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Microequity and Mutuality: Experimental Evidence on Credit with Performance-Contingent Repayment*

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Abstract

We conduct the first field experiment of a performance-contingent microfinance contract. A large food multinational wishes to help micro-distributors in its supply chain with the financing of a productive asset. Working with the firm in Kenya, we compare asset financing under a traditional debt contract to three alternatives: (i) a novel equity-like financing contract, (ii) a hybrid debt-equity contract, and (iii) an index-insurance financing contract. Experimental results reveal large positive impacts from the contractual innovations. These findings demonstrate the economic appeal of microfinance contracts that leverage improved observability of performance to achieve a greater sharing of risk and reward.

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1 Introduction

Many large multinational firms operate 'route-to-market' programmes in developing countries. To get their products to the end customer – especially in harder-to-reach rural areas and informal urban settlements – multinationals often rely on a network of 'micro-distributors': self-employed individuals, who move consumer products from the firm's stock points to customers. These micro-distributors are not formally employed by the firm, but often are highly reliant on the firm for their income. Such multinationals have access to high-quality administrative data on the performance of their distributors, and recent changes in technology and digital financial services is enabling new ways for them to manage, monitor and pay these 'dependent contractors' (Higgins, 2019; Suri, 2017). While route-to-market activities are highly prevalent in developing countries, there is a surprising lack of supply chain finance or trade credit provided by multinationals to their distributors (Jack, Kremer, de Laat, & Suri, 2022), and relatively little economics research on the topic.[1]

In this paper, we run the first field experiment of a performance-contingent microfinance contract. To do so, we work within the supply chain of one of the largest manufacturers of food products in the world, leveraging novel data to support lumpy capital investments by micro-distributors. We refer to this corporation pseudonymously as 'FoodCo'. FoodCo owns a large chewing gum producer in Kenya, and wishes to help its micro-distributors with the financing of a productive asset to increase their distribution activities. Traditionally, most micro-distributors travel on foot, without the help of a vehicle. In our experiment, we partner with a local microfinance institution ('MFI') to investigate the efficacy of alternative contractual structures for financing new bicycles. In doing so, we link asset finance repayments to the performance of micro-distributors, by using FoodCo's administrative data on stock purchases – from which we calculate a profit measure that is not reliant upon micro-distributors' self-reports. Our purpose is to test whether such performance-contingent financing contracts can share risk and reward more effectively than standard debt contracts. Specifically, we test four alternative contracts: a *debt* contract, an *equity-like* contract, a *hybrid* contract and an *index insurance* contract.

Our key result is that performance-contingent microfinance contracts can encourage investment and increase profits – and, as a result, increase household consumption. Specifically, we find that our two performance-contingent contracts (equity and hybrid) out-perform the debt contract in several key respects. First, we find no evidence that individuals assigned to performance-contingent payments move away from the activity in which they are being taxed; to the contrary, we actually find that they *increase* the proportion of their selling activities in chewing gum compared to individuals assigned to the debt contract. Further, our high-quality administrative data on profits reveals large positive impacts of the performance-contingent contracts on micro-distributor profits. Specifically, in intent-to-treat terms, we estimate an increase in monthly profits of US$34 for individuals assigned to the hybrid

[1] For related literature in other fields, see (for example) Kolk, Rivera-Santos, and Rufín (2014) and Singh, Bakshi, and Mishra (2015).

contract, on a control mean of US$11: a quadrupling of profit. As a consequence, we find a large and significant effect of the hybrid contract on the biggest category of household consumption expenditure, food (a 19% monthly increase relative to the control group), as well as a large positive impact of the hybrid contract on household expenditure on clothing.

Our paper draws together two previously disparate strands of research: microfinance and supply chain finance. The first literature has identified limited impacts of the standard rigid microcredit contract on business performance and household outcomes (Banerjee, Karlan, & Zinman, 2015), notwithstanding some evidence of significant heterogeneity in business impacts (Banerjee, Breza, Duflo, & Kinnan, 2019) and positive general equilibrium effects (Breza & Kinnan, 2021). A related body of work has demonstrated the benefits of introducing more flexibility into the standard contract through 'repayment grace periods' following the seminal work of Field, Pande, Papp, and Rigol (2013), and contracts better tailored to the cash requirements of farmers (Barboni & Agarwal, 2021; Battaglia, Gulesci, & Madestam, 2021; Burke, Bergquist, & Miguel, 2019). We push the frontier in this literature by investigating a more direct way to link repayments to income – with what, to our knowledge, is the first field experiment of a performance-contingent contract for microenterprises. Such contracts may be more appropriate than traditional debt contracts for financing investments of risk-averse microenterprises – but, until now, have only been tested in a laboratory setting or very small pilot studies.[2]

We also contribute to the supply chain finance literature, on which there is relatively little work in developing countries – despite the increasing prevalence of large multinational route-to-market programs, and despite strong demand for financing at various points in the supply chain. In a low-income agricultural setting, Jack, Kremer, de Laat, and Suri (2022) work within a milk supply chain (where output is also well observed, as in our context) and find large benefits to financing a productive asset for farmers (a rainwater harvest tank). Other literature in this space emphasises strong theoretical justifications for suppliers acting as financial intermediaries – due to their comparative advantage (relative to formal banks) in assessing the performance and creditworthiness of customers, and their ability to use informal means for guaranteeing repayment (such as the threat to cut off future supplies) (Beck, Pamuk, Ramrattan, & Uras, 2015; Breitbach, 2017; Breza & Liberman, 2017; Klapper, Laeven, & Rajan, 2012; Maksimovic & Demirgüç-Kunt, 2001; Mian & Smith Jr, 1992; Petersen & Rajan, 1997; Prahalad & Hammond, 2002; Sodhi & Tang, 2014).

By conducting an experiment with a large multinational, we shed light on the exciting potential for multinationals to help finance productive assets for dependent contractors. In doing so, we leverage innovations in technology and digital finance that improve the observability of microenterprise performance – mitigating the classic problems of costly state verification that traditionally limit the viability of performance-contingent financing contracts (Townsend, 1979). The rapid adoption of electronic point-of-sale technologies – including in many low-income settings – opens many possibilities for in-

[2] See Fischer (2013) and De Mel, McKenzie, and Woodruff (2019).

novative performance-based financing contracts in the years ahead. For this reason, we view this paper as an important proof of concept for a new class of microfinance contract.

2 Experimental design

2.1 Study context

In 2013, FoodCo developed a route-to-market micro-distribution program using self-employed micro-distributors in Kenya. The distribution system is built around small warehouses (called 'stockpoints'), which are located in both rural and urban areas. Stockpoints receive deliveries of FoodCo chewing gum, which they sell alongside various non-FoodCo products. Micro-distributors purchase chewing gum (as well as other products) from stockpoints, before selling to customers. 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 performance-related pay in the form of an end-of-month bonus via mobile money for every bag of gum sold. There is no obligation for distributors to sell gum exclusively, but selling FoodCo'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 (Prahalad & Hammond, 2002). On the basis of feedback from FoodCo and qualitative work that we conducted with micro-distributors, we hypothesised that bicycle access could substantially improve distributors' profits. However, bicycles are often prohibitively expensive, costing approximately $100 for a mid-market model.[3]

2.2 Contract variants

Our sample consists of micro-distributors who had been in the FoodCo program for at least three months and who had expressed an interest in purchasing a bicycle to expand their distribution activities. Interested micro-distributors were invited to a baseline workshop where they completed a survey and conducted behavioural games, and were randomly offered one of four microfinance contracts (designed in collaboration with FoodCo and our partner MFI). All contracts required the micro-distributor to pay an initial deposit of 10%, with the remaining 90% of the bicycle price financed by the local MFI; the MFI bore all of the credit risk, and maintained ownership of the bicycles until completion of each contract. The contracts were as follows:

(i). *Debt*: A contract requiring a total repayment amount equal to the asset financing amount plus a 15% mark-up, spread evenly over 12 fixed monthly payments.

[3] We use '$' to refer to US$, based on Kenyan Shilling (KES) amounts and a USD-KES exchange rate of 102 at baseline.

(ii). *Equity*: 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). Relative to the debt contract, the equity contract is particularly attractive for insuring downside risk: if the micro-distributor has a bad month, the equity contract reduces the payments required. (Conversely, it is possible for the micro-distributor to owe substantially more under the equity contract than under the debt contract, if monthly profits are high.)

(iii). *Hybrid*: A contract in which monthly payments were calculated in exactly the same manner as the equity contract, but with a flexible contract duration: repayments end when the cumulative payments reach the level required under the debt contract (*i.e.* the asset financing amount plus a 15% mark-up). The hybrid contract thus provides the advantages of insuring against downside risk, but without the disadvantage of the taxation of high performance. Further, if micro-distributors experience an endowment effect (Carney, Kremer, Lin, & Rao, 2022) – such that they would prefer to bring forward the day on which they own the bicycle outright – then this contract directly incentivises effort.[4]

(iv). *Insurance*: An index insurance contract, which had a similar repayment structure to the equity contract, with the difference being how the profit-sharing was calculated: the 10% sharing payments were based on an index constructed from the profits of other micro-distributors in their region (again, calculated using administrative data).[5] This contract shares a similar advantage to the equity contract – namely, that it insures the micro-distributor against common shocks. The index insurance contract is very similar in spirit to 'Area-based Yield Insurance' that is used to mitigate asymmetric information problems in agricultural settings by making payouts based on average yields over clearly defined geographic units (Carter, Galarza, & Boucher, 2007).[6]

Finally, respondents in the *control* group were not offered the opportunity to finance a bicycle using any contract, but maintained full 'business as usual' access to the FoodCo micro-distribution program. Similarly, individuals who had rejected the contract for which they drew a ball were not offered any contract for bike financing. Appendix Figure A1 illustrates the payoff structure of the debt, equity and hybrid contracts.

Profit-sharing payments under the equity, hybrid and insurance contracts were calculated using administrative data on stock purchases and a profit margin given to us by FoodCo, based on the retail

[4] The flexible duration of our hybrid contract shares similarities with relationship-based bank lending contracts traditionally implemented in Germany with small and medium sized enterprises ('Mittelstand'), in which for example any unpaid amounts from a one-year debt contract would roll over to a second year, providing a type of risk-sharing over time (Behr & Schmidt, 2015).

[5] To mitigate the risk of manipulation, we excluded from the index the profits of distributors in the individual's own stockpoint.

[6] For the index, we explored different levels of aggregation, and decided on a region-based index (for the five major regions in Kenya: Nairobi, Central Kenya, Kisumu, Eastern Kenya, Mumbasa).

price at which the micro-distributors were requested to sell their products. We designed the contracts to be similar in terms of expected net present value for the median micro-distributor, given (i) the baseline distribution of micro-distributor profits in the broader route-to-market program and (ii) estimates, based on qualitative interviews, of the expected impact of the bicycles.

2.3 Conceptual framework

To fix ideas, we now discuss the trade-offs facing a stylised micro-distributor. In this section, we provide an intuitive discussion; we present a formal framework in Appendix Section A1. Specifically, we consider a micro-distributor who is credit-constrained, and whose productivity will increase if she makes a lumpy purchase of a bicycle. The micro-distributor, faced with our menu of financing contracts, needs to answer two questions. First, the *incentive compatibility* question: "under each available contract, how much effort shall I invest in sales for FoodCo ('on contract'), and how much effort shall I invest in other activities ('off contract')?". Second, the *individual rationality* question: "given a take-it-or-leave-it decision, which contracts should I accept?".

Risk plays two important roles in our conceptual framework – each of which, in our view, reflects important features of the actual experience of micro-distributors in our experiment. First – as our incentivised baseline behavioural games show – micro-distributors are risk averse.[7] This implies that, *ceteris paribus*, micro-distributors value a contract that bundles some degree of risk-sharing. Second, micro-distributors operate in a risky environment – with the risk increasing along with the micro-distributors' use of the lumpy asset. This feature, too, is closely grounded in the real experience of our respondents. For example, a micro-distributor who cycles her bicycle further to serve new markets may increase and diversify her sales – but is also putting that bicycle at more risk of being stolen, or destroyed in an accident; similarly, new markets themselves are intrinsically likely to be more uncertain (Roll, Dolan, & Rajak, 2021).

As we show in Appendix Section A1, three implications follow from this conceptual framework. First, because micro-distributors are risk averse and risk exposure increases with effort, performance-contingent contracts can – relative to a debt contract – *increase* the marginal product of labour, and therefore can crowd *in* on-contract effort. This is the *opposite* prediction to the usual analysis of performance-continent remuneration (Holmström, 1979; Lazear, 2000) (including in the famous case of sharecropping: Burchardi, Gulesci, Lerva, and Sulaiman (2019); Stiglitz (1975); Stiglitz and Weiss (1981)) – where, as Angrist, Caldwell, and Hall (2021, p.274) elegantly put it, output sharing 'inserts a wedge between effort and income'.

[7] For example, using incentivised risk preference elicitation activities that we describe in more detail in Appendix Section A6, we find that – for a binary outcome lottery with expected payment of 500 KES – the average certainty equivalent was 374 KES; for a lottery with expected payment of 750 KES, the average certainty equivalent was 478 KES. A structural estimation of $u(x;\alpha) = x^{\alpha}$ using all the data from our incentivised games returns $\hat{\alpha} = 0.69$.

Second, performance-contingent contracts should be particularly attractive to clients who are more risk averse. This follows straightforwardly from the insurance element that is implicitly bundled in such contracts; indeed, this insight was central to Udry's (1994) analysis of state-contingent loans in northern Nigeria (see also Udry (1990)). Third, performance-contingent contacts may be profitable for the client, by facilitating capital investments – and, indeed, by encouraging additional effort – relative to the no-contract case. In this respect, our theoretical predictions follow the seminal insight of Boucher, Carter, and Guirkinger (2008) on 'risk rationing': namely, that when capital investment brings additional risks, an absence of bundled insurance implies that profitable investments often do not go ahead.

2.4 Descriptive statistics, contract assignment and take-up

Micro-distributors who had expressed an interest in purchasing a bicycle to expand their business were first invited to a baseline workshop, where they completed a household survey and a series of behavioural games. Micro-distributors were also given the opportunity to inspect several kinds of bicycles on offer; most bicycles were 'work friendly' models with a rear rack.[8]

At the end of the session, each of the microfinance contracts was carefully explained to the respondents; this included several example scenarios and tests of understanding. Respondents were then introduced to a manager from our partner microfinance institution, who explained that they would be offering the financing contracts for bikes to a randomly-selected subset of participants. When communicating with participants, the words 'debt', 'equity' and 'insurance' were never used; contracts were explained using their cash-flow structure in the local language (Swahili), with each contract colour-coded for ease of remembering.

The microfinance contracts were assigned using a public randomisation device (an opaque bag containing coloured balls). Micro-distributors had earlier made take-it-or-leave-it decisions for each of the contracts; respondents who drew a colour for which they had specified their acceptance were immediately directed to a representative from the MFI, to proceed to sign the contract. Individuals who drew a ball for the control group were not offered the opportunity to finance a bicycle using any contract, but they maintained full 'business as usual' access to the FoodCo micro-distribution program; similarly, individuals who had rejected the contract for which they drew a ball were also not given any contract. The choice of bicycle was made before contract decisions were elicited.

Between 2017 and 2019, 161 individual distributors participated in the study.[9] In total, 138 of the

[8] The menu of bikes included one model that is of a higher quality and nearly twice as expensive, and a 'female-friendly' bike with a dipped bar. See Fiala, Garcia-Hernandez, Narula, and Prakash (2022) for evidence of the significant benefits of bicycles for young women, in a setting geographically similar to ours and using the same local bicycle manufacturer.

[9] During the same period, there was an average of 478 active micro-distributors per month in the wider FoodCo programme from which our participants were drawn. The total number of unique micro-distributors in the programme over that period was 1,727.

161 participants were assigned to treatment (one of the four financing contracts), with the remainder assigned to control. Appendix Table A2 provides summary statistics, disaggregated by treatment assignment; the table also reports tests of randomisation balance. For all variables in Table A2, individual balance tests do not reject the null of no difference across treatment groups. Respondents' average age was 31, with 15% female and 70% married. 20% had a post-secondary education. On average, respondent households had three members. In the three months prior to the baseline survey, mean profits from all selling activities were $133 (median $107), and $53 (median $34) from just FoodCo products (for which we have administrative data). Only 16% of distributors had employees; 26% also engaged in another income-generating activity (mostly casual labour), with average income of $20 from that source (median $0).

Several variables suggest that the majority of micro-distributors in this sample face liquidity and credit constraints. First, total household income from all sources was $198 on average (median $142), and total household expenditure was $196 on average (median $174). Second, more than half of micro-distributors report that none of their FoodCo purchases are received on credit. Further, the median micro-distributor only extends trade credit for 5% of their sales. Even where trade credit is provided, the duration is extremely short – for those who receive trade credit from their stockpoint, the average number of days of credit is 2.9 (median of 1), and for those who extend trade credit, average days to repay is 2.2 (median of 1).

We now describe take-up – by which we mean that a respondent had agreed to an offered contract, provided the requisite deposit and supporting documentation, and received the bicycle. The highest take-up rate was for the hybrid contract, at 70%, followed by 69% for the debt contract and 53% for equity; the lowest take-up was for the insurance contract at 45%.[10] We obtain similar take-up patterns if we instead use the initial 'take-it-or-leave-it' decisions as our measure of take-up (see Appendix Figure A6).

In Appendix Section A3.1, we analyse heterogeneity in take-up using pre-specified variables for profits and risk preferences. Strikingly, we find little evidence of adverse selection: the most profitable micro-distributors (using baseline FoodCo-based profits and a median split) are no less likely to select into the performance-contingent contracts compared to the debt contract (Appendix Figure A7). Similarly, we find no evidence for lower selection into performance-contingent contracts for 'higher quality' micro-distributors – as proxied by their business management practices or cognitive-mathematical ability (Appendix Figure A8). Further, Appendix Figure A9 indicates evidence of higher selection into equity contracts for individuals who at baseline were measured to be more risk averse

[10] A formal statistical test does not reject that take-up of the equity contract is the same as for that of debt or hybrid contracts. A formal test *does* reject that take-up of the insurance contract is the same as that of the hybrid contract and the debt contract (p-values of 0.044 and 0.048 respectively). The relatively lower take-up for our index insurance contract is not surprising, given the important role here for basis risk (Carter, de Janvry, Sadoulet, Sarris, et al., 2014; Clarke, 2016; Cole et al., 2013). Appendix Figure A5 illustrates the relationship between micro-distributor performance and required payments under each contract.

and more loss averse (using both self-reported measures and incentivised games). This preference for equity contracts from risk- and loss-averse individuals is consistent with such individuals valuing the insurance-like characteristics of performance-contingent payments. The results are also consistent with our theoretical framework that suggests that the performance-contingent contracts can crowd-in effort and allow greater risk-taking and higher expected earnings from using the bicycle.

3 Treatment effects

We now analyse the consequences of the various contracts that we implemented. We had access to administrative data from FoodCo on stock purchases by all 1,727 unique distributors in their programme (regardless of whether they participated in our experiment); FoodCo performs meticulous checks with field officers and stockpoints to verify the quality of data on purchases, based on which distributors are paid their monthly bonuses.

We create a panel of monthly profits by using the purchase data and the profit margin made by distributors for each of the six possible chewing gum products, based on the fixed price at which FoodCo requests distributors to sell. We aggregate the profits across the six products to create our primary outcome variable.[11] We begin with the data for the 161 distributors who entered our experiment between 2017 and 2019. For all other variables, we use survey data collected quarterly for up to one year after treatment. Our data covers all available post-treatment months up until the COVID-19 lockdowns in March 2020.[12] For each outcome, we use an intent-to-treat ANCOVA specification:

$$y_{it} = \beta_0 + \sum_{k \in \{1,\ldots,4\}} \beta_k \cdot \texttt{Offered}_{ik} + \gamma \cdot y_{i0} + \varepsilon_{it}. \tag{1}$$

Here, $\texttt{Offered}_{ik}$ is a dummy for whether individual i had contract k randomly drawn. In this specification, y_{i0} refers to the baseline value for outcome y (or the average prior outcome, in the case of administrative data on profits). We winsorize at 95%, and we cluster standard errors at the individual level. In Appendix Section A3, we repeat all of the analysis using randomisation inference, and we also report Local Average Treatment Effect estimates.

[11] Technically speaking, our measure is gross profit, or "net income before non-working-capital expenses": it includes inventory expenditure but excludes other expenditure such as travel and labour costs. On average, inventory expenditure is 40 times larger than the next largest category (transportation costs).

[12] We ended the project in March 2020, with approximately 85% of the planned survey follow-up data collected before the COVID-19 lockdown. As in many other settings, the lockdown presented a huge shock to operations; in our case this affected not only the operations of micro-distributors, but also structural changes in the way FoodCo managed the program, and an inability for the MFI to collect microfinance repayments. All of our analysis uses data up until and not including the lockdown.

3.1 Impact of contracts on business activities

Our primary hypothesis, as specified in our pre-analysis plan, is that our treatments affected participants' profits. We find a large and significant positive effect of the hybrid and equity contract on profits. Column 1 of Table 1 shows this with the pooled variable, and column 2 displays the impacts separately for the equity and hybrid contracts. On average, micro-distributors assigned to the hybrid contract experienced a $34 increase in their monthly profits (significant at the 5% level), which is very large in comparison to the follow-up control mean of $11. The coefficient on the equity contract is $20 (significant at the 10% level), while the coefficients on the debt and insurance contracts are $10 and $12 (not significant). In Appendix Section A3, we show that results are robust to log and inverse hyperbolic sine transformations of the profits variable.

At baseline, by design, 100% of participants were engaging in micro-distribution work. Column 3 reveals that none of the contracts led to a reduction in the likelihood of doing some form of distribution work (whether of FoodCo or non-FoodCo products). Column 4 tests the intensive margin: the proportion of sales from FoodCo. We find no evidence of moral hazard for the performance-contingent contracts. Individuals assigned to the equity and hybrid contracts do not decrease the proportion of FoodCo activities in their selling portfolio; in fact, individuals assigned to the hybrid contract *increase* it significantly compared to individuals assigned to the debt contract.

This is consistent with our conceptual framework, which highlighted the potential for performance-contingent contracts to crowd in 'on-contract effort'. In Appendix Section A4, we present results that provide reassurance that our effects are not simply reflecting the heterogeneity induced by differential take-up. Specifically, we repeat the analysis of Table 1 while controlling for de-meaned baseline measures of profits, risk aversion and loss aversion, as well as the interaction of the de-meaned variables with each treatment indicator. All the previous results are robust, and the precision of the coefficients increases.

3.2 Mechanisms

We now test several mechanisms driving our results. First, we test whether our results are driven by 'business stealing' by treated respondents from control respondents. To do this, we use administrative data on the universe of micro-distributors who were in FoodCo's program but not in our experiment. We test the consequence on these micro-distributors of random variation in the number of treated respondents at the stockpoint, conditional upon the number of experimental participants at the stockpoint. Appendix Table A1 displays the results: we estimate an increase of about US$4 for each non-participating micro-distributor at the stockpoint, for each additional person offered a contract. These combined findings are reassuring for the robustness of our main results: it indicates that, if anything, our main results are likely to be slight underestimates of the treatment effects of our contracts.

Our estimate of positive spillovers from treatment is consistent with the provision of bicycles having expanded the geographical reach of the stockpoint. Figure 1 show several maps in support of this hypothesis, using GPS data from trackers that we installed on all bicycles. We can see that our bicycles were spread across all the most populous areas of Kenya, and – within a particular region – individuals are travelling across significant distances with the bicycles. We explore this further in column 1 of Table 2, where coefficients indicate a large increase in the likelihood a micro-distributor selling to customers further than 1km away from their stock-point, and particularly so for the hybrid and insurance contracts (an increase of 19 and 22 percentage points respectively, compared to a control mean of 58%).

Table 2 also explores other mechanisms. In column 2, we use information from daily administrative data on stockpoint visits by distributors. We find positive coefficients on all contracts; only the hybrid contract is significant, indicating a doubling of the number of visits per month ($p = 0.056$). Similarly, column 3 uses a Herfindahl index to measure the concentration of distributor sales within each month (where 1.0 indicates receiving all monthly income in one day). Coefficients are negative on all of the contracts, indicating a greater smoothing of monthly profits over different days; again, the only significant coefficient is on the hybrid contract ($p = 0.066$). Column 4 explores whether the contracts led to a greater variety of products sold in each distributor's portfolio (which ranges from one product to six of FoodCo's chewing gum products). Although not significant, the coefficient on the hybrid contract indicates a relatively large amount of portfolio diversification, from an average of 1.3 products for the control group to over 2.0 products per month ($p = 0.181$). Column 5 of provides evidence that individuals assigned to the hybrid contract significantly increased their own risk taking, through a 65% increase in the proportion of their customers offered trade credit ($p = 0.049$).

Column 6 shows that individuals assigned to the hybrid contract and the insurance contract experienced positive impacts on management practices (using an index comprising marketing, negotiation, cost, record-keeping, and sales targeting).[13] One plausible explanation is that these two contracts may require the greatest amount of 'mental engagement' in calculating payments. (For example, the hybrid contract requires participants to pay a proportion of their monthly income, as well as 'carrying forward' the cumulative payments made to date.) For further evidence consistent with this hypothesis, column 7 shows a positive effect of hybrid and insurance contracts on the record-keeping sub-category.

Finally, we explore usage of the financed asset. The vast majority of individuals who took up the bike report that they primarily used it themselves – only 7% report that someone outside of their household used it for any period of time. We find evidence that individuals assigned to the hybrid contract used their asset more intensively compared than those under the debt contract, with the cross-coefficient test significant at the 1% level, both in terms of the likelihood of using it for business

[13] All indices are calculated as weighted sums, using the covariance matrix from the control group (at baseline), as in Anderson (2008). The business management practice questions are based on McKenzie and Woodruff (2015), amended for our micro-distributors.

purposes (column 8) and number of hours using the asset (column 9). This is consistent with our earlier empirical findings, and our conceptual framework – showing that individuals assigned to a contract that provides more risk-sharing will themselves take more risk and exert greater effort in business activities.

3.3 Downstream outcomes

Table 3 presents treatment effects on three major components of household consumption expenditure. Column 1 shows a large and significant effect of the hybrid contract on the biggest category of household consumption expenditure: food. The coefficient of $8 implies a 19% increase in monthly household expenditure on food compared to the control group (significant at the 10% level). Column 2 indicates a $5 monthly increase in household expenditure on clothing for individuals offered the hybrid contract (significant at the 5% level, with effects not significant for any other contract). Column 3 investigates the effect on the third biggest category of household consumption expenditure: schooling. Though no coefficient here is individually significant from the control group, we find a significant positive difference from the hybrid contract over the debt contract ($p = 0.029$).

Finally, we consider health outcomes. This was one key motivation for providing bicycles – given respondent concerns about carrying large bags on their back. We test impacts on whether health impedes work (column 4, Table 3) and on whether work caused physical pain (column 5). Estimates are noisy and never significant (though most coefficients are negative, and relatively large).

4 Conclusion

In this paper, we run the first field experiment of a performance-contingent microfinance contract. We find especially large gains from our hybrid contract, containing both debt-like features (the need to repay a fixed nominal amount of money over the life of the contract) and equity-like features (performance-contingent repayments on a month-to-month basis). In particular, the hybrid contract led micro-distributors to earn higher overall profits, through selling more of FoodCo's products in their portfolio, exerting greater effort in using their bike for business, and taking more risk in their business (in terms of selling to new markets and extending trade credit to their customers).

To explore this further, in Appendix Table A11 we calculate a total return that sums the profits for micro-distributors, the profits for FoodCo (which could in theory decrease even with an increase in micro-distributor total profits if distributors shift to selling products with a lower profit margin for FoodCo), and total net payments made to the MFI for providing the financing. Overall, the magnitude of coefficient for total return is very large ($100 per month for the hybrid contract and $45 per month for the equity contract), highlighting the significant mutual benefits that are possible through combining administrative data on performance with a financial institution to provide financing for productive assets. While FoodCo made a very large gain, the MFI (which had to halt payment collection due

to Covid-19) made a small loss. Nonetheless, up until that point, repayments to the MFI from the hybrid and equity contracts were significantly higher than the debt and insurance contracts; this is consistent with our finding that performance-contingent contracts led to greater business effort and profits, especially in the hybrid contract that terminates early when profits are high. Our results are therefore also consistent with the finding of early repayment of asset-collateralised agricultural loans by Jack et al. (2022), who propose an endowment effect as an explanation. In our setting, we clearly show that higher repayment comes from higher effort (and higher profits) in the financed activity – and, strikingly, from the incentive-based contracts that many standard theories suggest are likely to disincentivise effort.

Our setting was an ideal one to test the effectiveness of performance-contingent contracts for productive asset financing in a low-income country – given, in particular, (i) the availability of detailed purchase data, and (ii) a clear mechanism for how the productive asset could be used to expand operations for microfinance clients. These two key features are already shared by a large variety of different self-employment contexts, in both low-income and high-income settings. First, the kind of micro-distributor program that we study is common to many route-to-market distribution programs, particularly for consumer goods and food and beverage firms. Second, and more generally, these characteristics are shared by many 'gig work' and 'dependent contractor' arrangements – where the host firm typically has a wealth of information about the quality and quantity of worker performance.

Indeed, as consumer markets expand in low- and middle-income countries, and as route-to-market programs grow, large companies are likely to place increasing reliance on 'dependent contractors' – most of whom are risk averse and face precarious economic circumstances, and many of whom lack access to the fixed capital necessary to do their work effectively. Our paper provides a proof of concept for a new class of microfinance contract, and our results show that such contracts may be particularly useful for such workers. Across a wide variety of contexts, rapid developments in financial technology – in particular, increasing adoption of mobile money and of electronic point-of-sale technologies – promise cheap access to credible information on the performance of microenterprises, gig workers and sub-contractors. The next generation of microfinance contracts can leverage these developments to expand the portfolio of products it offers clients – specifically, to include contracts with performance-contingent repayment obligations, offering better sharing of risk and reward.

Thus, for example, Uber and other ride-sharing platforms could use contingent-repayment contracts to help their drivers to finance the purchase of their cars.[14] Similarly, such contracts could readily apply to a very wide range of other sub-contractors – for example, farmers who 'finish' livestock animals for sale with equipment loans, or cut-and-trim manufacturers for their machinery, and so on. One could certainly imagine such contracts being offered by the host firm, such as Uber; however, one could also imagine third-party sharing agreements – more similar to the model adopted here by

[14] Several initiatives already exist in this space, including 'JUMO Drive'.

FoodCo – in which a specialized lender channels funds to a host firm for contingent lending to gig workers or sub-contractors, in return for clients agreeing to have the host firm share performance data with that lender.[15] This opens several novel possibilities for contractual innovations that benefit both low-income microentrepreneurs and large firms.

[15] This is broadly analogous to factoring – in which a company sells its accounts receivable to a financial company, which then collects payment.

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Tables and figures

Table 1: **Business outcomes**

	(1) FoodCo profits	(2) FoodCo profits	(3) Activity: seller	(4) FoodCo proportion	(5) Other earnings
Debt	10.39	10.39	-0.05	-0.11**	5.95
	(11.535)	(11.520)	(0.054)	(0.046)	(15.253)
Performance-contingent	25.96**				
	(10.786)				
Hybrid		34.43**	0.03	0.03	-7.73
		(15.227)	(0.044)	(0.060)	(13.347)
Equity		19.61*	-0.03	-0.01	-1.68
		(11.742)	(0.053)	(0.046)	(12.270)
Insurance	11.85	11.87	0.02	-0.06	3.07
	(10.312)	(10.269)	(0.040)	(0.045)	(15.415)
Observations	2598	2598	468	468	468
Individuals	161	161	160	160	160
Control mean	11.32	11.32	0.93	0.48	70.67
Test: Hybrid = Debt		0.133	0.181	0.018	0.319
Test: Hybrid = Equity		0.357	0.326	0.469	0.557
Test: Equity = Debt		0.472	0.741	0.023	0.541

Note: In this table we report *intent-to-treat* (ITT) estimates, obtained by least-squares estimation. In column 1, the variable 'Performance-contingent' pools both the equity and hybrid contracts, while in the remaining columns the two performance-contingent contracts are separated. Columns 1 and 2 use administrative data from FoodCo on business profits, for which there is an average of 15 months of post-treatment data (up to and excluding the start of Covid-19 lockdowns in March 2020). For all other columns, we use survey data collected by enumerators using quarterly follow-up surveys (again, up to and excluding Covid-19 lockdowns). Standard errors, clustered at the individual level, are reported in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 2: **Mechanisms**

	(1) Sales expansion	(2) Stockpoint visits	(3) Profit concentration	(4) Product varieties	(5) Credit extension	(6) Management practices	(7) Record keeping	(8) Bike use: business	(9) Bike use: hours
Debt	0.10	1.28	-0.05	-0.02	0.01	0.00	-0.02	0.73***	22.32***
	(0.082)	(1.154)	(0.048)	(0.441)	(0.023)	(0.061)	(0.072)	(0.055)	(2.142)
Hybrid	0.19**	2.96*	-0.10*	0.71	0.05**	0.10*	0.14**	0.90***	34.82***
	(0.090)	(1.539)	(0.054)	(0.532)	(0.026)	(0.055)	(0.068)	(0.037)	(5.553)
Equity	0.13	1.29	-0.03	0.10	0.01	0.03	0.01	0.71***	24.90***
	(0.087)	(1.032)	(0.044)	(0.468)	(0.020)	(0.055)	(0.067)	(0.058)	(2.067)
Insurance	0.22***	0.27	0.01	0.07	-0.00	0.11**	0.11*	0.79***	31.23***
	(0.076)	(1.124)	(0.042)	(0.391)	(0.019)	(0.052)	(0.069)	(0.068)	(5.981)
Observations	468	2598	2598	2598	468	468	468	468	468
Individuals	160	161	161	161	160	160	160	160	160
Control mean	0.58	2.42	0.55	1.33	0.08	0.68	0.65	0.00	0.00
Test: Hybrid = Debt	0.228	0.307	0.311	0.140	0.157	0.089	0.014	0.008	0.036
Test: Hybrid = Equity	0.486	0.241	0.137	0.231	0.104	0.161	0.036	0.006	0.094
Test: Equity = Debt	0.626	0.994	0.719	0.777	0.948	0.676	0.651	0.847	0.386

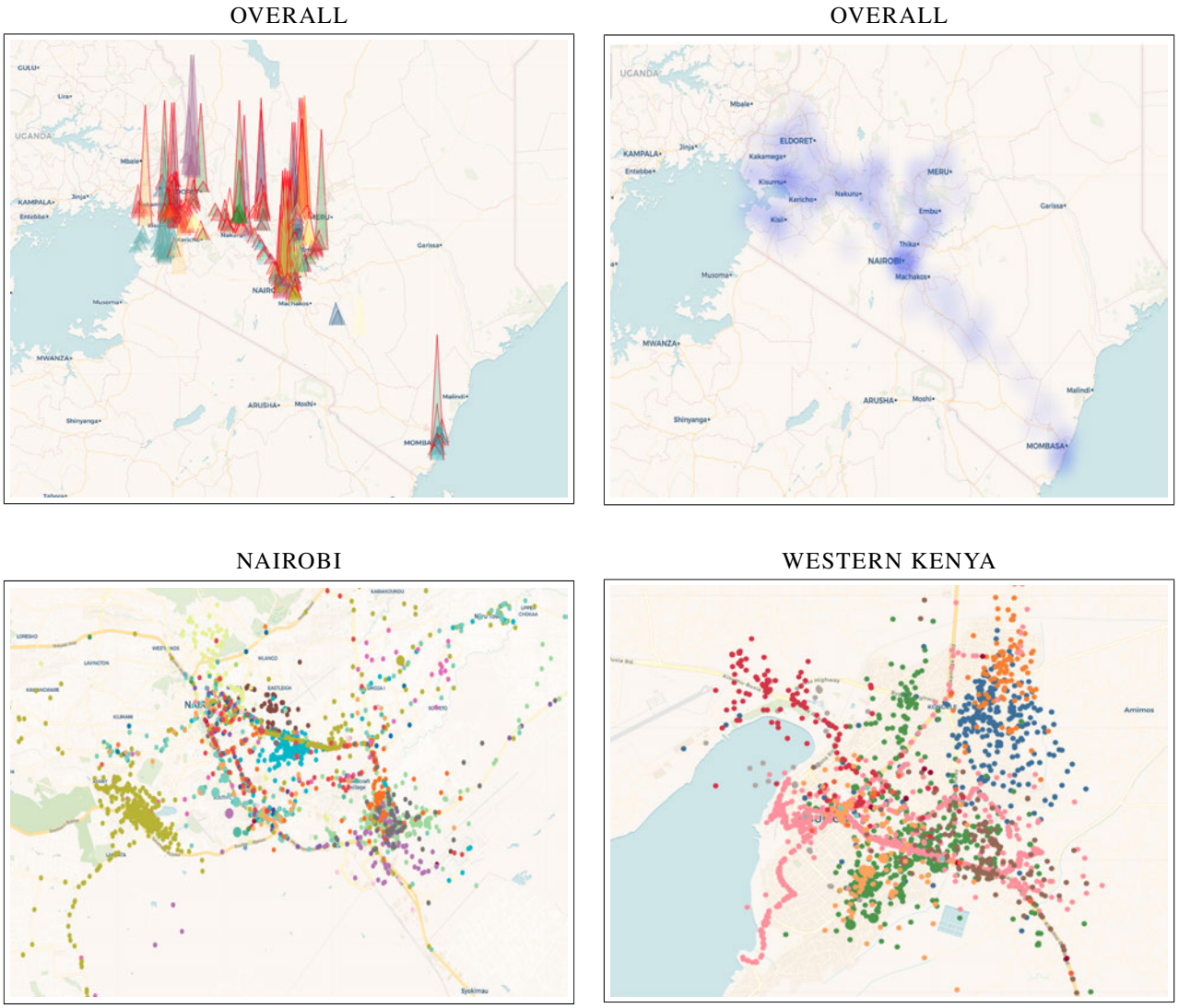
Note: In this table we report *intent-to-treat* (ITT) estimates. We use information from daily administrative data (columns 2 to 4), survey data from all participants (columns 1 and columns 5 to 7) and information on asset usage specifically from clients who took up the treatment (columns 8 and 9) to explore a number of variables that shed light on the mechanisms for our results from Table 1: how often distributors visit stock-points in a given month to purchase inventory (which ranges from 0 to 31), how concentrated their total monthly profit is over those visits (Herfindahl index), the number of FoodCo products they sell in their monthly portfolio (which ranges from 1 to 6), whether they sell to distant customers (greater than 1km from their stock-point), whether they extend credit to customers, their business management practices (an overall index and specifically record keeping) and finally whether they use the bicycle for business and the number of hours that they use it in a typical week. Standard errors, clustered at the individual level, are reported in brackets. * p < 0.10, ** p < 0.05, *** p < 0.01.

Table 3: **Household consumption and health**

	(1) Expenditure: food	(2) Expenditure: clothing	(3) Expenditure: schooling	(4) Health impedes work	(5) Work caused pain
Debt	8.99*	0.25	-4.91	-0.09	-0.10
	(5.075)	(1.965)	(3.420)	(0.070)	(0.062)
Hybrid	8.47*	4.92**	3.10	-0.06	-0.03
	(5.117)	(2.372)	(4.360)	(0.078)	(0.073)
Equity	1.54	-0.16	-0.81	-0.07	-0.02
	(4.152)	(2.146)	(3.649)	(0.072)	(0.067)
Insurance	8.18*	-2.34	-0.44	-0.03	0.02
	(4.247)	(1.974)	(3.355)	(0.079)	(0.078)
Observations	468	468	468	468	468
Individuals	160	160	160	160	160
Control mean	45.72	9.26	11.34	0.26	0.19
Test: Hybrid = Debt	0.927	0.032	0.029	0.644	0.204
Test: Hybrid = Equity	0.155	0.030	0.312	0.792	0.883
Test: Equity = Debt	0.111	0.831	0.150	0.827	0.084

Note: In this table we report *intent-to-treat* (ITT) estimates of the impact of treatments on household consumption expenditures and participants' self-reported health outcomes. Standard errors, clustered at the individual level, are reported in brackets. * p < 0.10, ** p < 0.05, *** p < 0.01.

Figure 1: **Bicycle GPS data**



Note: *In this figure, we display data from bicycle GPS trackers across the whole country, and also zooming in on the two most populous regions in Kenya. Each colour represents data points for a separate individual.*

Microequity and Mutuality: Experimental Evidence on Credit with Performance-Contingent Repayment

ONLINE APPENDIX

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Contents

A1 Theoretical model

In this appendix section, we present a stylised conceptual framework. We consider a microfinance client, maximising expected utility by deciding how much sales effort to invest both (i) 'on-contract' (e_c: sales for FoodCo) and (ii) 'off-contract' (e_n: sales through any other channel):

$$V(\omega, R; r, \kappa) = \max_{e_c \geq 0, e_n \geq 0} \int \int u\left[\omega \cdot \pi(e_c, \eta_c; \kappa) + \pi(e_n, \eta_n; \kappa) - C(e_c, e_n) - F; r\right] \; dF(\eta_c, \eta_n). \quad \text{(A1)}$$

To solve the client's problem, we use a standard CARA utility function (that is, $u(x) \equiv -\exp(-rx)$), and assume that the productivity shocks η are *iid* Normal: $\eta_c, \eta_n \sim_{iid} \mathcal{N}(0, \sigma^2)$. We use a standard constant-elasticity cost function: $C(e_c, e_n) \equiv \dfrac{(e_c + e_n)^{1+\gamma}}{1+\gamma}$. We consider a scenario in which profits are multiplicative in effort and productivity shocks: $\pi(e, \eta; \kappa) \equiv \kappa \cdot (1 + \eta) \cdot e$. This formalises the notion that, as clients exert more effort, they also expose themselves to more risk. For those with no bicycle, we normalise $\kappa \equiv 1$; therefore, $\kappa > 1$ refers to the returns capital (*i.e.* purchase of the bicycle).

This framework allows us to model several key contractual forms:

(i). *Debt*: Under the debt contract, clients retain all of their profits ($\omega = 1$), owe a fixed repayment ($F = F_d$), and enjoy higher productivity: $\kappa > 1$.

(ii). *Equity*: Under the equity contract, clients retain 90% of their on-contract profits ($\omega = 0.9$), owe half the fixed repayment of the debt contract ($F = F_e = 0.5F_d$) and enjoy higher productivity: $\kappa > 1$.

(iii). *Hybrid*: We can represent a stylised hybrid contract by taking the net present value of an income stream in which – for simplicity – we model the client as choosing effort and then earning the same retained profit in each month.[1] As in the debt and equity cases, clients under the hybrid contract purchase the bicycle and enjoy higher productivity: $\kappa > 1$.

[1] In our example, we use a monthly discount factor of 0.95 to illustrate.

(iv). *No-contract case*: For a client refusing to take a loan (and, therefore, not purchasing the bicycle), $\omega = 1$, $F = 0$ and $\kappa = 1$.

Figure A1 shows the repayment under each of these four scenarios. Specifically, it shows that repayments are invariant to profits under both the no-contract scenario and under the traditional debt scenario. Under the equity contract, repayments increase linearly – starting at half of the debt repayment, for a client earning zero profits. Under the hybrid contract, the net present value representation starts between the repayments under equity and debt (for a client earning zero profits), and is then an increasing concave function. This captures one key advantage to the client of the hybrid contract, relative to the equity contract: namely, that it limits the upside exposure. (Note that there are additional advantages to the hybrid contract, in the form of repayment flexibility; these could readily be captured in a more complicated dynamic programming framework, but this would lose much of the elegance and intuition of the static setup.)

Appendix Figure A1: **Contract repayments and retained earnings**

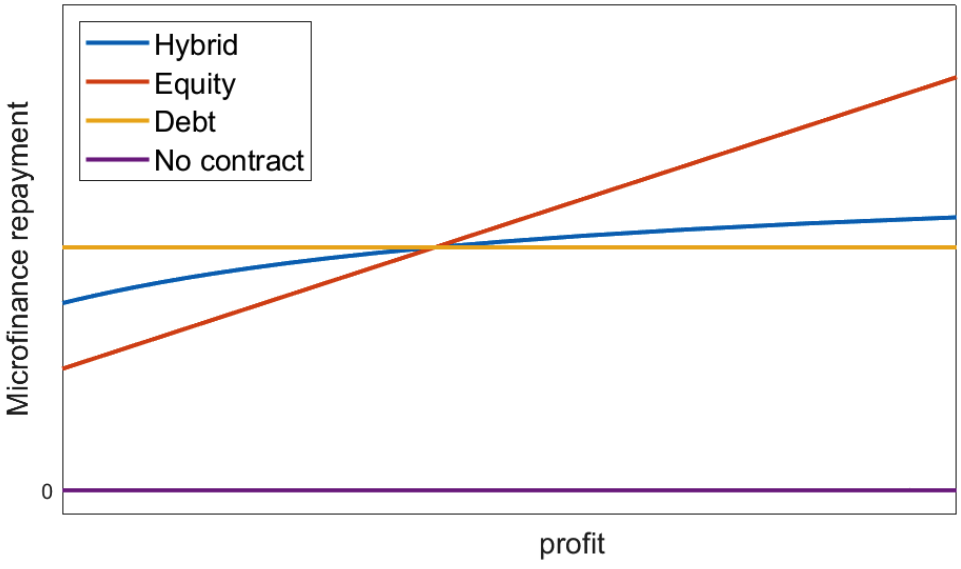


Figure A2 shows key model predictions, for reasonable parameter values.[2] Specifically, we conduct comparative static exercises for different values of the return to capital (κ) and risk aversion ($r\sigma^2$). Panel A compares optimal on-contract effort (e_c^*) under both the debt contract and the equity contract; in red, we shade the region where e_c^* is higher under equity, and in yellow, we shade the region where e_c^* is higher under debt. The panel shows that, because client risk is increasing in client effort, the equity contract can crowd *in* on-contract effort, for sufficiently high values of both risk aversion and capital returns.

Panel B shows which contract the client would prefer: none (in purple), debt (in yellow), equity (in red), or hybrid (in blue).[3] First, note that 'none' is preferred if the return to capital is low. This makes strong intuitive sense: such clients barely gain from having a bicycle, and certainly do not gain enough to justify the loan repayments. Second, debt is preferred for clients who have a high return to capital *and* who are not overly risk averse. In this region, we have a classic 'adverse selection' story: more profitable clients are more wary of sharing a proportion of their income, so prefer the fixed-repayment contract. However, for sufficiently high risk aversion, this incentive is outweighed by the implicit insurance provided by the equity contract. Third, this adverse selection story is mitigated in part by the hybrid contract: some clients who would prefer a standard debt contract over a performance-contingent contract would prefer the hybrid contract, because of the way that it limits upside exposure.

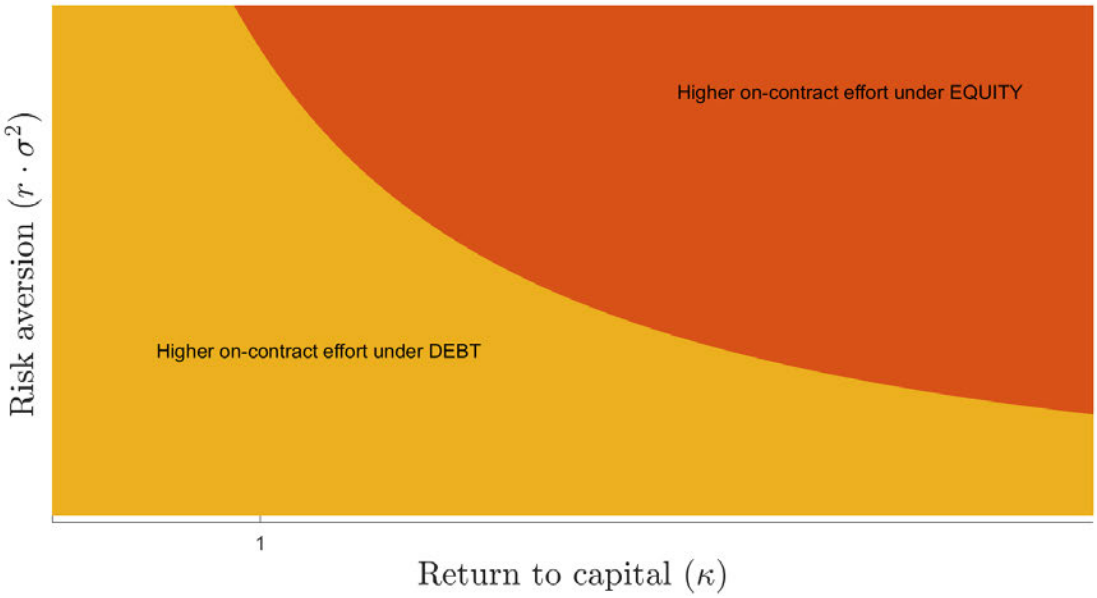
This stylised framework captures the key trade-offs facing micro-distributors. The model could readily be extended in several ways; this would include, in particular, providing for heterogeneity in micro-distributor productivity (which can be incorporated by allowing distributor-specific heterogeneity in $\mathbb{E}(\eta_c)$ and $\mathbb{E}(\eta_n)$). In our view, no intuitive insight is gained through these additional model complications.

[2] For this illustration, we use $\gamma = 0.35$ and $F_d = 0.1$.

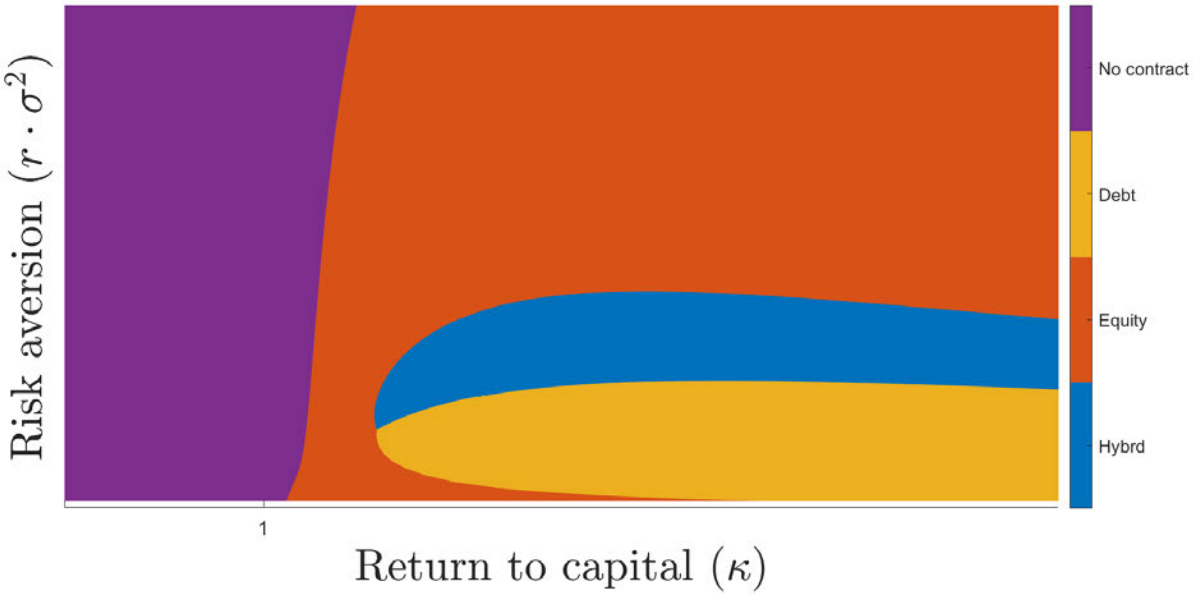
[3] To solve the model under the hybrid contract, we need to use numerical integration methods; specifically, we use the method of Tauchen (1986).

Appendix Figure A2: **Theoretical model: Key predictions**

PANEL A: CROWDING-IN EFFORT



PANEL B: PREFERRED CONTRACT



A2 Spillover effects

We test whether our results are driven by 'business stealing' by treated respondents from control respondents. To test for spillovers, we exploit the fact that we have administrative data on the universe of micro-distributors in FoodCo's program, regardless of whether they participated in our project; distributors who were neither assigned to treatment nor to control. We test the consequence on these micro-distributors of random variation in the number of treated respondents at the stockpoint, conditional upon the number of experimental participants at the stockpoint. Denote by y_{ist} the profits of non-participant i, at stockpoint s, in period t. Denote by A_{st} the total number of participants who had been assigned to treatment at stockpoint s by period t, and by C_{st} the total number assigned to control. Denote by P_{st} the total number of participants assigned at stockpoint s by period t; that is, $P_{st} \equiv A_{st} + C_{st}$. We estimate:

$$y_{ist} = \beta_0 + \beta_1 \cdot A_{st} + f(P_{st}) + \varepsilon_{ist}, \tag{A2}$$

where $f(P_{st})$ denotes a flexible function of the number of participants (Miguel & Kremer, 2004), and where we cluster by stockpoint.[4] In this specification, β_1 tests for spillovers at the level of the stockpoint: if there are positive spillovers from providing bicycles, then $\beta_1 > 0$, and if there are negative spillovers, $\beta_1 < 0$. This identification strategy relies crucially upon the random assignment to treatment: holding fixed the total number of participants at each stockpoint, A_{st} is determined randomly, so $\mathbb{E}(A_{st} \cdot \varepsilon_{ist}) = 0$. Table A1 displays the spillover results. Column 1 reports our primary specification. In column 2, we additionally control for time dummies. Columns 3 and 4 repeat the specifications in columns 1 and 2, but collapsing the analysis to the level of the stockpoint. In each case, we estimate significant *positive* spillovers from treatment. Specifically, we estimate an increase of about US$4 for each non-participating micro-distributor at the stockpoint, for each additional person offered a contract. These combined findings are reassuring for the robustness of our main results: it indicates that, if anything, our main results are likely to be slight underestimates of the treatment effects of our contracts.

[4] Specifically, we include a different dummy variable for each different value of P_{st}.

Appendix Table A1: **Spillovers**

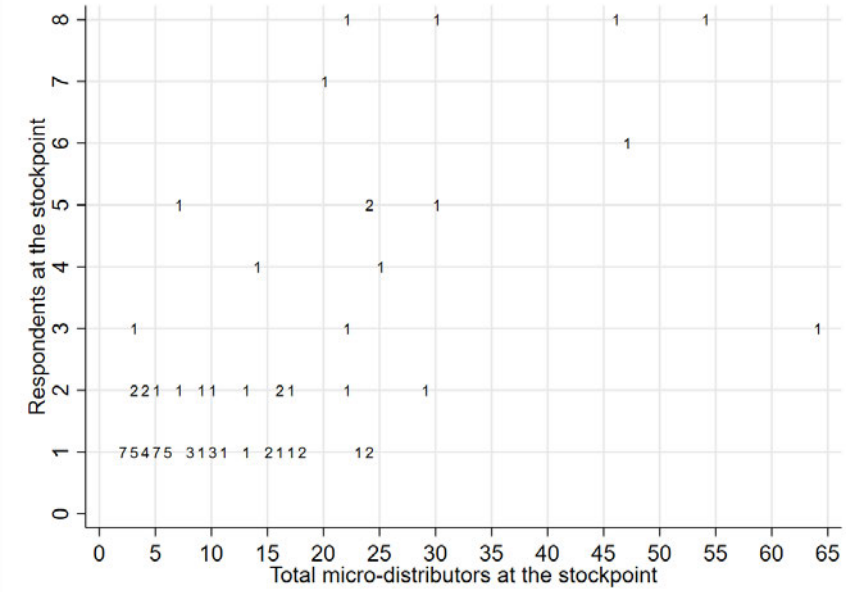
	(1)	(2)	(3)	(4)
Level of analysis:	Non-participating clients		Stockpoints	
Number treated at the stockpoint	3.96***	4.11***	4.07*	4.03**
	(1.343)	(1.388)	(2.075)	(2.039)
Constant	11.04***	10.97***	11.64***	11.64***
	(1.298)	(1.229)	(1.002)	(0.993)
Controls: Total participating at the stockpoint	yes	yes	yes	yes
Controls: Time	no	yes	no	yes
Observations	52948	52948	9737	9737

Notes: In this table, we use administrative data on micro-distributors who were not involved in our experiment, and test the consequence of random variation in the number of treated respondents at the stockpoint. We report intent-to-treat (ITT) estimates, and standard errors in parentheses (with clustering at the level of the stockpoint). * p < 0.10, ** p < 0.05, *** p < 0.01..

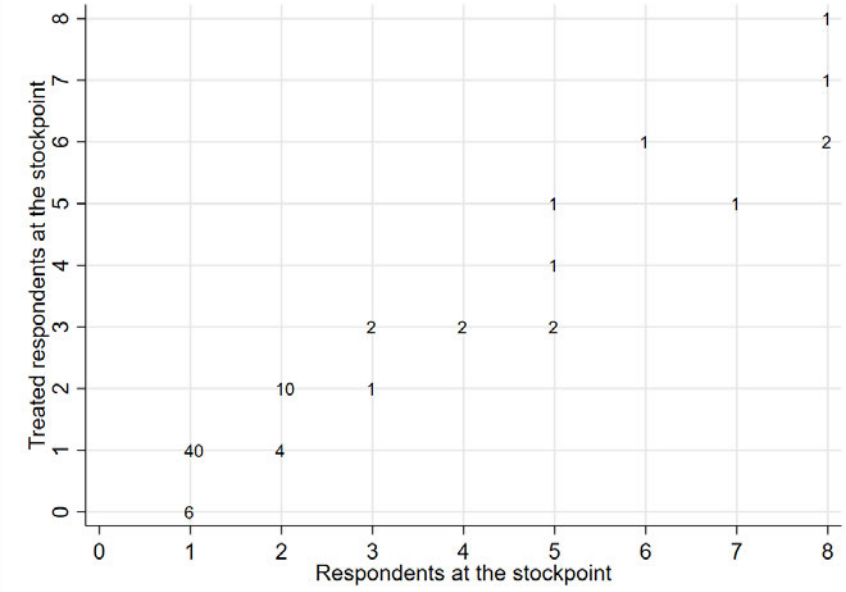
Figure A3 illustrates the underlying variation in (i) stockpoint size, (ii) number of research participants, and (iii) number of treated participants. Panel A shows the joint distribution of the number of respondents and the total number of micro-distributors at the stockpoint; the numbers on the scatterplot are the count of stockpoints having a given combination of the two variables. (Thus, for example, there are seven stockpoints that have five micro-distributors of whom one was in the research project.) Panel B shows the number of respondents at each stockpoint and the number of those who were treated; this is the exogenous variation that we rely upon for identification in this spillover analysis. (Thus, for example, there are 14 stockpoints in which we have two experimental respondents; of these, 10 of the stockpoints have both respondents treated, and four of the stockpoints have just one respondent treated.)

Appendix Figure A3: **Variation in treatment by stockpoint**

PANEL A: EXPERIMENTAL RESPONDENTS AND STOCK-POINT SIZE



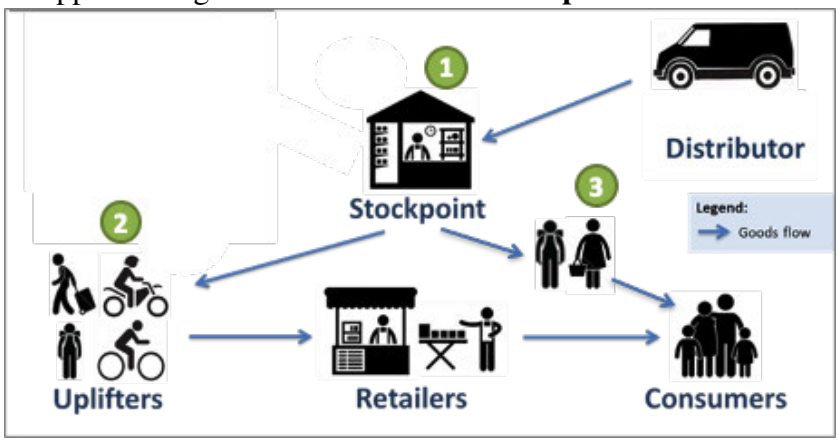
PANEL B: TREATED RESPONDENTS AND EXPERIMENTAL RESPONDENTS



This figure shows the variation that we exploit to test for spillover effects. Panel A shows the joint distribution of the number of respondents and the total number of micro-distributors at the stockpoint. Panel B shows the number of respondents at each stockpoint and the number of those who were treated; this is the exogenous variation that we rely upon for identification in this spillover analysis. In each panel, the numbers on the graph are the count of stockpoints.

A3 Additional figures and tables

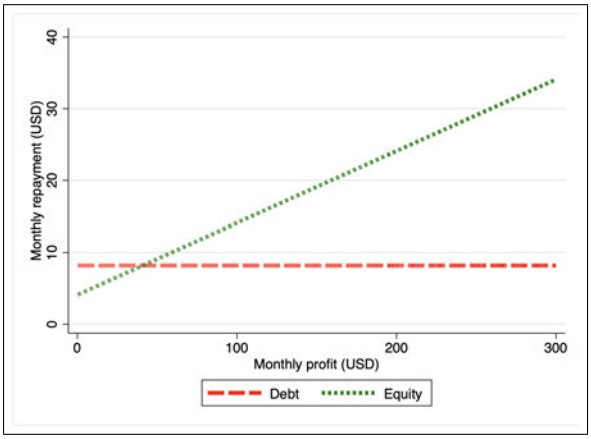
Appendix Figure A4: **Route-to market: product flowchart**



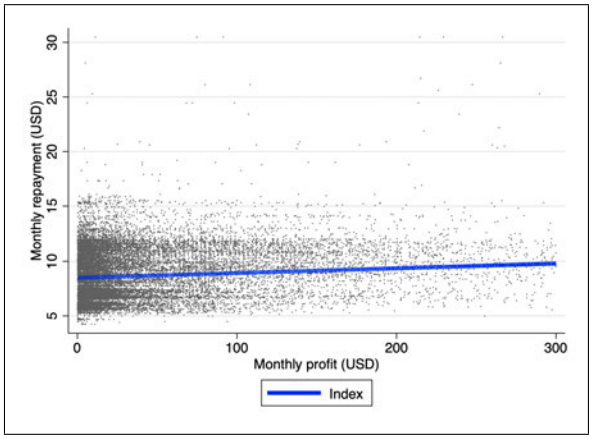
Notes: *Types of participant: (i) stockpoints — receive gum from FoodCo distributor and supply it to both 'uplifters' and 'hawkers'; (ii) uplifters — receive stock from stockpoint and sell door-to-door to retailers (kiosks, small outlets, table shops); and (iii) hawkers — receives stock from stockpoints and sell directly to end consumers.*

Appendix Figure A5: **Micro-distributor performance and contract payments**

PANEL A: DEBT AND EQUITY-LIKE CONTRACTS



PANEL B: INDEX CONTRACT



Notes: *In this figure, we plot required contract payments against micro-distributor performance (monthly profit in US$). Contract payments are based on the average bike price of US$95. Panel A illustrates payments under the 'deterministic' contracts, where payment amounts due are either completely unrelated to performance (debt contract, illustrated by the red line) or related only to one's own performance (equity and hybrid contracts, the monthly payments for both being represented by the green line). In contrast, Panel B illustrates payments under the index insurance contract, which are a realisation of a stochastic outcome (the sales of other micro-distributors in one's region), with the blue line representing the predicted payments following a regression of index payments on individual performance controlling for individual fixed effects.*

A3.1 Summary statistics and balance

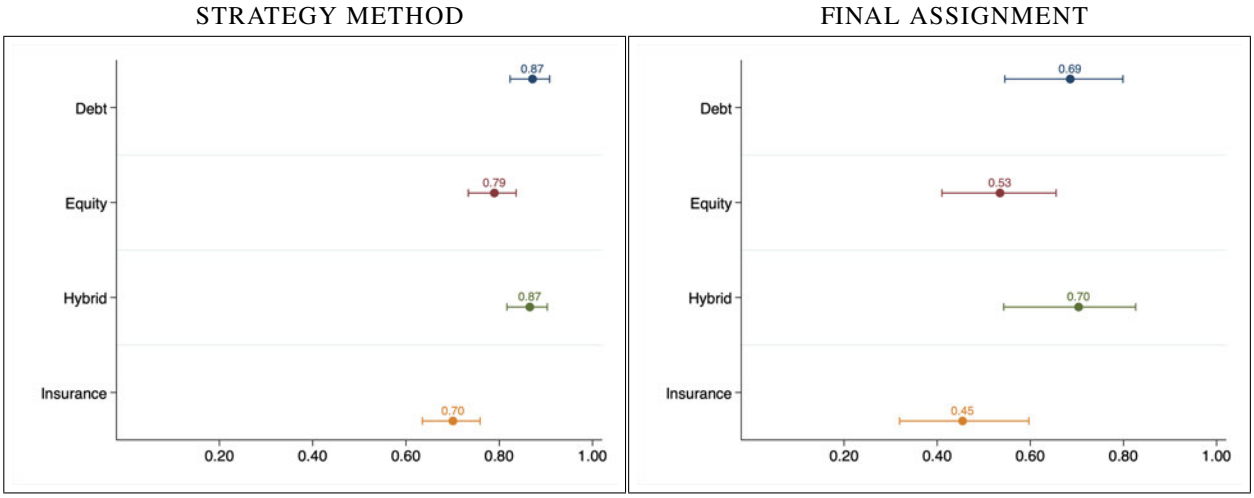
Appendix Table A2: SUMMARY STATISTICS AND BALANCE

	Control	Debt	Hybrid	Equity	Insurance	Equality test (p-val)
Age	30.29	31.32	31.62	29.41	32.31	0.219
Married	0.71	0.76	0.85	0.63	0.78	0.241
Female	0.14	0.12	0.08	0.20	0.19	0.431
Household size	3.21	3.38	3.27	3.17	3.81	0.486
Number of earners	1.43	1.44	1.35	1.34	1.56	0.256
Education (post-secondary)	0.18	0.15	0.27	0.27	0.09	0.145
Number of employees	0.46	0.12	0.15	0.02	0.16	0.109
Business profit (all sources)	131.54	123.51	138.44	101.44	151.36	0.101
Profits from selling FoodCo products	33.35	40.14	69.34	49.68	58.76	0.330
Has wage job	0.29	0.18	0.35	0.22	0.28	0.473
Wage earnings	17.54	14.47	14.62	13.29	25.78	0.675
Total household income	204.07	181.75	162.65	166.01	224.77	0.369
Consumption expenditure	173.07	207.14	221.72	179.50	200.76	0.584
Management practices	0.73	0.72	0.83	0.77	0.78	0.198
Maths score	0.61	0.66	0.65	0.63	0.66	0.798
Time preferences index	7.32	6.44	6.23	6.98	6.84	0.942
Risk aversion index	4.04	3.71	4.08	4.08	3.84	0.472
Loss aversion index	5.64	5.32	6.35	5.56	6.72	0.308
Number of individuals	28	34	26	41	32	

Notes: The first five columns present baseline summary statistics for individuals who were randomly assigned to the control, debt, hybrid, equity, or insurance arms, respectively. The sixth column presents a test of equality across the five groups. * p < 0.10, ** p < 0.05, *** p < 0.01. We also conducted an omnibus balance test of equality, which comfortably passes (p=0.497).

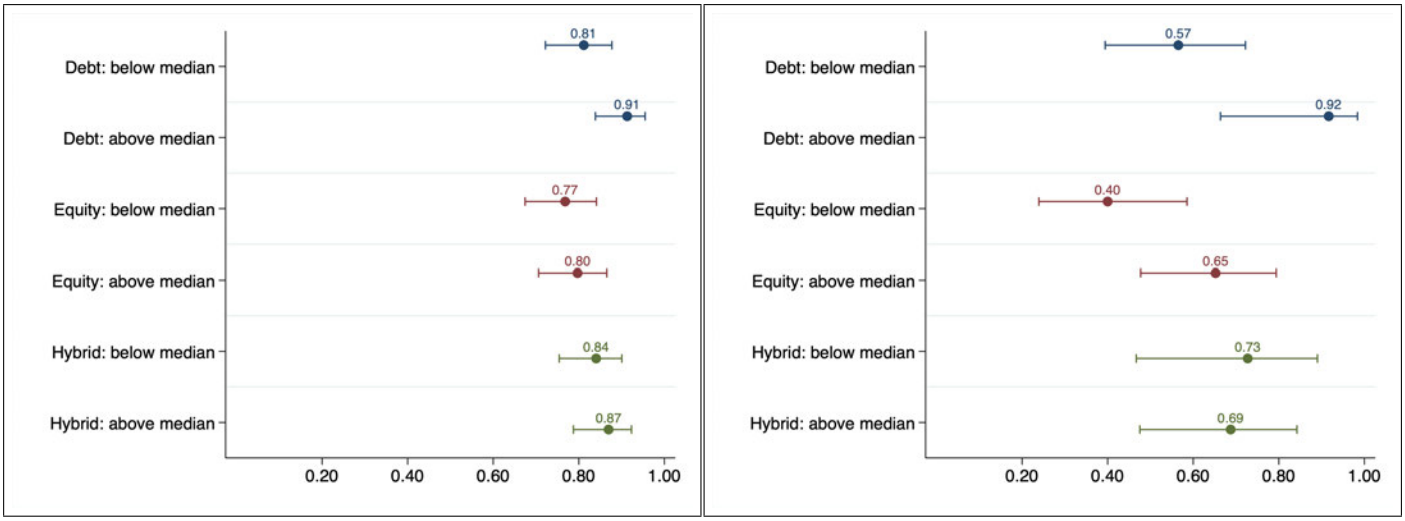
A3.2 Take-up analysis

Appendix Figure A6: Overall take-up rates



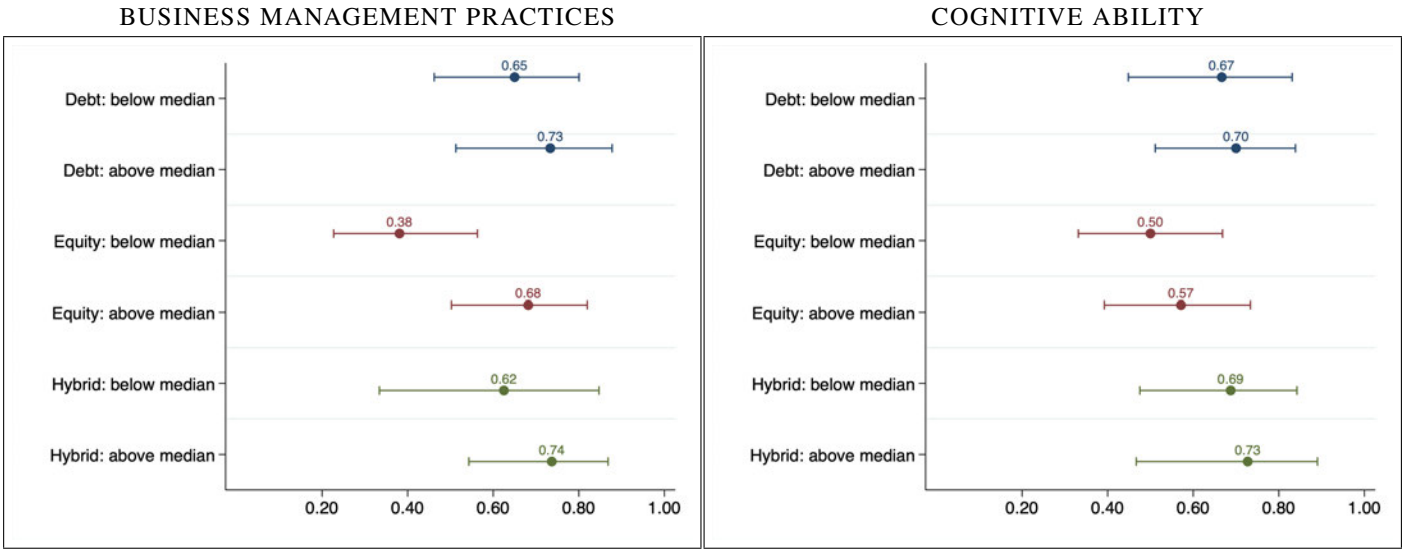
Notes: This figure displays the overall contract take-up rates, using the incentivised strategy method elicitation procedure in the left panel (four contract choices per participant), and the final random assignment for each participant in the right panel.

Appendix Figure A7: Take-up heterogeneity by baseline profits (FoodCo administrative data)



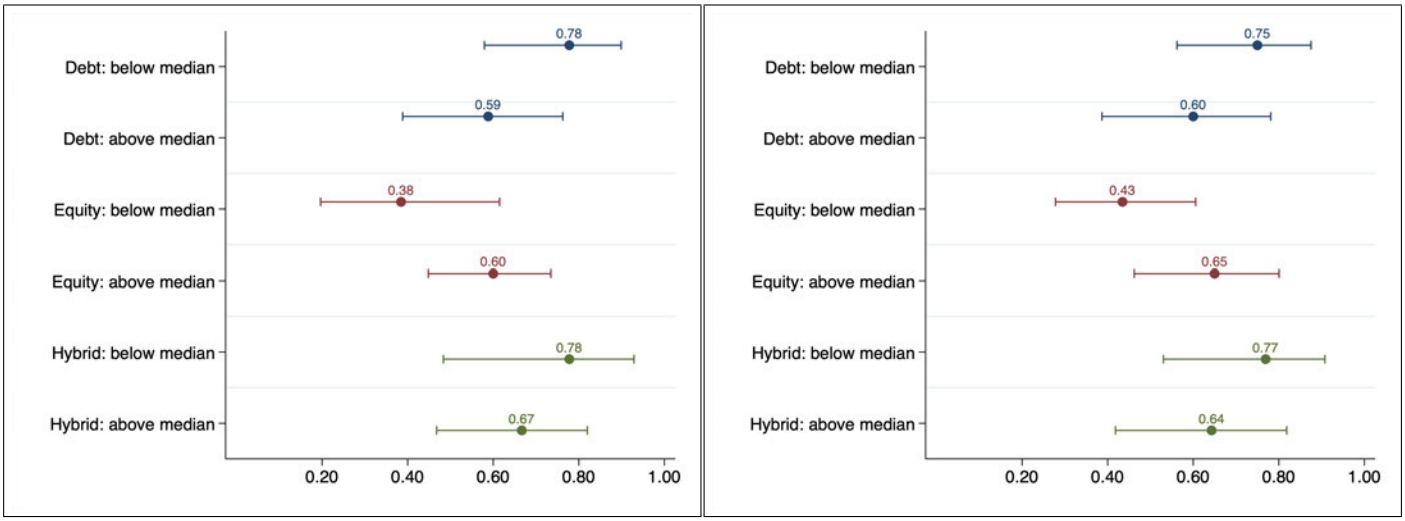
Notes: This figure displays heterogeneous take-up by baseline profitability (using FoodCo administrative data). We cannot reject equality of the difference in take-up for above- and below-median micro-distributors under the debt contract compared to the same difference for those under the equity contract ($p-$value of 0.615, or 0.663 if we also control for baseline risk preferences in the test).

Appendix Figure A8: Take-up heterogeneity by baseline management practices and cognitive ability



Notes: This figure displays heterogeneous take-up by baseline management practices (left panel) and baseline mathematical ability (right panel). We cannot statistically equality of the difference in take-up for above- and below-median ability micro-distributors under the debt contract compared to the same difference for those under the equity contract ($p-$values of 0.308 and 0.862 respectively).

Appendix Figure A9: Take-up heterogeneity: risk preferences



Notes: This figure displays heterogeneous take-up by baseline risk aversion (left panel) and loss aversion (right panel). The risk aversion measure is a combination of a broad survey on risk attitudes in a variety of domains, as well as a more narrowly-focused incentivised measure, and the loss aversion measure is from an incentivised activity. The $p-$value for a test of equality of the difference in take-up for micro-distributors with below- and above-median risk aversion under the debt contract compared to the same difference for those under the equity contract is 0.070, and 0.054 if we also control for baseline profitability in the test. The $p-$value for a test of equality of the difference in take-up for micro-distributors with below- and above-median loss aversion under the debt contract compared to the same difference for those under the equity contract is 0.094, and 0.108 if we also control for baseline profitability in the test.

A3.3 Log and IHS transformation of main outcome variable

Appendix Table A3: **Robustness: impact on transformed administrative profits**

	(1) FoodCo profits: Log	(2) FoodCo profits: IHS	(3) FoodCo profits: Log	(4) FoodCo profits: IHS
Debt	0.22	0.24	0.22	0.25
	(0.375)	(0.436)	(0.375)	(0.435)
Performance-contingent	0.74**	0.86**		
	(0.342)	(0.396)		
Hybrid			1.04**	1.21**
			(0.440)	(0.504)
Equity			0.53	0.61
			(0.384)	(0.445)
Insurance	0.08	0.09	0.09	0.10
	(0.346)	(0.402)	(0.345)	(0.402)
Observations	2598	2598	2598	2598
Individuals	161	161	161	161
Control mean	1.07	1.29	1.07	1.29
Test: Hybrid = Debt			0.074	0.066
Test: Hybrid = Equity			0.263	0.252
Test: Equity = Debt			0.441	0.430

Note: In this table we report *intent-to-treat* (ITT) estimates of the impact of treatments on the main outcome variable (administrative profits), transforming the outcome varable using both logs and inverse hyperbolic sine. Standard errors, clustered at the individual level, are reported in brackets. * p < 0.10, ** p < 0.05, *** p < 0.01.

A3.4 Local Average Treatment Effect (LATE) estimates

Appendix Table A4: **Business outcomes (LATE specification)**

	(1) FoodCo profits	(2) FoodCo profits	(3) Activity: seller	(4) FoodCo proportion	(5) Other earnings
Debt	13.55	13.55	-0.07	-0.15**	8.42
	(14.848)	(14.834)	(0.076)	(0.070)	(21.589)
Performance-contingent	37.87**				
	(15.214)				
Hybrid		43.93**	0.04	0.04	-10.32
		(19.762)	(0.059)	(0.080)	(17.671)
Equity		32.03*	-0.05	-0.02	-3.34
		(17.929)	(0.101)	(0.087)	(23.213)
Insurance	22.23	22.25	0.05	-0.12	6.48
	(18.308)	(18.250)	(0.080)	(0.096)	(32.112)
Observations	2598	2598	468	468	468
Individuals	161	161	160	160	160
Control mean	11.32	11.32	0.93	0.48	70.67

Note: In this table we report *local average treatment effect* (LATE) estimates, obtained by least-squares estimation. Columns 1 and 2 use administrative data from FoodCo on business profits, for which there is an average of 15 months of post-treatment data (up to and excluding the start of Covid-19 lockdowns in March 2020). For all other columns, we use survey data collected by enumerators using quarterly follow-up surveys (again, up to and excluding Covid-19 lockdowns). Standard errors, clustered at the individual level, are reported in brackets. * p < 0.10, ** p < 0.05, *** p < 0.01.

Appendix Table A5: **Mechanisms (LATE specification)**

	(1) Sales expansion	(2) Stockpoint visits	(3) Profit concentration	(4) Product varieties	(5) Credit extension	(6) Management practices	(7) Record keeping
Debt	0.14	1.66	-0.06	-0.03	0.02	0.00	-0.03
	(0.116)	(1.495)	(0.061)	(0.573)	(0.033)	(0.087)	(0.104)
Hybrid	0.25**	3.76*	-0.13*	0.90	0.07**	0.13*	0.19**
	(0.126)	(1.973)	(0.072)	(0.705)	(0.035)	(0.076)	(0.096)
Equity	0.26	2.08	-0.05	0.15	0.02	0.05	0.02
	(0.170)	(1.684)	(0.074)	(0.778)	(0.038)	(0.106)	(0.132)
Insurance	0.46***	0.52	0.01	0.13	-0.00	0.22**	0.24*
	(0.177)	(2.106)	(0.079)	(0.704)	(0.038)	(0.105)	(0.140)
Observations	468	2598	2598	2598	468	468	468
Individuals	160	161	161	161	160	160	160
Control mean	0.58	2.42	0.55	1.33	0.08	0.68	0.65

Note: In this table we report *local average treatment effect* (LATE) estimates, obtained by least-squares estimation. We use information from daily administrative data (columns 2 to 4) and survey data from all participants (columns 1 and columns 5 to 7) to explore a number of variables that shed light on the mechanisms for our results from Table 1: how often distributors visit stock-points in a given month to purchase inventory (which ranges from 0 to 31), how concentrated their total monthly profit is over those visits (Herfindahl index), the number of FoodCo products they sell in their monthly portfolio (which ranges from 1 to 6), whether they sell to distant customers (greater than 1km from their stock-point), whether they extend credit to customers, and their business management practices (an overall index and specifically record keeping). Standard errors, clustered at the individual level, are reported in brackets. * p < 0.10, ** p < 0.05, *** p < 0.01.

A3.5 Randomisation inference

Appendix Table A6: **Business outcomes**

	(1) FoodCo profits	(2) FoodCo profits	(3) Activity: seller	(4) FoodCo proportion	(5) Other earnings
Debt	10.39	10.39	-0.05	-0.11	5.95
	(0.369)	(0.369)	(0.389)	(0.022)**	(0.697)
	[0.470]	[0.489]	[0.410]	[0.038]**	[0.689]
Performance-contingent	25.96				
	(0.017)**				
	[0.038]**				
Hybrid		34.43	0.03	0.03	-7.73
		(0.025)**	(0.530)	(0.642)	(0.563)
		[0.028]**	[0.644]	[0.604]	[0.632]
Equity		19.61	-0.03	-0.01	-1.68
		(0.097)*	(0.627)	(0.788)	(0.891)
		[0.154]	[0.635]	[0.811]	[0.902]
Insurance	11.85	11.87	0.02	-0.06	3.07
	(0.252)	(0.249)	(0.590)	(0.178)	(0.843)
	[0.427]	[0.433]	[0.718]	[0.233]	[0.835]
Observations	2598	2598	468	468	468

Note: In this table we repeat the analysis from Table 1 of the paper, using randomisation inference. Standard errors, clustered at the individual level, are reported below each coefficient, with standard p-values in parentheses, and randomization inference p-values in square brackets. * p < 0.10, ** p < 0.05, *** p < 0.01.

Appendix Table A7: **Mechanisms**

	(1) Sales expansion	(2) Stockpoint visits	(3) Profit concentration	(4) Product varieties	(5) Credit extension	(6) Management practices	(7) Record keeping
Debt	0.10	1.28	-0.05	-0.02	0.01	0.00	-0.02
	(0.240)	(0.270)	(0.341)	(0.962)	(0.564)	(0.963)	(0.759)
	[0.229]	[0.333]	[0.349]	[0.970]	[0.554]	[0.972]	[0.754]
Hybrid	0.19	2.96	-0.10	0.71	0.05	0.10	0.14
	(0.035)**	(0.056)*	(0.066)*	(0.181)	(0.049)**	(0.074)*	(0.036)**
	[0.029]**	[0.036]**	[0.054]*	[0.183]	[0.030]**	[0.107]	[0.062]*
Equity	0.13	1.29	-0.03	0.10	0.01	0.03	0.01
	(0.128)	(0.214)	(0.480)	(0.829)	(0.551)	(0.627)	(0.897)
	[0.078]	[0.329]	[0.506]	[0.831]	[0.565]	[0.629]	[0.897]
Insurance	0.22	0.27	0.01	0.07	-0.00	0.11	0.11
	(0.004)***	(0.812)	(0.847)	(0.854)	(0.907)	(0.036)**	(0.097)*
	[0.003]***	[0.845]	[0.886]	[0.884]	[0.909]	[0.054]*	[0.128]
Observations	468	2598	2598	2598	468	468	468

Note: In this table we repeat the analysis from Table 2 of the paper, using randomisation inference. Standard errors, clustered at the individual level, are reported below each coefficient, with standard p-values in parentheses, and randomization inference p-values in square brackets. * p < 0.10, ** p < 0.05, *** p < 0.01.

Appendix Table A8: **Household consumption and health**

	(1) Expenditure: food	(2) Expenditure: clothing	(3) Expenditure: schooling	(4) Health impedes work	(5) Work caused pain
Debt	8.99	0.25	-4.91	-0.09	-0.10
	(0.078)*	(0.897)	(0.153)	(0.219)	(0.118)
	[0.058]*	[0.907]	[0.159]	[0.236]	[0.141]
Hybrid	8.47	4.92	3.10	-0.06	-0.03
	(0.100)*	(0.040)**	(0.478)	(0.475)	(0.691)
	[0.090]*	[0.038]**	[0.388]	[0.469]	[0.669]
Equity	1.54	-0.16	-0.81	-0.07	-0.02
	(0.710)	(0.942)	(0.824)	(0.310)	(0.761)
	[0.741]	[0.934]	[0.814]	[0.287]	[0.744]
Insurance	8.18	-2.34	-0.44	-0.03	0.02
	(0.056)*	(0.238)	(0.897)	(0.685)	(0.810)
	[0.092]*	[0.283]	[0.910]	[0.665]	[0.775]
Observations	468	468	468	468	468

Note: In this table we repeat the analysis from Table 3 of the paper, using randomisation inference. Standard errors, clustered at the individual level, are reported below each coefficient, with standard p-values in parentheses, and randomization inference p-values in square brackets. * p < 0.10, ** p < 0.05, *** p < 0.01.

A4 Controlling for baseline profits and risk preferences

Appendix Table A9: **Business outcomes**

	(1) FoodCo profits	(2) FoodCo profits	(3) Activity: seller	(4) FoodCo proportion	(5) Other earnings
Debt	10.33	10.27	-0.03	-0.06	4.46
	(8.781)	(8.867)	(0.059)	(0.048)	(18.519)
Performance-contingent	31.35***				
	(9.884)				
Hybrid		31.39**	0.07*	0.07	-8.43
		(13.090)	(0.039)	(0.050)	(16.106)
Equity		24.58**	0.02	0.01	-0.64
		(11.415)	(0.047)	(0.047)	(16.580)
Insurance	17.96*	17.82*	0.04	0.00	1.60
	(10.304)	(10.422)	(0.046)	(0.045)	(17.796)
Observations	2598	2598	468	468	468
Individuals	161	161	160	160	160
Control mean	11.32	11.32	0.93	0.48	70.67
Test: Hybrid = Debt		0.105	0.075	0.005	0.339
Test: Hybrid = Equity		0.636	0.234	0.190	0.447
Test: Equity = Debt		0.216	0.424	0.078	0.716

Note: In this table we report *intent-to-treat* (ITT) estimates that replicate the analysis from Table 1 in the main paper, while controlling for (de-meaned) baseline values of profits and risk preferences, as well as the de-meaned variables interacted with each treatment indicator. Standard errors, clustered at the individual level, are reported in brackets. * p < 0.10, ** p < 0.05, *** p < 0.01.

Appendix Table A10: **Mechanisms**

	(1) Stockpoint visits	(2) Profit concentration	(3) Product varieties	(4) Sales expansion	(5) Credit extension	(6) Management practices	(7) Record keeping	(8) Bike use: business	(9) Bike use: hours
Debt	1.52	-0.08	-0.07	0.08	0.03	0.05	0.01	0.73***	22.32***
	(1.028)	(0.055)	(0.395)	(0.078)	(0.024)	(0.075)	(0.083)	(0.055)	(2.142)
Hybrid	3.25**	-0.12**	0.71	0.18**	0.06***	0.15**	0.18**	0.90***	34.82***
	(1.408)	(0.055)	(0.493)	(0.086)	(0.024)	(0.057)	(0.072)	(0.037)	(5.553)
Equity	2.45**	-0.07	0.55	0.12	0.02	0.08	0.06	0.71***	24.90***
	(1.057)	(0.051)	(0.427)	(0.080)	(0.020)	(0.061)	(0.071)	(0.058)	(2.067)
Insurance	0.98	-0.04	0.18	0.19**	0.02	0.16***	0.15**	0.79***	31.23***
	(1.122)	(0.048)	(0.402)	(0.075)	(0.016)	(0.058)	(0.073)	(0.068)	(5.981)
Observations	2598	2598	2598	468	468	468	468	468	468
Individuals	161	161	161	160	160	160	160	160	160
Control mean	2.42	0.55	1.33	0.58	0.08	0.68	0.65	0.00	0.00
Test: Hybrid = Debt	0.238	0.345	0.090	0.136	0.216	0.116	0.015	0.008	0.036
Test: Hybrid = Equity	0.549	0.214	0.740	0.382	0.113	0.124	0.037	0.006	0.094
Test: Equity = Debt	0.396	0.873	0.109	0.517	0.867	0.653	0.463	0.847	0.386

Note: In this table we report *intent-to-treat* (ITT) estimates that replicate the analysis from Table 2 of the main paper, while controlling for (de-meaned) baseline values of profits and risk preferences, as well as the de-meaned variables interacted with each treatment indicator. Standard errors, clustered at the individual level, are reported in brackets. * p < 0.10, ** p < 0.05, *** p < 0.01.

A5 Aggregate profit analysis

Appendix Table A11: **Aggregate profit**

	(1) Micro-distributor profit	(2) FoodCo profit	(3) MFI profit	(4) Aggregate profit
Debt	10.39	1.49	-1.68***	7.09
	(11.520)	(37.089)	(0.349)	(45.672)
Hybrid	34.43**	75.77	-0.59**	100.39
	(15.227)	(70.574)	(0.291)	(84.743)
Equity	19.61*	31.39	-0.46	45.41
	(11.742)	(49.660)	(0.405)	(59.853)
Insurance	11.87	25.08	-1.42***	33.32
	(10.269)	(31.773)	(0.440)	(39.331)
Observations	2598	2598	2598	2598
Individuals	161	161	161	161
Control mean	11.32	47.97	0.00	59.29
Test: Hybrid = Debt	0.133	0.351	0.018	0.325
Test: Hybrid = Equity	0.357	0.586	0.787	0.571
Test: Equity = Debt	0.472	0.609	0.023	0.582

Note: In this table we report intent-to-treat (ITT) estimates, obtained by least-squares estimation. Column 1 displays monthly profits for micro-distributors (replicating the main outcome from column 2 of Table 1 of the paper). Column 2 displays the monthly profits for FoodCo over the same follow-up period, estimated from the per-product profit margin for each of the six possible FoodCo products that micro-distributors can sell (for which we observed the exact breakdown). Column 3 displays the profit for the MFI over the same follow-up period, based on the repayment data (up until the outbreak of Covid-19, when repayment collection was halted) for those micro-distributors who took up the financing contract offer, imputed by distributing the cumulative gain or loss over the number of follow-up periods to match the administraive data on profits from FoodCo. Finally, Column 4 displays the aggregate profit variable, combining the return to the micro-distributor, FoodCo and the MFI. Standard errors, clustered at the individual level, are reported in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

A6 Baseline workshop elicitation procedure

Micro-distributors who expressed their interest in the purchase of a bicycle were invited to a workshop, where they completed a baseline survey and several activities to measure risk preferences and loss aversion. There were two risk preference elicitation activities; the first was a self-reported measure, using a series of questions that asked individuals about their risk-taking in their occupation, in financial matters, in their faith in others, and a general question on overall risk taking. Responses were given on a scale of 1 to 10, with 0 representing 'risk-averse' and 10 representing 'fully prepared to take risks'. The questions were adapted from Dohmen et al. (2011), and have been used by other researchers in several settings, and often demonstrated a reasonably strong correlation with important 'real-world' outcomes. The second measure of risk preferences was incentivised. Respondents were asked 30 questions that required them to choose between a certain amount of money and an uncertain prospect, which had two possible outcomes: (i) a 'bad' outcome, with a payoff of zero; or (ii) a 'good' outcome, with a payoff of KES 1,000. We adapted the measures used by Barr and Packard (2002) and Vieider et al. (2015). We also measured loss aversion by adapting the measure used by Bartling, Fehr, and Herz (2014). Respondents had to choose between a series of binary-outcome prospects that involved a large positive outcome or a (gradually increasing) negative outcome, which they could accept or reject. If they accepted the investments and the loss aversion activity was chosen for payment at the end of the workshop, a realised loss was taken out of their guaranteed workshop participation fee; as such, this represented a potential real loss.

For the incentivised activities, participants were informed that, at the end of the behavioural games session, one of the activities would be selected for payment by physically drawing a ball from a bag. Within the selected activity, balls would be drawn to select the one final question that would be used for payment. As such, participants were required to answer all questions attentively, because any question could have been selected. This method also allowed the use of payment amounts that were relatively large, with the average payment being approximately three times as large as median daily business profits for micro-distributors.

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