Testing Evolutionary Theories of Cooperation via Meta-Analysis of Predictors of Repayment for Joint Liability Microfinance Loans

PRISMA-P Statement and Study Pre-Registration

SECTION 1: Administrative Information

Title

Item 1a. *Identify the report as a protocol of a systematic review or meta-analysis.*
Items in this document are based on the 'Preferred Reporting Items for Systematic Review and Meta-Analysis Protocols Statement' (PRISMA-P) (Moher et al., 2015; Shamseer et al., 2015).
Item 1b. *If the protocol is for an update of a previous systematic review, identify as such.*
This is an original study protocol for a novel set of meta-analyses.

Registration

Item 2. *If registered, provide the name of the registry and registration number.*
In accordance with open science guidelines (Munafò et al., 2017), this study was pre-registered on the Open Science Framework as an Open Ended Registration, submitted on 05/07/2021. The pre-registration and associated materials are available from: https://osf.io/wsdjn/.

Authors

Item 3a. *Provide the name, institutional affiliation, and email address of all protocol authors; provide physical mailing address of corresponding author.*
Dugald Foster[1], Alex Mesoudi[1], Erik Postma[1], Shakti Lamba[1]. Author affiliations and mailing address: **1.** College of Life and Environmental Sciences, University of Exeter Penryn Campus, Penryn, Cornwall, TR10 9FE, UK. Email addresses: df364@exeter.ac.uk, a.mesoudi@exeter.ac.uk, e.postma@exeter.ac.uk, s.lamba@exeter.ac.uk
Item 3b. *Describe contributions of protocol authors and identify the guarantor of the review (the author who takes overall responsibility for the scientific integrity of the study).*
DF, **AM**, **EP** and **SL** co-designed the study. **DF** drafted the protocol with input from **AM**, **EP** and **SL**, and all authors contributed to the final version. **DF** is the guarantor.

Amendments

Item 4. *If the protocol represents an amendment of a previously completed or published protocol, identify as such and list changes; otherwise, state plan for documenting important protocol amendments.*
*A*mendments to the protocol made post-submission will be maintained in a live document that records the date of the amendment and justification for any decisions that could affect study outcomes (see **Section 4, Protocol Deviations**). An updated copy of this document will be maintained on the Open Science Framework page for this project.

Support

Item 5a. *Indicate sources of financial or other support for the review.*
This study is funded by a Royal Society University Research Fellowship (UF150036) and

research grant (RG160537) awarded to Shakti Lamba.
Item 5b. *Provide name for the review funder and/or sponsor.*
This study was not commissioned or in receipt of specific sponsorship.
Item 5c. *Describe roles of funder(s), sponsor(s), and/or institution(s), if any, in developing the protocol.*
The Royal Society was not involved in the design of the study, data collection or analysis. The funder will have no input in the interpretation of or decision to publish the study results.

SECTION 2: Introduction

Rationale

Item 6. *Describe the rationale for the review in the context of what is already known.*

Study Background

Introduction to Joint Liability Microfinance Loans

Microfinance loans are designed for people who cannot access traditional loans from banks, either because they cannot provide the collateral (such as land, property or other material assets) required by banks as a guarantee against non-repayment, or because they are otherwise excluded from financial services, for example due to geographic barriers and lack of banking infrastructure (Armendariz and Morduch, 2010). Originally developed in the 1970s as a poverty alleviation tool, microfinance loans were intended to provide small amounts of capital to low-income borrowers at relatively low interest rates, allowing them to create and invest in entrepreneurial businesses (Hulme and Mosley, 1996). The goal was for these businesses to eventually become self-sustaining, thus reducing financial poverty. In practice, microfinance loans are also used by borrowers to insure themselves against financial risks such as drought or crop failure, for large expenses such as school or medical fees, and as a buffer against variability in income (Armendariz and Morduch, 2010). Microfinance loans are popular globally, with around 140 million customers borrowing 125 billion US dollars in 2018, and the largest markets operating in Southeast Asia, Latin America and the Caribbean, and East Asia and the Pacific (Microfinance Barometer, 2019).

Some microfinance institutions offer “joint liability” loans, provided to a group of borrowers who assume collective responsibility for repaying the loan (other names for this type of loan include “group loans” or “solidarity loans”). Once a loan group has been formed by individuals interested in taking out a loan, the group meets a representative from a lending institution (known as the “loan officer”) to sign a loan contract stipulating the size of the loan, the interest rate, and the repayment schedule. Crucially, all members of the group must also accept the terms of joint liability attached to the loan. The group of borrowers then receive and invest their loans at their discretion. At the agreed intervals, the loan group convenes at repayment meetings for members to repay their individual shares of the group loan, with payments collected by the group’s loan officer. If a borrower does not attend the meeting or fails to repay her share, the other members of her group are collectively liable for her repayment. If the entire loan is not repaid by the group one way or another, all members are banned from accessing further loans, and could face additional penalties (Armendariz and Morduch, 2010). According to prominent theoretical models in economics, joint liability loans therefore offer microfinance institutions a way to insure themselves against the risk of individual borrowers failing to repay, by replacing material collateral with social collateral (Armendáriz, 1999; Besley and Coate, 1995; Conning and Udry, 2007; Ghatak and Guinnane, 1999; Stiglitz, 1990; Van Tassel, 1999; Varian, 1990).

As these models illustrate, the behavioural dynamics of joint liability lending are complex. The shared responsibility of repaying a group loan creates a cooperative dilemma: a scenario in which "selfish" individuals who maximise their own success outperform cooperative individuals who pay a cost to benefit others in the group, but groups of cooperators outperform groups of non-cooperators (Dawes, 1980; Olson, 1971). This means individual- and group-level interests are in conflict, hence the dilemma. Under joint liability, microfinance borrowers seeking to maximise their immediate financial returns have an incentive to default on their repayment dues (in effect receiving a "free" loan), and to free-ride on the repayment efforts of others in their loan group. But the loan group succeeds only if the total loan amount is repaid, thereby ensuring continued access to future (and potentially larger) loans for all group members. To successfully repay a group loan, borrowers must therefore cooperate: first by repaying their own share of the loan, and if necessary by enforcing the payment of money owed by any defaulting group members, or else paying it themselves (Besley and Coate, 1995).

Given the global popularity of joint liability microfinance, it is important to understand what makes loan groups work, and what prevents them from becoming overrun by free-riding defaulters. While many microfinance institutions regularly report high repayment rates for group loans (Cull et al., 2007), there is considerable variation in loan repayment efficacy across time and space (Attanasio et al., 2015; Carpena et al., 2013; Gine and Karlan, 2014; Mahmud, 2019). For example, the Grameen Bank, one of the largest microfinance institutions in Bangladesh, has reported variation in repayment rates for group loans from 100% of loans repaid in one district of the country to 30% in another (Woolcock, 1999). During the Indian microfinance crisis of 2010, national group loan repayment rates dropped from 98% of loans repaid to 10% (Haldar and Stiglitz, 2016). We hypothesise that this variation in repayment rates reflects variation in the ability of loan groups to solve the cooperative dilemma underlying the joint liability model and successfully repay their loans. We therefore predict that if joint liability lending relies on cooperation between borrowers, factors which facilitate cooperation between borrowers will show a positive association with group loan repayment efficacy.

Applying Evolutionary Theories of Cooperation to Microfinance Loan Repayment

In the evolutionary sciences, cooperative behaviours are formally defined as those that provide a benefit to the evolutionary success of the recipient of the behaviour, and which have evolved at least partly due to that benefit (West et al., 2007). For example, a parent which provides care for its offspring increases the offspring's chances of survival, and parental care as a behaviour is likely to have evolved because of this benefit it provides (Royle et al., 2012). One of the primary research aims for evolutionary scientists is to understand how cooperative behaviours which benefit others, and which could even be individually costly to perform, could evolve and be maintained. Without some mechanism capable of preventing the exploitation of cooperators, it is difficult to explain how cooperative behaviours are reproduced over generations, or spread across populations.

Researchers have identified a number of such mechanisms that can support the evolution and maintenance of cooperation in humans and other species (Apicella and Silk, 2019; Clutton-Brock, 2009; Croft et al., 2014; Frank, 2009; Lehmann and Keller, 2006; Leigh, 2017; Nowak, 2006; Powers et al., 2019; Rand and Nowak, 2013; Sachs et al., 2004; West et al., 2007; West et al., 2011), and which could also explain why humans are more or less likely to cooperate under particular circumstances. Theoretical models, laboratory experiments and field studies have all been used to explore the viability of these mechanisms (Apicella and Silk, 2019; Nowak, 2006). However, most studies have tested the effects of individual mechanisms in isolation - few have tested and compared mechanisms simultaneously using real-world human behavioural data (Leimar and Hammerstein, 2006). Due to its global implementation across varied human ecologies, populations, and cultures, joint liability lending provides an opportunity to test multiple evolutionary mechanisms of cooperation within the context of the same real-world cooperative dilemma.

The necessary conditions for the evolution of cooperation in biology have been formalised in Hamilton's Rule, a statement originally proposed to explain why any given social interaction would be favoured by natural selection (Hamilton, 1963). Hamilton's Rule consists of the inequality:

$$\mathbf{rb > c}$$

This states that a behaviour will evolve if the benefit (**b**) to the recipient, scaled by the degree of relatedness (**r**) between the actor and the recipient relative to the population mean, is greater than the cost of cooperation (**c**) to the actor, with costs and benefits measured by the impact of the behaviour on reproductive success. Genetic relatives share a higher than average proportion of genes due to their common ancestry (any two individuals may share genes by chance, so (**r**) reflects the *increased* relatedness of the actor and recipient). This means that cooperating with a recipient of low relatedness could outweigh the costs of cooperation to the actor, if the benefit provided to the recipient is large enough. Conversely, a cooperative behaviour could evolve if it provides even a small benefit to a highly related recipient. Assuming cooperative behaviour is genetically heritable, by helping a relative to survive and reproduce, the actor indirectly promotes the reproduction of its own genes. Thus any trait's evolutionary success (i.e. its chances of being reproduced in future generations) depends on both its direct benefits to the individual, and its indirect benefits to the individual's relatives. W.D. Hamilton, the originator of this insight, called this the theory of "inclusive fitness" (Hamilton, 1964a). Inclusive fitness theory has been hugely successful in explaining the evolution of cooperation between kin across many species (Abbot et al., 2011; Bourke, 2011; Westneat et al., 2010).

However, in humans cooperation is also common between non-kin, creating a need for alternative explanatory mechanisms and broader theories of cooperation. While different mechanisms are likely to explain the evolution of cooperation in different contexts, some scholars have concluded that many supposedly distinct mechanisms supporting cooperation can be theoretically unified due to their ultimately equivalent effects - inducing "positive assortment" between individuals with the same cooperative traits, so that cooperators are more likely to interact with other cooperators, and free-riders with other free-riders (Eshel and Cavalli-Sforza, 1982; Fletcher and Doebeli, 2009; Fletcher and Zwick, 2006; Hamilton, 1975; Queller, 1985; Skyrms, 1996; Wilson and Dugatkin, 1997; Woodcock and Heath, 2002). The evolutionary logic of positive assortment is as follows: cooperators who interact with other cooperators receive greater benefits relative to both a) cooperators who interact with free-riders (these cooperators pay costs but receive no benefits); and b) free-riders who interact with other free-riders (these free-riders pay no costs but also receive no benefits). However, cooperators who interact with other cooperators will always be outperformed by free-riders who interact with cooperators, because these free-riders do not pay the costs of cooperation, but they do receive the associated benefits. A summary of these contingent interaction outcomes is displayed in **Table 1**.

Table 1. *A payoff matrix showing hypothetical returns to cooperation and free-riding strategies under random assortment (i.e. actors are equally likely to encounter cooperators or free-riders). Each cell shows the costs, benefits and total payoffs to the actor, of some theoretical quantity they are seeking to maximise (e.g. financial returns from a group loan). Cooperators always pay a cost (-1) to create the benefits of cooperation (+2), but these benefits only materialise if they interact with another cooperator. Free-riders on the other hand never pay a cost, but still receive the benefits of cooperation if they happen to interact with a cooperator. Free-riding therefore provides greater returns on average, making it the more successful strategy. This creates an obstacle for the evolution of cooperation.*

		Partner Strategy	
		Cooperate	**Free-ride**
Actor Strategy	**Cooperate**	Cost: -1 Benefit: +2 Total: +1	Cost: -1 Benefit: 0 Total: -1
	Free-ride	Cost: 0 Benefit: + 2 Total: +2	Cost: 0 Benefit: 0 Total: 0

In a population of randomly interacting cooperators and free-riders, if free-riding is on average the more successful evolutionary strategy, free-riders will outcompete cooperators and the proportion of free-riders in the population will grow. As a result of this, the likelihood of a cooperator encountering another cooperator declines, further reducing the returns to cooperating. Assortment-based mechanisms suggest that cooperation evolves when cooperators are more likely to interact with other cooperators on average, so that cooperators can accumulate some benefits of cooperation which are inaccessible to free-riders (for the extreme case of perfect positive assortment, see **Table 2**). These differential benefits promote selection for cooperators, so that cooperation can evolve.

Table 2. *A payoff matrix showing hypothetical returns to cooperation and free-riding strategies under full positive assortment (i.e. actors only ever encounter partners playing the same strategy). Each cell shows the costs, benefits and total payoffs to the actor, of some theoretical quantity they are seeking to maximise (e.g. financial returns from a group loan). Cooperators receive benefits denied to free-riders, so that cooperating is the more*

successful strategy. The “X” symbol denotes that these interactions do not occur, due to full positive assortment.

		Partner Strategy	
		Cooperate	**Free-ride**
Actor Strategy	**Cooperate**	Cost: -1 Benefit: +2 Total: +1	X
	Free-ride	X	Cost: 0 Benefit: 0 Total: 0

In a more generalised version of Hamilton’s Rule, the term for relatedness (**r**) can be expanded to denote not genetic relatedness, but instead the degree of cooperative assortment between the actor and recipient (this can also be thought of as how “related” two individuals are in their tendency to cooperate). This update to the rule means the evolution of cooperation is not necessarily reliant on genetic relatedness, and we can also relax the assumption of a genetic basis to cooperative behaviours. Assortment can instead be driven by any mechanism capable of inducing interactions between cooperators at greater-than-chance levels (Fletcher and Zwick, 2006; Grafen, 1985; Hamilton, 1975; Price, 1970). The problem of explaining the existence of cooperation then becomes to identify mechanisms which induce and maintain assortment between cooperators, enabling them to accrue benefits that are denied to free-riders, thus favouring the evolution of cooperation.

Shakti Lamba (Lamba, 2014) identified the potential of using joint liability lending as a model system to test evolutionary theories of cooperation, and provided links between the literature on the evolution of cooperation in biology and the literature on joint liability microfinance. This research programme was developed by (Gehrig et al., 2021), who qualitatively summarised the effects of a range of variables on loan repayment in a set of microfinance studies. The authors collected data on 142 associations between predictor variables and repayment outcomes in statistical models from 41 studies, and categorised variables by the concepts they measured (for example, “variables measuring the presence of relatives in loan groups”). They then matched these variable categories to evolutionary mechanisms capable of supporting cooperation (such as “common ancestry”). To estimate the importance of mechanisms in promoting repayment, they used the vote counting method, which involves summing the number of statistically significant associations between variable categories and loan repayment outcomes. Variable categories including a greater proportion of statistically significant positive associations with loan repayment were interpreted to show greater support for the role of the evolutionary mechanisms to which they were matched. However, as noted by the authors (Gehrig et al., 2021), the vote counting method carries severe limitations, including an inability to assess the magnitude of any effects, and a failure to assign differential weights to studies based on study characteristics such as study quality and statistical power (Higgins and Thomas, 2019). Nonetheless, (Gehrig et al., 2021) provided a useful preliminary evaluation of the loan repayment literature as a model system to test evolutionary theories of cooperation, and uncovered heterogeneity in the effects of variables on repayment which merits further investigation.

Study Aims

This study aims to test evolutionary theories of cooperation in the context of the real-world cooperative dilemma created by joint liability microfinance, developing previous work on the topic (Gehrig et al., 2021; Lamba, 2014) with more rigorous and extended analyses. The joint liability microfinance literature contains diverse and contradictory findings concerning the relative importance of factors which promote loan repayment, and many factors have only been assessed in one context (Banerjee, 2013; Galariotis et al., 2011; Hermes and Lensink, 2007; Lamba, 2014). Using an evolutionary approach we aim to explain and unify these behavioural insights under a general theoretical framework (Gehrig et al., 2021; Muthukrishna and Henrich, 2019). We will conduct the first ever meta-analyses of the effects of predictor variables on joint liability loan repayment to estimate their average effects, and to assess the uncertainty, heterogeneity and generalizability of these effects. In doing so we aim to simultaneously consolidate previous research on the determinants of joint liability loan repayment, and contribute to research on the evolution of cooperation in humans.

The results of these meta-analyses could inform microfinance research and practice by revealing important predictors of cooperation in loan groups, and their underlying mechanisms, which could lead to practical suggestions for enhancing borrower welfare and increasing loan repayment rates. Furthermore, joint liability loans share structural features with other cooperative dilemmas in which interdependent members of a group are required to cooperate by paying a personal cost to benefit others, such as the collective action problems involved in the management of natural resources (Hardin, 1968; Kraft-Todd et al., 2015; Ostrom, 1990). The ability of humans to generate solutions to cooperative dilemmas has also been proposed as a major cause of the evolutionary success of our species (Boehm, 1999; Bowles and Gintis, 2013; Kramer, 2019). Results from this study could therefore inform our understanding of the evolution and maintenance of cooperation in human social groups more generally. Finally, our research contributes towards recent attempts to explain contemporary human behaviour using applied evolutionary theory (Brooks et al., 2018; Creanza et al., 2017; Gibson and Lawson, 2014; Mesoudi, 2011; Muthukrishna, 2020; Nettle et al., 2013; Sear et al., 2016; Wells et al., 2017). The following section introduces evolutionary theories of cooperation, followed by an explanation of how we plan to test these by meta-analysing the effects of variables from loan repayment studies.

Study Hypotheses and Predictions

In the following section we specify seven hypotheses (**H1 - H7** below) based on prominent evolutionary mechanisms that could plausibly support cooperation among microfinance borrowers by increasing assortment between cooperators. Six of these hypotheses (**H1 - H6**) are the same as those tested in the preliminary analysis of (Gehrig et al., 2021), and we add a seventh (**H7**). For each hypothesised mechanism we:

1. Introduce its theoretical basis;
2. Describe how it could apply to joint liability loans;
3. Make predictions regarding its effect on group loan repayment outcomes;

4. List the relevant variable categories from loan repayment studies which we plan to meta-analyse in order to test these predictions, thus providing evidence either for or against the importance of the mechanism in supporting group loan repayment.

We declare no predictions concerning the relative magnitude of the effects of these mechanisms, which may coincide in complex ways. During a pilot analysis of the 41 studies included in (Gehrig et al., 2021) which we conducted to inform our meta-analysis protocol, we decided on a final set of 12 variable categories (**VC1**:**VC12**) to meta-analyse. We chose these variable categories based on both their frequent occurrence in group loan repayment studies, and on their suitability as proxies for the evolutionary mechanisms which we hypothesise to support cooperation in loan groups. We directly link 9 of these variable categories (**VC1**:**VC9**) to specific mechanisms, while the remaining 3 (**VC10**:**VC13**) are ambiguous in their association with individual mechanisms. Some hypotheses include predictions for how a single variable category should affect loan repayment, and others make predictions about multiple variable categories.

H1. Kin Selection via Common Ancestry - Cooperation can evolve when it is preferentially directed towards genetic relatives who are more closely related to the cooperator due to their common ancestry, relative to the population mean (Hamilton, 1964a, 1964b). Cooperative behaviours that evolve due to their positive impacts on the success of relatives despite their costs to the actor are said to result from "kin selection" (Grafen, 2007; Maynard Smith, 1964). This mechanism assumes some genetic basis to cooperative behaviour, so that assortment between relatives corresponds to assortment between cooperators. Cooperators can therefore assort with other cooperators by preferentially interacting with kin. This requires either some form of kin recognition to successfully identify true relatives (Bressan and Kramer, 2015), or limited migration away from the natal group resulting in a higher proportion of relatives in the local population (Lehmann and Rousset, 2010; Queller, 1992; Taylor and Irwin, 2000), and therefore greater opportunity for assortment.

Application to Joint Liability Microfinance: In joint liability loan groups composed of genetic relatives, the benefits provided to relatives by repayment could outweigh any costs of cooperation. This hypothesis assumes low levels of relatedness in the general population from which microfinance borrowers are drawn, and thus low levels of competition between kin (West et al., 2002). Cultural variation in the structure and function of borrowers' kin systems could also influence the costs and benefits of cooperating with relatives (Power and Ready, 2019).

Prediction 1: Loan groups composed of more relatives/more closely related borrowers will exhibit higher repayment rates compared to groups composed of fewer relatives/less closely related borrowers.

Variable Category for Meta-Analysis:

- **VC1. Relatives in the loan group:** Measures of relatedness between group members

H2. Prior Interaction and Reciprocity - Cooperation can evolve when it is preferentially directed towards individuals known to be cooperators based on their past behaviour (Trivers, 1971). Direct reciprocity describes an actor's decision to cooperate with an individual who has previously cooperated with that actor (Axelrod and Hamilton, 1981; Trivers, 1971). Under indirect reciprocity, an actor decides to cooperate based on their knowledge of prior interactions between an individual and others, or by using information regarding that individual's reputation for cooperation (Alexander, 1974; Nowak and Sigmund, 1998). Generalised reciprocity refers to the decision to cooperate with an individual, conditional on having been the recipient of cooperation from other individuals in the past (Barta et al., 2011; Rankin and Taborsky, 2009). Assuming the costs of identifying reciprocators are sufficiently low, reciprocity-based mechanisms therefore enable assortment between cooperators by using information regarding individuals' past behaviour. This has the effect of compensating the initial costs of cooperation with future reciprocated benefits, and directing the benefits of cooperation away from individuals with a history of free-riding.

Application to Joint Liability Microfinance: Joint liability loan groups offer multiple avenues for reciprocal cooperation to emerge. Repayment meetings present opportunities for direct reciprocity, for example by borrowers choosing to repay loans when they have previously experienced other members repaying theirs, or helping defaulters in their group to repay loans when they have previously been the beneficiary of repayment assistance. Besides facilitating direct interactions between loan group members, repayment meetings also provide collective information regarding each borrower's contributions, and thus opportunities for acquiring reputational information. Furthermore, existing social relationships between borrowers (prior to loan group formation) or the sharing of social ties outside the loan group could reflect opportunities for borrowers to obtain reputational information about each other's cooperative history, which could facilitate cooperation within the loan group.

Prediction 2: Loan groups composed of borrowers with experience or knowledge of one another's past cooperative behaviour will exhibit higher repayment rates.

Variable Categories for Meta-Analysis:
- **VC2. Prior acquaintance of group members**: Measures of interaction between group members prior to loan group formation
- **VC3. Group tenure**: Measures of the length of time for which the loan group has been active
- **VC4. Frequency of group meetings**: Measures of loan group meeting frequency
- **VC5. Geographic proximity of group members**: Measures of proximity between group members' houses or businesses

H3. Partner Choice - Cooperation can evolve when individuals are able to choose their interaction partners, so that cooperators can choose to preferentially interact with other known cooperators, and actively dissociate from free-riders, leading to positive assortment (Aktipis, 2004; Hauert et al., 2002; Hruschka and Henrich, 2006; McNamara et al., 2008; Noë and Hammerstein, 1994). If individuals are aware that cooperation will provide access to disproportionate benefits, and there is a limit on the partners available, this could drive competition for choosing the most cooperative partner (Noë and Hammerstein, 1994; Roberts, 1998). In addition, people could compete to be more cooperative when they know they could be chosen as partners in a beneficial relationship (Barclay and Willer, 2007). While reciprocity describes decisions to cooperate given the partners available, it does not encompass the choice of available partners. Selecting cooperative partners from the outset through partner choice may do more to facilitate cooperation than individual decisions made during future interactions (Hruschka and Henrich, 2006; Yamagishi et al., 1994).

Application to Joint Liability Microfinance: Partner choice could play a significant role in determining repayment outcomes in joint liability loans because loan group formation occurs at the start of the lending process, and therefore sets each borrower's interaction partners for the duration of the loan. While some loan groups are formed by the lending institution (Feigenberg et al., 2013; Karlan, 2007), others are formed by borrowers themselves (Banerjee et al., 2015; Morduch, 1999). Loan groups formed through self-selection should be more likely to consist of cooperators through effective screening of group members by individuals with relevant local knowledge regarding their cooperativeness. Some microfinance institutions also allow loan groups to alter their group membership, for example by ejecting a persistently defaulting borrower, to be replaced by a new borrower (Carpenter and Williams, 2014), which could also increase assortment between cooperators.

Prediction 3: Loan groups formed by borrowers themselves will exhibit higher repayment rates compared to groups formed by a lending institution with imperfect information, or compared to groups formed randomly. Groups that are able to manage their membership by choosing their own members initially, or by accepting or rejecting new members throughout the loan cycle, will exhibit higher repayment rates than groups that are unable to do so.

Variable Categories for Meta-Analysis:

- **VC6. Management of group membership:** Measures of selection or rejection of loan group members by the loan group, either when choosing members of the loan group to begin with, or when choosing new members to join an existing group

H4. Tag-Based Cooperation - Some researchers have proposed a role for arbitrary observable "tags" that reliably co-occur with cooperative tendencies, providing visible markers that facilitate assortment between cooperators (Boyd and Richerson, 1987; Dawkins, 1976; McElreath et al., 2003). Examples of tags include language, accent, socioeconomic position, religion and other ethnic markers signifying membership in a cultural group that preferentially directs cooperation towards its members (Barth, 1998; Cohen, 2012; Smaldino, 2019). Like prior interaction, tag-based cooperation differs from partner choice in that it may allow cooperation to be preferentially directed towards cooperators, given a set of available interaction partners.

Application to Joint Liability Microfinance: Tags which are known to reliably transmit information regarding cooperativeness could allow cooperators to assort without any prior interaction (Riolo et al., 2001), which could motivate borrowers to repay their loans in groups of strangers. Tags could also be important for borrowers deciding between strangers when forming a loan group, contributing to partner choice.

Prediction 4: Loan groups formed on the basis of shared tags will exhibit higher repayment rates, assuming those tags are faithful indicators of cooperativeness. Between groups, variation in repayment efficacy may be structured by observable tags (such as accent, religion, or other markers of an ethnolinguistic group or community).

Variable Categories for Meta-Analysis:

- N/A: Testing this hypothesis requires multilevel data to examine patterns of relative variation (Alfredo Sánchez-Tójar et al., 2020) in loan repayment between loan groups nested in communities, nested in regions, nested in countries. This will require results from multiple loan repayment studies of different levels of the same populations, and of different populations at the same levels. For all studies included in our analysis we will code the name of the lending institution, country, region, city/town/village, ethno-linguistic group, community, and any other population descriptors. Once we have completed data collection we will assess whether sufficient multilevel data exist to meta-analyse the effects of these mechanisms using data from joint liability loan repayment studies. If the data are available, we will pre-register this analysis separately.

H5. Social Learning of Cooperation - Social learning strategies, such as copying the behaviours practiced by the majority of one's social group (Boyd and Richerson, 1988a; Cavalli-Sforza and Feldman, 1981; Kendal et al., 2018; Mesoudi et al., 2016), can theoretically generate assortment between cooperators (Andrés Guzmán et al., 2007). Assortment can therefore occur through the shared acquisition of cooperative norms, defined as socially learned beliefs shared within a group regarding how group members ought to behave (Bicchieri, 2016; Fehr and Schurtenberger, 2018). Evidence suggests that such norms, along with the evolved features of human psychology by which they are acquired, may play a role in motivating cooperation in humans (Chudek and Henrich, 2011; House et al., 2019). Assuming there is stable variation between groups in cooperative behaviours which are individually costly but beneficial to the group, and some form of intergroup competition leading to differential group success, this selection between groups can support the evolution of cooperation (Henrich, 2004; Richerson et al., 2016). This is possible when circumstances favour cooperation at the group level to a greater degree than they favour free-riding at the individual level (Boyd and Richerson, 2009a; El Mouden et al., 2014). However, whether this occurs depends on both the relative strength of selection within and between groups, and the relative variation in cooperation within and between groups (Price, 1970). Studies including cross-cultural economic experiments appear to show variation between societies in their levels of cooperation (Bell et al., 2009; Henrich et al., 2005). However, it can be difficult to establish whether differences in cooperation are due to variation in inherited cultural norms, or due to other features that vary between groups, such as differences in local demography and ecology which also influence cooperative behaviour (Lamba, 2016; Lamba and Mace, 2011; Nettle et al., 2011).

Application to Joint Liability Microfinance: Microfinance borrowers who have previously participated in group loans or experienced other forms of cooperation-based economic interaction may be more likely to have socially learned cooperative norms. Exposure to market economies and financial services can also promote cooperation by introducing new norms, and through the establishment of social institutions that regulate economic exchange

(Gurven, 2004) and reinforce cooperative norms.

Prediction 5: If there are socially learned norms of cooperation associated with particular socio-cultural groups, variation in repayment rates will be structured by socio-cultural group boundaries. Repayment rates may be structured at any level at which norms of cooperation are reproduced, such as at the level of the community, village, or ethno-linguistic group. Joint liability loan groups from the same socio-cultural group will have more similar repayment rates compared to loan groups from a different socio-cultural group, after controlling for other differences.

Variable Categories for Meta-Analysis:

- N/A: Testing this hypothesis requires multilevel data to examine patterns of relative variation in loan repayment. Once we have completed data collection we will assess whether sufficient multilevel data exist to meta-analyse the effects of these mechanisms using data from joint liability loan repayment studies. If the data are available, we will pre-register this analysis separately.

H6. Demography and Ecology - The demography and ecology of the population from which a joint liability group is drawn may affect the members' cooperative behaviour and hence their likelihood of repayment. Assortment among cooperators may depend on demographic factors such as migration patterns, and population structure more generally (Eshel and Cavalli-Sforza, 1982; Ohtsuki et al., 2006). Low levels of migration or selective migration can maintain behavioural similarities within populations (Boyd and Richerson, 2009b), and therefore generate assortment between cooperators. Ecological factors can also influence cooperation by altering the costs and benefits associated with cooperating. Certain ecologies could create economic interdependencies between individuals which lead to mutual interests in cooperation (Roberts, 2005; Tomasello et al., 2012). Economic experiments across diverse cultural groups suggest that up to 68% of cross-cultural variance in cooperative behaviour can be jointly explained by the degree to which cooperation is necessary in local economic production, and the degree of market integration (Henrich et al., 2001). Harsh environments that favour cooperation can also lead to the extinction of groups with low proportions of cooperators, and thus positive assortment between surviving cooperators (Smaldino et al., 2013).

Application to Joint Liability Microfinance: Empirical studies have found population-level demographic traits such as population size and social network structure to influence cooperation (Apicella et al., 2012), in addition to individual demographic traits such as sex and age (Lamba and Mace, 2011; Wu et al., 2015). The demographic features of the population from which group loan borrowers are drawn could also interact with other cooperative mechanisms. For example, high levels of migration could destabilize groups previously assorted by cooperativeness (Lewis et al., 2014), unless migrants (i.e. new borrowers in a loan group) also adopt the cooperative behaviours of their groups (Boyd and Richerson, 2009b; Mesoudi, 2018; Smith et al., 2018).

Prediction 6: Loan groups drawn from populations with ecologically induced economic interdependencies will exhibit higher repayment rates. Loan groups drawn from populations with the same demographic and ecological features should exhibit more similar repayment rates to one another compared to loan groups from other populations. Smaller populations with low levels of migration should help to maintain assortment created by other mechanisms, for example by making it easier to gather reputational information and track the cooperative behaviour of others.

Variable Categories for Meta-Analysis:

- N/A: Testing this hypothesis requires multilevel data to examine patterns of relative variation in loan repayment. Once we have completed data collection we will assess whether sufficient multilevel data exist to meta-analyse the effects of these mechanisms using data from joint liability loan repayment studies. If the data are available, we will pre-register this analysis separately.

H7. Punishment - Punishment has been identified as central to solving cooperative dilemmas, in particular for large groups of unrelated individuals formed without assortment (Ågren et al., 2019; Fehr and Gächter, 2002; Frank, 1995). By attaching an extra cost to free-riding, punishment can alter the relative costs and benefits of cooperating, so that cooperation offers the highest payoffs (Lehmann and Keller, 2006), and would-be free-riders turn to cooperation, thereby increasing assortment. While policing free-riders and coordinating punishment may be associated with its own costs (Boyd and Richerson, 1992; Smaldino et al., 2013), cooperative punishers may be rewarded for their efforts through the receipt of additional benefits, as may be achieved through the ostracism of free-riders from the group, resulting in an increased likelihood of interacting with other cooperators (Bowles and Gintis, 2004; Frank, 2003). Similarly, if the costs of punishment are shared between a sufficiently large proportion of group members, punishment is both more effective and the individual costs of delivering punishment decline (Boyd et al., 2010, 2003). Studies of real-world collective action problems have verified punishment as an important mechanism for maintaining cooperation (Herrmann et al., 2008; Kaplan et al., 1985; Ostrom et al., 1992; Wiessner, 2005), and this is supported by experimental evidence (Ertan et al., 2009; Fehr and Gächter, 2002; Gürerk et al., 2006; Yamagishi, 1986).

Application to Joint Liability Microfinance: Economic theoretical models of joint liability lending assume members of the same loan group are able to exert social pressure on one another, at low cost (Besley and Coate, 1995; Varian, 1990). However, the exact role of punishment in incentivising loan repayment is poorly understood, as there is little data on exactly what happens to defaulters (including who punishes them, and at what personal cost) or on borrower beliefs regarding which repayment violations deserve punishment (Karim, 2011; Solli, 2015). Many microfinance institutions do not provide loan groups with explicit instructions on enforcement, leaving it to the group members to decide how best to extract payment from members who are believed to be defaulting strategically (Solli, 2015). Some microfinance institutions use “dynamic incentives”, whereby larger loans or other additional benefits are offered for groups with strong repayment records. These extra incentives are believed to motivate borrowers to enforce repayment within their loan groups via whatever means are available to them (Egli, 2004). The threat of lost access to privileges rewarded to cooperative groups could reduce the relative benefits of free-riding and motivate borrowers to increase their repayment efforts. Within groups, willingness to punish may correlate negatively with genetic relatedness if punishment is directly costly to the punisher, and the harm to the punished relative creates additional indirect costs for the punisher (Frank, 2003, 1995; Gardner and West, 2004). This could explain why some studies show loan groups with more family members to be associated with lower repayment rates, as described in (Gehrig et al., 2021).

Prediction 7: Loan groups with formally established rules enforcing repayment, or informal sanctions by group members, will exhibit higher repayment rates. Loan groups with increased monitoring by group members or a loan officer will exhibit higher repayment rates.

Variable Categories for Meta-Analysis:
- **VC7. Group sanctions**: Measures of sanctioning of members by members
- **VC8. Peer monitoring**: Measures of monitoring of members by members in the form of visits or the acquisition of loan-related information (e.g. financial performance)
- **VC9. External monitoring**: Measures of monitoring of members by the lending institution or loan officer

Summary of Hypotheses for Meta-analyses of Evolutionary Mechanisms
We have declared 7 predictions based on prominent evolutionary mechanisms capable of supporting cooperation by increasing assortment between cooperators, to be tested via meta-analysis of 9 variable categories from the group loan repayment literature. The relationship between these 9 variable categories and our hypothesised evolutionary mechanisms is summarised in **Table 3**.

Testing Hypotheses 4, 5 and 6 (Tag-Based Cooperation, Social Learning, and Demography and Ecology) will likely require multilevel data to examine patterns of relative variation in loan repayment. In our pilot analysis of the 41 studies assessed in (Gehrig et al., 2021), we did not find any such data, nor did we find regularly occurring variables that represented direct or indirect measures of cooperative tags, socially learned cooperation norms, or demographic and ecological conditions. Our analyses will therefore focus on testing Hypotheses 1, 2, 3, and 7 (Common Ancestry, Prior Interaction, Partner Choice and Punishment).

We also plan to conduct exploratory analyses of the effects of three variable categories that appear regularly in the loan repayment literature (Group Size, Borrower Age, and Borrower Sex), but which do not represent discrete mechanisms or clearly align with any particular hypotheses. We do however have theoretical reasons to investigate the role of these variables, all of which have been implicated in evolutionary theories of cooperation and assortment. For example, some models suggest cooperative behaviour and reputations could be harder to track in larger groups (Suzuki and Akiyama, 2005), and experiments have shown a reduction in marginal returns with increasing group size can reduce the benefits of cooperation (Isaac and Walker, 1988). Depending on the method of group formation, larger groups could also require a greater proportion of cooperators to maintain cooperation, potentially creating an obstacle to the evolution of cooperation via reciprocity (Boyd and Richerson, 1988b). We therefore predict that larger loan groups will show worse repayment efficacy on average. We do not make directional predictions for borrower sex or age, but still plan to model their average effects, as this could provide insights of applied relevance to microfinance lending. We also plan to test the role of each of these three variables in explaining heterogeneity between studies (see **Item 15c**).

Table 3. *Variable categories created from common predictor variables analysed in loan repayment studies, and their association with evolutionary mechanisms which we hypothesise could support cooperation in loan groups.*

Variable Category	Evolutionary Mechanism	Justification
VC1. Relatives in the loan group	Common Ancestry	Measures of the presence of family members in loan groups provide measures of genetic relatedness within groups.
VC2. Prior acquaintance of group members	Prior Interaction	Borrowers who know each other prior to joining a group are more likely to have information about each other's cooperative histories.
VC3. Group tenure	Prior Interaction	Borrowers belonging to more longevous loan groups are more likely to have information about each other's cooperative histories.
VC4. Frequency of group meetings	Prior Interaction	Borrowers who meet more frequently are more likely to have information about each other's cooperative histories.
VC5. Geographic proximity of group members	Prior Interaction	Borrowers who live or work closer to one another are more likely to have information about each other's cooperative histories.
VC6. Management of group membership	Partner Choice	Loan groups which actively manage their membership (e.g. accepting/rejecting new members) enable the selection of cooperative partners.
VC7. Group sanctions	Punishment	Loan groups which impose their own penalties on defaulters create additional costs for non-repayment.
VC8. Peer monitoring	Punishment	Borrowers who experience higher levels of monitoring by their loan group are more likely to increase their repayment effort to avoid punishment.
VC9. External monitoring	Punishment	Borrowers who experience higher levels of monitoring by the loan officer or lending institution are more likely to increase their repayment effort to avoid punishment.
VC10. Group size	N/A	No particular mechanism
VC11. Borrower Age	N/A	No particular mechanism
VC12. Borrower Sex	N/A	No particular mechanism

We considered whether we should meta-analyse all variable categories associated with a mechanism together (e.g. producing one meta-analytic estimate for the effect of "Prior Interaction" on loan repayment, combining estimates from all four of the associated variable categories), or whether we should analyse each variable category separately. We decided on the latter for a number of reasons. Firstly, our pilot analysis revealed variation in the methods of measuring the same variables between studies, and the statistical methods used to estimate their impact on loan repayment. We decided to minimise this measurement and statistical heterogeneity by focussing on synthesising results for individual variable categories. Secondly, evolutionary mechanisms have not been directly assessed in loan repayment studies, as the literature on the evolution of cooperation and the literature on microfinance loan repayment have developed independently until now. This means we needed to find suitable proxies of evolutionary mechanisms in studies from the microfinance literature. We decided it would be more useful for the field of microfinance research to estimate meta-analytic effects for variables which are commonly studied in this literature. Thirdly, the more variable categories are associated with a mechanism, the harder it would be to interpret any meta-analytic effects, especially when the mechanism is associated with multiple, diverse variables (e.g. Prior Interaction). Fourthly, by conducting separate meta-analyses for each variable category, those who disagree with us concerning the mechanisms to which they have been assigned are free to interpret them individually. Despite the fact that we assign each variable category to one mechanism, there is likely to be some overlap between mechanisms for multiple variable categories. For example, while geographical proximity reasonably constitutes a proxy for prior interaction, it is also likely that borrowers who live closer to one another are more easily able to deliver punishments for defaulters. Similarly, while relatedness between borrowers denotes common ancestry and could therefore promote kin-directed cooperation, it is also likely that relatives have more experience of interacting with one another, enabling the formation of cooperative relationships based on reciprocity.

In summary, we will conduct at least 12 meta-analyses to test the average effects of each variable category on loan repayment. Furthermore, depending on the sample size and statistical comparability of effect estimates for these variable categories reported in the microfinance literature, we may conduct multiple meta-analyses for some variable categories (see **Item 15a**).

Objectives

Item 7. *Provide an explicit statement of the question(s) the review will address with reference to participants, interventions, comparators, and outcomes (PICO).*

Our meta-analyses will address two questions:

1. What are the average effects of 12 predictors on repayment in group loans?
2. To what extent do evolutionary theories of cooperation explain repayment patterns in group loans?

We will analyse data from both experimental and observational group loan repayment studies. For the former, the interventions of interest are manipulations of group composition and lending approaches that are associated with some measure of loan repayment. In the original studies, these interventions will have been compared to control groups which did not receive the relevant treatment, or which received a common baseline treatment. Outcomes will include various measures of loan repayment including repayment delinquency (i.e. late repayment), default and loan group survival time, which serve as measures of cooperation within the loan group. These could include binary, continuous and categorical outcome measures at both the level of the borrower and the level of the group.

SECTION 3: Methods

Eligibility criteria

Item 8. *Specify the study characteristics (e.g., PICO, study design, setting, time frame) and report characteristics (e.g., years considered, language, publication status) to be used as criteria for eligibility for the review.*
Studies will be considered eligible if they meet the following three criteria:

- ***Relevant predictor variables and outcome measure***

Studies must report quantitative analysis of a predictor variable relevant to one of the 12 variable categories we plan to meta-analyse, and its association with an outcome measure of joint liability loan repayment (see **Item 13** for details). This includes experimental and cross-sectional studies of group loan repayment, including studies comparing repayment between group and individual loans.

- ***Publication status***

Studies will only be eligible if they have undergone peer review or some form of expert assessment, including scientific journal publications, and unpublished but examined doctoral theses. This combination of sources aims to strike a balance between ensuring a higher quality of studies and including relevant results which may exist outside journal publications. Any study that does not meet quality criteria as measured by our risk of bias threshold (see **Item 14**) will be excluded from our main analyses.

- ***Years and languages considered***

We will consider all English-language studies published online before July 2021.

Information sources

Item 9. *Describe all intended information sources (e.g., electronic databases, contact with study authors, trial registers, or other grey literature sources) with planned dates of coverage.*
For the primary literature search we will use the Google Scholar, Web of Science, EconLit, and ProQuest search engines, searching all available databases for studies published before July 2021, with the aim of improving search performance by combining results from multiple databases and multiple search engines (Bramer et al., 2017). The specific search syntax we will use for each search engine is detailed in Appendix 1a. To check for eligible papers we may have missed in our primary search, we will also hand-search the reference lists of eligible studies, and use the Co-cites literature search tool (Janssens et al., 2020) to identify the most frequently co-cited papers of the most relevant publications as defined by our inclusion criteria. Co-cites works by identifying all articles cited together with an eligible target study, and ranks them in order of their co-citation frequency, assuming that articles with a higher co-citation frequency address more similar questions.

Search strategy

Item 10. *Present draft of search strategy to be used for at least one electronic database,*

including planned limits, such that it could be repeated.
The entire search strategy is visualised in **Figure 1** below, and we will repeat it separately for each of the 12 variable categories we plan to meta-analyse. Search terms are presented in **Table 4**, in which each column represents a key search term, and the rows contain synonyms corresponding to each of those terms. In addition to these general terms, for each literature search we will include an additional search term for the relevant variable category (terms are listed in Appendix 1b). Assuming these relatively specific searches will return a small number of hits, we plan to screen all results for eligibility. If any search returns a number of results too numerous to screen due to resource constraints, only the first 300 search results of each database will be screened. We decided on this cutoff due to the recommendation of (Haddaway et al., 2015) for maximising results from the academic literature in Google Scholar.

Table 4. *Literature search terms. To be indexed, studies will need to mention at least one of the terms listed in each column (e.g. microfinance AND group lending AND performance). Asterisks enable searches for all words with the specified root (e.g. a search for "repay*" will return studies including the words "repay", "repaying", "repayment" etc.)*

Microfinance	**Joint Liability**	**Loan Repayment**
microfinance	joint liability	repay*
microcredit	group loan*	default
microloan	group lending	delinquen*
micro-finance	solidarity loan*	arrears
micro-credit	solidarity lending	performance

We will also use the *litsearchr* text mining package in R (Grames et al., 2019) to identify additional search keywords. This package creates keyword co-occurrence networks in eligible studies discovered through the use of naive search terms, enabling the identification of more efficient and less biased search terms. As a test of the functionality of this relatively new automation tool, we will conduct keyword searches using the study results discovered through our primary search. We will use the resulting set of novel keywords to conduct an additional literature search, to be screened for eligible studies missed when using our naive keyword search terms.

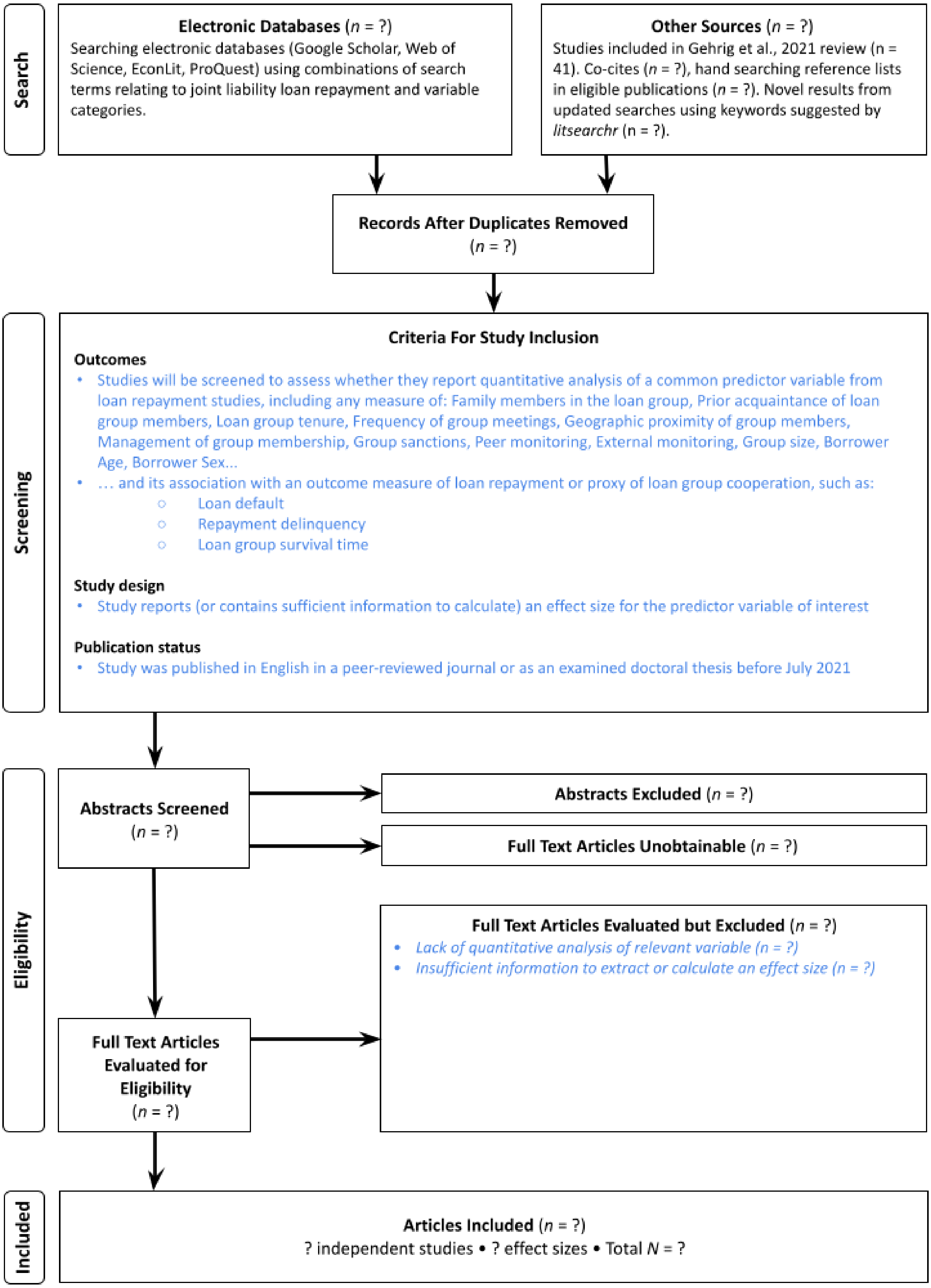

Figure 1. Skeleton outline of PRISMA flow chart, to be populated for each variable category

Study records

Item 11a. *Describe the mechanism(s) that will be used to manage records and data throughout the review.*

We will use the free systematic review management software Rayyan (Ouzzani et al., 2016) to manage study records, screen abstracts, and track inclusion/exclusion justifications. A summary of all search results (*FosterMA7_SearchResults*) will be uploaded to the OSF project page.

Item 11b. *State the process that will be used for selecting studies (e.g., two independent reviewers) through each phase of the review (i.e., screening, eligibility, and inclusion in meta-analysis).*

DF will be the primary reviewer for decisions regarding screening, eligibility and inclusion in the meta-analysis. The reviewer will screen study abstracts to assess whether they meet our inclusion criteria. **AM**, **EP** and **SL** will provide feedback for contentious or borderline cases.

Item 11c. *Describe planned method of extracting data from reports (e.g., piloting forms, done independently, in duplicate), any processes for obtaining and confirming data from investigators.*

Data will be extracted and coded by **DF**, and entered into our data extraction template (for a description of all variables in the data extraction form, see Sheet 1 of *FosterMA8_DataExtracted*). We will hire a research assistant to double-code study effect estimates in an attempt to identify any coding errors. Any discrepancies and disagreements regarding coding choices will be resolved through consulting the original text and discussion with the research team. If our research funds are not sufficient to employ an assistant to double-code the entire dataset, we aim to double-code 30% of the data to provide a measure of inter-rater reliability, or else as much as our funds will allow. Where necessary, additional information will be requested from study authors. As recommended by (Muka et al., 2020), we have piloted our data extraction form using the 41 loan repayment studies identified in (Gehrig et al., 2021), all of which are likely to be included in our final list of eligible studies.

To mitigate inclusion bias and HARK-ing (Hypothesising After the Results are Known) (Kerr, 1998), the primary reviewer (**DF**) made efforts to avoid learning the results of loan repayment studies that will potentially be included in the meta-analysis. While scoping the literature to determine its suitability for a meta-analysis, this reviewer focussed on the methods sections of studies while avoiding reading the results sections. The chief exception to this was reading narrative review papers (Banerjee et al., 2015; Galariotis et al., 2011; Gehrig et al., 2021; Hermes and Lensink, 2007; Lamba, 2014) that were necessary for sufficient introduction to the topic, and eventually for the pilot study. However, a defining feature of these studies is ambiguity regarding both the direction and magnitude of effects for many predictors of repayment. Finally, all hypotheses were derived a priori from evolutionary theories of cooperation, and without reference to the results of group loan repayment studies.

Data items
Item 12. *List and define all variables for which data will be sought (e.g., PICO items, funding sources), any pre-planned data assumptions and simplifications.*

Model Selection Criteria
In our pilot study, we collected data on all models for the 41 studies reviewed in (Gehrig et al., 2021) to learn what types of variables have been studied in the microfinance literature. This helped us to better understand the variation that exists within and between loan repayment studies regarding different measures of loan repayment used, the ways in which the same variable (e.g. geographic proximity of loan group members) might be measured (e.g. continuous versus binary measures) and operationalised, and the different types of statistical analyses that have been conducted.

We decided to extract one estimate per study for each meta-analysis we conduct, under the reasoning that one estimate consistently selected from each study is preferable to multiple estimates from differing model specifications, even if this comes at the cost of a smaller total sample of effect estimates. By choosing one estimate per study we also avoid the statistical and inferential issues associated with three-level meta-analysis: extracting multiple estimates from the same studies would introduce statistical dependencies between effect estimates, invalidating one of the core assumptions of conventional meta-analysis (Cheung, 2014; Van den Noortgate et al., 2013)). For each study, we will use the following criteria to select a model from which to extract effect estimates:

1. The model is the only model in the study
2. The model includes the most relevant predictor variable
3. The model is the most statistically appropriate for the type of data being analysed
4. The model includes the most relevant outcome variable for loan repayment
5. The model provides the most comparable effect measure (e.g. log odds)
6. The model is applied to the largest sample of data
7. The model includes our two pre-specified controls (a measure of borrower SES, wealth, or education, and a measure of loan size or interest rate), with the fewest additional covariates
8. The model is the best-fitting model

The criteria are hierarchical, so that competing models are judged on the basis of how well they meet the criteria in the order they appear. We will select models from studies independently for each variable category we meta-analyse, so that different models from the same study could potentially provide estimates for different meta-analyses. Estimates from variables included in models as controls are considered unreliable (Westreich and Greenland, 2013) and ideally should not contribute to meta-analyses. However, based on our pilot study we anticipate severe sample size restrictions using that approach, and we will therefore include estimates for variables originally modelled as controls.

Outcomes and prioritisation
Item 13. *List and define all outcomes for which data will be sought, including prioritization of main and additional outcomes, with rationale.*

Primary outcome variables include all measures of loan repayment efficacy. Repayment efficacy is measured in diverse ways in the microfinance literature including measures of default, repayment delinquency, arrears, and loan group survival time. We interpret greater repayment efficacy as higher levels of cooperation. Even when non-repayment is not intentional, risky loan investment decisions by borrowers and a lack of sufficient monitoring by their loan group members are themselves plausibly demonstrative of a lack of cooperation in the loan group (Ghatak and Guinnane, 1999). Ultimately, borrowers who fail to repay their share of a group loan prioritise their individual welfare over that of the loan group, so that lower repayment efficacy can generally be considered indicative of non-cooperation within the loan group.

Risk of bias in individual studies

Item 14. *Describe anticipated methods for assessing risk of bias of individual studies, including whether this will be done at the outcome or study level, or both; state how this information will be used in data synthesis.*

Although multiple tools have been developed for assessing the risk of bias of studies in the evidence synthesis literature, during our pilot study we were unable to find a tool that suited our need to assess primarily cross-sectional studies in non-clinical settings. We therefore designed a new tool which we call ROBOS ("Risk of Bias in Observational Studies"). To do so we took inspiration from the ROBINS-I tool (Sterne et al., 2016), which involves answering prompts to record factual information about how studies were conducted. This information is used to formulate subjective judgements of the risk of bias for each study across 7 domains of potential bias, and for the study overall. We created a simplified, one-page version of the ROBINS-I tool which consolidates the 7 original domains into 4 to be assessed for bias, which are:

1. Study Design
2. Sampling Method
3. Data Collection
4. Analysis Methods

The ROBOS tool provides a free-text box to enter information for each domain when assessing a study, with specific criteria to guide the assignment of a "Low", "Moderate", or "High" risk of bias rating. Based on this information, we assign an overall risk of bias rating for the study, which takes the value of the highest rating out of all 4 domains. For example, a study which scored "Moderate", "Low", "Moderate", and "High" across the 4 domains would receive an overall rating of "High" risk of bias. While this approach may seem conservative, it follows the approach used in the ROBINS-I tool, and ensures a stricter and more objective distinction between studies at different risk of bias. A template of the tool is available in Appendix 2. For our primary analysis we will restrict effect estimates to those from studies scoring a "Low" or "Moderate" risk of bias, although sensitivity analyses will test the effects of including results from studies with a "High" risk of bias (see Item 15c). ROBOS assessments conducted for 44 effect estimates in our pilot analysis are available in the folder (*FosterMA10_ROBOS*).

Data synthesis
Item 15a. *Describe criteria under which study data will be quantitatively synthesized.*

Sufficiently Comparable Effect Measures
Our pilot dataset included results from 189 models, analysing the relationship between 663 unique predictors and 65 repayment outcomes, using data collected on borrowers from 36 microfinance institutions based in 59 regions across 32 countries (the full pilot dataset is available in *FosterMA8_DataExtracted*). The dataset showed a wide range of variable types analysed in loan repayment studies (examples are displayed in Table SM1 of (Gehrig et al., 2021)), including binary, categorical and continuous measures of predictor variables, measured at the borrower- and loan group-level. Effect estimates were reported using 14 different types of effect measure (an effect measure is a statistical construct that summarises the magnitude and direction of a relationship between two variables). The type and frequencies of effect measures reported across all variable categories are shown in **Table 5**.

Table 5. *Frequencies of effect measures reported in our pilot dataset of 41 group loan repayment studies drawn from (Gehrig et al., 2021).*

Effect Measure	Frequency
Log odds	376
Hazard ratio	187
Unstandardized beta coefficient	169
Unstandardised tobit coefficient	65
Unstandardised probit coefficient	62
Log counts	40
Unstandardized marginal effect	40
Odds ratio	15
Spearman correlation	11
Log hazard rate	8
Difference-in-difference estimate	6
Standardized marginal effect	4
SEM path coefficient	2
Group means	1

Meta-analysis is technically possible with just two estimates, although an analysis of all meta-analyses contained in the Cochrane Database of Systematic Reviews identified a median of three studies per meta-analysis (Davey et al., 2011). We therefore decided to conduct separate meta-analyses for each measure of effect for which at least three estimates were provided, assuming contributing studies were sufficiently homogenous in their study design and measurement of variables. In our subsequent pilot analysis of 6 variable categories, this almost always meant conducting meta-analyses of log odds ratios, which were the most frequently reported effect measure in our pilot dataset. **Table 6** describes the availability of effect estimates for 7 variable categories we attempted to meta-analyse (one of which did not report any estimates in the form of log odds).

Table 6. *The total number of effect estimates available for 7 variable categories in our pilot dataset, and the number of comparable log odds estimates (brackets show log odds estimates as a percentage of total estimates).*

Variable Category Meta-Analysed	Total Effect Estimates Available	Log Odds Estimates Available
Relatives in loan group	10	3 (30%)
Prior acquaintance of group members	17	6 (35%)
Group tenure	17	8 (47%)
Geographic proximity of group members	11	3 (27%)
Frequency of group meetings	5	0 (0%)
Group sanctions	15	10 (67%)
Peer monitoring	9	6 (67%)

Based on our pilot analysis, we expect the majority of meta-analyses we conduct in our main study with a larger sample of estimates to also rely on log odds. If we find at least three comparable studies which report results from single-level linear regression models, we also plan to meta-analyse Fisher's z-transformed partial correlations, which we will calculate from the t-values reported in the model. Converting to partial correlations has the added advantage of being able to control for the number of covariates in the model from which estimates are drawn (Aloe, 2013; Aloe and Becker, 2012; Aloe and Thompson, 2013). However, our pilot dataset did not include sufficient data to meta-analyse partial correlations. While we also considered converting multiple effect measures to a summary measure such as Hedge's *g* (Hedges and Olkin, 1985), we decided against this in this particular instance in order to maintain the improved interpretability of a single measure of effect (e.g. log odds, which can be exponentiated to provide odds ratios). An additional advantage of analysing log odds is that its posterior distribution is close to normality, even for relatively small sample sizes (Gelman et al., 2013).

The major disadvantage of conducting separate meta-analyses for each measure of effect is a major reduction in sample size for each analysis (as shown in the final column of **Table 6**). Because methods for effect measure conversions are rapidly evolving, once we have completed coding all studies and the range and frequency of effect measures in our full data sample for each variable category is known, we will reconsider whether appropriate effect measure conversions exist that could enable the synthesis of multiple types of effect measure. To enable comparison between effect estimates from studies with different but comparable outcome variables, we will code all estimates so that positive effect signs reflect increased loan repayment, and negative effect signs reflect reduced loan repayment.

Item 15b. *If data are appropriate for quantitative synthesis, describe planned summary measures, methods of handling data, and methods of combining data from studies, including any planned exploration of consistency (e.g., I 2 , Kendall's tau).*
For small sample sizes, Bayesian methods are often preferable due to improved estimation relative to frequentist alternatives (Meager, 2019; Williams et al., 2018), and for avoiding the common problems associated with null hypothesis significance testing (Gelman, 2018). Based on our pilot study, we predict that many of the eligible studies in our sample will not meet our relatively strict risk of bias threshold, resulting in small sample sizes for our primary analyses. We therefore plan to fit Bayesian hierarchical models to estimate meta-analytic effects for each of our 12 variable categories on group loan repayment. The model we plan to use is equivalent to a random effects meta-analytic model, in which effect sizes are nested in studies, and we assume that the "true" effect of the predictor being modelled differs between studies, either due to actual variation in the effect, or due to sampling variability. The Bayesian meta-analytic model takes the form:

$$y_i \sim \text{Normal}(\theta_i, \sigma_i)$$

where the effect estimate y from each study (i) is assumed to be drawn from a Normal distribution centred on θ_i. The estimates from each study also have an associated standard error, denoted σ_i, which provides the standard deviation for the Normal distribution from which estimates are assumed to be drawn. As part of the model we also assume that θ_i is itself drawn from a distribution:

$$\theta_i \sim \text{Normal}(\mu, \tau)$$

where μ is the mean of the distribution of effect sizes, and τ is the standard deviation around that mean. These two parameters represent the two primary estimands of any meta-analysis: μ as the "average" effect across all exchangeable studies, and τ as the standard deviation of effects between studies. A further advantage of Bayesian models which motivates our use of them is the ability to interpret posterior distributions from the model as probability distributions of the effects of interest (Salanti et al., 2019). Our models will provide us with posterior distributions for the meta-analytic effect size μ, and for the heterogeneity of the underlying effect τ^2 (the between-study variance). This approach allows us to model the uncertainty associated with the meta-analytic effect for each of our predictors of loan repayment, and τ^2 additionally allows us to estimate how likely it is that our meta-analytic effects are generalizable to other settings (Vivalt, 2020). We will interpret τ in line with the categorisation suggested in (Spiegelhalter et al., 2004), whereby values of $0.1 < \tau < 0.5$ are considered as "reasonable" levels of heterogeneity, $0.5 < \tau < 1$ as "fairly high", and $\tau > 1$ as "fairly extreme".

As this is the first formal meta-analysis of the group loan repayment literature, and because individual studies appear to show conflicting results regarding the direction of effects (Gehrig et al., 2021), we have little robust information to inform our choice of priors. For our meta-analyses of log odds estimates, we will therefore assign a Normal prior centred on zero for μ, to spread the probability diffusely and allow the data to dominate our inferences, as recommended by (Gelman, 2019). For τ we will use a half-Cauchy prior, a distribution with a broad peak around zero and heavy tails, recommended as a generally applicable prior without strong accompanying assumptions (Gelman, 2006; Polson and Scott, 2012), and to reflect the fact that the between-study variance can only be positive (Brockwell and Gordon, 2001). This choice of prior also reduces the risk of inflated estimates for the summary effect μ (Williams et al., 2018). We will also explore the impact of our choice of priors for both μ and τ via sensitivity analyses (see **Item 15c**). Our full Bayesian meta-analytic model is as follows:

$$
\begin{gathered}
y_i \sim \text{Normal}(\theta_i, \sigma_i) \\
\theta_i \sim \text{Normal}(\mu, \tau) \\
\mu \sim \text{Normal}(0, 1) \\
\tau \sim \text{HalfCauchy}(0, 1)
\end{gathered}
$$

The effect estimates that provide data for the model will be weighted using the generic inverse variance method, in which each study's effect estimate is given a weight equal to the inverse of its variance. This method provides more weight for studies which have larger samples and therefore estimates with smaller standard errors, and thus reduces the imprecision of the meta-analytic effect estimate (Higgins and Thomas, 2019).

We will use R (R Core Team, 2020) via RStudio (RStudio Team, 2020) and the *metafor* package (Viechtbauer, 2019) to calculate Fisher's z-transformed partial correlations (if applicable), and *brms* (Bürkner, 2017) to fit our Bayesian meta-analytic models in the Stan programming language (Carpenter et al., 2017). Stan provides Markov Chain Monte Carlo sampling with the No U-Turn Sampler (Hoffman and Gelman, 2014; McElreath, 2020) to approximate the posterior distributions of model parameters. The analysis script we plan to use is available from: https://github.com/dugaldfoster/MicrofinanceMetaAnalysis.

Item 15c. *Describe any proposed additional analyses (e.g., sensitivity or subgroup analyses, meta-regression).*

Sensitivity Analysis 1: Investigating the Influence of Choice of Priors

Based on our pilot study, we predict that most of our meta-analyses will feature a small number of studies. In this situation the choice of priors has a greater impact, as there is less data capable of informing estimates or overruling the prior (Gelman et al., 2013). Sensitivity analysis with varying priors for τ are argued to be particularly important due to their impact on the certainty of estimates for the meta-analytic effect μ (Carlsson et al., 2017). We will therefore investigate the influence of priors by re-running our primary analyses with a range of alternative priors for the μ and τ parameters, depending on the distributional properties of the effect measure used (Smith et al., 1995).

Sensitivity Analysis 2: Investigating the Influence of the Level of Analysis

Our pilot study data revealed a distinction in levels of analysis between studies which report associations between variables and repayment outcomes at the level of the borrower (individual repayment rates), and those that analyse outcomes at the loan group level (group repayment rates). It is possible that when group-level features are analysed at an individual level or vice versa, information about the effect of a variable might be lost or become complex (for example, when data are only collected from a subset of loan group members to calculate an average to assign to the group for analysis). We will therefore conduct a sensitivity analysis separating effect estimates by their level of analysis.

Sensitivity Analysis 3: Inclusion of Studies at High Risk of Bias
Our decision to analyse only studies at “Low” or “Moderate” risk of bias (according to our ROBOS assessments) in our primary analysis is likely to reduce our sample size and affect the precision of our meta-analytic effect estimates. We will therefore conduct sensitivity analyses to explore how our results are influenced by the inclusion of studies scoring a “High” risk of bias.

Sensitivity Analysis 4: Adding Random Effects for Lending Institutions
Loan repayment studies with data collected from the same lending institution could introduce statistical dependencies in our data. Although this situation was rare in our pilot dataset due to the small number of studies contributing to each meta-analysis, if at least two estimates for a variable category are taken from studies of borrowers from the same lending institution, we will expand our models to include random effects for the lending institution. This could also serve to control for differences between institutions in the specific details of joint liability loan contracts, which can vary in their duration, interest rate, or other features that could influence repayment.

Investigating the Role of Effect Moderators
We will use meta-regression to investigate heterogeneity of effects between studies, and to explore the roles of the following moderator variables. To assess the impact of effect moderators we plan to use approximate leave-one-out cross validation (LOO-CV) (Vehtari et al., 2017) to compare the out-of-sample predictive accuracy for models with and without terms for moderators.

Meta-regression 1: Study Covariates
During our pilot study we learned of significant variation in the number and nature of covariates for estimates from different studies. Our model selection criteria aim to reduce this variation by selecting the model from each study with the fewest covariates in addition to our pre-specified controls, with the aim of including at least partially exchangeable effect estimates (Higgins et al., 2009). We will also run a meta-regression to investigate the number of covariates in the models from which effect estimates have been drawn as an effect moderator.

Meta-regression 2: Group Size
While many loan repayment studies do not analyse the effects of loan group size on repayment, they do provide descriptive statistics including the average size of loan groups. Using this information we will run a meta-regression including a term for group size to investigate the role of group size in moderating the effects of each of our variable categories on loan repayment.

Meta-regression 3: Borrower Age
As with group size, many loan repayment studies may not produce direct effect estimates for borrower age, but do report statistics on the average age of borrowers in the population. Using this information we will run a meta-regression including a term for average borrower age, to investigate the role of borrower age in moderating the effects of each of our variable categories on loan repayment.

Meta-regression 4: Borrower Sex
Using the same information contained in loan repayment studies descriptive statistics, we will run a meta-regression including a term for the proportion of males in the study population, to investigate the role of borrower sex in moderating the effects of each of our variable categories on loan repayment.

Item 15d. *If quantitative synthesis is not appropriate, describe the type of summary planned.* If meta-analyses of certain variable categories are not possible, we will conduct a narrative summary with tables to display the frequencies of positive and negative effects, and the magnitude of these effects. We will explore the causes of heterogeneity between studies, and highlight evidence gaps for future studies of joint liability loan repayment.

Meta-bias(es)
Item 16. *Specify any planned assessment of meta-bias(es) (e.g., publication bias across studies, selective reporting within studies).*
The microfinance literature is potentially affected by selection bias, whereby certain lending institutions or loan groups are more likely to be studied if they share some non-random feature such as high repayment rates (Allcott, 2015; Pritchett and Sandefur, 2015; Woolcock, 1999), limiting the generalizability of findings from the published literature. By collecting descriptive information on eligible studies (e.g. country, region, lending organisation) we will assess the generalisability of our findings and describe patterns of study availability.

Another problem affecting the reliability of meta-analytic effects is that researchers may be more likely to publish studies with results that support their hypotheses, or those that include statistically significant results (Rosenthal, 1979; Sterling, 1959). If studies are repeatedly left unpublished for any reason that is associated with their outcomes, this could result in publication bias, producing a research literature with distorted findings and therefore biased estimation of meta-analytic effects. Because we do not have strong assumptions or good evidence regarding the level of publication bias likely to affect the microfinance loan repayment literature, we will model the potential impact of publication bias with a Bayesian Copas selection model (Copas, 1999; Copas and Shi, 2001), using the *RobustBayesianCopas* package (Bai, 2020) in R. The Copas selection model assumes the probability of a study being selected (i.e. published) is a function of the size of its effect estimate and the standard error of this estimate. Unlike graph-based or regression test methods, the Copas selection model includes an explicit mechanism linking the publication process with the pattern of observed study estimates (Schwarzer et al., 2010). By calculating the difference between the posterior distribution of our original meta-analytic model, and that of an equivalent Copas selection model, we can estimate the potential impact of publication bias (Bai et al., 2020). To do so we will use Bai's *D* measure (Bai et al., 2020), for which values close to 0 indicate the distributions are nearly identical (suggesting negligible publication bias), and values close to 1 indicate non-overlapping distributions (suggesting severe publication bias).

Confidence in cumulative estimate
Item 17. *Describe how the strength of the body of evidence will be assessed (e.g., GRADE).*

Causal Interpretation of Meta-Analytic Estimates
We know from our pilot study that studies of the determinants of group loan repayment vary in their quality and susceptibility to bias. We should be careful in making causal interpretations of estimates taken from loan repayment studies without an appropriate study design capable of identifying causal relationships, or a causal model (Pearl et al., 2016) used to outline the assumed relationships between variables that has been used to inform statistical modelling decisions. Even for repayment studies designed to identify causal relationships, it is difficult to know how to interpret a statistical association between a variable which has been adjusted for multiple factors and a loan repayment outcome. This issue is further compounded by the fact that the individual study estimates which contribute to our meta-analyses are likely to come from models with different combinations of covariates. This is an unavoidable feature of meta-analysing the effects of variables from a relatively small and methodologically diverse literature. However, we aim to address this limitation with the following measures for each of our analyses:

1. Systematically assessing each contributing study's risk of bias, including the extent to which they have failed to adjust for well-known confounds in the loan repayment literature, and thus weakening our confidence in a causal interpretation.
2. Calculating prediction intervals (IntHout et al., 2016) to estimate where the effects of 95% of future exchangeable studies are likely to lie.
3. Assessing effect estimate sign consistency between studies. Assuming true exchangeability between studies, variable categories with effect estimates with consistent signs (providing meta-analytic effects with low heterogeneity, or heterogeneity confined among predominantly positive or predominantly negative estimates) could provide greater evidence of a causal relationship (Hill, 1965; Höfler, 2005).
4. Evaluating the risk of publication bias in distorting meta-analytic effect estimates.

On the basis of the results provided by these steps, we will discuss our confidence in the quality of evidence provided by our analyses, and our ability to draw causal inferences.

SECTION 4: Additional information

Protocol Deviations
All deviations from this plan will be documented in the *FosterMA9_ProtocolDeviations* file uploaded with the pre-registration. This file will include information on which PRISMA-P item was altered, the justification for any changes, and assessment of how these changes could influence our results, analysis or interpretation, and the date on which this change was made. This documentation will be uploaded to the project OSF page and maintained as a live document for the duration of the project.

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