. These technological advancements enhance the ability to screen for high-potential clients and open up numerous possibilities for innovative financial contracts that better match contract repayments to underlying small business cash flows, while avoiding the challenges of traditional equity stakes, such as legal enforcement constraints and limited exit strategies (De Mel, McKenzie, & Woodruff, 2019). I demonstrate a demand-side explanation for the limited adoption of seemingly advantageous equity-like contracts. These insights can guide subsequent research on hybrid financial contracts in the field. This complements studies highlighting the supply-side constraints faced by financial institutions in offering more innovative and higher-risk products (Choudhary & Limodio, 2022), such as incentive structures for agents making credit allocation decisions in financial institutions (Rigol & Roth, 2021). In this paper, I focus on risk preferences and deliberately abstract from agency frictions that remain even in data-rich environments (e.g., moral hazard via side selling (Russel et al., 2025)), since these frictions are expected to ease significantly with the dramatic increase in digital payments and enhanced real-time monitoring via open banking APIs. As digital financial systems in developing economies rapidly evolve, my findings underscore the potential of integrating insights from finance theory and practice—namely, contractual features tailored to uncertain valuation environments that mitigate firm owners' behavioral biases—to design financial products that unlock investment and growth in small firms.

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