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

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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.

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1. Introduction

Hundreds of millions of small firms operate in low- and middle-income countries, and finance is often cited as a critical factor in stimulating their growth. Microfinance institutions (MFIs) have emerged to fill this financing gap, rapidly expanding to serve over 150 million borrowers while maintaining high repayment rates (Impact Finance Barometer, 2022; Rigol & Roth, 2021). However, strikingly, a large wave of experimental evaluations identified zero average impacts of the classic microcredit product on the profits of small firms (Banerjee, Karlan, & Zinman, 2015). These disappointing results pose a significant puzzle to the finance and development literature, given a large body of influential work that provides: (i) macro-level evidence of a positive relationship between financial access and growth (Beck, Demirgüç-Kunt, & Levine, 2007); and (ii) remarkably consistent micro-level evidence that small firms have very high returns to capital (5%-10% returns per *month*) (De Mel, McKenzie, & Woodruff, 2008; Liu & Roth, 2022). Motivated by why microcredit has not unlocked those high returns, I explore if its rigid contract structure is partly to blame, and if equity-like contracts can more effectively spur investment for certain borrowers.

The classic microcredit contract contains several theoretically appealing features that alleviate adverse selection and moral hazard in informationally-opaque lending markets. For example, required payments are rigid and high-frequency – sometimes even weekly – beginning almost immediately after funds are disbursed. This approach is quite distinct from lending in high-income countries, where several forms of repayment flexibility such as grace periods are available even for low-income clients (Barboni, 2024). Importantly, such rigidity may discourage the higher-risk, higher-return investments that are often needed to stimulate small firm growth. Equity-like contracts with performance-contingent repayments may be preferred for financing the investments of the many small businesses with high but volatile returns, and especially for risk-averse business owners (De Mel, McKenzie, & Woodruff, 2019). From the supply side, implementing such contracts has traditionally been challenging due to costly state verification (Townsend, 1979), with risk-bearing capital predominantly allocated to larger firms. Notably, rapid digitization in many low- and middle-income countries has dramatically expanded "digital footprints" and significantly lowered monitoring costs (Annan, Cheung, & Giné, 2024; Demirgüç-Kunt, Klapper, Singer, & Ansar, 2022; Higgins, 2019), enabling novel forms of flexible finance even for small firms.

I evaluate the impact of equity-like contracts on small firm investment and the role of risk preferences, combining data from 'artefactual field experiments' (Harrison & List, 2004), two field experiments, and structural estimation. By focusing on small firms seeking financing for business expansion and excluding those without growth plans, I target a subset of businesses with greater potential to drive broader economic development beyond mere subsistence. I demonstrate the value of incorporating behavioral finance insights, which have been underutilized in the development finance literature, to provide a demand-side explanation for the limited adoption of seemingly advantageous equity-like contracts. This approach also helps identify contractual innovations that could enhance their viability. My sample comprises 765 small firm owners who expressed an interest in expanding their operations and participated in two field experiments in Kenya and Pakistan, where they were offered asset financing. Kenya offers an ideal testing ground for new financial contract structures due to its technological advancements and status as the mobile money capital of Africa (Riley, 2018; Suri, 2017). There, I collaborated with one of the world's largest multinational food companies to recruit micro-distributors seeking to grow their businesses. Pakistan provides another important setting to explore equity-like contracts, as these instruments have the potential to serve hundreds of millions of financially excluded business owners (El-Gamal, El-Komi, Karlan, & Osman, 2014; IMF, 2015; World Bank, 2012). Moreover, given Pakistan's climate vulnerabilities and similar challenges across South Asia, there is a pressing need for novel risk-sharing contracts to support climate-friendly, high-upside but uncertain investments (Asian Development Bank, 2022; Lane, 2022). In Pakistan, I partnered with a leading financial institution, drawing on its pool of graduated borrowers looking to expand business operations. Both samples consist of policy-relevant, growth-oriented small firms in key developing countries, yet differences in setting offer a valuable test of external validity.

In the first part of the paper, I employ investment games designed to replicate the difficulty small business owners face in accessing higher-expected-return investments due to financial constraints. This choice task is implemented at a critical juncture when participants are actively considering asset financing in the broader field experiments, enhancing the naturalness of the setting. I find that equity-like contracts lead business owners to make investment decisions that increase expected profits by 0.35 standard deviations compared to those made under debt contracts. These findings are consistent across Kenya and Pakistan, where I observe nearly identical treatment effect sizes, strengthening external validity. Furthermore, the results remain robust across multiple rounds of the investment game, across equity contracts with varying sharing ratios, controlling for order effects in the within-subject design, and adjusting for multiple hypothesis testing.

I then show the important yet nuanced role of risk preferences. I adopt a holistic view of risk preferences, supplementing the standard measure of risk aversion as utility curvature, as in expected utility theory, with two dimensions of prospect-theoretic preferences. I begin with simple non-parametric measures of risk preferences based on approximately 30,000 incentivized questions to business owners and reduced-form regressions. First, I find that risk-averse business owners perform better under equity contracts compared to debt, choosing more profitable investments, and prefer equity when given a choice. This is consistent with the benefits of implicit insurance for individuals with more concave utility functions. Second, I present what to my knowledge is the first evidence of loss aversion as a motivation for equity contracts. I find that loss-averse business owners also perform better under equity contracts, and prefer them. This is consistent with individuals 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. Third, and strikingly, I find the opposite result when introducing the second key component of prospect theory, probability weighting. I find that business owners who overweight small probabilities, and who constitute a sizeable proportion of the sample, fare better under debt, and prefer debt when offered a choice. The results remain robust to alternative risk preference specifications, and I show they are not driven by various business and owner characteristics. Additionally, I show that the findings on probability weighting reflect genuine probability distortions rather than over-optimism.

The reduced-form results highlight the value of incorporating a broader conception of risk preferences when exploring contract design for financing small firm investments. However, they also reveal conflicting implications of incorporating the two prospect-theoretic dimensions of risk preferences, loss aversion and probability weighting, leading to ambiguous welfare implications. I therefore adopt a structural approach that incorporates the experimental variation, enabling counterfactual analysis and a deeper exploration of the impact of contractual innovations on borrowers and capital providers (DellaVigna, 2018; Floyd & List, 2016; Whited, 2023). To begin, rather than presupposing the validity of prospect theory over expected utility theory, I initially estimate a mixture model that incorporates both theories and allows the data to indicate which has more empirical support. The results significantly favor the prospect-theoretic framework, and I therefore proceed to structurally estimate its three risk preference parameters. The estimation reveals a moderate level of utility curvature in the sample. I also estimate a majority of business owners to be loss averse, with a loss aversion parameter that is within the 2.00 to 2.25 range commonly found in the literature (Brown, Imai, Vieider, & Camerer, 2024; DellaVigna, 2018). Finally, and notably, I estimate a bimodal distribution for the probability weighting parameter. The first mode features a small group exhibiting 'standard' (linear) probability weighting, as in expected utility theory. The second mode is characterized by a substantial subgroup exhibiting an 'inverse-S-shaped' probability weighting function that leads to overweighting of small probabilities, with an estimated parameter very close to the range documented in high-income country studies. (Comeig, Holt, & Jaramillo-Gutiérrez, 2022; Dimmock, Kouwenberg, Mitchell, & Peijnenburg, 2021). Estimating risk preference parameters very close to those in the behavioral finance literature enhances the generalizability of the findings, suggesting that the estimated distribution of preferences is unlikely to differ radically from that of the broader target population of small firms.

I then examine selection into different contracts using the structurally estimated risk preference parameters for each individual, combined with the 'real-world' business profit distribution from the broader field experiments from which participants are drawn. Additionally, I calculate a compensating-variation measure of the benefits of introducing equity-like contracts into MFI portfolios. In line with the reduced-form results, loss aversion provides a strong justification for offering equity contracts to individuals who particularly value downside protection. Conversely, individuals who overweight small probabilities are more likely to select into debt. Crucially, their aversion to equity is directly linked to the skewness of the returns distribution. A lognormal distribution, which most closely aligns with the observed profit distribution in the field data, exhibits inherent skewness that drives many to reject equity contracts. Individuals exhibiting non-linear probability weighting overweight the low chance of very high profits, which they would have to share under an equity contract. They also underweight the high probability of low-profit outcomes – where an equity contract's downside protection is most beneficial. Considering that equity-like contracts can stimulate more profitable investments among many small firms in developing countries – including those not captured in my dataset who may have opted out of credit markets due to debt aversion (Azmat & Macdonald, 2020; Martínez-Marquina & Shi, 2024; Meissner & Albrecht, 2022; Paaso, Pursiainen, & Torstila, 2020) – this poses a considerable demand-side challenge. This is especially true given that firm outcome distributions are more skewed in low- and middle-income countries (Hsieh & Olken, 2014). Importantly, I find that changing the underlying returns distribution from lognormal to normal causes the observed results to disappear. This aligns with the findings of Barberis and Huang (2008), who demonstrated that with normally distributed returns, the pricing implications of prospect theory are indistinguishable from those of expected utility theory.

Using the model framework, I demonstrate that a simple contractual modification can unlock small firm investment by addressing the demand-side challenge to adopting equity-like contracts. I analyze a 'hybrid' contract that provides a similar performance-contingent payment structure and risk-sharing benefits as equity, but with a debt-like capped upside. Such a contract is particularly attractive to individuals who overweight small probabilities, and leads to significantly higher take-up rates. A financial capital provider with a more linear probability weighting function can profitably offer hybrid contracts, thereby stimulating small firm investment and mutual benefits. Hybrid contracts share features with certain contractual arrangements in venture capital, like equity clawbacks, performance ratchets, and convertibles, which incentivize performance while aligning the interests of investors and business owners through adaptable reward structures based on achieved targets (Feld & Mendelson, 2019; González-Uribe & Mann, 2024; Jansen, Phalippou, & Noe, 2024; Kaplan & Strömberg, 2003). Rapid increases in digital footprints as countries shift toward open banking models create opportunities to implement similar innovative structures even among small firms.

The combination of artefactual field experiments and structural estimation provides an ideal approach for estimating individual-level risk preferences and assessing the welfare effects of new financial contracts, by controlling for the many confounding factors present in field data (Barberis, 2013; Harrison & Ng, 2016). This is particularly true for richer models of risk preferences that go beyond utility curvature, and especially for measuring probability weighting, in which there is a fundamental identification problem in separating probability weighting from biased beliefs when using field data alone (Barberis & Huang, 2008; Dimmock et al., 2021). Notwithstanding this, to address external validity, I test the robustness of the results 'outside of the lab', by analyzing take-up data in the field experiment from which participants were drawn. Applying the same risk measures used in the investment games, I find that risk-averse and loss-averse individuals are more likely to take up equity-like asset financing contracts. In contrast, those who overweight small probabilities have a higher take-up of debt. Finally, I use data from the field experiment to test the model prediction that a hybrid contract can increase take-up of equity-like contracts for individuals who initially favored debt due to their overweighting of small probabilities. The actual take-up results align with the model's predictions—when a hybrid contract is offered, take-up rates are high among both individuals who overweight small probabilities and those who do not.

I contribute to the finance and development literature by drawing together two distinct strands of research in development economics and behavioral finance. Banerjee et al. (2015) identify the following key challenges for the next generation of finance and development studies: (i) investigating how innovations to contract structure can improve take-up rates and effectiveness; (ii) addressing the limited evidence on graduated borrowers; and (iii) broadening our understanding of non-credit product features. I also connect to the classic sharecropping and risk-sharing under limited commitment literature (Ligon, 1998; Udry, 1990), noting that modern digital ecosystems—by greatly reducing verification and enforcement frictions—hold promise for expanding the contracting space for high-potential small firms. De Mel, Mckenzie, and Woodruff (2019) also highlight the need for more conceptual work on equity-like contracts for such firms. I contribute to all of these objectives by examining the feasibility of equity-like contracts, using a policy-relevant sample of existing small business owners seeking expansion. My paper also connects with important recent studies that evaluate repayment grace periods in standard microcredit contracts, and demonstrate benefits for businesses through reducing repayment rigidity (Barboni & Agarwal, 2021; Battaglia, Gulesci, & Madestam, 2021). However, flexible-repayment microcredit contracts have sometimes led to increased MFI default rates (Brune, Giné, & Karlan, 2022; Field, Pande, Papp, & Rigol, 2013). While grace periods appeal to many borrowers, they expose lenders to greater downside risk while not providing them with the upside from the resulting more profitable business investments. As discussed by Barboni (2017), lenders could potentially charge higher interest rates for such flexibility, but are often prevented from doing so by interest rate regulations and social norms. Equity-like contracts provide a more direct link between business income and repayments, better aligning the interests of borrowers and capital providers.

By adopting a prospect-theoretic approach to studying investment behavior among small firms in developing countries, I build upon the artefactual field experiment of Fischer (2013), who uses an expected utility framework to show that – within joint-liability credit arrangements – adding profit-sharing features improves outcomes for the most risk-averse. My work, which considers a broader conception of risk preferences than typically considered in the development economics literature, also responds to growing calls for more research on 'behavioral firms' in developing countries (Kremer, Rao, & Schilbach, 2019). There is recent evidence that non-expected-utility measures of risk preferences could be important in the design of agricultural index insurance (McIntosh, Povel, & Sadoulet, 2019) and prize-linked personal savings products to increase bank deposits (Dizon & Lybbert, 2021; Gertler, Higgins, Scott, & Seira, 2023), but little work on how such preferences influence small firm investment and growth (Carney, Kremer, Lin, & Rao, 2022). My findings reveal that this expanded framework yields significant insights; however, in the context of financial contract design, it also uncovers contrasting implications from incorporating the two key dimensions of prospect theory.

I also contribute to an expanding field in behavioral finance and asset pricing that has predominantly focused on high-income countries. There is a vast literature emphasizing the significance of reference-dependent preferences for investment behavior (Barberis, Jin, & Wang, 2019; Benartzi & Thaler, 1995; Imas, 2016; List & Haigh, 2010; Shefrin & Statman, 2000). I present, to my knowledge, the first suggestive evidence that loss-averse business owners may both prefer and make more profitable investment decisions under equity than debt. This is demonstrated through both cleanly estimated risk preferences and real-world business decisions outside the laboratory. A smaller literature focuses on the often-neglected second component of non-expected-utility models — probability weighting — which has explanatory power for many financial market phenomena, particularly in contexts of positively skewed return distributions (Barberis & Huang, 2008; Carlson & Lazrak, 2015; Fehr-Duda & Epper, 2012; Polkovnichenko & Zhao, 2013). Holzmeister et al. (2020) provide global survey evidence indicating that investors prioritize skewness over variance in investment decisions, despite the latter being the more common risk measure in academic models.

My results provide a novel counterpoint to the behavioral finance literature's finding 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 such individuals in their design of pay packages by implicitly selling them deeply out-of-the-money stock options that they overvalue (Spalt, 2013). I demonstrate the flip-side of this: small business owners who overweight low-probability, high-profit scenarios are equity-averse, since equity contracts entail them *selling* skewness and sharing large amounts in high-profit states of the world that they overweight. A financial institution with a more linear probability weighting function can unlock mutual gains from trade by offering financing that caps upside and waives profits in the low-probability, high-profit scenarios overweighted by many small firm owners. Such an approach shares similarities with theoretical work on risk-sharing networks that explores the potential for more risk-tolerant individuals to absorb risk from more risk-averse individuals (Chiappori, Samphantharak, Schulhofer-Wohl, & Townsend, 2014). While recent work has advanced our understanding of the cognitive foundations of preferences (Bohren, Hascher, Imas, Ungeheuer, & Weber, 2024; Bordalo, Gennaioli, & Shleifer, 2022; Enke & Graeber, 2023; Frydman & Jin, 2023; Oprea, 2024), I document the consistency of observed behavior among small firm owners in my sample with standard prospect-theoretic models and document the important implications of such preferences for small firm investment, without taking a stance on the underlying cognitive mechanisms. I also contribute to the behavioral corporate finance literature, which highlights the importance of managerial traits for financial contract design and shows that overconfident managers prefer debt over equity (Landier & Thesmar, 2008; Malmendier, Tate, & Yan, 2007). I show that, even after ruling out over-optimism as the mechanism, the seemingly related but distinct behavioral bias of probability weighting leads to a similar preference for debt over equity. In contrast to the prevailing security design literature—which typically assumes a uniform type of entrepreneur—my approach employs direct, incentivized elicitation to measure firm owners' risk preferences and directly links these to their subsequent financial contract choices.

I address external validity throughout the paper using the framework of List (2020). Specifically, I highlight how the selection of a policy-relevant sample of growth-oriented firms actively seeking financing, the naturalness of the decision-making environment at a critical business juncture, and the consistency of results — both with prospect-theoretic predictions from other studies and within this study across replicated experiments in two countries, as well as with actual take-up data from the field — enhance the generalizability of the findings. These insights can guide subsequent research on increasingly feasible equity-like contractual innovations in the field.

Section 2 describes the study settings in Kenya and Pakistan, while Section 3 outlines the experimental design and data collection methods. Section 4 presents the reduced-form results, and Section 5 explores counterfactual contracts and validates the findings using field data. Section 6 concludes.

2. Study setting

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 policy-relevant populations of growth-oriented small firms in key developing countries, there remain differences; however, this provides a test of external validity. I implemented a series of investment games during a baseline workshop with business owners prior to their random assignment to financial contract offers in the broader field experiments, thereby increasing the naturalness of the setting (List, 2020). The

[1] For impact evaluations of the asset finance product in these two experiments, see Bari, Malik, Meki, and Quinn (2024) and Cordaro et al. (2022).

activities took place on the same day, ensuring no attrition for the investment games.

The first experiment was implemented in Pakistan between 2017 and 2018. Pakistan presents an ideal setting to test equity-like contracts – such products, though not restricted to any one particular religion or group, have the potential to reach hundreds of millions of financially excluded Muslim business owners (El-Gamal et al., 2014; IMF, 2015; Nimrah, Michael, & Xavier, 2008; 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 the prevailing market rates) (Pakistan Microfinance Network, 2020). Akhuwat is based in Lahore, and I sampled from microenterprises in and around Lahore that had passed a simple screening process of having graduated from repaying small-scale business loans, and reaching the maximum borrowing amount of just under $500. Clients who had 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 a baseline workshop, where enumerators conducted a detailed household survey and incentivized behavioral games to elicit risk preferences. The investment games used in this paper took place during this workshop, and before any of the sample was offered the asset financing products.

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 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] As a comparison to two of the most prominent studies on capital returns in microenterprises, average microenterprise profits in De Mel et al. (2008) and Fafchamps, McKenzie, Quinn, and Woodruff (2014) were $25. The average business in my

[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).

[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.

sample is much larger in terms of business profits, which is unsurprising given that the target population was graduated borrowers.

The second experiment was implemented in Kenya, also in 2017. Kenya represents an ideal 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 gum 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. This was a single type of transportation asset – a bicycle. The unique setting of the experiment, in particular 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 5.6 to assess the external validity of the elicited risk preference measures and model predictions outside of 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, described in the next section, followed identical procedures in both countries. During a baseline workshop lasting approximately half a day — prior to the random offering of financing contracts in the broader field experiments—I conducted surveys, risk preference elicitation, and investment games. (The take-up results from these broader field experiments are detailed in Section 5.6.)

3. Experimental design

I now describe the activities in the artefactual field experiment, which — in combination with structural estimation — presents an ideal approach for estimating individual-level risk preferences and examining investment behavior, controlling for numerous potential confounding factors present in field data (Barberis, 2013; Harrison & Ng, 2016). This is particularly relevant for richer models of risk preferences that extend beyond utility curvature. I first explain the process of eliciting risk preferences, which I use for heterogeneity analysis in the reduced-form regressions in Section 4, and for structural estimation of risk preference parameters in Section 5. In Section 5.6, I investigate whether the estimated risk measures are predictive of actual business decisions made by individuals outside of the controlled environment of the artefactual field experiment. By embedding the experiments within the baseline workshops of the two larger field studies, I minimize attrition and increase participant engagement throughout the activities, enhancing external validity (List, 2020).

3.1. Measuring risk preferences

All participants answered 44 questions designed to assess their attitudes towards risk. These included domain-specific, self-reported measures of risk attitudes, as well as incentivized choices among lotteries that varied in payoffs and probabilities. 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 the domains of gain and loss enables the structural estimation of risk preference parameters by applying specific functional forms. All activities utilized real currency notes and business framing to aid comprehension.

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 games. 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.[4] 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 individual, I calculate their certainty equivalent for the set of 10 questions with $p_g \in \{0.25, 0.50, 0.75\}$, defined as the mid-point between the highest certain payment they rejected in favor of the risky prospect and the lowest certain payment they accepted instead. An individual's risk premium is then calculated as the difference between their certainty equivalent and the expected value of the two risky prospects (250, 500, and 750, respectively). 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.[5] For the $p_g = 0.25$ prospect, I find a mean risk premium of *negative* 23.6 (indicating a mean certainty equivalent of 273.6 that was actually higher than the 250 expected value of the risky prospect), and a standard deviation of 308.5. For the $p_g = 0.50$ prospect, I find a mean risk premium of 126.4 (reflecting a mean certainty equivalent of 374.6, compared to the expected value of 500), with a standard deviation of 336.2. For the $p_g = 0.75$ prospect, I find a mean risk premium of 272.0 (reflecting a mean certainty equivalent of 478.0 – much lower than the expected value of 750), with a standard deviation of 356.5.

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

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

[5] 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 5, I do impose structure on the estimation in order to conduct counterfactual contract analysis with individual-level parameters.

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 mid-point between the x loss that they would tolerate (to accept the risky prospect) and the smallest x for which they would reject the prospect. The mean switching point is 601, with a standard deviation of 278.

Before conducting all activities, participants were informed that at the end of the behavioral games session one of the incentivized activities would be selected for payment by physically drawing a ball from a bag, thereby requiring attentive responses to all questions, and allowing the use of relatively large amounts for payoffs (approximately three times median daily business profits for individuals in the sample).[6] 18.5% of participants failed standard comprehension tests by choosing a guaranteed zero over an option with a positive expected value or by exhibiting multiple switches (i.e., inconsistent transitions between preferring the lottery and the sure payment) in the risk and loss aversion tasks. This rate is lower than that reported in several studies reviewed by Charness, Gneezy, and Imas (2013). Although one alternative would have been to enforce a single switching point, doing so would force confused individuals into the sample and introduce noise that could bias the estimated preferences. In line with standard practice in the experimental literature, I drop these observations from the analysis.

3.2. Investment game

Following the risk preference elicitation activities, business owners were introduced to the investment game, which was designed to replicate key aspects of 'real-world' business investment behavior. The game mimicked challenges small business owners face in accessing higher-expected-return investments due to financial constraints, and explores the impact of different financing contract structures on investment decisions and the role of risk preferences. The design's simplicity, 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 and generalizability (List, 2020).

The game was calibrated using pilot data and simulations from a simple model, which is developed further in Section 5. The investment game was explained to participants using business-related vignettes, after which they were asked several questions to test understanding. The basic structure of the game 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

[6] Charness, Gneezy, and Halladay (2016) show that paying for only a randomly selected subset of all activities is at least as effective as paying for all of them, and can actually be more effective by avoiding wealth effects and hedging within the behavioral games session.

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 game ended).

Table 1: **INVESTMENT GAME OPTIONS**

INVESTMENT OPTION	COST	PAYOFF: LOW	PAYOFF: 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 game. 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:[7]

(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 game. 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.

(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

[7] 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.

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 game is more generally described as:

$$Y_T = W_T(1 - \alpha \cdot ET) - DT \cdot K, \tag{1}$$

where T is the number of investment decision rounds, Y_T is the net payoff after settling contractual payments, W_T is wealth after realization of investment outcomes after T rounds, K is the amount of external financing provided in DT and ET, and α controls the sharing ratio for ET. The game was designed using simulations and a simple model with a utility maximizing agent choosing investment options over multiple rounds to maximize terminal profits. Section 5 further develops the model for the purpose of counterfactual contract analysis. To summarize the pre-specified baseline model predictions, 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 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 game T. As described above, in the final design, $T = 2$, $k = 500$, and $\alpha \in \{0.5, 0.25\}$. The final parameters were chosen after piloting with the aim of a simple design that would allow an understanding of the implication of differences in contractual structure on investment behavior, and the role of risk preferences.[8]

4. Experimental results

I now present results from the artefactual field experiments in Kenya and Pakistan. The main empirical specifications and variables were pre-specified.[9] The sample consists of 3,060 observations—one decision per treatment arm for each of the 765 respondents. The panel is fully balanced,

[8] 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.

[9] 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).

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 effects in the Appendix.

Result 1: Equity leads to more profitable investment choices

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

$$y_i = \beta_0 + \beta_1 \text{Debt}_i + \beta_2 \text{Equity}_i + \varepsilon_i, \tag{2}$$

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, whilst 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, where equity-financed business owners selected investment options in the first round of the game 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 6.2% increase in absolute expected return. The replication of results across the two countries increases confidence in the external validity and generalizability of the findings.

Column 4 analyzes choices in the second round of the investment game, 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.2 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 next section, I proceed using the pooled equity indicator and first-round investment decisions. In Appendix Table A.3, 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 game, 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 1 presents results from estimation of the following specification:

$$y_i = \beta_0 + \beta_1 \, \mathrm{Debt}_i + \beta_2 \, \mathrm{Equity}_i + \beta_3 \, \mathrm{HighX}_i + \beta_4 \, \mathrm{Debt}_i \cdot \mathrm{HighX}_i + \beta_5 \, \mathrm{Equity}_i \cdot \mathrm{HighX}_i + \varepsilon_i, \quad (3)$$

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 3.1: (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 D and E, 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.

Panel 1 of Figure 1 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 control mean 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 $Debt \cdot Probability-weigher$ is 8.57 ($p = 0.059$), while the coefficient on $Equity \cdot Probability-weigher$ is -0.46 ($p = 0.906$), with the cross-coefficient test indicating that debt-financed business owners who overweight small probabilities are much more likely to make profitable investments under debt rather than equity ($p = 0.014$).

Robustness

In Appendix D, I show that the results from Figure 1 are robust to using a trichotomized measure for each of the three risk preference variables, rather than a median split. Appendix E demonstrates the stability of results to using three alternative methods for constructing the probability weighting index. In Appendices F, G, H, I, and J, 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 K, 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 N, I show that the estimated probability weighting parameter is not correlated with business owner optimism.)

5. Structural estimation of risk preference parameters and counterfactual contract analysis

The reduced-form results are consistent with a simple and intuitive prediction: that equity-like contracts with performance-contingent payments encourage higher-risk, higher-return investments and can be particularly beneficial for the most risk-averse business owners. However, a more nuanced relationship emerged when allowing for the two main components of the leading alternative to expected utility theory. Specifically, loss aversion highlights an additional value of equity contracts, whereas probability weighting indicates a preference for debt contracts. These contrasting effects call for further exploration of the implications of introducing equity-like contracts, by explicitly incorporating the distribution of individual risk preferences. This is the approach advocated by Harrison and Ng (2016), who argue that relying solely on take-up decisions from experiments offering new contracts provides at best an incomplete assessment of welfare. In Section 5.6, I examine actual take-up decisions both in the controlled setting of the artefactual field experiment and also in the broader field experiments from which participants are drawn; prior to this, I introduce a more formal structure that enables counterfactual analysis. The findings confirm the significance – and opposing effects – of loss aversion and probability weighting for selection into different financial contracts. Further, they highlight the potential for contractual innovations that take into consideration such preferences to more effectively unlock profitable investment and provide mutual benefits for small firms and capital providers.

5.1. Estimating risk preference parameters

Rather than presupposing the validity of prospect theory (PT) over expected utility theory (EUT), I begin by estimating a mixture model that incorporates both theories and allows the data to indicate which has more empirical support. I follow the method of Harrison and Rutström (2009), whereby one likelihood function is defined for the EUT model and one for the PT model; a grand overall likelihood function then allows each theory to co-exist and to explain the data from the risk preference elicitation activities described in Section 3.1.

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.[10] 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:

$$\ln L^{\mathrm{EUT}}(r; y_i, X_i) = \sum_i \ln l_i^{\mathrm{EUT}} = \sum_i [y_i \ln G(\nabla EUT) + (1 - y_i)\ln(1 - G(\nabla EUT))] \tag{4}$$

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

[10] 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; Fezzi et al., 2021; Wakker, 2008).

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:

$$PU_i = \sum_{k=1}^{n} \pi_k \cdot v(x_k), \tag{5}$$

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:

$$\pi_k = w(p_k + \cdots + p_n) - w(p_{k+1} + \cdots + p_n) \tag{6}$$

for $k = 1, \ldots, n-1$, and

$$\pi_k = w(p_k) \tag{7}$$

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):

$$w(P) = \frac{P^\gamma}{(P^\gamma + (1-P)^\gamma)^{1/\gamma}}, \tag{8}$$

where γ controls the shape of the probability weighting function (and $\gamma = 1$ characterises linear probability weighting, as in the EUT model). One-parameter weighting functions have been found in several studies to provide an excellent fit to the data, almost as well as the two-parameter, linear-in-log-odds weighting functions (Wu & Gonzalez, 1996).[11] To summarise, 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:

$$v(x_k) = \begin{cases} x_k^\alpha & \text{if } x_k \geq 0 \\ -\lambda(-x_k^\alpha) & \text{if } x_k < 0, \end{cases} \tag{9}$$

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

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.[12]

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.

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:

$$\ln L^{PT}(\alpha, \lambda, \gamma; y, X) = \sum_i \ln l_i^{PT} = \sum_i [y_i \ln G(\nabla PU) + (1 - y_i) \ln(1 - G(\nabla PU))]. \tag{10}$$

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.[13] The overall likelihood can be written as the probability weighted average of the conditional likelihoods:

$$\ln L(r, \alpha, \lambda, \gamma; y, X) = \sum_i \ln[(\pi^{\text{EUT}} \times l_i^{\text{EUT}}) + (\pi^{\text{PT}} \times l_i^{\text{PT}})]. \tag{11}$$

The mixture probabilities are constrained to be between 0 and 1. Estimation results are presented in Appendix L, and clearly favour 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 of introducing different financial contracts.[14] Standard errors are corrected for the possibility that the 40 responses are clustered for

[12] As discussed in Section 3.1, 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.

[13] 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).

[14] 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).

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:

$$\hat{r} = \hat{r}_0 + \hat{r}_1 \cdot \text{Savings} + \hat{r}_2 \cdot \text{Profits} + \hat{r}_3 \cdot \text{Education} + \hat{r}_4 \cdot \text{DecisionMaker} + \hat{r}_5 \cdot \text{Female} + \hat{r}_6 \cdot \text{Age} + \hat{r}_7 \cdot \text{Kenya} \tag{12}$$

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 (12) 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 et al., 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 et al., 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.[15] In Appendix M, I repeat the estimation while allowing for errors in the decision-making process

[15] See, for example, Abdellaoui (2000); Booij, Van Praag, and Van De Kuilen (2010); Bruhin, Fehr-Duda, and Epper (2010); Camerer and Ho (1994); Polkovnichenko and Zhao (2013); Prelec (1998); Starmer (2000); Stott (2006); Van De Kuilen and Wakker (2011); Verschoor and DExelle (2020); Wu and Gonzalez (1996). An inverse-S-shaped probability weighting function does not imply that all small probabilities are overweighted. Whether a small probability is overweighted depends on the rank of the associated outcome; typically, extreme outcomes are likely to be overweighted because of their salience (Fehr-Duda & Epper, 2012; Quiggin, 1982) This point will have important implications for the valuation of different financial contracts depending on the assumption about the skewness of the underlying distribution of business returns, which I discuss shortly. It is also worth noting that, due to the controlled setting of the artefactual field experiment, the estimated probability weighting function is not being driven by subjective probabilities, but rather a distortion of the true objective probabilities presented to participants in the investment games. For example. individuals may agree that the probability of a fair coin landing on heads is 0.5, but in their decision-making they distort that probability (Kahneman, 1979; Wu & Gonzalez, 1996).

of business owners, using a structural noise parameter.[16] Results indicate even more pronounced loss aversion ($\lambda = 2.50$) and probability weighting ($\gamma = 0.61$), and much lower utility curvature ($\alpha \approx 1$).

Appendix N 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.[17] 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".

5.2. Modeling selection into contracts

I next model how business owners evaluate different financing contracts. 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. In focusing on risk preferences I deliberately abstract from agency frictions that remain even in data-rich environments (e.g., moral hazard via side selling), since these issues are expected to ease significantly with the dramatic increase in digital payments and enhanced real-time monitoring via open banking APIs (Alok, Ghosh, Kulkarni, & Puri, 2024; Demirgüç-Kunt et al., 2022)

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

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

[16] I employ the 'Fechner error' specification of Hey and Orme (1994) that posits the latent index $\nabla EU = \frac{(EU_1 - EU_2)}{\mu}$; as μ gets larger, the choice that individuals make between prospects essentially becomes random.

[17] For example, as shown in Table A.8, 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 not meaningfully large given that mean monthly profits in the sample are \$231.

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 (5) used for estimating risk preference parameters in the discrete choice elicitation activities of Section 5.1, 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 5.1:

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

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 $\sigma = 0.43$.[18] Further details are provided in Appendix O. I model business owners as receiving \$1,500 in financing from the MFI, which is comparable to the financing amount received 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 MFI and its clients (while abstracting from the differential investment impacts of each contract observed in the reduced-form results)

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

and to align them with local lending rates in this setting.[19] and to equate the expected payments across contracts to make them equally attractive for the MFI and clients. Given the similar *average* payments, the difference between contracts is reflected in the *distribution* of post-payment returns, as illustrated in Figure 3. 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.

5.3. How contract valuation varies with risk preference parameters

Figure 4 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 5.1.

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.

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.

[19] 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 MFIs 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.

To illustrate the importance of skewness, in Appendix P 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. The model comparative statics are also consistent with the previous experimental findings in Section 4 that equity was more impactful than debt for risk- and loss-averse business owners, while debt was more impactful for those who overweight small probabilities.

5.4. 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, Shi, & Clarke, 2023) 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 et al., 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 the 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 the hybrid contract is contrasted with those under debt and equity in Figure 3. 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.

Panel D of Figure 4 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 the next section.

5.5. 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 5.1. 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:

$$PU_i^{\text{hybrid}} = \int v\big(\widetilde{W}^{\text{hybrid}}\big)\, dw(P(\widetilde{W})) = \int v\big(\widetilde{W}^{\text{debt}} + T\big)\, dw(P(\widetilde{W})) = PU_i^{\text{debt}}, \tag{13}$$

where final wealth ($\widetilde{W} = W_0 + X - C - RP$) and contract-specific payments (C) are defined as in Section 5.2. $T = 0$ for business owners who prefer debt over the hybrid contract. 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.

Appendix Q illustrates the resulting distribution of profits for the MFI, 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 MFI of 27% on the \$1,500 capital provided. The distribution of profits for the MFI 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 MFI 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 MFI returns may be unacceptable to many conventional microcredit lenders, especially given their organizational structures and loan officer incentives, which I discuss further in the conclusion.[20]

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 MFI 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 to 11% when incorporating results from the reduced-form analysis that equity-financed business owners chose investments that were 6.2% more profitable than under debt.

5.6. Testing model fit: 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, to assess the external validity of the lab-elicited risk preference measures and model 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, 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 owners had above-median utility curvature, loss aversion, and probability weighting, respectively, 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 5, 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,

[20] 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).

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.[21]

The first panel of Figure 5 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).

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). In Appendix R, 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.[22]

[21] The debt contract 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' 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 the previous section to ensure no contract was clearly advantageous in terms of expected payments.

[22] 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 R, 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.

6. 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 microcredit 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 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). This paper has demonstrated 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., 2023)), since these frictions are expected to ease significantly with the dramatic increase in digital payments and enhanced real-time monitoring via open banking APIs (Alok et al., 2024; Demirgüç-Kunt et al., 2022). 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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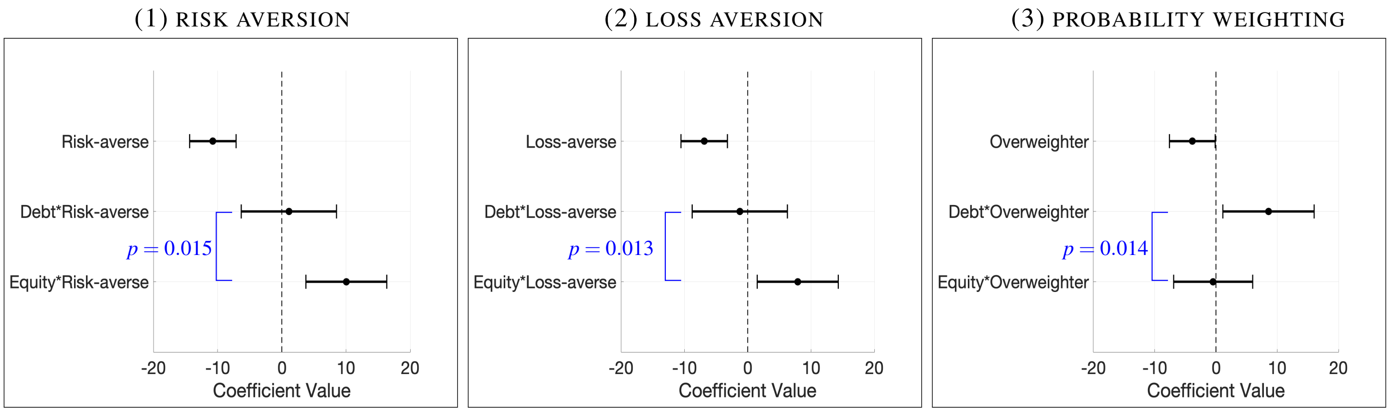
TABLES AND FIGURES

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 3: 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 (%)	5.6	9.2	6.2	8.9	4.3
Effect size (standard deviations)	0.35	0.37	0.35	0.49	0.15

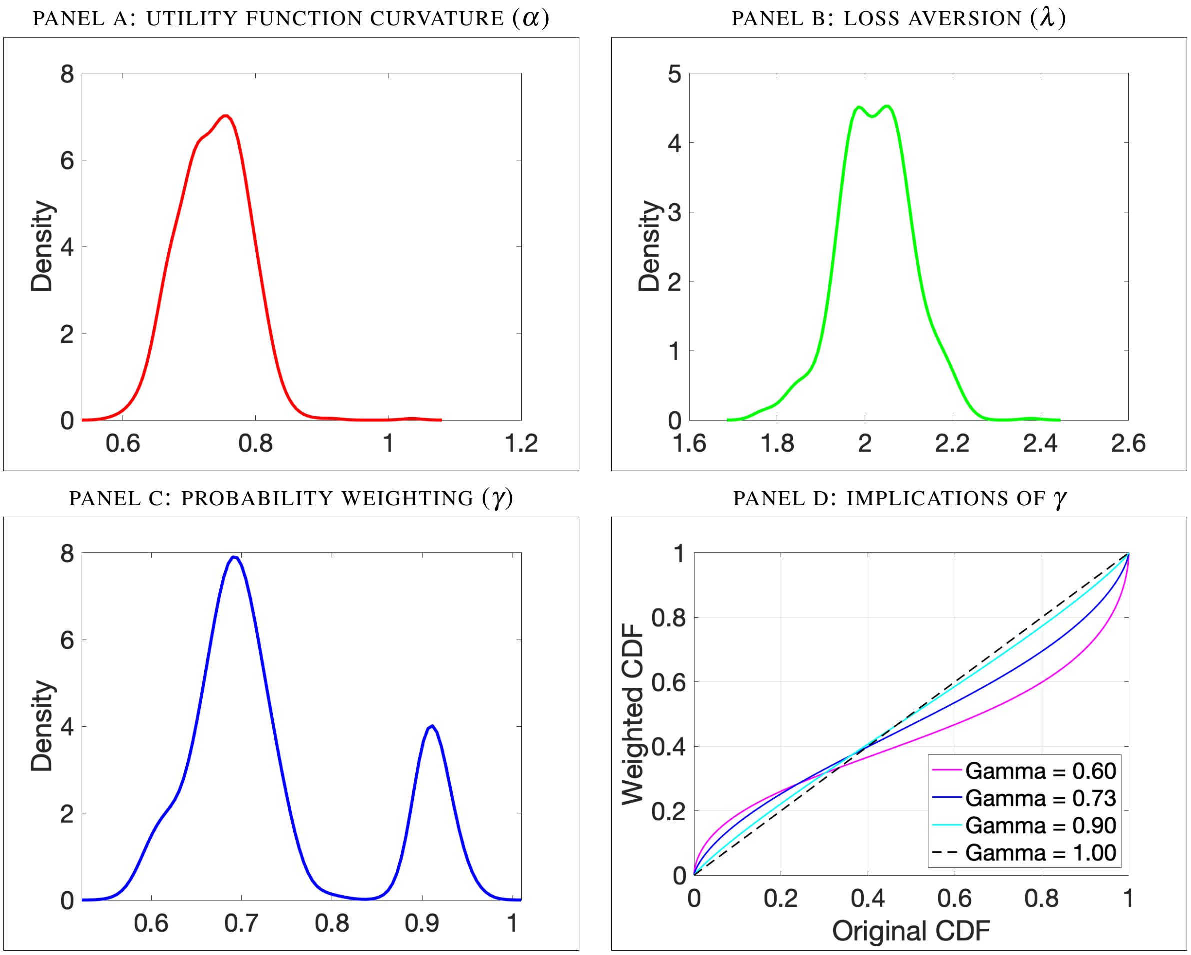
Note: In each column, the dependent variable is the expected profit of the chosen investment option in that particular round. *Debt* and *Equity* are dummy variables for the business owner making the investment decision while financed by the debt and equity contract, respectively. The reported coefficient represents the average expected profit of the investment option chosen under that particular contract relative to the average expected profit of the investment option chosen by the control group. Columns 1 and 2 run the regression separately for each country, while columns 3 to 5 pool both countries. Below each coefficient, a standard error is reported in parentheses, clustered at the level of the business owner. A *p*-value is reported in square brackets, and an adjusted *p*-value is reported in curly braces. I adjust *p*-values for multiple hypothesis testing using the method of List et al. (2023), which builds on Romano and Wolf (2010), to control for the familywise error rate. In the panel below the table, the sixth row presents multiple hypothesis-adjusted *p*-values for the null hypothesis that the effect of being assigned to *Debt* is equal to the effect of being assigned to *Equity*. The seventh and eighth rows quantify the estimated treatment effect (of equity compared to debt) as a percentage of the control group mean and in standard deviations of the control group mean, respectively. *** p<0.001, ** p<0.05, * p<0.10.

Figure 1: INVESTMENT CHOICE: HETEROGENEITY BY RISK PREFERENCES



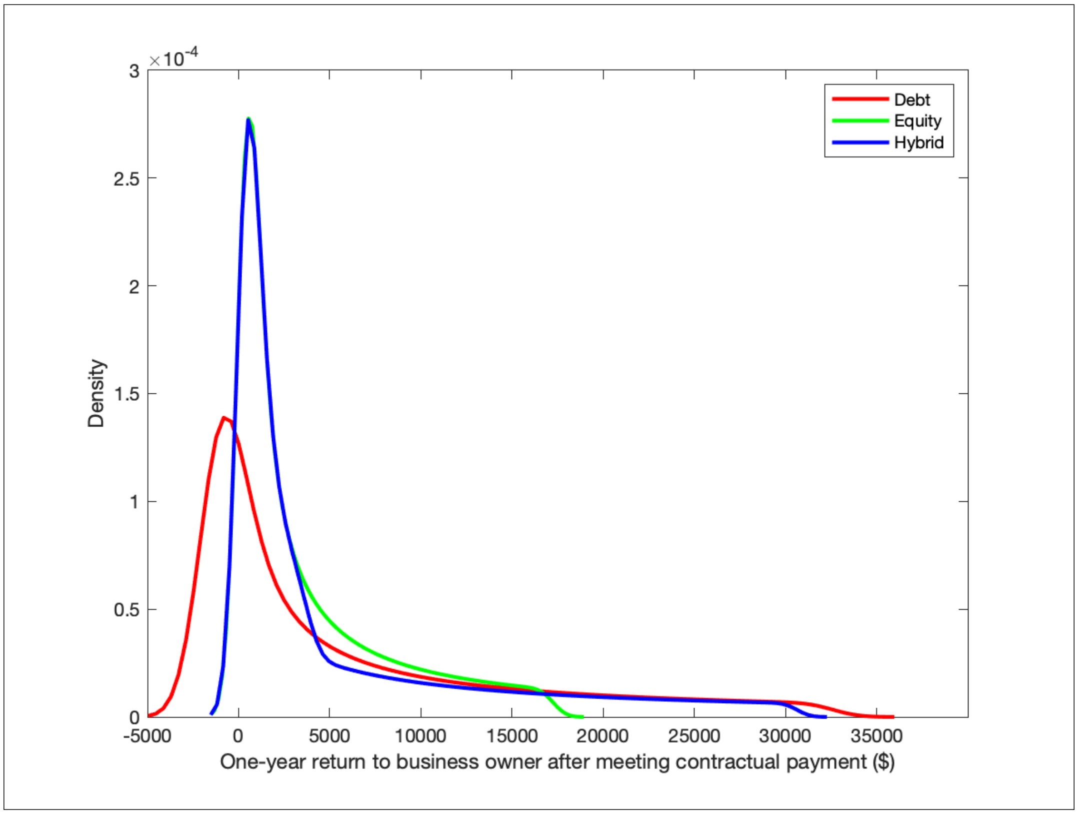
Note: Each panel presents heterogeneous treatment effects estimated from the following specification: $y_i = \beta_0 + \beta_1 \text{Debt}_i + \beta_2 \text{Equity}_i + \beta_3 \text{HighX}_i + \beta_4 \text{Debt}_i \cdot \text{HighX}_i + \beta_5 \text{Equity}_i \cdot \text{HighX}_i + \varepsilon_i$, based on 3,060 observations from 765 unique business owners, as in Table 2. The dependent variable y_i is the expected profit of the investment option chosen by the business owner, and $HighX_i$ is a dummy for individuals with an above-median value for the three distinct dimensions of risk preferences (X_i) measured using incentivized activities at baseline: (1) risk aversion; (2) loss aversion; and (3) probability weighting. For example, in panel (1), *Equity * Risk-averse* represents the expected profit of the investment option chosen by the most risk-averse business owners when financed with equity relative to the expected profit of the investment option chosen by the most risk-tolerant business owners under equity, and *Debt * Risk-averse* represents the expected profit of the investment option chosen by the most risk-averse business owners when financed with debt relative to that chosen by the most risk-tolerant under debt, with an analogous interpretation for loss aversion and probability weighting in panels (2) and (3), respectively. $H_0 : \beta_4 = \beta_5$ tests whether individuals with higher values of X_i are differentially affected by the *Equity* and *Debt* treatments, and the p-values from a test of the null hypothesis that *Equity * Risk-averse* = *Debt * Risk-averse*, *Equity * Loss-averse* = *Debt * Loss-averse*, and *Equity * Overweighting* = *Debt * Overweighting* are displayed in each panel. In Appendices D and E, the analysis is repeated 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.

Figure 2: STRUCTURALLY ESTIMATED RISK PREFERENCE PARAMETERS



Note: Panel A displays the estimated distribution of the utility curvature parameter α, with a mean of 0.74 indicating a moderate average amount of risk aversion (where $\alpha = 1$ represents risk neutrality given the simple power utility specification $U(x) = x^{\alpha}$). Panel B illustrates the distribution of the loss aversion parameter λ, with a mean of 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 et al., 2024; DellaVigna, 2018; Kremer et al., 2019). Panel C illustrates a bimodal distribution for the probability weighting parameter γ, with a mean of 0.73, a mass at almost-linear probability weighting ($\gamma \approx 1$), and a large mass with a non-linear probability weighting parameter of $\gamma \in [0.5, 0.8]$; results are also consistent with estimates of $\gamma \approx 0.7$ in the literature from high-income countries (Dimmock et al., 2021). Panel D illustrates the implication of $\gamma = 0.73$: overweighting of small probabilities and underweighting of large probabilities, and the famous 'inverse-S' shape that has been documented in the majority of empirical studies of probability weighting (Comeig et al., 2022).

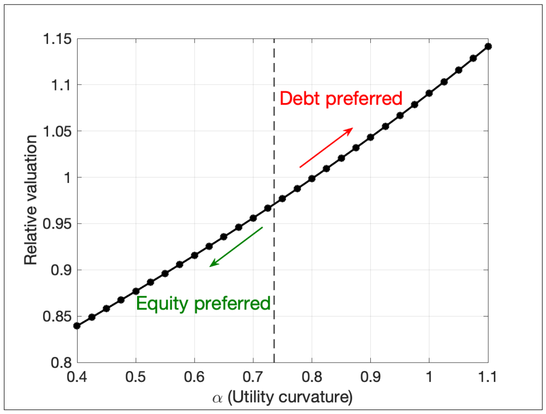
Figure 3: MODEL-BASED DISTRIBUTION OF RETURNS UNDER EACH FINANCING CONTRACT



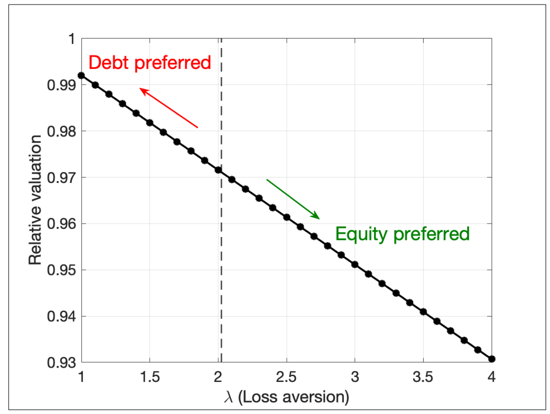
Note: Business owners are modeled as receiving $1,500 in financing, which is the average amount financed in the broader experiment from which the majority of the sample is drawn, and drawing returns from a lognormal distribution (with parameters $\mu = 8.25$ and $\sigma = 0.43$, corresponding to an actual mean and standard deviation of $4,198 and $1,892 respectively). The underlying (pre-contractual-payment) distribution of returns was fitted based on a data-driven method (described in Appendix O) and the actual distribution of business profits from the broader experiment. The distribution of returns to the business owner one year after the financing (and after meeting contractually obligated payments) is illustrated in the above figure, for the three different contracts that are modeled: a debt contract with a 27% interest rate; (ii) an equity contract where 50% of returns are shared; and (iii) a 'hybrid' contract that involves equity-like payments with a 'debt-like' cap set at twice the payment due under the debt contract. The contract parameters were chosen to be consistent with local lending rates in this setting and to equate the expected payments across contracts to make them equally attractive for the MFI and clients (abstracting from individual preference parameters and not allowing for differential impacts of different contracts on effort or investment choice). Given the equated *average* payments, the difference across contracts is reflected in the distribution of post-payment returns, which are illustrated in this figure using kernel density plots. All amounts are in US$.

Figure 4: CONTRACT PREFERENCE AND RISK PARAMETERS

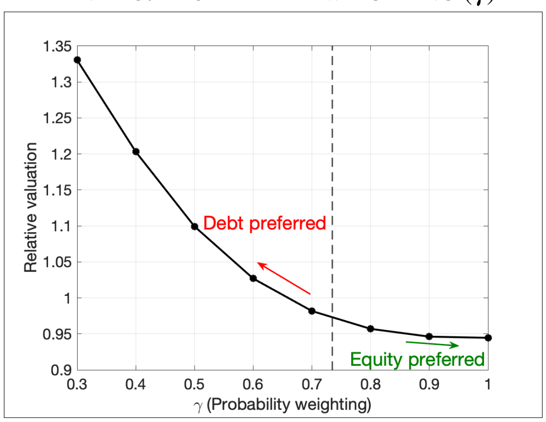
PANEL A: UTILITY FUNCTION CURVATURE (α)



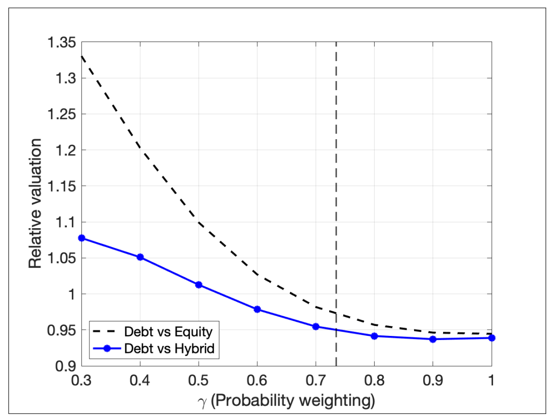
PANEL B: LOSS AVERSION (λ)



PANEL C: PROBABILITY WEIGHTING (γ)

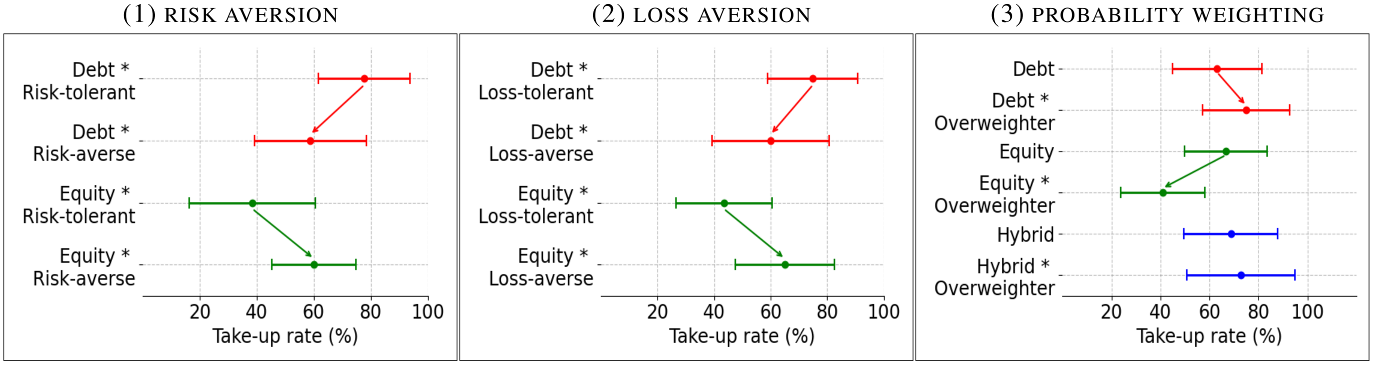


PANEL D: INTRODUCING HYBRID CONTRACT



Note: Panels A, B, and C illustrate how variations in the three 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 D illustrates the impact of introducing the hybrid contract on the relationship between contract preference and probability weighting.

Figure 5: **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 5.