# 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. Using artefactual field experiments in two countries, 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 exhibit non-linear probability weighting prefer debt. Using structural estimation and simulations, 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 business borrowers (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 for 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 grants (5%-10% returns per *month*) (De Mel, McKenzie, & Woodruff, 2008; Liu & Roth, 2022). Motivated by why microcredit hasn't 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 credit 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 the most risk-averse business owners (De Mel, McKenzie, & Woodruff, 2019). In this paper I conduct 'artefactual field experiments' (Harrison & List, 2004), in two countries, with a policy-relevant sample of growth-oriented microenterprises. I first establish that equity-like contracts stimulate profitable investment more effectively than standard microcredit. Drawing on insights from behavioral finance that have not been previously applied in the development finance literature, I then offer an explanation for the rare use of seemingly beneficial equity-like contracts.

Using incentivized measures, I illustrate the important but nuanced role of risk preferences. I find that risk-averse and loss-averse business owners perform better under equity contracts, and prefer them. Conversely, individuals who weigh probabilities in a non-linear fashion (overweighting small probabilities), and who constitute a sizeable proportion of the sample, fare better under debt contracts. These results provide a novel counterpoint to the behavioural finance literature's finding that individuals who overweight small probabilities have a preference for skewness in investment returns, and that large firms can profit by implicitly providing such individuals with out-of-the-money call options that they overvalue (Dimmock, Kouwenberg, Mitchell, & Peijnenburg, 2021; Spalt, 2013). I complement these results by demonstrating that small business owners with a propensity to 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 think are more likely than is objectively true.

Using structural estimation and counterfactual analysis, I demonstrate that contractual innovations – specifically equity-like contracts with capped returns – can alleviate demand-side frictions and unlock investment. A financial capital provider with a more linear probability weighting function can profitably offer such contracts, stimulating investment and increasing overall welfare. From the supply-side perspective, recent financial technology developments mitigate traditional challenges to the implementation of equity-like contracts with small firms. In particular, advancements in digital payment systems have expanded firms' 'digital footprints' (Annan, Cheung, & Giné, 2024; Higgins, 2020; Suri, 2017), facilitating the implementation of performance-contingent financing.

My sample comprises 765 microenterprise owners who expressed interest in business expansion through the acquisition of a fixed asset. These business owners were taking part in two separate field experiments in Kenya and Pakistan, where they were offered financing for this lumpy investment. In the first part of the paper, I demonstrate through investment games that equity-like contracts resulted in business owners making choices that increased expected profits by 0.35 standard deviations compared to debt contracts. I establish the robustness of the results across the two countries, across various rounds of the investment game, for equity contracts with varying sharing ratios, and accounting for order effects in the within-subject experimental design. I next examine heterogeneous treatment effects, using non-parametric measures of three dimensions of risk preferences. First, I find that the increase in profitable investment is most pronounced among risk-averse business owners, which 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. Business owners who are more sensitive to losses than gains value the downside protection offered by equity contracts, and are more willing to share upside in return. Third, and strikingly, I find the opposite result when introducing probability weighting: individuals who overweight small probabilities prefer debt and invest more profitably under debt.

An artefactual field experiment is an ideal method for estimating individual-level risk preferences and examining welfare effects of new financial contracts, by controlling for numerous confounds 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, I further validate 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.

The reduced-form results highlight the value of incorporating a broader conception of risk preferences when exploring optimal contracts for financing small firm investments. However, they also reveal conflicting implications of 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 contractual innovations that can improve welfare (DellaVigna, 2018; Floyd & List, 2016; List, 2011; Whited, 2023). To begin, rather than presupposing the validity of prospect theory over expected utility, 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, 2021; 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. The second mode is characterised by a large proportion of individuals with an 'inverse-S-shaped' weighting function, leading to them overweight small probabilities.

I use the structurally estimated risk preference parameters for each individual, combined with the 'real-world' business profit distribution from survey data, to calculate a compensating-variation measure of welfare gains from 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 reject equity contracts. Crucially, their aversion to equity is directly related to the skewness of the returns distributions. A lognormal distribution best fits the actual profit distribution, and its inherent skewness leads 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 equity. They also undeweight the high probability of low-profit outcomes – where an equity contract's downside protection is most beneficial. Considering that equity-like contracts might be important for fostering more profitable investments by small firms in developing countries, this poses a considerable demand-side challenge. This is especially true in light of the well-documented skewness in firm outcome distributions in low- and middle-income countries (Hsieh & Olken, 2014).

In the final section of the paper, I demonstrate how a contractual modification, informed by earlier findings, can unlock small firm investment. I explore a hybrid contract, which combines equity-like profit-sharing with a debt-like repayment cap. Such a contract is particularly attractive to individuals who overweight small probabilities, and can be profitably offered by financial institutions with more linear probability weighting functions. I present evidence from 'outside the lab' for take-up of a hybrid contract that is consistent with model predictions. Hybrid contracts share features with certain contractual arrangements in venture capital, like equity clawbacks and performance ratchets, which incentivise performance while aligning the interests of investors and business owners through adaptable reward structures based on achieved targets. In the conclusion, I discuss similar contracts provided by fintech firms in high-income countries and their increased viability in developing countries, facilitated by greater digital footprint of firms.

I contribute to the finance and development literature by drawing together two distinct strands of research: microfinance and behavioral finance. In their summary of the first wave of microcredit impact evaluations, Banerjee et al. (2015) identify the following key challenges for the next generation of microfinance studies: (i) investigating how innovations to microfinance 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 microfinance activities. Further, while there is a rich older literature on sharecropping contracts, De Mel, Mckenzie, and Woodruff (2019) highlight the scarcity of conceptual work on microequity contracts. 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 MFIs to greater downside risk while not providing them with any of the upside from the resulting more profitable (but riskier) business investments. As discussed by Barboni (2017), MFIs 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 that allow a better alignment between business and MFI performance are increasingly viable with technological advances in developing countries and provide a direct link between repayments and income, better aligning the interests of borrowers and lenders.

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 examined in the development economics and microfinance 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 personal savings products and for increasing bank deposits (Dizon & Lybbert, 2021; Gertler, Higgins, Scott, & Seira, 2023), but little work on how such preferences influence small business investment and growth (Carney, Kremer, Lin, & Rao, 2022). My findings reveal that using this expanded framework yields significant new insights; however, in the context of financial contract design, it also uncovers contrasting effects from the second and third 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 emphasising the significance of reference-dependent preferences for investment behavior (Barberis, Jin, & Wang, 2019; Benartzi & Thaler, 1995; Haigh & List, 2005; Imas, 2016; List & Haigh, 2010; Shefrin & Statman, 2000). I present, to my knowledge, the first evidence that loss-averse business owners 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, 2013; Barberis & Huang, 2008; Carlson & Lazrak, 2015; Fehr-Duda & Epper, 2012; Polkovnichenko & Zhao, 2013). Holzmeister et al. (2020) provide global survey evidence indicating that investors prioritise skewness over variance in investment decisions, despite the latter being a common risk measure in academic models. I build upon the work of Dimmock et al. (2021), who show that individuals who overweight low-probability events have a preference for skewness in their investment choices. I also build upon the work of Spalt (2013), who shows that overweighting of small probabilities leads individuals to overvalue deeply out-of-the-money options, which employers can exploit in designing compensation packages. I demonstrate the flip-side of this: small business owners with non-linear probability weighting are much less likely to '*sell* skewness' by entering into equity contracts that share profits in overweighted high-profit states of the world. Importantly, I find that altering 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.

Section 2 describes the setting of the studies in Kenya and Pakistan. Section 3 outlines the experimental design, with reduced form results presented in Section 4. Section 5 presents the estimation of risk preference parameters, welfare analysis under different counterfactual contracts, and evidence from 'outside of the lab'. Section 6 concludes.

# 2 Study setting

I conducted artefactual field experiments with 765 microenterprises participating in two distinct microfinance field experiments in Kenya and Pakistan.[1] The artefactual field experiment, comprising a series of investment games, was conducted during a baseline workshop with business owners before their random assignment to microfinance contracts within the broader field experiments. Working with this policy-relevant, growth-oriented sample of business owners – at a pivotal moment when they sought to expand operations via significant asset financing – offers an ideal context to investigate preferences for, and impacts of, equity-based contracts. Such contracts are generally unsuitable for subsistence-level microenterprises with no expansion ambitions.

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, El-Komi, Karlan, & Osman, 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

[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).

(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 relatively simple screening process of having graduated from repaying small-scale business loans, and reaching the maximum borrowing amount of approximately $475. Clients who had expressed an interest in expanding their business with the purchase of a fixed asset (up to the value of $1,900) were invited to a baseline workshop, where enumerators conducted a detailed household survey and incentivised 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 approximately $25. The average business in my 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 out novel financial contract structures, 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. The company had developed a route-to-market

[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.

micro-distribution program using self-employed micro-distributors. The distribution system is built around small warehouses (called 'stockpoints'), which are located in both rural and urban areas. Stockpoints receive deliveries of chewing gum, which they sell alongside various other products. Micro-distributors purchase chewing gum (as well as other products) from stockpoints, before selling to customers (often on foot). They initially purchase the gum 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 the company'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 utilise in Section 5.4 to explore robustness of the results 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 experiments were conducted using an identical procedure in both countries. Surveys, risk preference elicitation, and investment games were all part of the baseline workshop. This workshop, spanning approximately half a day, was held before any participants were randomly selected for microfinance contract offers in the broader field experiments.

# 3 Experimental design

I now describe the activities in the artefactual field experiment, which presents an ideal environment for estimating individual risk preferences and examining investment behavior, controlling for numerous potential confounds 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 to assess welfare in Section 5. In Section 5.4, I investigate whether the elicited risk measures are predictive of actual business decisions made by individuals outside of the controlled environment of the artefactual field experiment.

### 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 utilised real currency notes and business framing to aid comprehension.

The self-reported measure of risk attitudes asked each business owner to rate on a scale of 1 to 10 their willingness to take risks in the following domains: (i) their financial matters; (ii) their business; (iii) faith in other people; and (iv) their general perception about whether they were a person fully willing to take risks or more likely to 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 strong and significant positive correlation of 0.30 between the risk aversion measures derived from the more general self-reported questions and those from incentivized games. 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 measure of risk aversion with responses from a more narrowly defined incentivised 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. 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 certain payment that they would reject in favour of the risky prospect and the lowest certain payment that they would take over the risky prospect. 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% as probabilities is common in developing country settings (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.[4] 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), and very similar to that used in the large recent population representative survey of individual-level loss aversion by Chapman, Snowberg, Wang, and Camerer (2022). In each question, business owners had to accept or reject an equal-probability binary-outcome prospect that either paid 1,000 or incurred a loss of $x$, with $x$ beginning at 0 and gradually increasing to a loss of 1,000, in increments of 100. If a loss was incurred in the activity, then the amount would be taken from the participation fee of 1,000 that all business owners received for taking part in the broader survey and workshop for the field experiment i.e. it was a real loss. I then construct a variable representing each individual's switching point, which is the 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.

[4] 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 removes 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 and welfare analysis with individual-level parameters.

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).[5]

## 3.2 Microequity investment game

Following the risk preference elicitation activities, business owners were carefully introduced to the microequity investment game. The game was designed to mirror key aspects of 'real-world' business investment behavior, with the aim of understanding the impact of different financing contract structures on investment choice, and the role of risk preferences. The game was calibrated using pilot data and simulations from a simple model, which is developed further in Section 5. The microequity 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 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 were 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).

[5] 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.

Table 1: **MICROEQUITY GAME INVESTMENT OPTIONS**

| INVESTMENT OPTION | COST | PAYOFF: LOW | HIGH | EXPECTED PROFIT |
|---|---|---|---|---|
| 1 | 0 | 0 | 100 | 50 |
| 2 | 100 | 0 | 400 | 100 |
| 3 | 200 | 0 | 700 | 150 |
| 4 | 300 | 0 | 1000 | 200 |
| 5 | 400 | 0 | 1300 | 250 |

*Note*: Business owners had a choice of five investment options in the microequity 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 experiment), and the order of treatments randomized:

(i). **Control Treatment (CT):** Participants were provided with an initial capital endowment of 200, thereby limiting the choice of investment in the first round to the first three options (options 4 and 5 may be affordable in the second round, conditional on a high outcome in the first round).

(ii). **Debt Treatment (DT):** In addition to the initial capital endowment of 200, participants received 500 as a zero-interest loan, to be repaid at the end of the two-round game. This mimics 'external debt capital' that could be used to finance higher expected return but costlier investment options.

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

When communicating with participants, the words 'debt' or 'equity' were not used; instead the more neutral words 'loan contract' and 'sharing contract' were used (in the local language). The net payoff to participants at the end of the investment 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 $\alpha$ controls the sharing ratio for ET. As described above, in the final design, $T = 2$, $k = 500$, and $\alpha \in \{0.5, 0.25\}$. The game was designed using simulations and a simple model with a utility maximising agent choosing investment options over multiple rounds to maximise terminal profits. Section 5 further develops the model for the purpose of counterfactual contract and welfare analysis. To summarise 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 $T$. 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, including the role of risk preferences.[6]

# 4 Results

I now present results from the artefactual field experiments in Kenya and Pakistan. The main empirical specifications and variables were pre-specified.[7] The sample consists of just over 3,000 observations, representing one decision for each of the 765 respondents under each of the four treatment arms, with the order of financing treatments randomized within subjects.

## Result 1: Equity leads to more profitable investment choices

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

$$y_i = \beta_0 + \beta_1 DT_i + \beta_2 ET_i + \varepsilon_i, \tag{2}$$

where $y_i$ is the expected profit of the investment option chosen by individual $i$, $DT_i$ is a dummy for assignment to debt financing and $ET_i$ 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. $\beta_0$ represents the average expected return of investments chosen by individuals in the control group, whilst $\beta_1$ and $\beta_2$ represent the change in expected profit of investments chosen by debt-financed and equity-financed in-

[6] 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.

[7] 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).

dividuals relative to the control group, respectively.

In each column, the dependent variable is the expected profit of the chosen investment option in that particular round. Column 1 displays results for the Pakistani sample. Equity-financed business owners chose investment options in the first round of the game that were $0.35$ standard deviations higher in expected return than the investments chosen by debt-financed individuals (with a $p-$value from a cross-coefficient test of less than $0.001$). Column 2 repeats the exercise for the Kenyan sample, with very similar results: an effect size of $0.37$ standard deviations ($p = 0.001$ for the difference between equity and debt). Column 3 pools the two samples, and unsurprisingly reveals a statistically significant and economically meaningful difference between investment choice under equity and debt, with a pooled effect size of $0.35$ standard deviations (which represents a $6.2\%$ increase in absolute expected return).

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 investment 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 ($p < 0.001$). Columns 6 to 8 explore whether there is a differential impact between the $25\%$ and $50\%$ equity sharing ratios in rounds 1, 2, and 3 of the game. In each of the three columns, the coefficients on equity are almost identical for the two sharing ratios, and I cannot reject the null that there is no difference in effects ($p = 0.640$, $p = 0.650$, and $p = 0.178$, respectively). In the next section, I proceed with using the pooled equity indicator and first-round investment decisions. In Appendix B, I demonstrate robust 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 & D'Exelle, 2020). Table 3 presents results from estimation of the following specification:

$$y_i = \beta_0 + \beta_1 DT_i + \beta_2 ET_i + \beta_3 HighX_i + \beta_4 DT_i \cdot HighX_i + \beta_5 ET_i \cdot HighX_i + \varepsilon_i, \quad (3)$$

where $HighX_i$ is a dummy for individuals with an above-median value of the heterogeneity variable $X_i$. A test of $H_0 : \beta_4 = \beta_5$ explores 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 C and D, 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.

Column 1 of Table 3 shows that, in the control group, more risk-averse individuals chose investment options with a lower expected profit than more risk-tolerant individuals, as one would expect: 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 ($p = 0.808$) suggests 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.

Column 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, but of the opposite sign to, that on $Loss-averse$. As a robustness check, column 3 simultaneously controls for risk aversion and loss aversion with similar patterns of greater differential impact on profitable investment for the most risk-averse and loss-averse individuals under equity.

Finally, column 4 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 C, I show that the results from Table 3 are robust to using a trichotomized measure for each of the three risk preference variables, rather than a median split. Appendix D demonstrates the stability of results to using three alternative methods for constructing the probability weighting index. In Appendix E, the analysis is replicated controlling for the number of years of education of the business owner; results suggest that the findings on risk aversion, loss aversion, and probability weighting are not driven by heterogeneity in education levels of business owners. 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 F, 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 I, I show that the estimated probability weighting parameter is not correlated with business owner optimism.)

# 5 Structural estimation of risk preference parameters, counterfactual contract analysis and welfare

The reduced-form results are consistent with a simple and intuitive prediction: that equity-like contracts with performance-contingent payments encourage higher-risk, higher-reward investments and can be particularly beneficial for the most risk-averse business owners. However, a more nuanced relationship emerges when allowing for the two leading alternatives to expected utility theory. Specifically, loss aversion highlights an additional value to equity contracts, whereas probability weighting indicates a preference for debt contracts. These contrasting effects call for further exploration of the welfare implications of introducing microequity 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 5.4, 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 undertake a more formal assessment of welfare. 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 enhance overall welfare, including MFI profits.

## 5.1 Estimating risk preference parameters

To begin, rather than presupposing the validity of prospect theory (PT) over expected utility theory (EUT), I initially estimate 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.

To recap, participants were each asked 40 incentivized questions where they chose between two 'prospects'.[8] To estimate the EUT model, I assume a simple constant relative risk aversion (CRRA) utility function $U(x) = x^r$, where $r$ is the risk aversion parameter to be estimated, and $x$ is wealth after the realization of outcomes for the prospect under considera-

[8] These are often referred to as 'lotteries' in the literature; henceforth I adopt the more general term 'prospect' (Tversky & Kahneman, 1992; Wakker, Thaler, & Tversky, 1997).

tion.[9] The expected utility for a prospect $i$ is simply the probability-weighted utility of each possible outcome $k$ in the prospect, using the experimentally induced probabilities that all business owners were made aware of through detailed explanations and tests of probabilistic understanding: $EUT_i = \sum_k p_k \cdot U(x_k)$. The expected utility for each pair of prospects is calculated for a candidate estimate of $r$, and the difference $\nabla EUT = EUT_1 - EUT_2$ forms an index that is then used to define the cumulative probability of the observed choice using the logistic function $G(\nabla EUT) = exp(\nabla EUT)/[1+exp(\nabla EUT)]$. The likelihood, conditional on the EUT model being true, depends on the estimates of $r$ and the observed choices:

$$\ln L^{\text{EUT}}(r; y, X) = \sum_i \ln l_i^{\text{EUT}} = \sum_i [y_i \ln G(\nabla EUT) + (1 - y_i)\ln(1 - G(\nabla EUT))] \quad (4)$$

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

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

$$PU_i = \sum_{k=1}^{n} W(p_k) \cdot U(x_k), \quad (5)$$

where :

$$W_k = \omega(p_k + \cdots + p_n) - \omega(p_{k+1} + \cdots + p_n) \quad (6)$$

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

$$W_k = \omega(p_k) \quad (7)$$

for $k = n$, where $x$ are the monetary outcomes, of which there are $n$ possible outcomes for

[9] 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).

each prospect (with subscript $k$ ranking outcomes from worst to best), $W(\cdot)$ is now the decision weight, and $w(\cdot)$ is a probability weighting function that is defined over the cumulative distribution and transforms the experimentally induced probabilities. It is useful to clarify the distinction between the probability weighting function and the decision weight – the probability weighting function models the distortion of probability, and the decision weight is the term that multiplies the value of each outcome. I use the popular probability weighting function of Tversky and Kahneman (1992):

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

where $\gamma$ controls the shape of the probability weighting function (and $\gamma = 1$ charaterises linear probability weighting, as in the EUT model). One-parameter weighting functions have been found in several studies to provide an excellent fit to the data, almost as well as the two-parameter, linear-in-log-odds weighting functions (Wu & Gonzalez, 1996).[10] I again use a simple CRRA power utility functional form, but now defined separately over gains and losses:

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

where $\alpha$ controls the curvature of the utility function and $\lambda$ 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.[11] Identification of the loss aversion parameter $\lambda$ comes from decisions comprising payoffs in the loss domain, and identification of the probability weighting parameter $\gamma$ 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 $\alpha$, $\lambda$, and $\gamma$. I then link the latent index $\nabla PU = PU_1 - PU_2$ to the observed choices in the experiment using the logistic cumulative distribution function $G(\nabla PU)$. The conditional log-likelihood is:

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

To estimate the mixture model, let $\pi^{\text{EUT}}$ and $\pi^{\text{PT}} \equiv (1 - \pi^{\text{EUT}})$ denote the probability

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

[11] 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.

that the EUT and PT models are correct, respecitvely.[12] 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 G, 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 important of loss aversion and probability weighting for investment decisions, I proceed with estimating the PT model and using the estimated parameters to assess the welfare implications of different financial contracts.[13] I allow for the parameters to be functions of the observable individual-level characteristics $X$, and standard errors are corrected for the possibility that the 40 responses are clustered for the same individual.

Figure 1 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 $\lambda$ between 2.00 and 2.25 that is estimated in much of the literature (Brown et al., 2021; DellaVigna, 2018; Kremer et al., 2019). For probability weighting, I estimate a bimodal distribution, with a mean of $\gamma = 0.73$, a mass at almost-linear probability weighting ($\gamma \approx 1$), and a large mass with a non-linear probability weighting parameter of $\gamma \in [0.5, 0.8]$. This is also very consistent with estimates in the literature from high-income countries, where $\gamma = 0.7$ is typical (Comeig, Holt, & Jaramillo-Gutiérrez, 2022; Dimmock et al., 2021). The fourth panel of Figure 1 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

[12] 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).

[13] 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).

weighting.[14] In Appendix H, I repeat the estimation while allowing for errors in the decision-making process of business owners, using a structural noise parameter.[15] Results indicate even more pronounced loss aversion ($\lambda = 2.50$) and probability weighting ($\gamma = 0.61$), and much less utility curvature ($\alpha \approx 1$).

Appendix I presents correlations of the estimated parameters with covariates collected from business owners in the baseline survey. In general, there is little correlation of the parameters $\alpha$, $\lambda$, and $\gamma$ with demographic variables, household wealth, or business profits – some coefficient are statistically significant, but the magnitudes are relatively small.[16] This is consistent with the findings from a low-income setting of Chiappori, Samphantharak, Schulhofer-Wohl, and Townsend (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 Using estimated preferences to explore contract selection

I next proceed to use the estimated risk preference parameters to explore the welfare implications of different financial contract structures. I model business owners as drawing returns from the same stochastic distribution, which is fitted based on the actual distribution of business profits from the broader experiment in Pakistan, from which the majority of participants are drawn. I thereby focus on the heterogeneity in risk preferences, rather than permanent heterogeneity in risk, building upon the finding of Cohen and Einav (2007) that unobserved

[14] 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 D'Exelle (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 nothing 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).

[15] 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 $\mu$ gets larger, the choice that individuals make between prospects essentially becomes random.

[16] 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.

heterogeneity in risk aversion is greater and more important (for profits and pricing) than unobserved heterogeneity in risk. 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 $\sigma = 0.43$, corresponding to an actual mean and standard deviation of \$4,198 and \$1,892 respectively.[17] Further details are provided in Appendix J. The moderate amount of skew will turn out to have important implications for the impacts of alternative contract structures for individuals with different risk preferences, and in particular those who overweight small probabilities.

I use a simple static framework to focus on the impact of different dimensions of risk preferences on contract choice; a dynamic framework may provide further support for equity-like contracts through inter-temporal smoothing.[18] I model business owners as receiving \$1,500 in financing, which is the average amount financed in the aforementioned broader experiment. Initially, I implement two types of financing contract that are provided by a microfinance institution (MFI): (i) a debt contract with 27% interest rate; and (ii) an equity contract where 50% of returns are shared. The parameters were chosen to be consistent 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 (abstracting from individual preference parameters and not allowing for differential impacts of contracts on effort or investment choice). Given the equated *average* payments, the difference between contracts is reflected in the distribution of post-payment returns, as illustrated in Figure 2. 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.

In the first model exercise, I calculate the utility for each business owner – given their individually-estimated risk preference parameters and the aforementioned distribution of returns that they face – under three scenarios, to sequentially identify the impact of the three different dimensions of risk preferences on contract selection:

(i). An expected utility framework where risk aversion is defined solely by the curvature of

[17] The mean and standard deviation of the lognormal distribution are $e^{\mu+\frac{\sigma^2}{2}}$ and $\sqrt{(e^{\sigma^2}-1)e^{2\mu+\sigma^2}}$, respectively. I generate 10 million random draws from a lognormal distribution, and then use histogram-based discretization with $1,000$ bins to generate the final distribution over which I calculate utility under different financial contracts.

[18] See Webb (1992) for an extension to the classic one-period model of Townsend (1979) that shows the optimality of debt under costly state verification; Webb finds optimality of equity-like contracts in a multi-period model.

[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.

the business owner's utility function, as captured by their estimated parameter $\alpha$;

(ii). A prospect-theoretic framework where I initially only allow for reference-dependent preferences, with individuals choosing based on their $\alpha$ and $\lambda$, where the reference point is set at the business owner's level of savings (as measured during the baseline survey);

(iii). A prospect-theoretic framework where probability distortion is also allowed to affect decision-making, based on the individual's weighting parameter $\gamma$.

For each individual, I calculate their choice between debt and equity, under the three environments. Results are presented in Panels A, B, and C of Figure 3. Beginning with the expected utility framework in Panel A, model-based take-up rates are roughly equal for debt and equity (53% and 47%, respectively). Panel B illustrates that – when decision making is based on the possibility of reference-dependent preferences as well as utility curvature – the take-up rate of the equity contract increases to 58%, compared to 42% for debt. This is consistent with the reduced-form results from the artefactual field experiment that demonstrated the greater impact on profitable investment under equity for the most loss-averse individuals. Panel C then illustrates the impact of also allowing distortions of objective probabilities to affect decision-making. Take-up of the equity contract drops sharply to 26%, with take-up of debt at 74%. The average value of $\gamma$ for the 26% of individuals who choose equity in both prospect-theoretic environments (i.e. with or without probability weighting being a determinant of choices) is 0.81; this compares with $\gamma = 0.69$ for the 31% of individuals who choose equity when only reference-dependent preferences (and utility curvature) form part of the decision-making process, but switch to choosing debt when probability weighting is introduced. The result is consistent with findings from the artefactual field experiment, and with the hypothesis that overweighting of small probabilities has particularly significant implications for the choice between debt and equity contracts; specifically, individuals who overweight small probabilities have a strong preference for debt contracts over equity.

## 5.3 Probability weighting and skewness of returns distribution

The extent to which the overweighting of small probabilities has significant implications for the choice between debt and equity contracts depends critically on the skewness of the underlying returns distribution. Specifically, if the returns distribution is positively skewed, individuals with an inverse-S-shaped weighting function overweight the small probability of very high business profits – a scenario in which they would have to share a large amount of money with the MFI under an equity contract. Further, they underestimate the (objectively much larger) probability of low business profits, where equity contracts can be very beneficial in terms of loss-sharing (and where debt contracts can lead to an inability to meet fixed loan payments from business returns, and the requirement to draw down on household savings). The distribution used in the model was fit based on the actual underlying distribution of profits in the sample of business owners, which turned out to be a lognormal distribution with a moderate amount of skew. To illustrate the importance of skewness, in Appendix K I repeat the model analysis using a return distribution with zero skew, by changing the shape parameter – which controls the 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 differential pattern of take-up between debt and equity when allowing for 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.

I next illustrate a contractual tweak that can benefit those individuals who value equity contracts but select out of them due to their overweighting of small probabilities. Specifically, I implement a 'hybrid' contract that contains both debt- and equity-like features. The contract operates by providing the same performance-contingent payment structure as the equity contract, but with a capped upside: once payment reaches a maximum amount, the contract terminates. I initially set the maximum possible amount paid at twice the amount due under the debt contract, in order to equate the expected payments to the MFI under the hybrid contract to those under debt and equity. The post-payment distribution of returns under the hybrid contract are contrasted with those under debt and equity in Figure 2 – the hybrid contract takes an intermediate shape between that of the debt and equity contract. It reduces exposure of the business owner to the losses that would be possible under the fixed-repayment debt contract. It also caps the upside-sharing in a way that still provides significantly more of a right tail than the equity contract, under which large amounts of money would have to be shared in the low-probability high profit states of the world that are overweighted by a significant proportion of individuals. Results for model take-up when the hybrid contract is offered are presented in Panel D of Figure 3. Recalling that take-up rates when only the debt and equity contracts were offered were 74% and 26% respectively (Panel C), the main finding is that the introduction of a hybrid contract leads to 50% of individuals choosing hybrid, 40% preferring debt, and only 10% preferring the equity contract.

Appendix L illustrates the resulting distribution of profits for the MFI. 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 the 50% of business owners0 that select into the hybrid contract has a higher mean of \$530, along with a higher standard deviation of \$816. Results therefore suggest that MFIs 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.

Finally, I calculate the welfare gains from introducing equity-like contracts. I use numerical optimisation to solve for a compensating-variation measure of welfare (Hicks, 1939):

$$PU_i^{equity} = \sum_{k=1}^{n} W(p_k) \cdot U\left[(1-\tau) \cdot x_k\right] = \sum_{k=1}^{n} W(p_k) \cdot U(x_k - d + T) = PU_i^{debt} \quad (12)$$

where $\tau$ is the sharing ratio under equity (set at 50% in the default specification), $x_k$ is the payoff under each of the $n = 1,000$ possible states of the world, d is the fixed-repayment requirement under debt (set at principal plus 27%), and $T$ is the monetary amount that would need to be paid to a debt-financed business owner to equalise their utility under debt and equity. $T = 0$ for business owners that prefer debt. I solve for individual-specific valuations of equity contracts ($T$), using the individually-estimated preference parameters $\alpha$, $\lambda$, and $\gamma$. The average value to clients 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 6.1% 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.

## 5.4 Testing model fit: contract take-up 'inside and outside the lab'

In this section, I test the previous model predictions for contract preference using actual take-up decisions, in two settings: (i) within the artefatual field experiment; (ii) 'outside the lab', in the broader field experiment from which participants are drawn.

In the previous reduced-form results, the impact of debt and equity on investment choices was analyzed using a within-subject design where each business owner was exposed to each treatment (in random order). In Panel A of Figure 4, I analyze take-up decisions in the artefactual field experiment, where each individual was asked about their preferred contract. Their choice increased the probability of that contract being selected for payment at the end of the workshop, and so it provides a direct and incentivised measure of contract preference. I estimate a simple linear probability model, where the dependent variable is a dummy for whether the business owner chose to take an equity contract over debt; covariates are dummies for 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 4, I analyze take-up decisions 'outside the lab'. This provides a validation test for the predictive power of the lab-elicited measures of risk preferences, as well as a test of model predictions for take-up of different contracts among individuals with varying levels of risk aversion, loss aversion, and probability weighting. Specifically, I analyze asset finance take-up decisions from the broader Kenyan field experiment. In that experiment, business owners had the opportunity to finance an asset, and were randomly offered take-it-or-leave-it decisions for different types of contract. Acceptance of the offer meant that they proceeded to sign the contract with the microfinance institution, and subsequently have their asset delivered. As such, all decisions were incentivized, for a real business asset.[20]

The first figure of Panel B 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 figure of Panel B demonstrates the opposite result for probability weighting. Take-up rate of debt among business owners who have closer-to-linear probability weighting

[20] 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.

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 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 M, 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.[21]

# 6 Conclusion

An unresolved puzzle in the finance and development literature is how to reconcile the high returns found in studies providing capital grants to small firms with the modest returns observed in microcredit studies. In this paper, I focus on the rigidity of the microcredit contractual structure as an impediment to higher-risk, higher-return investments, and I explore equity-like contracts that better match payments to cashflows. I conduct artefactual field experiments with small business owners in Kenya and Pakistan who were participating in field experiments that provided substantial capital injections. I find that equity-like contracts lead to more profitable investment choices, particularly for the most risk averse individuals. Loss aversion provides an additional and novel benefit of equity contracts for individuals who particularly value downside protection. However, individuals who overweight small probabilities prefer debt contracts, especially when faced with a positively skewed profits distribution. I structurally estimate these three distinct dimensions of risk preferences using a prospect-theoretic model to show that relatively simple tweaks to contract design can improve the feasibility of equity-like contracts. I provide evidence of take-up of such novel contracts from 'outside of the lab' that is consistent with model predictions. Results suggest that financial institutions serving micro- and small firms can significantly boost client welfare by broadening their product offerings to include equity-like contracts.

[21] 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 M, 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.

My sample comprised a policy-relevant group of business owners seeking expansion through fixed asset purchases. Both Kenya and Pakistan are ideal settings to evaluate innovative financial contracts, albeit for distinct reasons. First, Kenya is the epicenter of mobile money and digital innovations in Africa, with notable advancements in fintech (Suri, 2017). Second, while equity-like products aren't exclusive to any specific religion or group, they hold the potential to cater to hundreds of millions of financially excluded business owners in Pakistan and other countries with large Muslim populations (El-Gamal et al., 2014; IMF, 2015; World Bank, 2012). Further, given the climate vulnerabilities of Pakistan and other South Asian countries, there's a pressing need for innovative risk-sharing contracts to support climate-friendly investments that offer high but unpredictable returns (Asian Development Bank, 2022; Lane, 2022).

Several supply-side factors may explain why MFIs typically do not currently offer equity-like products. First, the difficulty in assessing profits for small, informal firms, suggests non-state-contingent debt contracts may be optimal (Townsend, 1979). Second, the skill-set required of traditional microfinance loan officers differs significantly from the venture-capital-like skills needed to finance high-potential firms. The compensation of microcredit loan officers is usually tied to the default rate of their portfolios, providing little incentive to identify businesses with higher-risk, higher-reward investment opportunities, or to transition their most promising clients to more sophisticated financing options (Rigol & Roth, 2021). Finally, the enforcement of ownership claims poses significant legal challenges if MFIs or their investors were to take equity stakes in small firms in low-income countries, and the exit strategies for investors in underdeveloped financial markets are unclear (De Mel, McKenzie, & Woodruff, 2019).

Historic economic contract structures are endogenous to the prevailing technological environment, and advances that relax constraints on the flow of information can expand contracting opportunities (Townsend & Zhang, 2023). In developing countries, despite the traditional supply-side challenges to offering equity-like contracts, there have been significant recent advancements in financial technology (Higgins, 2019; Suri, 2017). These developments have greatly facilitated digital transactions and enhanced the observability of income streams in increasingly varied contexts, such as online marketplaces or businesses accepting digital payments through point-of-sale systems (Annan et al., 2024). These technological advancements can enhance the screening of clients with high potential (mitigating adverse selection) and enable more effective monitoring of client transactions and performance (addressing moral hazard concerns). They open up numerous possibilities for innovative financial contract offerings to small firms in developing countries (Barboni, 2024). Particularly, they offer exciting opportunities for designing equity-like microfinance contracts that involve shared ownership of income streams, rather than the business itself, thus alleviating legal enforcement challenges and leveraging digital payment methods for capital distribution and repayment.

Notwithstanding the alleviation of supply-side challenges to implementing equity-like contracts, in this paper I highlight a novel demand-side challenge related to risk preferences. I show that a significant proportion of individuals overweight small probabilities, and that such individuals are equity-averse. Crucially, their equity aversion depends on the skewness of the returns distribution: individuals who overweight small probabilities only reject equity contracts under positively skewed returns distributions, where there is a small probability of very high profits (which they would have to share). Such a finding is particularly important for low- and middle-income countries, given the well-documented skewness in firm outcome distributions compared to high-income countries (Hsieh & Olken, 2014). I propose a straightforward solution: a hybrid contract with equity-like performance-contingent payments and a debt-like cap on the total amount payable. Financial institutions that have more linear probability weighting functions can profitably offer such contracts, and charge a higher interest rate in return for the flexibility (Barboni, 2017). 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 et al., 2014). It is also similar to results from behavioural finance that demonstrates how firms can profit by implicitly selling out-of-the-money call options to the significant proportion of individuals who overweight small probabilities, without needing complex methods to assess these individual-level preferences (Spalt, 2013). The proposed hybrid contract also shares features with certain contractual arrangements in venture capital, like equity clawbacks and performance ratchets, which incentivise performance while aligning the interests of investors and business owners through adaptable reward structures based on achieved targets. While such hybrid contracts are novel in this context, they are increasingly being implemented in high-income settings, for example by digital payments companies in the US and Europe (Rishabh & Schäublin, 2021). Incorporating a more holistic view of risk preferences can aid in designing better-tailored financial products for small businesses.

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# Tables and figures

Table 2: OVERALL EFFECT OF CONTRACTS ON INVESTMENT CHOICE

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

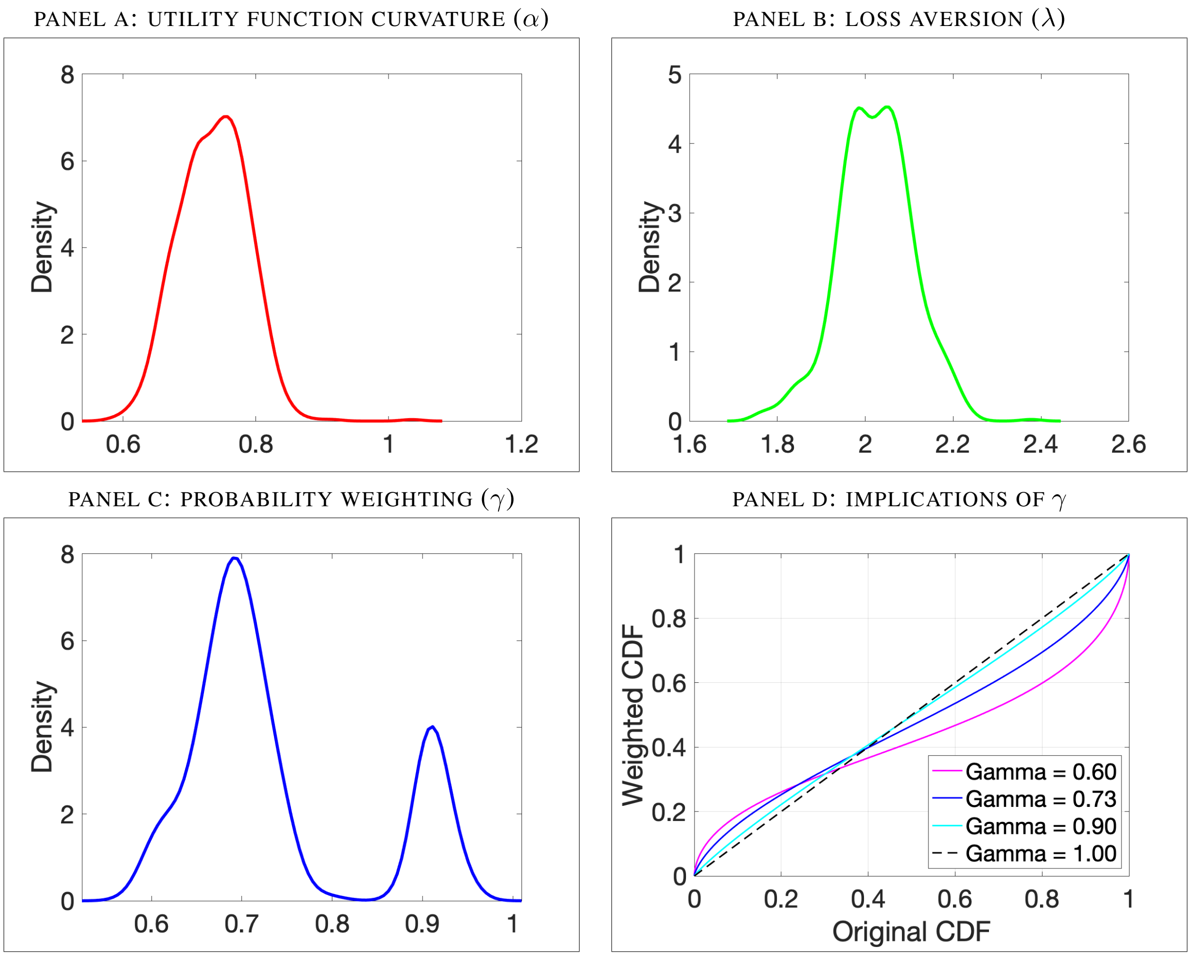
*Note*: In each column, the dependent variable is the expected profit of the chosen investment option in that particular round. Each of the 765 unique business owners were assigned — in a randomly perturbed order — to each of the four treatment groups: *Control*, *Debt*, *Equity (25% sharing ratio)* and *Equity (50% sharing ratio)*. *Debt* and *Equity* are dummy variables for the debt and equity contracts respectively, with the reported coefficient representing 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. In columns 3 to 8, the Pakistan and Kenya samples are pooled, and a Kenya country dummy is included. In columns 1 to 5, *Equity* pools both the 25% sharing ratio contract and the 50% sharing ratio contract, whereas columns 6 to 8 estimate impacts of each equity contract separately. Standard errors are clustered at the individual level and are reported in parentheses below each coefficient estimate. In the panel below the table, the sixth row presents $p$-values for the null hypothesis that the effect of being assigned to the equity contract is equal to the effect of being assigned to the debt contract. 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. The ninth row presents $p$-values from test of the null hypothesis that the effect of being assigned to the equity contract with 25% sharing ratio is equal to the effect of being assigned to the equity contract with 50% sharing ratio. *** p<0.001, ** p<0.05, * p<0.10.

Table 3: INVESTMENT CHOICE: HETEROGENEITY BY RISK PREFERENCES

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

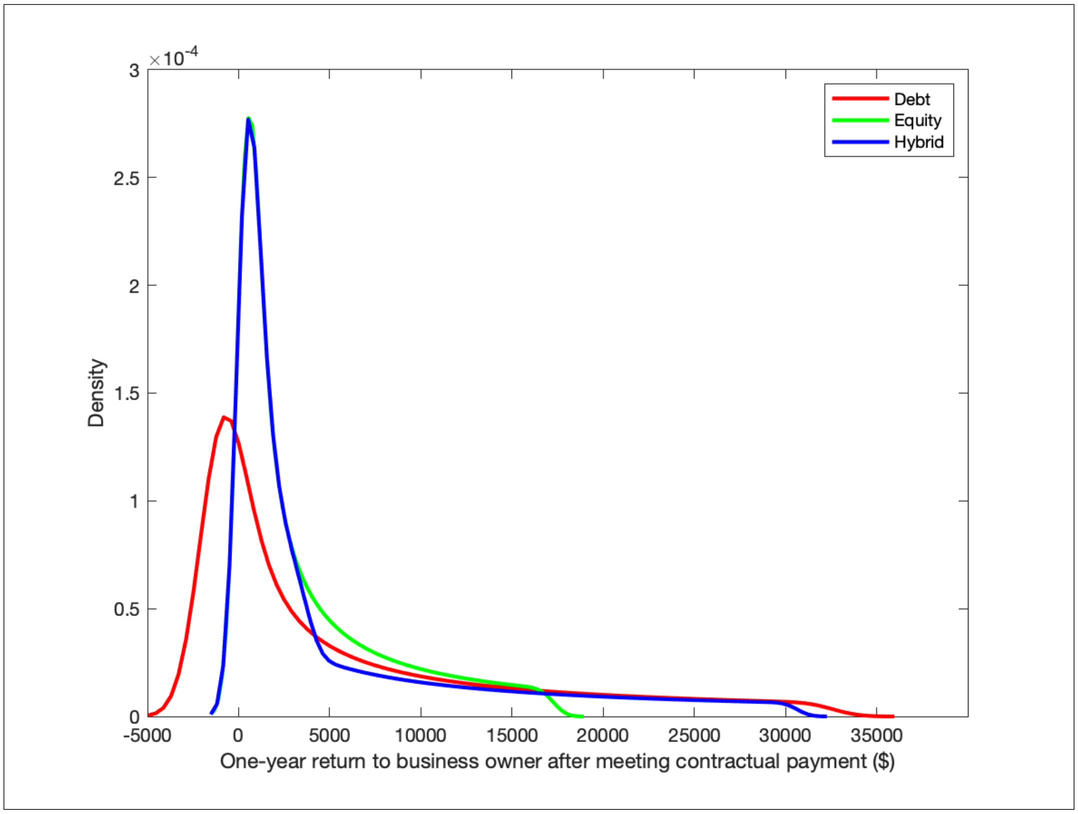
*Note*: In all columns, the dependent variable is the expected profit of the investment option chosen by the business owner. *Risk-averse* and *Loss-averse* are dummy variables for whether a business owner was measured to have above-median risk aversion or loss aversion respectively in the baseline preference elicitation exercises, and *Probability-weigher* is a dummy for whether the individual has an above-median value of the non-parametric measure of non-linear probability weighting (which indicates that they are more likely to overweight small probabilities). *Equity * Risk-averse* represents the expected profit of the investment option chosen by the most risk averse business owners over and above the expected profit of the investment option chosen by the most risk tolerant business owners (which is represented by the coefficient on *Equity*), with an analogous interpretation for the other interaction terms. In the panel below the table, the fourth, fifth and sixth rows present $p$-values from a test of the null hypothesis that *Equity * Risk averse = Debt * Risk averse*, *Equity * Loss averse = Debt * Loss-averse*, and *Equity * Probability weigher = Debt * Probability-weigher*, respectively. *** p<0.001, ** p<0.05, * p<0.10.

Figure 1: STRUCTURALLY ESTIMATED RISK PREFERENCE PARAMETERS



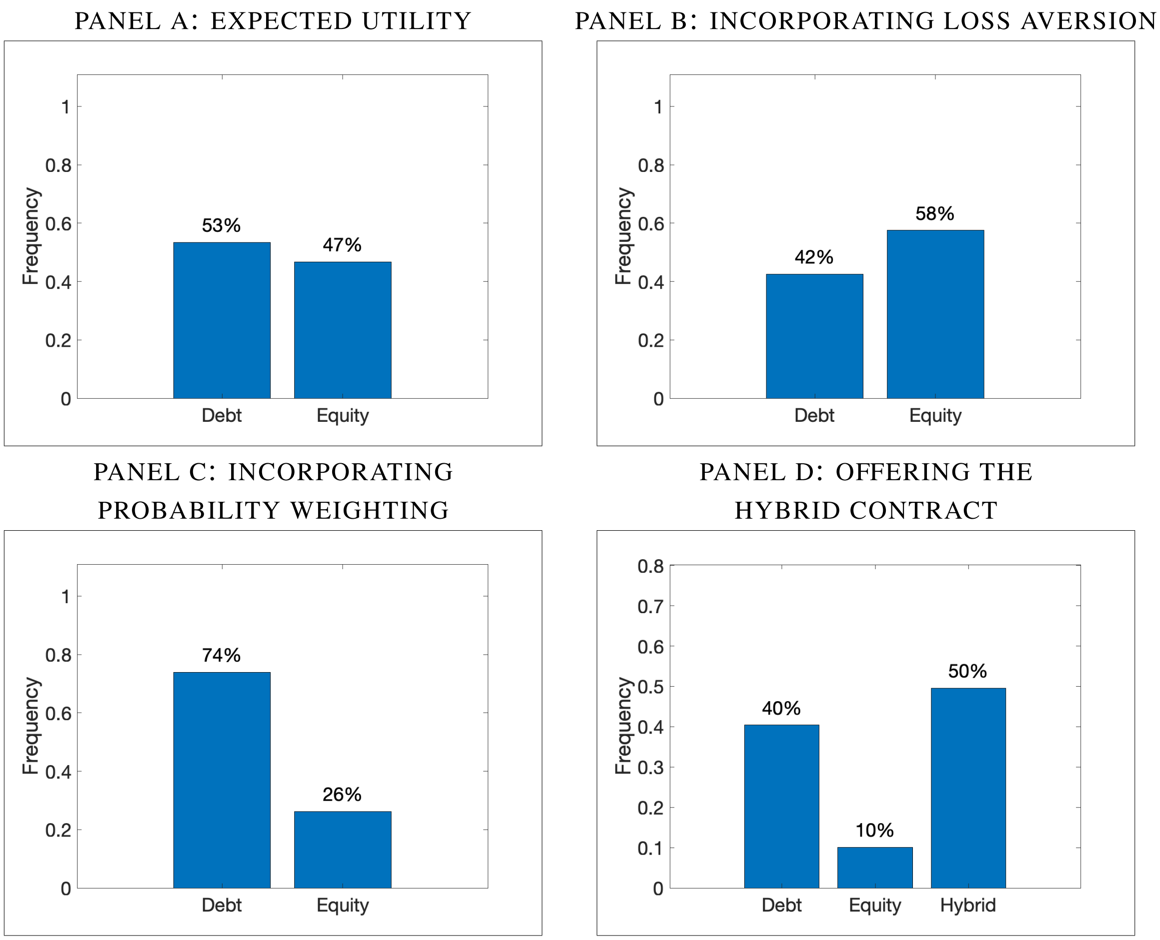

*Note:* Panel A displays the estimated distribution of the utility curvature parameter $\alpha$, with a mean of $0.74$ indicating a moderate average amount of risk aversion (where $\alpha = 1$ represents risk neutrality given the simple power utility specification $U(x) = x^{\alpha}$). Panel B illustrates the distribution of the loss aversion parameter $\lambda$, 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 $\lambda$ between $2.00$ and $2.25$ that is estimated in much of the literature (Brown et al., 2021; DellaVigna, 2018; Kremer et al., 2019). Panel C illustrates a bimodal distribution for the probability weighting parameter $\gamma$, 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 2: MODEL-BASED DISTRIBUTION OF RETURNS UNDER EACH FINANCING CONTRACT




*Note:* Business owners are modelled 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 J) 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 modelled: 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\$.

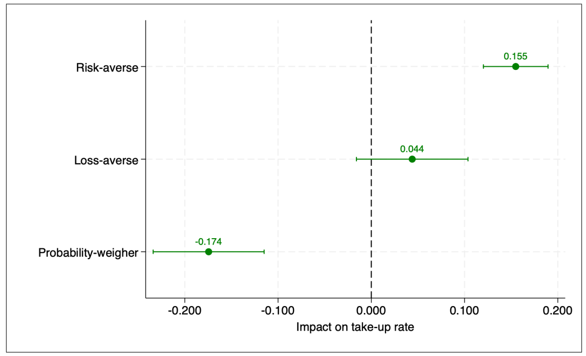
Figure 3: **MODEL TAKE-UP UNDER DIFFERENT DECISION-MAKING ENVIRONMENTS**




*Note:* Each panel summarises model-based take-up rates for the 765 business owners, based on their utilities calculated with individually-estimated risk preference parameters, under each financial contract. Panel A summarises take-up rates assuming an expected utility framework where risk aversion is defined solely by the curvature of the business owner's utility function, as captured by their parameter $\alpha$. Panel B presents take-up rates under a prospect-theoretic framework that only allows for reference-dependent preferences, with individuals choosing based on their estimated $\alpha$ and $\lambda$, with the reference point set at their initial household stock of savings (as measured in the baseline survey with business owners). Panel C extends the prospect-theoretic framework to also allow for distorted probabilities to affect decision-making, based on the individual's probability weighting parameter $\gamma$. In Panels A, B, and C, the choice is between a 27% interest rate debt contract and a 50%-sharing equity contract. In Panel D, the choice set of contracts is expanded to include the hybrid contract that involves equity-like payments with a 'debt-like' cap set at twice the payment due under the debt contract. The average value of the probability weighting parameter $\gamma$ for the 26% of individuals who choose equity in both Panel B and C is 0.81; this compares with $\gamma = 0.69$ (more non-linear probability weighting, and overweighing of small probabilities) for the 31% of individuals who choose equity in Panel B but switched to debt in Panel C.

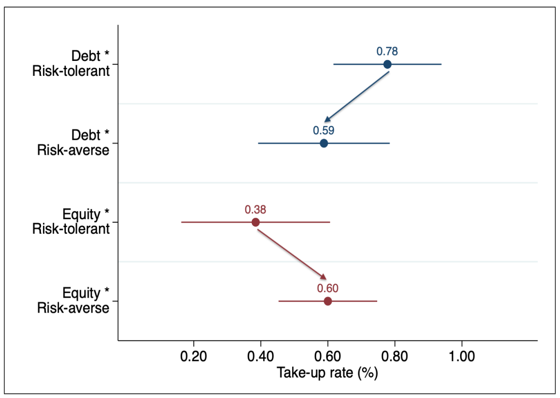
Figure 4: **TESTING MODEL FIT: CONTRACT TAKE-UP 'INSIDE AND OUTSIDE THE LAB'**

PANEL A: TAKE-UP IN THE ARTEFACTUAL FIELD EXPERIMENT

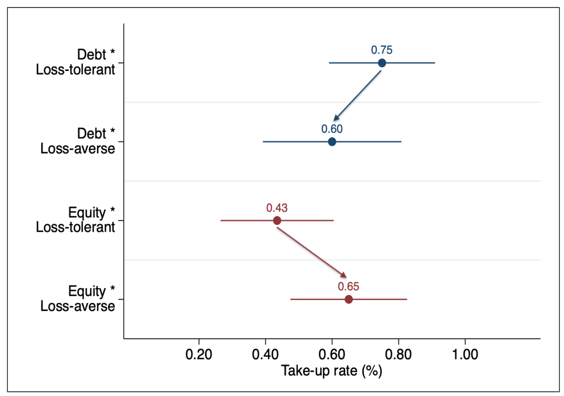



PANEL B: TAKE-UP IN THE BROADER FIELD EXPERIMENT

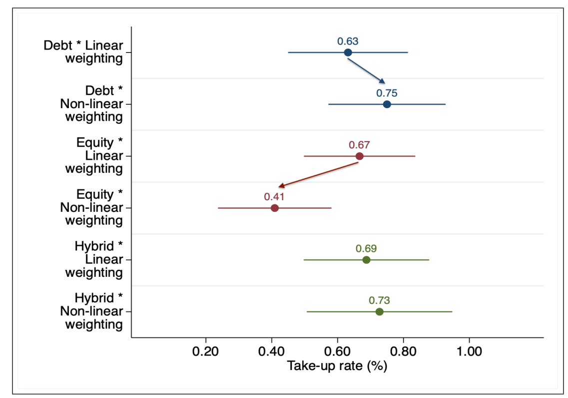
(I) RISK AVERSION




(II) LOSS AVERSION




(III) PROBABILITY WEIGHTING




*Note:* Panel A presents coefficient plots from a take-up regression in the artefactual field experiment. The dependent variable is a dummy for whether the business owner chose to take an equity contract over debt, for the final (incentivized) contract choice. The overall take-up rate of equity was 46%. *Risk-averse* and *Loss-averse* are dummy variables for whether a business owner has above-median risk aversion or loss aversion respectively, and *Probability-weigher* is a dummy for being more likely to overweight small probabilities. Panel B presents take-up results from the field experiment in Kenya. The dependent variable is a dummy for whether the business owner accepted the asset financing product that was offered to them, interacted with a dummy for whether they had above-median risk aversion, loss aversion, and probability weighting. 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.

# Appendix for Online Publication

## Small Firm Investment under Uncertainty: The Role of Equity Finance

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# A Baseline summary statistics

Table A.1 provides baseline summary statistics for the sample of business owners.

Table A.1: SUMMARY STATISTICS

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

**Note:** Baseline summary statistics are presented for the 765 business owners in the sample, pooling Kenya and Pakistan. P10, P25, P75, and P90 represent the 10th, 25th, 75th, and 90th percentiles, respectively. Business profits (monthly), household expenditure (monthly), and household savings (stock) are measured in US$.

# B Robustness: order effects

Table A.2 demonstrates that overall treatment effects from Table 2 are robust to controlling for order effects, given the within-subject experimental design that randomized whether participants were first allocated to the debt or equity treatment arms.

Table A.2: ROBUSTNESS: ORDER EFFECTS

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

**Note:** In each column, the dependent variable is the expected profit of the chosen investment option. Each of the 765 unique business owners were randomly assigned to Debt, and Equity; 'Order 1' is an indicator variable for whether Debt was randomly assigned before Equity, and interaction terms with Debt and Equity are also included in the regression. Standard errors are clustered at the individual level and are reported in parentheses below each coefficient estimate. In the panel below the table, the fifth row presents $p$-values for the null hypothesis that the effect of being assigned to the equity contract is equal to the effect of being assigned to the debt contract. *** p<0.001, ** p<0.05, * p<0.10.

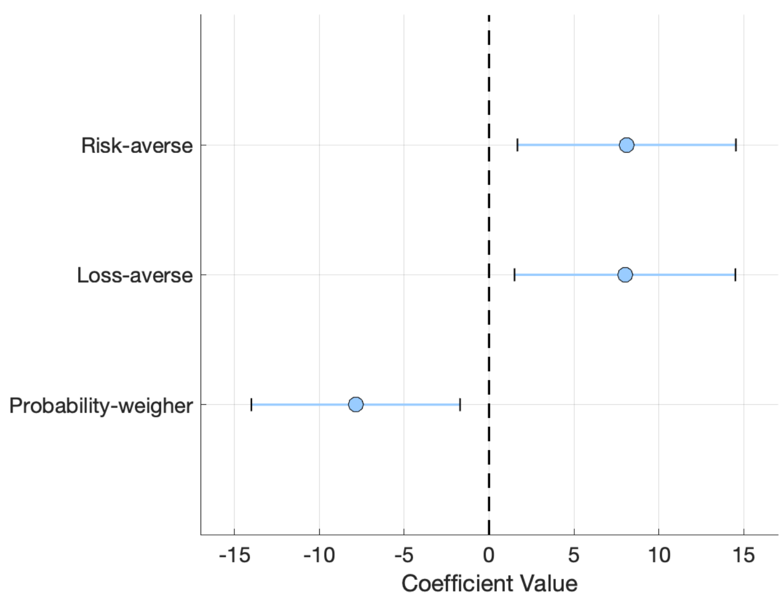
# C Robustness: trichotomized risk preference measures

I repeat the heterogeneous treatment effect analysis from Table 3, using trichotomized measures for risk preferences, rather than a median split:

$$\begin{aligned} y_i = \beta_0 + \beta_1 DT_i + \beta_2 ET_i + \beta_3 Tercile2_i + \beta_4 Tercile3_i + \\ \beta_5 DT_i * Tercile2_i + \beta_6 DT_i * Tercile3_i + \\ \beta_7 ET_i * Tercile2_i + \beta_8 ET_i * Tercile3_i + \varepsilon_i \end{aligned} \quad (13)$$

where $Tercile2_i$ and $Tercile3_i$ indicate that the business owner is in the middle or the top tercile of the risk heterogeneity variable, respectively. The heterogeneity variables are: (i) risk aversion; (ii) loss aversion, and (iii) probability weighting (overweighting of small probabilities). A test of $H_0 : \hat{\beta}_6 = \hat{\beta}_8$ explores whether individuals with the highest values of $X_i$ are differentially affected by the $Equity$ and $Debt$ treatments. In Figure A.1, I find that the result in Table 3 – that the most risk-averse and loss-averse business owners are more likely to make profitable investments under equity compared to debt, and that those who overweight small probabilities are *less* likely to make profitable investments under equity compared to debt – is robust to using terciles rather than a median split.

Figure A.1: ROBUSTNESS TO TRICHOTOMOZING RISK PREFERENCE MEASURES




**Note:** Each line depicts point estimates and 90% confidence intervals from testing $H_0 : \hat{\beta}_6 = \hat{\beta}_8$, following estimation of equation A.1. A positive coefficient indicates more profitable investment choices under equity compared to debt for individuals in the top tercile of each heterogeneity variable being tested: (i) risk aversion; (ii) loss aversion, and (iii) probability weighting (overweighting of small probabilities)

# D Robustness: probability weighting measure

I repeat the heterogeneous treatment effect analysis from Table 3:

$$y_i = \beta_0 + \beta_1 DT_i + \beta_2 ET_i + \beta_3 PW_i + \beta_4 DT_i * PW_i + \beta_5 ET_i * PW_i + \varepsilon_i, \quad (14)$$

where $PW_i$ is a dummy for whether the business owner has an above-median value of the non-parametric index of probability weighting (the implication of which is an overweighting of small probabilities). I test $H_0 : \hat{\beta}_4 = \hat{\beta}_5$ to explore whether business owners who overweight small probabilities select more or less profitable investments when these financed through debt versus equity. In Figure A.2, I find that the result in Table 3 – that business owners who overweight small probabilities are *less* likely to make profitable investments under equity compared to debt – is robust to using four alternative measures of probability weighting (based on Dimmock et al. (2021)).

(i). $RP_{75\%} - RP_{25\%}$;

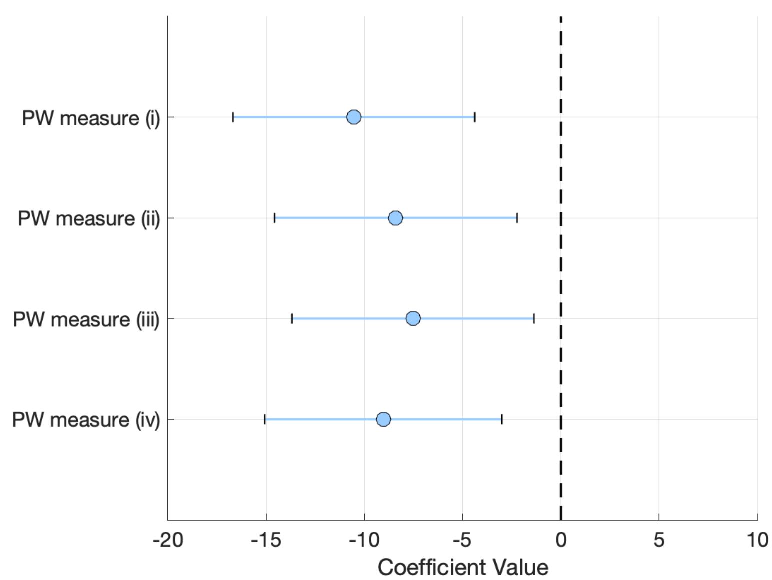
(ii). $\frac{RP_{75\%}}{750} - \frac{RP_{25\%}}{250}$;

(iii). $0.5 \cdot (\frac{RP_{75\%}}{750} + \frac{RP_{50\%}}{500}) - \frac{RP_{25\%}}{250}$; and

(iv). $0.5 \cdot (RP_{75\%} + RP_{50\%}) - RP_{25\%}$.

where $RP_{x\%}$ represents the risk premium, calculated as the difference between an individual's certain equivalent and the expected value of the risky prospect in the set of 10 elicitation questions where there was an $x\%$ chance of a good outcome. (iv) is the measure used in Table 3.

Figure A.2: ROBUSTNESS TO ALTERNATIVE MEASURES OF PROBABILITY WEIGHTING




**Note:** Each line depicts point estimates and 90% confidence intervals from testing $H_0 : \hat{\beta}_4 = \hat{\beta}_5$, following estimation of equation 14 using four different methods for constructing the binary probability weighting index. A negative coefficient indicates less profitable investment choices under equity compared to debt.

# E Robustness: education levels

In Table A.3, the heterogeneous treatment effect analysis from Table 3 is replicated, while controlling for the number of years of education of the business owner. Results indicate that the findings on risk aversion, loss aversion, and probability weighting are not driven by heterogeneity in education levels of business owners.

Table A.3: ROBUSTNESS: EDUCATION LEVELS

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

**Note:** This table replicates the analysis in Table 3, controlling for education of business owners. In all columns, the dependent variable is the expected profit of the investment option chosen by the business owner. The 3,060 observations are generated from the within-design experimental setup with 765 unique business owners. *Risk-averse* and *Loss-averse* are dummy variables for whether a business owner was measured to have above-median risk aversion or loss aversion respectively in the baseline preference elicitation exercises, and *Probability weighting* is a dummy for whether the individual has an above-median value of the non-parametric measure of non-linear probability weighting. *Equity * Risk averse* represents the expected profit of the investment option chosen by the most risk averse business owners over and above the expected profit of the investment option chosen by the most risk tolerant business owners (which is represented by the coefficient on *Equity*), with an analogous interpretation for the other interaction terms, including education. In the panel below the table, the second, third and fourth rows present $p$-values from a test of the null hypothesis that *Equity * Risk-averse = Debt * Risk averse*, *Equity * Loss averse = Debt * Loss-averse*, and *Equity * Probability-weigher = Debt * Probability-weigher* respectively. *** p<0.001, ** p<0.05, * p<0.10.

# F Robustness: optimism

In Table A.4, the heterogeneous treatment effect analysis from Table 3 is replicated, while controlling for optimism of business owners. Optimism is based on the response to the following question at baseline: "Imagine that I give you 10,000 tomorrow. If you invested this money in your current business, how much profit could you make on this money in the next month?". The response is then divided by their actual business profits in the last month, and a median split is used to create a dummy variable where a 1 indicates being more optimistic about one's return to capital. Results indicate that the results on risk aversion, loss aversion, and probability weighting are not driven by heterogeneity in optimism levels of business owners.

Table A.4: ROBUSTNESS: OPTIMISM

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

**Note:** This table replicates the analysis in Table 3, controlling for optimism. In all columns, the dependent variable is the expected profit of the investment option chosen by the business owner. The 3,060 observations are generated from the within-design experimental setup with 765 unique business owners. *Risk-averse* and *Loss-averse* are dummy variables for whether a business owner was measured to have above-median risk aversion or loss aversion respectively in the baseline preference elicitation exercises, and *Probability-weigher* is a dummy for whether the individual has an above-median value of the non-parametric measure of non-linear probability weighting. *Equity * Risk-averse* represents the expected profit of the investment option chosen by the most risk averse business owners over and above the expected profit of the investment option chosen by the most risk tolerant business owners (which is represented by the coefficient on *Equity*), with an analogous interpretation for the other interaction terms, including education. In the panel below the table, the second, third and fourth rows present $p$-values from a test of the null hypothesis that *Equity * Risk-averse = Debt * Risk-averse*, *Equity * Loss-averse = Debt * Loss-averse*, and *Equity * Probability-weigher = Debt * Probability-weigher* respectively. *** p<0.001, ** p<0.05, * p<0.10.

# G Estimating the mixture model

Rather than presupposing the validity of prospect theory (PT) over expected utility theory (EUT), I initially estimate 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 a likelihood function is written for the EUT model, and one for the PT model, and the two are combined to define a weighted likelihood that allows them both to explain the data from the incentivized elicitation activities. To estimate the mixture model, let $\pi^{\text{EUT}}$ denote the probability that the EU model is correct, and $\pi^{\text{PT}} = (1 - \pi^{\text{EUT}})$ as the probability that the PT model is correct. The grand likelihood can be written as the probability weighted average of the conditional likelihoods:

$$\ln L(r, \alpha, \lambda, \gamma, y'; y, X) = \sum_i \ln[(\pi^{\text{EUT}} \times l_i^{\text{EU}}) + (\pi^{\text{PT}} \times l_i^{\text{PT}})]. \tag{15}$$

I then directly estimate the log-likelihood. Results are presented in Table A.5, and significantly favour the PT model.

Table A.5: MIXTURE MODEL ESTIMATION

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

**Note**: The mixture probabilities are constrained to be between 0 and 1. $\pi^{\text{EUT}}$ represents the proportion of observations that are better characterized by the EUT model, and $\pi^{\text{PT}} \equiv (1 - \pi^{\text{EUT}})$ is the proportion of observations that are characterized by PT.

# H Structural estimation with stochastic errors

In Table A.6, I repeat estimation of the prospect-theoretic model allowing for 'behavioural errors' in the decision-making process of agents, using a structural noise parameter. 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 $\mu$ gets larger, the choice essentially becomes random. Results indicate more pronounced loss aversion and probability weighting.

Table A.6: STRUCTURAL ESTIMATION WITH STOCHASTIC ERRORS

| | Coefficient | Std. err. | P>\|z\| | 95% confidence interval |
|---|---|---|---|---|
| $\alpha$ | 1.032 | 0.020 | 0.000 | [0.993, 1.072] |
| $\lambda$ | 2.504552 | 0.044 | 0.000 | [2.418, 2.592] |
| $\gamma$ | .6109845 | 0.011 | 0.000 | [0.590, 0.632] |
| $\mu$ | 2.342888 | 0.117 | 0.000 | [2.113, 2.573] |

**Note**: $\alpha$, $\lambda$, and $\gamma$ are utility curvature, loss aversion, and probability weighting parameters for the estimated prospect theoretic model. $\mu$ is the structural noise parameter. Number of observations: 30,600.

# I Correlates of estimated risk preference parameters

Table A.7 presents simple correlations between the structurally estimated risk-preference parameters, and Table A.8 presents regressions of the parameters with covariates. In general, there is little correlation of $\alpha$, $\lambda$, and $\gamma$ with demographic variables, household wealth, or business profits – some coefficient are statistically significant, but the magnitudes are relatively small. 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.

Table A.7: CORRELATION OF ESTIMATED RISK PREFERENCE PARAMETERS

| | $\alpha$ | $\lambda$ | $\gamma$ |
|---|---|---|---|
| $\alpha$ | 1.000 | | |
| $\lambda$ | -0.125*** | 1.000 | |
| $\gamma$ | -0.174*** | -0.731*** | 1.000 |

**Notes:** This table presents the Pearson correlation coefficients between the estimated parameters for $\alpha$ (utility curvature), $\lambda$ (loss aversion), and $\gamma$ (probability weighting) from the prospect theoretic model. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.8: ESTIMATED RISK PREFERENCE PARAMETERS: CORRELATION WITH COVARIATES

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

**Note**: This table presents the estimated risk preference parameters from the prospect-theoretic model, as a function of individual-level observables. $\alpha$ represents the utility curvature parameter, where $\alpha = 1$ denotes risk neutrality in the context of a simple power utility specification. $\lambda$ is the loss aversion parameter, where $\lambda = 2$ implies twice the sensitivity to losses as to gains. $\gamma$ is the probability weighting parameter, where $\gamma = 1$ indicates linear probability weighting, and $\gamma < 1$ suggests an inverse-S probability weighting function, characterized by overweighting of small probabilities and underweighting of large probabilities. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.9 displays the correlation between the estimated parameters and business owner optimism, both with and without controls. In summary, the estimated risk preference parameters are not correlated with optimism. In particular, the probability weighting parameter is not simply capturing optimism.

Table A.9: CORRELATION BETWEEN RISK PARAMETERS AND OPTIMISM

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | $\alpha$ | $\alpha$ | $\lambda$ | $\lambda$ | $\gamma$ | $\gamma$ |
| Optimism: return to capital | -0.00 | -0.00 | -0.00 | -0.00 | -0.00 | -0.00 |
| | (0.00) | (0.00) | (0.01) | (0.00) | (0.01) | (0.00) |
| Constant | 0.74*** | 0.71*** | 2.02*** | 2.33*** | 0.73*** | 0.55*** |
| | (0.00) | (0.00) | (0.01) | (0.00) | (0.01) | (0.00) |
| Observations | 747 | 747 | 747 | 747 | 747 | 747 |
| Controls | | ✓ | | ✓ | | ✓ |

**Note**: optimism of business owners. Optimism is based on the response to the following question at baseline: "Imagine that I give you 10,000 tomorrow. If you invested this money in your current business, how much profit could you make on this money in the next month?". The responses is then divided by their actual business profits in the last month, and a median split is used to create a dummy variable where a 1 indicates being more optimistic about one's return to capital. *** p<0.001, ** p<0.05, * p<0.10.

# J Selecting the distribution of business returns for counterfactual analysis

The distribution of returns for the counterfactual analysis was chosen based on a data-driven method to determine the best-fitting distribution, based on the distribution of business profits in the experiment from which participants were drawn. Table A.10 displays results: the best-fitting distribution is 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.[22]

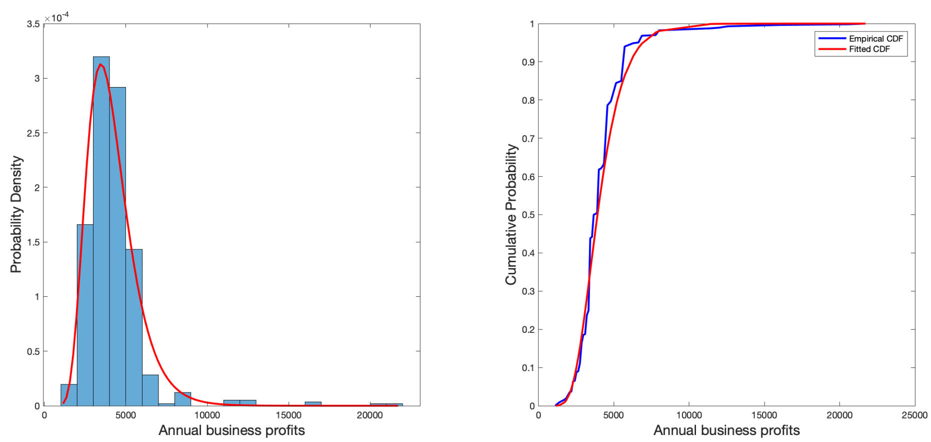
Table A.10: DISTRIBUTIONAL FIT

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

**Note**: A data-driven method was employed to determine the distribution that best fit the actual distribution of business profits in the experiment from which participants were drawn. The table presents the different fitted distributions and their corresponding Sum of Squares Error.

Table A.10 provides a visual assessment of the distributional fit of the chosen lognormal distribution with the observed empirical distribution of business profits.

Figure A.3: VISUAL ASSESSMENT OF DISTRIBUTIONAL FIT




**Note**: In the left panel, the empirical probability density function (PDF) is juxtaposed with the PDF of the fitted distribution. On the right, the empirical cumulative distribution function (CDF) is contrasted with the CDF of the fitted distribution. All amounts are in US\$.

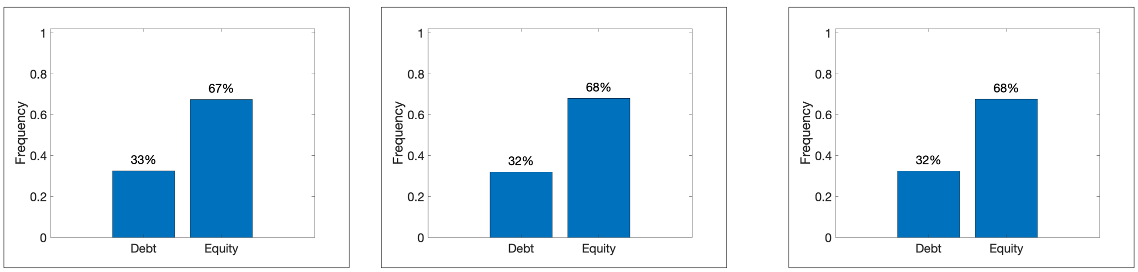
[22] The mean and standard deviation of the lognormal distribution are $e^{\mu+\frac{\sigma^2}{2}}$ and $\sqrt{(e^{\sigma^2}-1)e^{2\mu+\sigma^2}}$, respectively.

# K Removing skew from the returns distribution

Figure A.4 illustrates the impact of removing skewness from the underlying distribution used in the model, effectively transforming it from a lognormal to a normal distribution. This adjustment results in a notable change to results from the counterfactual analysis discussed in Section 5.3. Specifically, the previously observed differential patterns of take-up between debt and equity, when accounting for probability weighting, disappear. This aligns with the findings of Barberis and Huang (2008), who show 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.

Figure A.4: CONTRACT CHOICE, REMOVING SKEW FROM DISTRIBUTION

PANEL A: EXEPCTED UTILITY  PANEL B: LOSS AVERSION  PANEL C: PROBABILITY WEIGHTING



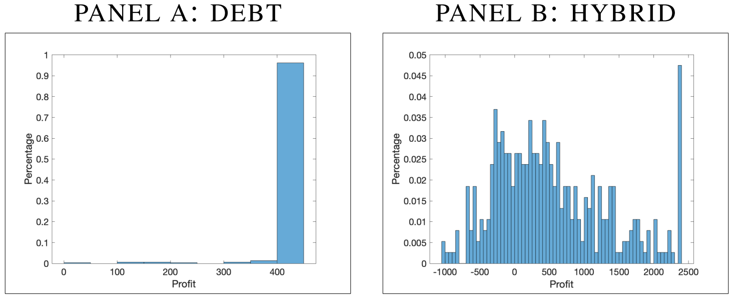

**Note:** Each panel summarises model-based take-up rates for the 765 business owners, based on their utilities calculated with individually-estimated risk preference parameters, under each financial contract. Panel A summarises take-up rates assuming an expected utility framework where risk aversion is defined solely by the curvature of the business owner's utility function, as captured by their parameter $\alpha$. Panel B presents take-up rates under a prospect-theoretic framework that only allows for reference-dependent preferences, with individuals choosing based on their estimated $\alpha$ and $\lambda$, with the reference point set at their initial household stock of savings (as measured in the baseline survey with business owners). Panel C extends the prospect-theoretic framework to also allow for distorted probabilities to affect decision-making, based on the individual's probability weighting parameter $\gamma$. In Panels A, B, and C, the choice is between a 27% interest rate debt contract and a 50%-sharing equity contract.

# L Counterfactual MFI profits

Figure A.5 illustrates the distribution of MFI profits after introducing the hybrid contract in the counteractual analysis of Section 5.3. Mean profits under debt are \$400, with a standard deviation of \$38, representing a net return of 27% on the \$1,500 capital provided. The distribution of profits for the MFI from the 50% of the sample that select into the hybrid contract has a higher mean and higher standard deviation.

Figure A.5: DISTRIBUTION OF MFI PROFITS

PANEL A: DEBT  PANEL B: HYBRID

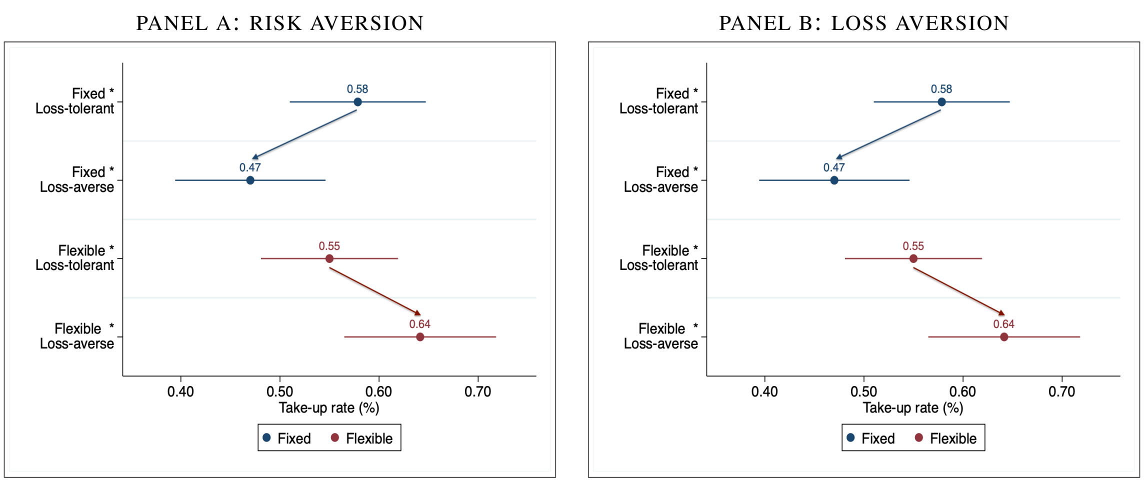



**Note:** This figure illustrates the distribution of MFI profits after introducing the hybrid contract in the counteractual analysis of Section 5.3. The left panel illustrates the distribution of MFI profits from business owners who select into the debt contract, with a mean of \$400 and standard deviation of \$38, representing a net return to the MFI of 27% on the \$1,500 capital provided. The right panel displays MFI profits from the 50% of business owners who select into the hybrid contract, with a higher mean of \$530 and standard deviation of \$816.

# M Further take-up results 'outside of the lab'

This section provides further evidence of take-up decisions 'outside the lab'. In Section 5.4, I analyzed asset finance take-up decisions from the broader Kenyan field experiment from which participants were drawn. In this section, I analyze take-up decisions of the asset financing product offered in the broader experiment in Pakistan. The contracts were 18-month hire-purchase agreements to finance a fixed asset up to the value of approximately US$1,900. The contracts obliged clients initially to purchase 10% of the asset, with the MFI purchasing the remaining 90%. The contracts then required repayments of the MFI's share over the following 18 months. There were two forms of contract. The first was a more debt-like fixed-repayment contract in which the client was required to purchase 5% of the asset value each month (so that, after 18 months, the client would fully own the asset). The second version was a more equity-like flexible-repayment contract in which the client was only obliged to purchase 2.5% of the MFI's ownership share each month, and also had the option to pay more than what was required in any given month. The contractual variation in the field experiment in Pakistan 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, Figure A.6 shows that the most risk-averse individuals and the most loss-averse individuals had significantly higher take-up of the more equity-like flexible-repayment contract compared to the more debt-like fixed-repayment contract.

Figure A.6: **TAKE-UP OUTSIDE THE LAB: PAKISTAN**




*Note:* This figure presents coefficient plots from a take-up regression of the two financing contracts offered in the field experiment in Pakistan: a more debt-like fixed-repayment contract, and a more equity-like flexible-repayment contract. *Risk-averse* and *Loss-averse* are dummy variables for whether a business owner has above-median risk aversion or loss aversion respectively, using the same measures as the main paper.