Banker My Neighbour: Matching and Financial Intermediation in Savings Groups*

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May 15, 2019

Abstract

Efforts to promote financial inclusion have largely focused on microcredit and micro-savings separately, less so on promoting financial intermediation across poor borrowers and savers. Village Savings and Loan Associations (VSLAs) may enable borrowers and savers to meet each others' needs, by combining a borrowing and a commitment savings technology. On the other hand, frictions such as imperfect information and enforcement difficulties may limit VSLAs' ability to attract both borrowers and savers into the same group. To investigate whether VSLAs provide effective financial intermediation, we use a large-scale survey of mature VSLA groups in rural Malawi. We find that VSLAs mobilize large quantities of savings that are then lent to individual members at a high interest rate, yielding savers a large return on their savings. We examine whether this process is assisted by the sorting of members across VSLAs. We find that present-biased individuals tend to group with time-consistent members, consistent with the hypothesis that the former gain a commitment savings technology by lending to the latter. In contrast, members of the same occupation sort into groups together, indicating unrealised intermediation possibilities between farming and non-farming households. This has implications for the design of such groups.

Keywords: Microfinance, commitment savings, savings groups, financial inclusion
JEL codes: O1, O12, O16

*We are grateful to Nava Ashraf, James Fenske, Climent Quintana-Domeque, Simon Quinn, Chris Roth, Chris Woodruff, participants at the IIG Conference 2015 and CSAE Conference 2015, and two anonymous referees for useful comments. We thank Waluza Munthali and all at Invest in Knowledge Initiative for surveying assistance, Hardish Bindra for data entry, and Smit Gade for research assistance. We also thank Helene Bie Lilleør, Christopher Ksoll, Jonas Helth Lønberg, Ole Dahl Rasmussen and the Rockwool Foundation for granting access to supplementary data, and Sam Asher and Paul Novosad for sharing their "fuzzy matching" algorithm. All errors are our own. This project was funded by the UK Department for International Development (DFID) as part of the research consortium Improving Institutions for Pro-Poor Growth (iiG), which studies how to improve institutions in Africa and South Asia. Rachel Cassidy's work on this project was supported by the Economic and Social Research Council [grant ref. ES/J500112/1]. The views expressed are not necessarily those of DFID nor the ESRC. Ethical approval for this project was obtained from the University of Oxford's Department of Economics DREC [ref. 1213/0015]. A previous version of this paper was circulated under the title "Can community-based microfinance groups match savers with borrowers? Evidence from rural Malawi".

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1 Introduction

Two billion adults worldwide are still unbanked (Demirgüç-Kunt et al., 2015). Recent evidence suggests that efforts to financially include the poor via mainstream microfinance produce little or no impact on welfare (Banerjee et al., 2015). In contrast, access to formal savings products — especially those with commitment features — appears to be beneficial (Ashraf et al., 2006; Brune et al., 2011; Dupas and Robinson, 2013). Yet it is difficult to find sustainable ways to offer savings accounts to the poor, and particularly ones that carry favourable interest rates. One possible solution is to foster peer-to-peer saving and lending institutions, such that the cost of providing a savings technology is borne by borrowers, and the interest charged on loans is reaped by savers. Rotating Savings and Credit Associations (ROSCAs) can be seen as a basic and ubiquitous version of this idea, although typically without the interest component. More recently, practitioners have promoted more sophisticated savings and credit institutions known as "Village Savings and Loan Associations" (VSLAs) or "Self-Help Groups" (SHGs).[1] Such institutions now have over 100 million members worldwide (Greaney et al., 2016).

Impact evaluations have shown positive effects of access to VSLAs on household food security (Beaman et al., 2014; Ksoll et al., 2016).[2] However, little is known about how individuals sort across such groups. Understanding such sorting patterns is key to understanding whether such groups promote financial intermediation between potential savers and borrowers. Instead, it may be that frictions such as limited liability, imperfect information or transaction costs lead some groups to focus entirely on saving and others almost entirely on borrowing, limiting the potential welfare benefits to both savers and borrowers.

In this paper, we therefore ask whether VSLAs bring together individuals with a demand for a savings technology and individuals with a demand for credit, enhancing financial intermediation in communities with low access to formal banking. To do so, we use novel data from a census of all members of mature VSLA groups in a region of Malawi. We test two hypotheses. First, we examine whether those engaged in agriculture sort into groups with those engaged in non-farm activities. This would allow farmers to save harvest income across the year, whilst enabling those engaged in a small business to take short-term loans for investment. The results indicate that members do not sort in this way, most likely due to informational or social constraints, or transaction costs. A possible policy implication is that VSLAs should be linked into a larger credit system, to allow funds to flow across sectors. Second, given that VSLAs have the features of a multi-faceted commitment savings technology, we ask whether present-biased individuals join VSLAs and group with time-consistent individuals who desire low-interest borrowing. More promisingly, the results provide evidence that this is the case. This suggests an important way in which these groups may enhance efficiency – albeit only within occupational groups – and raise the welfare of both savers and borrowers.[3]

[1] Other acronyms for such groups include VSLs, SBGs, SILCs, and SfCs, depending on the NGO.

[2] Ksoll et al. (2016) suggest that this may be linked to increased agricultural investments. Similar to evaluations of formal microfinance, neither of the studies cited finds significant effects of VSLAs on business profits, health, education or female empowerment. However, this may be an artefact of short evaluation time-frames, as most of those who joined Self-Help Groups had completed at most one savings cycle by the time of the endline surveys.

[3] Policymakers may nonetheless be concerned about the distribution of these welfare gains across commitment savers and borrowers. Sophisticated individuals with severe present-bias problems may in principle accept a very low or even negative interest rate when lending out to borrowers, whom they would essentially be paying to keep saving funds away from temptation. In section 5.1 we offer evidence that this is not the case: interest rates on

There exists a small literature focused on understanding how VSLAs function. Greaney et al. (2016) use a field experiment to show how such groups may screen credit risk, especially if asked to pay for their own training. In theoretical work, Burlando et al. (2016) highlight the potential inefficiency within VSLAs, arising from the supply of saving exceeding or falling short of the demand for borrowing. Burlando and Canidio (2017) then randomise the proportion of ultra-poor individuals across groups. They show that there is a trade-off between including such individuals and reducing groups' capacity to lend, because ultra-poor members contribute fewer savings to the group's fund. Most related to our paper, Burlando and Canidio (2016) consider financial intermediation within groups, and provide evidence from individual passbook data that on average poorer members borrow from richer members. The authors also show that VSLAs do not appear to help members to smooth out occupation-specific shocks. Our finding that members positively assort on occupation may help to explain this result.

This paper complements the literature in two ways. First, we consider the question of how, conditional on participating, members sort across groups. As outlined above, sorting may be crucial in determining how well VSLAs can fulfil a financial intermediation role between members with different financial needs. Our data allow us to look at sorting in a natural setting, without randomisation of types of individuals across groups, and over the longer term, once groups are more likely to be in equilibrium. Second, we highlight the nature of these groups as offering a commitment savings technology. The fact that many individuals join such groups out of a demand for commitment has been somewhat overlooked in the literature, but has important implications for interest rates, lending dynamics, and the distribution of welfare gains.

Our motivation is conceptually related to a broader body of work that examines sorting in informal financial institutions. Ghatak (2000) and Ahlin (2016) develop theoretical models of how sorting might enable the efficient pricing of risk in the context of joint-liability microfinance. Banerjee et al. (1994) study a similar problem in the design of credit cooperatives, while Eeckhout and Munshi (2010) examine sorting for credit motives across chit funds in India. Others such as Wang (2014) have looked at the formation of mutual insurance groups. Our contribution differs insofar as we examine sorting in groups when opportunities for financial intermediation exist: that is, when some members are primarily interested in saving, while others are interested in borrowing.

Our empirical strategy uses a dyadic regression framework to test whether individuals who belong to a VSLA sort into specific groups based on occupation or present-bias. This builds on work by Arcand and Fafchamps (2012) who use dyadic regressions to study sorting and inclusiveness in community-based organisations. Other authors have used dyadic analysis to examine sorting on risk preferences for risk-sharing games (Attanasio et al., 2012; Barr et al., 2012). Our approach adds to this literature in that we study sorting on time preferences. We also do so in the context of a fully-fledged programme setting, rather than a framed field experiment.

lending are in line with the "fair" benchmark of members' average long-run monthly discount rates.

2 VSLAs as a commitment savings and a credit technology

The design of self-funded microfinance groups and the procedures used to train members is similar across NGOs and countries. The VSLA intervention that we study — run by the NGO SOLDEV in northern Malawi — is representative of industry standards.

The NGO first holds a large public information meeting in each targeted community. Interested participants are then invited to self-select into groups of 15-25 members. The only guidance provided by the NGO on selection is that members should have the ability to save small amounts and repay loans, be honest and cooperative, and have confidence in one another. With the help of the NGO, each group purchases a cash box with three separate locks, and elects three different members to act as key-holders. This is to reduce the probability that any funds placed into the box are subject to theft. The NGO or an NGO-trained field agent then assists the group in writing a constitution, and trains the group in financial literacy and account-keeping over a period of several weeks.

At the end of the training period, the group begins to hold weekly meetings. In each meeting, individual group members must save by purchase between one and five "shares" in the group, the price of which is fixed beforehand by the group.[4] After a month of meetings, members can begin requesting loans, to be repaid at a fixed monthly rate of interest which is again set by the group at the start of the cycle. At the end of each cycle — usually a year — the group's total savings funds plus the successfully-recovered loan principals and interest are "shared out" in proportion to individual members' savings (hence the term "shares").

Comparing the structure of VSLAs to that of other savings and credit institutions, VSLAs lie somewhere between credit cooperatives and ROSCAs. VSLAs have a similar function to credit cooperatives and credit unions, but are much smaller and less formalised. For example, VSLAs typically have no legal status, unlike some of the larger rural credit unions. As a consequence, VSLAs rely exclusively on interpersonal relationships for monitoring and enforcement of loan repayment — a feature that may have both advantages and disadvantages. Insofar as VSLAs are informal savings and credit groups embedded in social ties between villagers, they are close in spirit to ROSCAs. However, they are more sophisticated in that they allow more flexibility. On the savings side, each member can choose to buy between one and five shares each week, rather than committing to a fixed payment identical for all members and all weeks. On the lending side, members can affect the size and timing of the loans they receive, rather than having to wait for their turn in a rotation.[5] VSLAs also differ from joint-liability microcredit groups insofar as they combine a pure savings technology with credit to members.

VSLAs typically offer access to credit at a lower interest rate than both traditional moneylenders and microfinance lenders, making them attractive to potential borrowers. VSLAs can also be seen as a multi-faceted commitment savings technology, making them attractive to individuals with a demand for commitment. First, there is a deposit commitment, since

[4] In principle each member is also required to make a small weekly contribution to the group's insurance fund, to cover events such as illness or death of a group member's relatives. We found that most groups set the level of such contributions to be very small — around 20 Malawi Kwacha (MK) or \$0.06) — or dropped this component altogether, citing past disagreements about payouts. Where implemented, the insurance fund is kept separate from the savings and loan fund and is not shared out at the end of the cycle.

[5] Bidding ROSCAs do allow members some choice over when they receive the pot. However, each member can only receive the pot once, and cannot choose the pot size.

all members are required to purchase at least one share per week.[6] Second, VSLAs enforce a withdrawal commitment, since savings made into the box (i.e. all shares purchased) cannot be liquidated until the end of the savings cycle.[7] Third, group meetings may operate as additional "soft" deposit commitment device, harnessing active peer pressure to save (Gugerty, 2007), a desire to save in order to appear reliable to peers (Breza and Chandrasekhar, 2015), and reminders to save (Kast et al., 2012). Indeed, there is evidence that similar features of microfinance may enable individuals to use microcredit as a commitment savings device (Bauer et al., 2012; Afzal et al., 2017). Fourth, any member requesting a loan must demonstrate that it is for a good purpose, and the whole group must agree for the loan to be granted. It is therefore unlikely that members can undo the commitment savings feature of the VSLA by borrowing for consumption, except in cases of demonstrable emergencies.

VSLAs may therefore offer an attractive package to individuals who have problems with self-control, as long as they are sophisticated enough to recognise the value of commitment devices. Anecdotally, members do seem sophisticated in this way: when asked about the reasons for joining, many individuals say that being in a VSLA "overcomes the temptation of spending savings kept at home". If VSLAs manage to lend and thereby offer on saving, they may also be attractive for savers without a demand for commitment. This includes time-consistent savers and naïve present-biased individuals, if the latter can manage to meet the minimum deposit requirement each week.

3 Testing strategy

The extent to which VSLAs generate financial intermediation depends on the extent to which they are able to recruit each of these types of members — commitment savers, ordinary savers, and borrowers — and the extent to which they are able to sort into groups with one another. This is ultimately an empirical question. For example, if limited liability concerns prove too strong, then VSLAs may end up consisting only of savers. Alternatively, there may be some all-commitment-saver groups where members are unwilling to lend out their savings, and some all-borrower groups where members are willing to take the risk of depositing a minimum amount in order to gain access to credit. The purpose of our paper is therefore to investigate whether, four years after their introduction, VSLAs in Malawi have blossomed into organizations capable of providing proper financial intermediation. We consider two types of financial intermediation: neoclassical financial intermediation without demand for commitment; and financial intermediation in the presence of the existence of demand for commitment saving.

3.1 Neoclassical financial intermediation

A first possible role of the financial intermediary is to match ordinary savers with borrowers. Savers are individuals willing to save in exchange for a return on their savings; borrowers are individuals willing to pay interest in order to finance a high return investment opportunity.

[6]In practice we see that some groups occasionally relax this requirement, allowing individuals to purchase zero shares in certain weeks. It is likely that the groups strike a balance between commitment and liquidity to cover shocks, by relaxing the deposit commitment but keeping the withdrawal commitment strong.

[7]There is a provision that individuals can withdraw a small number of their own shares in the case of a medical emergency or similar. However, we see very few instances of this in individual account records.

In the context of our study, the most salient need for neoclassical financial intermediation is between individuals with different occupations. People in the study area are primarily engaged in two occupations with different cash-flow profiles: agriculture (overwhelmingly subsistence crop farming, with a small fraction growing rice or tobacco as cash crops), and small entrepreneurship (examples include selling vegetables and goods from nearby markets, bricklaying and carpentry, driving bicycle taxis, and sewing). Farming households have a large outflow of funds for investment during the winter planting season, and they receive one major inflow of resources just after the maize and rice harvest in April, with a small cassava harvest around November. In contrast, households engaged in business and other non-farm activities typically have frequent monetary inflows, but they require access to capital whenever a business opportunity with a large upfront investment cost arises, which can happen at any time of the year.

If VSLAs serve a neoclassical financial intermediation purpose, we would therefore expect sorting of members across groups to display *negative* assorting on occupation: we would see farmers sorting into groups with small entrepreneurs. Farmers would act as savers for most of the cycle, except for occasional agricultural investments and emergencies. Meanwhile entrepreneurs would borrow out of the farmers' savings, thereby generating dividends through loan interest repayments. Sorting could be achieved through a wide variety of ways, e.g. through direct bargaining between villagers, or through the guidance of an 'enlightened' local leader. It could also arise over time as the result of a tatonnement process: competition for borrowing funds amongst entrepreneurs within a given VSLA would bid up the interest rate on lending, pushing some of them to leave for another VSLA with more savers and available funds per borrower.

However, a variety of frictions may prevent such sorting from occurring. The fact that most VSLA lending is done on a limited-liability basis means that if members can better screen, monitor and punish delinquent borrowers when they have the same occupation, this friction may lead to *positive* assorting on occupation.[8] A similar argument applies if transaction costs are lower among those with the same occupation, for example if members of the same occupation find it convenient to meet at a particular place or time, or to share out at a particular time of year. This can be seen as a friction compared to a set-up which allows different VSLA members to deposit or withdraw at different times. The presence of one or more of these frictions may lead to positive rather than negative assorting. Positive assorting implies unrealised financial intermediation possibilities between farmers and non-farmers, which would be attainable under full commitment, perfect information and reduced transaction costs.[9]

Aside from financial intermediation motives, risk-sharing motives may also imply benefits from negative assortative matching — if, as is likely, shocks are more correlated within rather than across occupational groups (Wang, 2014). If frictions lead to positive assortative matching, this implies that groups are less diversified against the risk of shocks that particularly impact members of one occupation. This may limit members' ability to smooth shocks through borrowing from VSLAs,[10] and make VSLAs less sustainable by increasing the correlation in

[8] A member's own shares can be seized as collateral in the case of non-repayment, but these may not be enough to cover the value of the loan.

[9] It may also be that individuals derive larger social or learning benefit from interacting with others in the same occupation. This can be viewed as a positive externality, or a type of friction compared to a situation in which socialising and learning decisions are separable from banking decisions.

[10] Of course, the full extent to which individuals and households are exposed to common shocks depends not only on the diversification of VSLA groups but also on the diversification of household income sources across

individuals' risk of loan default.

3.2 Commitment saving

As detailed above, VSLAs also offer a commitment savings technology, which has the potential to attract sophisticated present-biased individuals. VSLAs may also attract regular savers, if lending to members who repay with interest leads to a return on saving. Two scenarios are possible ex ante: pure saving; or a combination of saving and borrowing. Each scenario has different implications for the composition of VSLA membership, and thus on sorting into groups

VSLAs can generate potentially large welfare gains by attracting not only savers but also members who wish to borrow and can be trusted to repay. In doing so, VSLAs would serve borrowers but also serve the needs of commitment savers without imposing a financial cost on them: a feature that distinguishes VSLAs from MFIs that only offer credit to their members, and from costly commitment devices. VSLAs that sustainably combine borrowing and saving should be composed of a mix of members: some with a demand for commitment or regular saving; and others with a solvent demand for credit. The former group will contain sophisticated (and potentially naïve) present-biased individuals, while the latter group will typically be time-consistent individuals with an investment opportunity — naïve present-biased individuals may also wish to borrow, but they are more likely to be denied credit after an initial learning period given that they are more likely to default. Hence we should observe *negative* assorting on present-bias.

On the other hand, if reliable borrowers cannot be found, then VSLAs are capable of operating purely as a savings organization, collecting savings and returning them to members at the end of the cycle. Membership in such a group would appeal to individuals with a demand for commitment, including individuals who are present-biased and sophisticated about their present-bias. Because a group composed of such members would makes few loans (except perhaps for emergencies), no interest would be paid on savings, which means that savers with no demand for commitment would have little reason to join: they could often do better by saving flexibly on their own.[11] This means that VSLAs that do not lend should predominantly attract present-biased individuals, and we should observe *positive* assorting on present-bias into such groups.

3.3 Tests of sorting

We therefore test for the presence of negative assorting on occupation and present-bias:

- Evidence of *negative* assorting on occupation is an indication that borrowing frictions are low and VSLAs can perform a neoclassical financial intermediation role between time-consistent savers and borrowers.

- In contrast, *positive* assorting on occupation would suggest the existence of frictions on borrowing across occupations, e.g. because of monitoring or enforcement issues.

occupations.

[11] It is theoretically possible that time-consistent individuals might join to engage in speculative behaviour, if they seek to "pile in" towards the end of the savings cycle in an attempt to suck out any profits from lending up until that point. However, the scope for such behaviour is limited by the purchase limit of five shares per week.

- Evidence of *negative* assorting on present bias is an indication that VSLAs serve a demand for commitment while at the same time serving a group of (primarily time-consistent) borrowers. This indicates that VSLAs provide a "behavioural" financial intermediation service.

- In contrast, *positive* assorting on present-bias would again indicate that information or enforcement frictions were too high to support this type of intermediation between savers and borrowers.

4 Survey design

In order to test these predictions empirically, we surveyed in the Summer of 2013 some 150 VSLA groups in Karonga District, northern Malawi (Figure 1). These VSLAs were originally formed as part of a cluster-randomised controlled trial, which ran from 2009 to 2011. The intervention was implemented by the Rockwool Foundation and CCAP Synod of Livingstonia Development Department (SOLDEV). The results of the impact evaluation are detailed in Ksoll et al. (2016).[12]

Figure 1: Location of Karonga District within Malawi

Given that we surveyed the groups two to four years after the groups were initially trained, our data is uniquely suited to studying the long-run equilibrium sorting of members across

[12]The training of these groups was funded by the Rockwool Foundation, rather than by members themselves. Greaney et al. (2016) show that whether the NGO or members pay for training affects who participates in VSLAs. Thus our empirical results on sorting may only be representative of groups in which the NGO pays for the training. However, this is still by far the most widely-used model for Self-Help Group interventions.

groups, and the long-term functioning of the groups more generally. Surveyed individuals had enough time to learn about the savings and borrowing technologies provided by VSLAs and the benefits of grouping with different members. They also had a chance to join different VSLA groups, switch across groups at the end of savings cycles, or indeed drop out of groups altogether.

Forty-six villages were included in the initial study, half of which were invited to form groups and began receiving VSLA training in late 2009-early 2010. The other half only received training in late 2011. In Ksoll et al. (2016) these are referred to as treated and control villages, respectively. Since we visited the area two years after the control villages were phased into treatment, our sample covers all VSLA groups that were eventually trained by SOLDEV in both treatment and control villages.[13] Two remote, control villages dropped out of the programme in 2011 and never established any groups. Our 2013 sample covers the remaining 44 villages.

The survey protocol was as follows. We contacted each group via the NGO, who invited all group members to a meeting at the group's usual meeting place. We first explained the purpose of our survey, and obtained the consent of all group members to share their information. The data collection then proceeded in three steps. First, we used the set of individual account books to construct a roster of all group members, past and present. We then elicited basic demographic information for each member as well as their membership history, by reading out each member's name to the group and then asking a series of questions about that individual. This constitutes what we refer to as the "2013 member census data".

Second, we conducted a short group survey covering the group's history and practices, such as the typical use of savings and loan funds, the interest rate charged on loans, and the typical punishment for late loan repayments. Finally, we photographed each individual's passbook, which details their weekly savings decisions and their borrowing behaviour for the current cycle.

To test whether members sort on present-bias, we use a measure of individuals' time preferences elicited in the 2009-11 panel dataset which was collected for the initial impact evaluation. This measure was elicited largely prior to members joining VSLAs;[14] hence using it rules out possible reverse causation, if being members of the same group leads individuals to have a greater similarity or differences in their choices over time. To obtain this measure, we matched the members of our 2013 census by name and village back to the 2009-11 panel survey. The 2009-11 panel covers a stratified random sample of households from the treatment and control villages.[15] Since the 2009-11 panel contains only a random subsample of each village's population — whereas our 2013 member census covers all members — many members in our member census were not interviewed as part of the 2009-11 panel. Overall we are able to match around a fifth of the members from our 2013 census (722 out of 3,801) to the 2009-11 panel.

[13] Anecdotally, we learned that a number of "replication" groups did form without SOLDEV training, either autonomously or with the help of members of SOLDEV-trained groups who had been encouraged to teach others.

[14] We report time preference values from the 2010 wave, since the 2009 wave did not include the far frame for female respondents. Only a very small number of the VSLA groups had begun to form by early 2010, and thus time preferences are still plausibly exogenous to the characteristics of other group members.

[15] By construction, the 2009-11 panel therefore includes some individuals who after baseline went to become members of VSLAs and whom we match to our 2013 member census, and others who did not and who therefore do not appear in our 2013 member census. The 2009 baseline was stratified insofar as households who declared an interest in joining VSLAs were over-sampled. For us this simply increases the probability that we are able to match members of our 2013 census to the 2009-11 panel.

From now on we refer to this subsample as "matched individuals".[16] These individuals are evenly spread across groups: we matched at least one member in 95.3% of the groups, and on average we match 4.7 members out of an average group size of 25.3 members. Of these, 352 randomly received the full time preference module (which for budgetary reasons was only administered to a subset of the 2009-11 panel sample) and so can be used to test the predictions of sorting on present-bias.

5 Data

Since our data provide a rich characterisation of mature VSLA groups, we begin with descriptive statistics on saving and borrowing in VSLAs, and on individual VSLA members. We then present summary statistics for the variables used in the analysis.

5.1 Characteristics of saving and borrowing products

From the group survey, we see that the median price of a share was 100 MK in 2013, equivalent to around \$0.30. Members of the median group could therefore save between \$0.30 and \$1.50 per week, or \$16-\$80 per year. For comparison, Malawi's GNI per capita in 2013 was \$390 (`http://data.worldbank.org`); hence these modest amounts represent a significant fraction of household income. Regressing the share price on group composition in terms of occupation (and village fixed effects) shows that the price of a share is 5.17 MK less ($p<0.01$) for every additional 10% of the group members that are farmers. This may reflect the fact that farmers are on average poorer, as detailed below.

Most of the groups choose to share out in October to January, which is during the planting season and also the lean season. Increasing the proportion of farmers by 10% makes a group 3.15 percentage points ($p=0.016$) more likely to share out and start a new cycle during this period. The remaining groups choose to share out in April-June. This may reflect other savings priorities; or simply that the intervention was introduced at this time of year, and groups with a low proportion of farmers stuck to that date.

Loan sizes vary greatly, but typical amounts for larger loans are between 5,000 MK and 10,000 MK (\$15 to \$30). The official monthly interest rate on borrowed funds is set at an average of 17% across the VSLA groups in 2013. This rate is 0.25 percentage points lower ($p=0.03$) for every additional 10% of the group members that are farmers; which may reflect the fact that demand for borrowing is lower in farmer-heavy groups (see Section 6.4). While interest rates of this magnitude may seem high, they are close to the most natural benchmark for a "fair" interest rate available in the data: namely, individuals' average monthly discount rates over the longer term (see Section 5.2).[17]

[16] The panel members should be more representative of the villages' populations than the census of all members is. For example, whilst only 25% of members in our 2013 member census are male, since women disproportionately join VSLA groups, close to 50% of the respondents in the 2009-11 survey were male due to it being representative. Thus we are disproportionately likely to match a male 2013 member back to the 2009-11 survey compared to a female 2013 member. Section 7 describes how all of our results are robust to re-weighting to take account of this.

[17] Inflation in 2010 versus 2013 should of course be taken into account in order to compare in real terms the interest rates in 2013 to the discount rates measured in 2010. Inflation in Malawi was fairly stable at around 8% y-o-y (corresponding 0.64% per month) from the beginning of 2009 until the beginning of 2012. After a devaluation of the Kwacha by 33% in May 2012, inflation spiked and ran at an average of 28% in 2013 overall

Savers appear to earn a healthy return on their shares: the internal rate of return on savings is approximately 6% per month, as calculated from the average reported annual return per share of 45% at the end of the cycle.[18] Since this return per share can only be achieved via lending saved funds, it demonstrates that VSLAs do serve an important financial intermediation function. A natural question is whether VSLAs are reaching their full potential for financial intermediation. Assuming away losses from occasional defaults, late payments, and debt forgiveness, a simple back-of-the-envelope calculation reveals that an annual return in excess of 70% (with an internal rate of return of 10% per month) could be in principle achieved if all saved funds were lent continously during the cycle.[19] The average realised return across groups hides considerable variation, however, with some VSLAs achieving a return much closer to the theoretical limit and some performing much weaker intermediation. There is also considerable variation within VSLA on the net financial position of members at the end of the cycle: those who only save enjoy a sizeable positive return, while those who borrow a lot by the end the year make a financial loss. We revisit these points in Section 6.4.

The patterns of how savings and loaned funds are used is quite distinct. The predominant use of savings is for agricultural inputs, with 58% of groups reporting that this is one of the three largest uses of saved funds. The other most prominent uses of savings are food, and durable household items, such as kitchenware. Loans on the other hand are highly concentrated on trading and business purposes: 74% of groups say this is the most important use of loaned funds, and altogether 95% say this is among the three most important uses of loaned funds. This reinforces the argument in Section 3.1 that, in the absence of frictions such as imperfect information and limited liability, there are potential benefits of negative assorting on occupation such that farmers can lend to those engaged in business. The other most commonly-reported uses of loan funds are education, emergencies, and purchasing food. Insofar as emergencies and times of food scarcity are likely to be more positively correlated within occupation than across occupation, this implies an additional risk-sharing motive for negative assortative matching on occupation.

5.2 Individual member characteristics

Table 1 presents some of the key demographic characteristics of the 3,801 individuals in our member census. 73% of members report farming as their primary economic activity, whilst 21% report working in a business (mainly a family business) as their main activity. Although the NGO imposes no rules on the gender of participants, 75% of the members are female.

The data document a large degree of churn in individual membership, which suggests scope for sorting across groups over time. 32% of members joined sometime after the first cycle, and 11% of members left individually, with an additional 4% leaving after their whole

(corresponding to 2.1% per month). Groups do not appear to have taken this into account in the nominal loan interest rate set at the beginning of the 2013 cycle, which in most groups remained unchanged from previous cycles. However, even the high 2013 inflation rate is still negligible on a monthly basis compared to such a high monthly loan interest rate. Thus accounting for monthly inflation does not alter our conclusion that the interest rate on loans appears to be broadly in line with monthly discount rates.

[18] The internal rate of return is approximated by assuming a constant savings rate over the cycle. This return is straightforward to reconcile with a monthly interest rate on borrowing of 17%, since only a fraction of the group's funds are lent out at any given time.

[19] If all saved funds and paid interest are lent at 17% interest each month, the annual internal rate of return per share is 142% – 70% if all available funds are lent at 10% a month and 170% if they are lent at 20% a month.

group disbanded. Of those leaving individually, 35% left during the first rotation and 44% at the start of or during the second rotation, with fewer appearing to leave in later rotations (although fewer groups have reached such maturity). The most common reasons for leaving are moving away (26% of individual leavers) or no longer wanting to be a member (31%). 17% are reported to have left because they could not save, and 22% because they defaulted on loans or were excluded for other reasons. Farmers are seven percentage points less likely to have joined after the first cycle, indicating that other occupational groups tend to have joined later and/or switched VSLAs. Conditional on leaving, farmers are eight percentage points more likely to have left because they could not save. This could be because farmers are on average poorer, or because their income is seasonal. Other aspects of joining and leaving are uncorrelated with occupation.[20]

Table 1: Individual member characteristics – 2013 member census

	Full CSAE Sample				
	Mean	Std dev	Min	Max	N
Occupation					
Farmer	0.73	(0.44)	0.0	1.0	3801
Businessperson	0.21	(0.41)	0.0	1.0	3801
Other	0.06	(0.23)	0.0	1.0	3801
Demographic Variables					
Male	0.25	(0.43)	0.0	1.0	3799
Female-headed household	0.21	(0.41)	0.0	1.0	3796
Age	36.15	(12.05)	12.0	83.0	3785
Education					
Some primary educ. (only)	0.76	(0.43)	0.0	1.0	3801
Some post-primary educ.	0.18	(0.39)	0.0	1.0	3801
Literate (read & understand newspaper)	0.83	(0.38)	0.0	1.0	3795
Wealth					
Father well-off in village (scale 1-5)	3.34	(1.31)	1.0	5.0	3573
Spouse's father well-off in village (scale 1-5)	3.42	(1.32)	1.0	5.0	3566
Income Poverty Indicators					
Household well-off in group (scale 1-9)	7.52	(1.28)	1.0	9.0	3770
HH owns a bicycle	0.51	(0.50)	0.0	1.0	3796
# Goats	1.29	(2.59)	0.0	40.0	3792

Notes: All variables as measured during the 2013 member census, N=3,801 members. 519 members were no longer active, but are included to avoid selection bias. Analysis is conducted with and without these individuals, see Section 7. Missing observations reflect answers of "do not know" or "not applicable". Occupation denotes an individual's primary economic activity, if engaged in multiple activities.

As described above, we matched 722 individuals by name to the baseline data of the 2009-11 impact evaluation. Merging with this additional dataset yields richer information on individual characteristics for panel individuals, as summarized in Table 3. In particular, activities to

[20]We are underpowered to detect their correlation with time preferences, given that the latter variables are only available for a subsample of members.

Table 2: Individual economic activity & schooling – 2013 member census

Category	N	% of responses
Occupation	**3780**	**100%**
Farmer	2,786	73.34%
Business	793	20.87%
Self-employed	*108*	*2.84%*
Family business worker	*685*	*18.03%*
Fishing	61	1.61%
Fishing, employed	*17*	*0.45%*
Fishing, self-employed	*44*	*1.16%*
Employee	89	2.34%
Casual labour (ganyu)	24	0.63%
Student	4	0.11%
Unemployed, not seeking work	9	0.24%
Other	14	0.37%

Notes: All variables as measured during the 2013 member census, N=3,801 members. 519 members were no longer active, but are included to avoid selection bias. Analysis is conducted with and without these individuals, see Section 7. Missing observations reflect answers of "do not know" or "not applicable". Occupation denotes an individual's primary economic activity, if engaged in multiple activities.

measure time preferences were administered to both the head and the spouse in a random subset of the panel data households in 2010, and can be matched to 352 individuals.

The time preference activities took the form of multiple price lists. Participants were first asked whether they would prefer to receive 2000 Kwacha (approximately $13 in 2010) now or increasing amounts in one month.[21] This constitutes the near frame. Participants were then asked whether they would prefer to receive 2000 MK in one year or the same increasing amounts in one year and one month. This constitutes the far frame. The average respondent prefers 2000 MK now to 2332 MK in one month, and 2000 MK in one year to 2402 MK in one year and one month. If participants answered these questions without considering their background consumption, and if utility was linear, this would imply an average near-frame monthly discount rate of 17% and an average far-frame monthly discount rate of 20%. However, taking into account any curvature of the utility function implies a lower discount rate (Andersen et al., 2008).

We classify an individual as "present-biased" if she makes a more impatient choice in the near frame than in the far frame. The choices of members classified as "present-biased" imply an average near-frame discount rate of 16% with linear utility, and an average far-frame monthly discount rate of close to zero. This is consistent with the idea that present-biased individuals

[21] Due to practical constraints, responses were unincentivized. The limited evidence comparing incentivized and unincentivized responses to time preference questions suggests that unincentivized responses are unbiased, although they may be more noisy (John, 2017).

exhibit excessive short-run discounting but modest long-run discounting.[22] Overall, 11% of individuals are classified as "present-biased". This is very similar to the rate of 10% found by Brune et al. (2011) in rural Malawi. Other estimates from developing countries find a larger proportion of individuals to be "present-biased" (Ashraf et al., 2006; Giné et al., 2016; Janssens et al., 2017). However, estimates of "present-bias" over money may be exaggerated at times of tight liquidity constraints (Carvalho et al., 2016; Cassidy, 2018). Tight liquidity constraints are much less of a concern here, since the 2009-11 survey was conducted shortly after the harvest. If anything, we may under-estimate the number of present-biased individuals, if some present-biased individuals have enough liquidity to arbitrage experimental payments (Augenblick et al., 2015). This would reduce our chances of observing assortative matching, positive or negative, on this measure. Similarly, our measure does not proxy whether individuals categorised as "present-biased" are sophisticated or not. If only a subset of individuals classified as "present-biased" are sophisticated and have a demand for commitment, then this would also reduce our chances of observing assortative matching on this measure.

The fact that the far frame refers to one year after the near frame eliminates concerns that seasonality in consumption and liquidity constraints may act as a confound in the measure of "present-bias" (Epper, 2015). Nonetheless, individuals may still spuriously appear "present-biased" if they are expecting a decrease in the marginal rate of intertemporal substitution next year compared to this year – for example if this year's harvest was particularly bad for their household. We therefore employ a number of tests to check whether measured "present-bias" appears to be capturing a decreasing marginal rate of intertemporal substitution, rather than truly present-biased preferences.

Data on saving and borrowing mitigate against the idea that "present-biased" individuals are systematically expecting to be better off next year. If this were the case, we expect these individuals to exhibit higher recent borrowing and lower saving. Instead, we observe a strong negative correlation between appearing "present-biased" in 2010 and data on borrowing from 2009 and 2010: in 2009, individuals categorised as "present-biased" are 13.7 percentage points less likely to have asked for a loan in the past year, 7.3 percentage points less likely to have any current loans, and have 746 MK fewer in outstanding loans; whilst in 2010 they are 16.8 percentage points less likely to have asked for a loan in the past year, and have 4957 MK fewer in outstanding loans, although the latter is marginally insignificant (p=0.134). All of this is more consistent with the idea that "present-biased" individuals are not deemed credit-worthy, or avoid borrowing because they are aware of their own tendency to over-consume. "Present-biased" individuals also have higher total savings from 2009 (4468 MK, p=0.075), which further goes against the idea that individuals appear "present-biased" because they are liquidity-constrained now but anticipate higher income in the future.[23] Meanwhile, the measure of "future-bias" is uncorrelated with measures of saving and borrowing from the 2009-10 data.

Next, if individuals who appear "present-biased" are actually those facing a higher mar-

[22] Again, the estimate of 16% is an approximation if utility is linear, but is an upper bound if utility is concave. Those classified as "time-consistent" actually exhibit far-frame switch-points consistent with a higher far-frame discount rate than those classified as "present-biased". However, these "time-consistent" individuals appear equally impatient in the near and the far frames.

[23] The fact that "present-biased" individuals may be able to save outside of VSLAs is still consistent with them having a demand for VSLAs as a commitment savings device, since VSLAs may offer a better return than other forms of saving such as cash-under-the-mattress. Moreover, exercising self-control by oneself may be costly (Gul and Pesendorfer, 2001; Toussaert, 2015).

ginal rate of intertemporal substitution than they expect to face in one year's time, we might expect the measure of "present-bias" to be correlated with low recent consumption. Vice versa, we might expect individuals classified as "future-biased" (26% of the sample) to exhibit high recent consumption. In fact the measures of "present-bias" and "future-bias" in early 2010 are completely uncorrelated with a measure of monthly household consumption per capita in 2009. Whilst "future-bias" is correlated with better food security in 2009 (the household is 8.9 percentage points less likely to have had fewer than two meals per day on average in the last week, p=0.025), "present-bias" is also marginally correlated with better food security (14.0 percentage points, p=0.112). This cross-sectional comparison is only suggestive – i.e., it does not measure whether the marginal utility of consumption is high or low compared to its expected value in one year's time. Nonetheless it suggests that, if anything, it is those individuals who appear "time-consistent" – not those who appear "present-biased" – who have experienced recent hardship. We do find that the measure of "present-bias" is marginally correlated with subjects' subjective report that they have had a bad harvest in 2010 compared to the past decade (correlation of 0.292 on a 1-5 Likert scale, p=0.101). Therefore, in Section 6 we run a further set of tests to check that our results on sorting are driven by true present-bias rather than by a decreasing marginal rate of intertemporal substitution.

Finally, the 2009-11 panel dataset further provides measures of the matched individuals' risk aversion — elicited using standard Binswanger lotteries — intra-household bargaining power, and more detailed measures of consumption and food security. These are also summarised in Table 3, and are used as additional controls in robustness checks.

5.3 Group composition by member characteristics

Table 4 describes the distribution of groups across villages. Thirty-five villages have at least two groups — hence sorting is identified in these villages — and some villages have up to fourteen. The presence of more than one group per village is itself suggestive of inefficiency: there is no secondary market for capital in these villages, and so VSLAs with excess capital cannot lend to other VSLAs. Having one large VSLA per village would maximise the scope for lending out savings deposits and alleviating credit constraints. However, transaction costs and ability to monitor and sanction borrowers likely become too large over a certain group size, explaining why we observe multiple groups per village. Given this, sorting across groups becomes a key determinant of efficiency.

Table 5 describes how groups are composed in terms of member characteristics. The average group size is 25 members, although groups range in size from 10 to 45 members. Groups also range in gender composition from all-male to all-female, although most groups (i.e. groups within one standard deviation of the mean) are mixed but with a majority of female members. In some groups, as many as 62% of members come from female-headed households.

There is also clear heterogeneity across groups in terms of occupational composition: some groups consist purely of farmers, whereas others contain almost no farmers. However, dyadic regression analysis is needed to determine whether such heterogeneity is evidence of individuals sorting across groups within villages, or whether it represents differences in population characteristics across villages.

Table 3: Individual member characteristics – matched subsample

	Matched individuals				
	Mean	Std dev	Min	Max	N
Time Preferences					
Present-biased	0.11	(0.31)	0.0	1.0	350
Future-biased	0.26	(0.44)	0.0	1.0	350
Minimum switch-point, near frame	2332.36	(369.62)	1900	2800	352
Minimum switch-point, far frame	2401.39	(378.38)	1900	2800	352
Risk Preferences					
Risk-neutral	0.11	(0.32)	0.0	1.0	330
Intra-Household Bargaining					
Ever hides money from spouse	0.44	(0.50)	0.0	1.0	307
Female HH decision-making power (index 0-8)	2.87	(1.81)	0.0	8.0	377
Social Variables					
HH important in village decisions (scale 1-6)	3.27	(1.14)	1.0	6.0	721
HH ever speaks at village meetings	0.57	(0.50)	0.0	1.0	718
Income					
Monthly consumption per capita, MK	2176.95	(973.09)	648.7	7811.1	721
Food security poor (dummy)	0.28	(0.45)	0.0	1.0	722
Credit					
HH asked for credit in last year	0.15	(0.36)	0.0	1.0	383
HH has any loans outstanding	0.09	(0.29)	0.0	1.0	383
Total value of loans outstanding, MK	779.90	(4238.64)	0.0	45000	383

Notes: N=722 individuals are matched from the 2013 census to the 2009-11 panel data. N=383 of these individuals are matched to the longer panel survey including preference modules. Missing values reflect "do not know", "not applicable", or inconsistent answers in the case of risk preferences. All variables presented here were measured in the 2009 wave of the panel survey, except time preferences, which are taken from the 2010 survey wave since the 2009 wave did not include the far frame for females. Present-biased (future-biased) is a dummy equal to one if the response to the near frame is more impatient (patient) than the response to the far frame. Minimum switch-point is the lower bound of the interval in which the respondent switched to preferring the one-month-later payment compared to a 2000 MK payment on the earlier date. 150 MK $\approx$ 1 USD at the time of the 2009 and 2010 surveys. Risk-neutral is a dummy equal to one if the respondent prefers a 50-50 lottery to its expected value for certain, and thus could indicate risk-neutral or risk-seeking behaviour. Female HH decision-making power is constructed from questions over four types of economic decisions, scoring one if the female has some say in the decision and two if she has complete control. Malawi's GNI per capita in 2009 was $26.6/month, but these are particularly poor households in a very remote region. Food security poor is equal to one if the household reports consuming fewer than three meals yesterday.

Table 4: VSLA groups per village

# groups	**# villages**	**% of villages**
1	9	20.5%
2	17	38.6%
3	4	9.1%
4	4	9.1%
5	3	6.8%
6	2	4.6%
7	2	4.6%
11	1	2.3%
13	1	2.3%
14	1	2.3%
Total	**44**	**100%**

Notes: From the 2013 member census, N=150 groups, N=44 villages. Eight of these groups were no longer active, but were included in the survey to avoid selection bias. Analysis is conducted with and without these groups, see Section 7.

Table 5: Group composition by member characteristics

Variable	**Average**	**Std. Dev**	**Min**	**Max**
# members	25.34	5.69	10	45
% members farmers	74.2	26.3	3.3	100.0
% members businesspeople	20.2	22.2	0.0	93.3
% members fisherman/woman	1.6	5.5	0.0	30.4
% members female	74.9	19.0	0.0	100.0
% members female-headed HH's	20.9	13.0	0.0	61.9
Mean age of members	36	4.6	23	49
% members literate	82.5	12.2	40.9	100.0
% members some primary only	81.6	11.4	38.7	100.0
% members own bicycle	52.1	18.6	0.0	95.0
Mean # goats owned by members	1.32	0.98	0.04	7.48

Notes: From the 2013 member census, N=150 groups, N=44 villages. Eight of these groups were no longer active, but were included in the survey to avoid selection bias. Analysis is conducted with and without these groups. Similarly, 519 of these members were no longer active, but were included in the survey for completeness. Analysis is conducted with and without these members, see Section 7.

5.4 Dyad characteristics

For the analysis, we construct all possible pairs – dyads – of members in the same village from the 2013 member census.[24] Of these dyads, 17% comprise two individuals who are both members of the same group, whereas the other 83% comprise two individuals who are members of different groups in the same village. Table 6 describes the dyads in more detail.

When we restrict attention to the dyads in which both individuals are matched to the full version of the 2009-11 panel dataset, including the time preference modules, this gives us a sample size of 1,641 dyads.[25] Table 7 highlights key additional data for the matched dyads.

6 Empirical strategy and results

6.1 Dyadic regression analysis

To test the predictions on sorting, we employ a dyadic regression framework (Fafchamps and Gubert, 2007). The intuition behind this approach is as follows: if there are multiple groups in a village, and if there is *positive* sorting on a given characteristic, then in equilibrium two members who are less similar on that characteristic are, *ceteris paribus*, less likely to be observed as members of the same group. Vice versa, if there is *negative* sorting on a given characteristic, then two members who are less similar on that characteristic are more likely to be members of the same group. We provide further intuition and detailed simulations on how sorting into groups relates to dyadic regressions in Online Appendix A.2.

Our main estimating equations are undirected dyadic logit models, with observations at the dyad level. These take the following form:

$$\begin{aligned}\Pr(D_{ijv} = 1 | D_{iv} = 1 \ \& \ D_{jv} = 1; \boldsymbol{Z_{iv}}, \boldsymbol{Z_{jv}}, \boldsymbol{W_{ijv}}, v) \\ = \Pr(\alpha + \boldsymbol{\beta}|\boldsymbol{Z_{iv}} - \boldsymbol{Z_{jv}}| + \boldsymbol{\gamma}(\boldsymbol{Z_{iv}} + \boldsymbol{Z_{jv}}) + \boldsymbol{\delta W_{ijv}} + \mu_v + \varepsilon_{ijv} > 0)\end{aligned} \quad (1)$$

where D_{iv} and D_{jv} denote dummies equal to one if i and j are members of some VSLA group,[26] and D_{ijv} is a dummy equal to one if i and j are members of the same group. $\boldsymbol{Z_{iv}}$ and $\boldsymbol{Z_{jv}}$ are vectors of i's and j's individual characteristics, in which we include measures of present-bias. We minimize omitted variable bias by controlling for a rich set of characteristics that may affect sorting and are possibly correlated with occupation and present-bias. We list below the full set of controls used in the main specification and in the robustness checks. $\boldsymbol{W_{ijv}}$ is a vector of characteristics of the dyad, including whether i and j share the same category of occupation. μ_v is a vector of village fixed effects. These control for the average probability of matching in each village, which depends on the number of groups and the relative size of each group. Village fixed effects also absorb a range of factors that affect the probability of being in the

[24] In practice we found it to be extremely rare that an individual would join a group outside of his or her village of residence. Thus *de facto* only the other members from an individual's village of residence are candidates to be members of the same group as that individual.

[25] Table 12 shows that the dyads which can be matched to the full version of the panel survey have small but significant differences from the whole universe of dyads from the 2013 member census. Therefore, we later re-run all of our time preference specifications weighting each dyad by the inverse probability of that dyad being matched to the full 2009-11 survey. This does not change our results; see Section 7.

[26] This is for notational completeness: by construction both dummies will always be equal to one in our analysis, since our data contains only members.

Table 6: Dyad characteristics – 2013 member census

	Full CSAE Sample				
	Mean	Std dev	Min	Max	N
Membership					
Same VSLA group	0.17	(0.37)	0.0	1.0	289914
Occupation					
Same economic activity	0.56	(0.50)	0.0	1.0	289914
Absolute differences - Demographic Variables					
Male	0.38	(0.48)	0.0	1.0	289467
Female-headed household	0.32	(0.47)	0.0	1.0	288740
Age	12.64	(10.25)	0.0	65	286763
Absolute differences - Education					
Some post-primary educ.	0.33	(0.47)	0.0	1.0	289914
Literate (read & understand newspaper)	0.26	(0.44)	0.0	1.0	288342
Absolute differences - Wealth					
Father well-off in village (scale 1-5)	1.41	(1.10)	0.0	4.0	253041
Spouse's father well-off in village (scale 1-5)	1.43	(1.13)	0.0	4.0	252485
Absolute differences - Income and Poverty					
Household well-off in group (scale 1-9)	1.40	(1.15)	0.0	8.0	284485
HH owns a bicycle	0.46	(0.50)	0.0	1.0	288740
# Goats	1.84	(2.73)	0.0	40	288240
Sum - Occupation					
Farmer	1.37	(0.70)	0.0	2.0	289914
Businessperson	0.48	(0.63)	0.0	2.0	289914
Sum - Demographic Variables					
Male	0.53	(0.63)	0.0	2.0	289467
Female-headed household	0.40	(0.57)	0.0	2.0	288740
Age	72.12	(16.69)	24.0	163	286763
Sum - Education					
Some post-primary educ.	0.43	(0.58)	0.0	2.0	289914
Literate (read & understand newspaper)	1.68	(0.52)	0.0	2.0	288342
Sum - Wealth					
Father well-off in village (scale 1-5)	6.76	(1.85)	2.0	10.0	253041
Spouse's father well-off in village (scale 1-5)	6.85	(1.88)	2.0	10.0	252485
Sum - Income and Poverty					
Household well-off in group (scale 1-9)	15.04	(1.83)	3.0	18.0	284485
HH owns a bicycle	0.99	(0.73)	0.0	2.0	288740
# Goats	2.44	(3.38)	0.0	70	288240

Notes: All variables as measured during the 2013 member census, N=3,801 members. 519 of these members were no longer active, but are included to avoid selection bias. Analysis is conducted with and without these individuals, see Section 7. All possible dyads in which both individuals live in the same village are constructed, N=289,914. Missing observations reflect answers of "do not know" or "not applicable". Occupation denotes an individual's primary economic activity, if engaged in multiple activities.

Table 7: Dyad characteristics – matched subsample

	Matched dyads				
	Mean	Std dev	Min	Max	N
Absolute differences					
Present-biased	0.16	(0.37)	0.0	1.0	1641
Future-biased	0.37	(0.48)	0.0	1.0	1641
Minimum switch-point, near frame	366.05	(321.43)	0.0	900	1655
Minimum switch-point, far frame	351.92	(337.30)	0.0	900	1651
Risk-neutral	0.20	(0.40)	0.0	1.0	1513
Ever hides money from spouse	0.45	(0.50)	0.0	1.0	1269
Female HH decision-making power (index 0-8)	1.95	(1.57)	0.0	8.0	1914
HH important in village decisions (scale 1-6)	1.08	(1.11)	0.0	5.0	7314
HH speaks at village meetings	0.47	(0.50)	0.0	1.0	7266
Sums					
Present-biased	0.19	(0.42)	0.0	2.0	1641
Future-biased	0.53	(0.64)	0.0	2.0	1641
Minimum switch-point, near frame	4761.51	(558.00)	3800	5600	1655
Minimum switch-point, far frame	4908.17	(563.28)	3800	5600	1651
Risk-neutral	0.22	(0.44)	0.0	2.0	1513
Ever hides money from spouse	0.79	(0.71)	0.0	2.0	1269
Female HH decision-making power (index 0-8)	5.90	(2.71)	0.0	16.0	1914
HH important in village decisions (scale 1-6)	6.54	(1.69)	2.0	12.0	7314
HH ever speaks at village meetings	1.16	(0.71)	0.0	2.0	7266

Notes: N=722 individuals are matched from the 2013 census to the 2009-11 panel data. N=383 of these individuals are matched to the longer panel survey including preference modules. All possible dyads in which both individuals live in the same village are constructed, N=7,314 for the general survey and N=1,641 for the full survey including preference modules. Missing values reflect "do not know", "not applicable", or inconsistent answers in the case of risk preferences. All variables presented here were measured in the 2009 wave of the panel survey, except time preferences, which are taken from the 2010 survey wave since the 2009 wave did not include the far frame for females. Present-biased (future-biased) is a dummy equal to one if the response to the near frame is more impatient (patient) than the response to the far frame. Minimum switch-point is the lower bound of the interval in which the respondent switched to preferring the one-month-later payment compared to a 2000 MK payment on the earlier date. 150 MK $\approx$ 1 USD at the time of the 2009 and 2010 surveys. Risk-neutral is a dummy equal to one if the respondent prefers a 50-50 lottery to its expected value for certain, and thus could indicate risk-neutral or risk-seeking behaviour. Female HH decision-making power is constructed from questions over four types of economic decisions, scoring one if the female has some say in the decision and two if she has complete control. Food security is an indicator equal to one if a member reports in 2009 to have had fewer than two meals per day on average in the last week.

same group but remain constant at the village level: for example, whether the village is served by other NGO programmes. Inclusion of village fixed effects means that sorting is identified from villages in which there is more than one group. ε_{ijv} is a dyad-specific error term, which we assume takes a logistic distribution. We cluster standard errors at the village level in all estimations.[27]

It follows from the logic outlined above that an estimate of $\hat{\beta} < 0$ indicates positive assortative matching on the characteristic in question, whilst an estimate of $\hat{\beta} > 0$ indicates negative assortative matching on that characteristic. Since we estimate Equation 1 on a sample which only includes individuals who are members of at least one group, an estimate of $\hat{\gamma} > 0$ indicates that, conditional on being member of at least one group, individuals with a high value of that particular variable are more likely to be members of more than one group.[28] This is important to control for since it increases the probability that such individuals are in the same group as a randomly-chosen other member, simply because such individuals are members of multiple groups.

6.2 Sorting on occupation

We begin by estimating Equation 1 on the full 2013 member census.[29] Table 8 describes the results. Most strikingly, there is evidence of strong *positive* assortative matching on occupation: if two individuals share the same occupation then they are 8.6 percentage points more likely to be members of the same group (p<0.01). This is a large effect, equivalent to 53% of the baseline probability of being in the same group (16.1%).

It therefore appears that the full potential of financial intermediation across farmers and non-farmers is not being realised. Instead, positive assorting suggests that informational or enforcement frictions or transaction costs are lower among members of the same occupation, or that the social benefits of participating in VSLAs are higher within occupational groups than across them. Table 14 in the Online Appendix shows that the positive assorting on occupation is about half as large in treated villages, which have had the VSLA programme for two years longer than control villages, and in villages with an above-median number of groups (which is positively correlated with being a treated village). This suggests that positive assorting on occupation does weaken over time as more groups form, although there is still sizeable positive assorting in villages that have had VSLAs for around four years. The fact that assorting weakens over time may suggest that assorting is driven more by information and screening concerns than by social or repeated transaction cost concerns.

The other large effect in terms of size is the positive assortative matching on gender: *ceteris paribus*, a male and a female are 5.3 percentage points less likely to be members of the same group than an all-male pair or an all-female pair (p<0.01). Female-headed households are also more likely to group together, although the effect size is just 1.2 percentage points (p<0.01). A number of other characteristics are highly significant, although the estimated marginal effects are small. Specifically, we observe positive assorting on: age; whether a member's spouse's

[27] This is more conservative than the method of clustering by dyad (Fafchamps and Gubert, 2007).

[28] We observe 146 individuals who are members of more than one group in the 2013 member census.

[29] To avoid selection bias, in our main analyses as we include all individuals who have ever been a member including those who have left by 2013, and all groups including the eight groups which had disbanded by 2013. However, our results are all robust to including only those individuals who are still current members in 2013, and only those groups which had not disbanded; see Section 7.

Table 8: Dyadic regressions – 2013 member census

	(1) **Full member census** Mfx / (s.e.)
Occupation	
Same economic activity	0.086***
	(0.008)
Absolute differences	
Male	-0.053***
	(0.015)
Female-headed household	-0.012***
	(0.004)
Age	-0.001***
	(0.000)
Some post-primary educ.	-0.008
	(0.005)
Literate (read & understand newspaper)	-0.013*
	(0.007)
Father well-off in village (scale 1-5)	-0.013***
	(0.002)
Spouse's father well-off in village (scale 1-5)	-0.013***
	(0.003)
Household well-off in group (scale 1-9)	-0.010***
	(0.002)
HH owns a bicycle	-0.003
	(0.003)
# Goats	-0.006***
	(0.001)
Sums	✓
Village f.e.'s	✓
Observations	219747
Pseudo R^2	0.129
Baseline predicted probability	0.161

Notes: *, ** and *** represent p<0.10, p<0.05 and p<0.01 respectively. All variables from the 2013 member census, N=3,801 members. 519 of these members were no longer active, but are included here to avoid selection bias. Results are robust to excluding these individuals, see Section 7. All possible dyads in which both individuals live in the same village are constructed, N=289,914. Missing observations reflect answers of "do not know" or "not applicable". Occupation denotes an individual's primary economic activity, if engaged in multiple activities. Reported effects are marginal effects estimated at the mean.

father is relatively well off and whether a member's own father is relatively well-off compared to the rest of the village (proxies of exogenous wealth, or social class more generally); the number of goats the member's household possesses and whether her household owns a bicycle (standard poverty indicators for this region of Malawi); and whether a member's household is reported to be well-off at least compared to the rest of the group.[30] Again, such positive assorting may take place purely due to homophily, i.e., if people prefer to be in a group with people like them. Alternatively, it may be due to lower costs of monitoring, enforcement or transaction between people who are similar.

6.3 Sorting on time preferences

To test for evidence of sorting on present-bias, we re-estimate Equation 1 for the subsample of matched individuals whose time preferences are measured in the 2009-11 panel data. Table 9 shows the effect of adding the measure of "present-bias" for these individuals. The key result is that we see strong evidence of *negative* assorting on "present-bias": the absolute difference between two members' "present-bias" carries a large, positive coefficient of 16.6 percentage points (p=0.013).

In contrast to the sorting on occupation, Table 15 in the Online Appendix shows that negative assorting on present-bias appears to be much stronger in treated villages, and in villages with an above-average number of groups. A possible interpretation is that over time, better information allows better sorting on individuals' saving and borrowing needs (conditional on occupation) to occur.

We still observe a large, positive effect of two individuals having the same primary occupation: 18.1 percentage points (p=0.019), which is again equivalent to over half the baseline probability of two members being in the same group in this subsample. The pattern of coefficients for the other controls is also similar to that obtained in the full sample. Table 13 in the Online Appendix formally tests for equality of marginal effects across the full sample and the matched subsample (excluding the measure of "present-bias" since it is not available for the full sample). The signs of the marginal effects are consistent across both samples, although there are few significant or marginally insignificant differences in magnitudes. Thus it appears that, at least qualitatively, assorting in the matched subsample is broadly representative of assorting in the full census. In Section 7 we further show that the results on "present-bias" are robust to re-weighting the estimations in order to make the matched subsample exactly representative of the full sample.

Columns (1)-(5) of Table 10 confirm that the negative assorting on "present-bias" is not driven by matching on short-run or long-discount rates (or marginal rates of inter-temporal substitution).[31] Column (1) repeats the preferred specification shown in Table 9 for comparison. Columns (2) and (3) show that we observe no sorting on the respondent's switch-point in the near or the far frame respectively. Similarly, column (4) shows that there is no evidence of sorting on whether the respondent is below or above the median patience in the near frame or the far frame. Since by definition "time-consistent" individuals' are equally impatient in the

[30] Given that "household well-off in group" is a within-group ranking, we would expect its coefficient to be biased towards a positive value. The negative coefficient therefore suggests that individuals understood this question to be more about absolute consumption.

[31] Table 17 in the Online Appendix confirms that the results in Table 10 also hold when the subsample is re-weighted.

Table 9: Dyadic regressions – matched subsample

	(1) **Matched subsample** Mfx / (s.e.)
Occupation	
Same economic activity	0.181**
	(0.077)
Absolute differences	
Present-biased	0.166**
	(0.067)
Male	-0.004
	(0.035)
Female-headed household	-0.176**
	(0.070)
Age	-0.006**
	(0.003)
Some post-primary educ.	-0.038
	(0.054)
Literate (read & understand newspaper)	-0.033
	(0.042)
Father well-off in village (scale 1-5)	-0.020
	(0.012)
Spouse's father well-off in village (scale 1-5)	-0.043***
	(0.014)
Household well-off in group (scale 1-9)	-0.044**
	(0.019)
HH owns a bicycle	0.008
	(0.030)
# Goats	-0.013*
	(0.007)
Sums	✓
Village f.e.'s	✓
Observations	1292
Pseudo R^2	0.222
Baseline predicted probability	0.296

Notes: *, ** and *** represent p<0.10, p<0.05 and p<0.01 respectively. N=722 individuals are matched from the 2013 census to the 2009-11 panel data. N=383 of these individuals are matched to the longer panel survey including preference modules. All possible dyads in which both individuals live in the same village are constructed, N=7,314 for the general survey and N=1,641 for the full survey including preference modules. Missing values reflect "do not know", "not applicable", or inconsistent answers in the case of risk preferences. Time preferences are taken from the 2010 survey, wave since the 2009 wave did not include the far frame for females. Present-biased (future-biased) is a dummy equal to one if the response to the near frame is more impatient (patient) than the response to the far frame. Reported effects are marginal effects estimated at the mean.

near and the far frame, sorting appears driven by the fact that the long-run choices of "present-biased" individuals' are more patient than their short-run choices, as opposed to the idea that "present-biased" individuals have impatient short-run choices or patient long-run choices.

However, as discussed in Section 5.2 it remains possible that our measure of "present-bias" is instead capturing individuals expecting to have a lower marginal rate of intertemporal substitution in the future. Such individuals should have had a demand for borrowing, at least when the VSLAs were first formed. Conversely, individuals classified as "future-biased" may in fact have been anticipating a higher marginal rate of intertemporal substitution in the future, and thus may have had a demand for saving. If so, we would expect to observe two empirical regularities. First, in terms of who sorts into groups with "time-consistent" individuals, we would now expect those individuals spuriously classified as "future-biased" to do so. This is because individuals classified as "future-biased" are now the ones providing savings, which "time-consistent" individuals borrow when investment opportunities arise. We should therefore observe negative assorting on "future-bias". Second, we would expect to see the strongest matching between "present-biased" individuals, who in fact are individuals with a demand for credit, and "future-biased" individuals, who in fact are individuals with a demand for saving. That is, we would observe negative assorting "present-bias" when "time-consistent" individuals are dropped from the sample.

Columns (5)-(7) of Table 10 show that neither of these empirical regularities are observed in the data. Column (5) shows that, unlike "present-bias", there is no observed sorting on "future-bias". Column (6) reports the results when "time-consistent" individuals are dropped from the sample, and thus only "present-biased" and "future-biased individuals" remain. There is no significant evidence of negative assorting within this subsample, i.e. no evidence that "present-biased" individuals sort into groups with "future-biased" individuals. In contrast, column (7) reports the results when "future-biased" individuals are dropped, leaving a sample of only "present-biased" and "time-consistent" individuals. The estimated coefficient on "present-biased" remains large and highly significant. Thus there is strong evidence that "present-biased" individuals are matching with "time-consistent" individuals. This pattern of results is more in line with the predictions of Section 6.3, and thus with the idea that our measure of "present-bias" truly captures individuals with present-biased preferences.

6.4 Individual and group financial performance

We use the page-by-page photographs of the individual passbook of each member of each VSLA to compute measures of individual- and group-level saving and borrowing. We first regress measures of an individual's financial behavior on their occupation and whether or not they are present-biased. As in our dyadic analysis we condition on village fixed effects, but the results are very similar if we condition on group fixed effects (in the spirit of Burlando et al. (2016)).

The results confirm our hypothesis that farmers and present-biased individuals join as a way to save, while non-farmers and time consistent individuals join as a way to borrow. Farmers take 22,917 MK ($\approx$ 55 USD at 2013 exchange rates) fewer total loans than non-farmers (p=0.021), and as a consequence also pay far less loan interest. Instead, farmers purchase on average 14.8 more shares than non-farmers, and have a total savings net of total borrowing that is 4224 MK larger (p=0.029) than that of non-farmers. As a consequence, on average a farmer's total loan-to-savings ratio is 0.624 lower (p<0.01) than a non-farmer's. Net financial gain — calculated as

Table 10: Dyadic regressions – time preference measures, matched subsample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Mfx / (s.e.)	Mfx / (s.e.)	Mfx / (s.e.)	Mfx / (s.e.)	Mfx / (s.e.)	Mfx / (s.e.)	Mfx / (s.e.)
Occupation							
Same economic activity	0.181**	0.175**	0.180**	0.187**	0.178**	0.108	0.145
	(0.077)	(0.081)	(0.079)	(0.079)	(0.077)	(0.073)	(0.106)
Absolute differences							
Present-biased	0.166**		0.179**	0.175**	0.168**	0.055	0.195**
	(0.067)		(0.073)	(0.072)	(0.067)	(0.060)	(0.083)
Future-biased					-0.017		
					(0.036)		
Minimum switch-point (MK), far frame		0.000	0.001				
		(0.005)	(0.005)				
Minimum switch-point (MK), far frame		-0.003	-0.005				
		(0.006)	(0.007)				
Patience above median, near frame				0.011			
				(0.036)			
Patience above median, far frame				-0.032			
				(0.031)			
Wealth & income controls (abs. diffs)	✓	✓	✓	✓	✓	✓	✓
Demographic controls (abs. diffs)	✓	✓	✓	✓	✓	✓	✓
Sums	✓	✓	✓	✓	✓	✓	✓
Village f.e.'s	✓	✓	✓	✓	✓	✓	✓
Observations	1292	1292	1292	1292	1292	184	665
Pseudo R^2	0.222	0.220	0.225	0.226	0.224	0.331	0.233
Baseline predicted probability	0.296	0.296	0.296	0.296	0.296	0.273	0.293

Notes: *, ** and *** represent p<0.10, p<0.05 and p<0.01 respectively. N=722 individuals are matched from the 2013 census to the 2009-11 panel data. N=383 of these individuals are matched to the longer panel survey including preference modules. All possible dyads in which both individuals live in the same village are constructed, N=7,314 for the general survey and N=1,641 for the full survey including preference modules. Missing values reflect "do not know", "not applicable", or inconsistent answers in the case of risk preferences. All variables presented here were measured in the 2009 wave of the panel survey, except time preferences, which are taken from the 2010 survey wave since the 2009 wave did not include the far frame for females. Present-biased (future-biased) is a dummy equal to one if the response to the near frame is more impatient (patient) than the response to the far frame. Minimum switch-point is the lower bound of the interval in which the respondent switched to preferring the payment dated one month later compared to a 2000 MK payment on the earlier date. 150 MK $\approx$ 1 USD at the time of the 2009 and 2010 surveys. Patience above median is a dummy for having a switch-point below the median in that frame. Column (6) restricts the sample to "present-biased" and "future-biased" individuals, dropping "time-consistent" individuals. Column (7) restricts the sample to "present-biased" and "time-consistent" individuals, dropping "future-biased" individuals. Reported effects are marginal effects estimated at the mean.

gross return on savings minus total interest payments — is 1421 MK greater for farmers than non-farmers when they are the only farmer in the group (p=0.044). However, this declines at a rate of 14.83 MK for every 10% increase in the proportion of the group members that are farmers. The latter reflects the fact that when there are more farmers in a group, less borrowing takes place, and more shares are purchased over which loan repayment interest is shared out.

Meanwhile, present-biased individuals borrow 19,608 MK less in total (p<0.01) than non-present-biased individuals, or 25,979 MK (p<0.01) compared only to time-consistent individuals, excluding "future-biased" individuals. As a consequence of this lower borrowing, present-biased individuals have a loan-to-savings ratio that is 0.799 lower (p=0.05) than non-present-biased individuals, or 1.02 lower (p=0.03) compared to time-consistent individuals only. This finding lends strong support to our suggestion that sophisticated present-biased individuals join VSLAs as a way to save, and/or that any naïve present-biased individuals who join are denied credit.

We next compare group-level financial outcomes across the 150 groups, depending on group composition in terms of PAM in occupation. The total loans distributed by a group are 13,418 MK lower for every 10% increase in the proportion of group members who are farmers, although this is marginally insignificant (p=0.11). Total loan interest payments and total loan repayments are significantly lower in groups with a higher proportion of farmers. As a consequence, the payout per share is 12.2 MK lower (p=0.01) for every 10% increase in the proportion of the group that are farmers. There is thus evidence that the decreased lending volumes in groups with a higher proportion of farmers lead to lower returns on saving. In other words, groups with too many farmers relative to business people fail to achieve their full financial intermediation potential. If such groups positively assort in order to achieve lower loan default and higher repayment rates, this still does not offset the lower lending volumes achieved compared to groups with a higher proportion of business people.

Finally, it appears that groups that positively assort on being farmers are much more homogenous in their financial behavior, with a much lower standard deviation in loan size and interest paid, and a much lower standard deviation of net financial gain. This again suggests that much less financial intermediation occurs within such groups.

7 Robustness

Additional controls: The coefficients on economic activity and "present-bias" are robust to the inclusion of a host of additional controls from the 2009-11 panel survey, as shown in Table 11. Column (1) repeats the preferred specification shown in Table 9 and is included for reference only. Column (2) shows that negative assorting on present-bias holds unconditional on occupation. Columns (3) and (4) show no evidence of sorting on being risk-neutral as compared to risk-averse, or indeed on the degree of risk-aversion. Columns (5) and (6) show no evidence of sorting on measures of intra-household bargaining, either unconditionally or conditional on present-bias. This suggests that participants do not sort on "other-control" motives, in contrast to the strong sorting on "self-control" motives proxied by present-bias.[32] Column (7) shows

[32] Qualitatively, some members mention a demand for commitment so that other family members cannot appropriate funds, claiming that VSLA membership "addresses the problems encountered within the household". The coefficients on the dyadic sums of "ever hides money from spouse" and "female HH decision-making power" are also insignificant (not shown). Thus there is no evidence that women with lower or higher household bar-

that there is significant evidence of negative assorting on whether the individual comes from a household that speaks at village meetings — a proxy of how active or powerful the household is in local civil society. This is consistent with the idea that certain "leaders" encourage their "followers" to join their group. In column (8), we use GPS coordinates to estimate and control for the distance between individuals' homes in 2009. As might be expected, living further apart within the village is strongly negatively correlated with being members of the same group. However, adding these controls in columns (7) and (8) does not change the estimated effect of occupation or present-bias, suggesting that sorting on occupation and present-bias is uncorrelated with sorting on these dimensions. Finally, in column (9) we control for the difference in household monthly consumption per capita in 2009. Farmers have on average 10% (250 MK) lower consumption per capita. However, there is no evidence of sorting on consumption conditional on occupation, and this does not explain the observed sorting on occupation.

Weighting: As explained in Section 4, the 2009-11 panel survey was conducted on a random sample of the population in each of the surveyed villages. This does not mean that the subset of 2013 members that can be matched back to the 2009-11 panel are a random subset of all 2013 members. Table 12 in the Online Appendix shows that matched dyads are slightly unrepresentative of the full population of 2013 dyads. However, Table 13 shows that only the estimated coefficients on gender and female-headed household are significantly different between the full sample and the matched subsample, and they maintain the same sign and significance. Nevertheless, as a robustness check, we re-weigh the regressions to estimate the effect sizes we hypothetically would obtain if the matched subsample were a fully random subsample of all 2013 members. To construct the weights, we first estimate a probit equation on the probability of each dyad in the 2013 data also appearing in the 2009-11 data, as a function of the full set of dyad characteristics listed in Table 6 and of village fixed effects.[33] We then use the estimated coefficients to generate the predicted probability that each 2013 dyad is matched to the 2009-11 data, and we take the inverse of this predicted probability as the dyad-specific weight. We then re-estimate the various columns of Table 11 with these weights.Tables 16, 17 and 18 in the Online Appendix show that re-weighting slightly reduces the size of the estimated coefficients on occupation and present-bias — albeit never significantly so — and that they always maintain the same level of significance.

Other robustness checks: We run a set of further robustness checks on both the full sample and the matched subsample (see Online Appendix for tables). Results do not significantly change if we restrict the sample to current members only (i.e., dropping individuals listed as past members in the 2013 census), or if we drop the eight groups which had disbanded by 2013. Nor do the results significantly change if we restrict attention to dyads in which both members

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gaining power join more groups conditional on being a member of at least one group — our best proxy of the strength of demand for VSLA participation. Other literature has examined effects of the square of household decision-making (Anderson and Baland, 2002). However, this does not make sense in a dyadic setting, as the sum or difference of two individuals' squared decision-making has no natural interpretation.

[33]This is not equivalent to the the product of the separate probabilities that individual i and individual j are matched to the 2009-11 data, because of differences in the number of groups per village and members per group, and hence in the number of dyads across villages and groups.

Table 11: Dyadic regressions – effects of controls, matched subsample

	(1) Mfx / (s.e.)	(2) Mfx / (s.e.)	(3) Mfx / (s.e.)	(4) Mfx / (s.e.)	(5) Mfx / (s.e.)	(6) Mfx / (s.e.)	(7) Mfx / (s.e.)	(8) Mfx / (s.e.)	(9) Mfx / (s.e.)
Occupation									
Same economic activity	0.181**		0.204**	0.207**	0.150**	0.154**	0.181**	0.158*	0.162**
	(0.077)		(0.097)	(0.096)	(0.075)	(0.072)	(0.075)	(0.084)	(0.076)
Absolute differences									
Present-biased	0.166**	0.164***	0.107*	0.115**		0.188**	0.167***	0.187**	0.128**
	(0.067)	(0.063)	(0.055)	(0.050)		(0.077)	(0.064)	(0.075)	(0.062)
Risk-neutral			0.016						
			(0.058)						
Risk aversion above median				-0.019					
				(0.039)					
Ever hides money from spouse					-0.006	-0.017			
					(0.029)	(0.027)			
Female HH decision-making power (index 0-8)					0.006	0.006			
					(0.011)	(0.012)			
HH important in village decisions (scale 1-6)							-0.038**		
							(0.019)		
HH speaks at village meetings							0.009		
							(0.031)		
GPS distance between hhs (km)								-0.072**	
								(0.033)	
Monthly consumption per capita, 1000 MK									-0.034
									(0.029)
Wealth & income controls (abs. diffs)	✓	✓	✓	✓	✓	✓	✓	✓	✓
Demographic controls (abs. diffs)	✓	✓	✓	✓	✓	✓	✓	✓	✓
Sums	✓	✓	✓	✓	✓	✓	✓	✓	✓
Village f.e.'s	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	1292	1292	1031	1031	980	958	1277	1249	1159
Pseudo R^2	0.222	0.212	0.214	0.216	0.194	0.206	0.228	0.252	0.205
Baseline predicted probability	0.296	0.296	0.285	0.285	0.294	0.295	0.292	0.294	0.276

Notes: *, ** and *** represent $p<0.10$, $p<0.05$ and $p<0.01$ respectively. N=722 individuals are matched from the 2013 census to the 2009-11 panel data. N=383 of these individuals are matched to the longer panel survey including preference modules. All possible dyads in which both individuals live in the same village are constructed, N=7,314 for the general survey and N=1,641 for the full survey including preference modules. Missing values reflect "do not know", "not applicable", or inconsistent answers in the case of risk preferences. All variables presented here were measured in the 2009 wave of the panel survey, except time preferences, which are taken from the 2010 survey wave since the 2009 wave did not include the far frame for females. Present-biased (future-biased) is a dummy equal to one if the response to the near frame is more impatient (patient) than the response to the far frame. Risk-neutral is a dummy equal to one if the respondent prefers a 50-50 lottery to its expected value for certain, and thus could indicate risk-neutral or risk-seeking behaviour. Female HH decision-making power is constructed from questions over four types of economic decisions, scoring one if the female has some say in the decision and two if she has complete control. Reported effects are marginal effects estimated at the mean.

are female: the pattern of sorting holds irrespective of gender. If we split "same occupation" and separately estimate the effect of both members being farmers, or of both being engaged in business, the coefficients remain positive and significant and do not differ significantly between the two occupations. Thus the effect of "same occupation" is not being driven by farmers or non-farmers in particular.

For the subsample of matched individuals, we run additional robustness checks including controls for consumption and food security from the 2009-11 panel (as described in Table 3). We also re-estimate the main specifications using individual occupation as recorded in the 2009 baseline instead of the 2013 member census. The coefficients on same occupation and the absolute difference in "present-bias" remain positive and highly significant. Finally, we re-run the model without individuals who never choose a late amount in one or both time frames of the time preference elicitation activity. These individuals may have either failed to understand the activity, or distrusted the enumerators. Dropping these individual does not affect our results: the coefficient on "present-bias" remains positive and significant.

8 Conclusion

This paper has highlighted the potential role of VSLAs in providing financial intermediation, especially in communities with low access to formal financial services. VSLAs offer not only a source of credit, but also a commitment savings technology. In light of this, we have investigated whether individuals with a demand for saving, and in particular commitment saving, successfully sort into groups with individuals with a demand for borrowing.

We posit that there are large potential benefits to negative assorting on occupation, in terms of generating financial intermediation across occupations with different cash-flow profiles. Yet we instead find positive assorting on occupation. This finding could reflect high costs of screening, monitoring and enforcing loans, or transacting with individuals from a different occupation. To further understand the potential implications for efficiency, future work might examine to what extent VSLAs still manage to fund the local projects with the highest returns.

Positive assortative matching on occupation also potentially leaves VSLA groups exposed to common shocks that affect one occupation, most notably farmers. A common shock could increase competition for emergency consumption loans while increasing the probability that borrowers default, thereby endangering the sustainability of the group. A possible solution might be to integrate VSLAs into a larger credit union, or to provide stop-gap finance to VSLAs from other channels. The former is effectively the approach taken with some Self-Help Groups in India, although more research is needed to demonstrate whether it has been successful.

More promisingly, we observe negative assorting on present-bias, indicating that VSLAs attract both commitment savers and time-consistent individuals who are prospective borrowers. This should enhance efficiency by allowing funds saved by commitment savers to be put to productive use. Equity may nonetheless be a concern, if willingness to pay for commitment leads present-biased individuals to accept low interest rates on loaned funds. There is nothing wrong *per se* in allowing sophisticated present-biased individuals to pay for commitment, in this case by accepting a lower interest rate.[34] However, if savers receive a zero or negative return,

[34] Heidhues and Koszegi (2010) show that lenders can exploit partial naifs. However, in the context of VSLAs such exploitation of partial naiveté is less of a concern, since there are no penalties for failing to meet the

or experience high default rates, this would be cause for concern.[35] Reassuringly, this is not what we find: monthly interest rates on loaned funds are broadly in line with elicited discount rates, and savers earn a positive nominal interest on their savings. Thus VSLAs do appear to promote a degree of financial intermediation between commitment savers and borrowers, albeit only within occupational groups.

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minimum share-purchase requirement each week.

[35] On the other hand, it is not clear what commitment savers' outside option would be in the absence of VSLAs, and thus what the correct counterfactual is in assessing whether commitment savers are receiving "too low" an interest rate.

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A Appendix - for online publication

A.1 Additional data and results

Table 12: Test of representativeness – matched dyads vs. 2013 census dyads

	Mean All Dyads	Mean Matched Dyads	Diff.	Std. Error	T stat	Full N	Matched N
Group membership							
Same VSLA group	0.17	0.30	-0.13***	(0.01)	-24.27	289914	7309
Occupation							
Same economic activity	0.56	0.71	-0.15***	(0.01)	-27.11	289914	7309
Absolute differences							
Male	0.38	0.39	-0.02**	(0.01)	-2.89	289467	7309
Female-headed household	0.32	0.34	-0.03***	(0.01)	-4.64	288740	7309
Age	12.64	12.17	0.46***	(0.12)	3.94	286763	7309
Some post-primary educ.	0.33	0.26	0.07***	(0.01)	13.29	289914	7309
Literate (read & understand newspaper)	0.26	0.29	-0.03***	(0.01)	-5.12	288342	7309
Father well-off in village (scale 1-5)	1.41	1.42	-0.00	(0.01)	-0.12	253041	6415
Spouse's father well-off in village (scale 1-5)	1.43	1.40	0.03*	(0.01)	2.44	252485	6954
Household well-off in group (scale 1-9)	1.40	1.29	0.11***	(0.01)	8.31	284485	7309
HH owns a bicycle	0.46	0.46	0.01	(0.01)	1.21	288740	7309
# Goats	1.84	2.30	-0.45***	(0.04)	-11.14	288240	7309
Sums							
Farmer	1.37	1.61	-0.24***	(0.01)	-33.75	289914	7309
Businessperson	0.48	0.32	0.16***	(0.01)	24.67	289914	7309
Male	0.53	0.55	-0.02**	(0.01)	-2.68	289467	7309
Female-headed household	0.40	0.45	-0.05***	(0.01)	-6.69	288740	7309
Age	72.12	77.04	-4.92***	(0.19)	-25.52	286763	7309
Some post-primary educ.	0.43	0.31	0.11***	(0.01)	18.76	289914	7309
Literate (read & understand newspaper)	1.68	1.63	0.04***	(0.01)	6.87	288342	7309
Father well-off in village (scale 1-5)	6.76	6.64	0.12***	(0.02)	5.11	253041	6415
Spouse's father well-off in village (scale 1-5)	6.85	6.87	-0.02	(0.02)	-0.84	252485	6954
Household well-off in group (scale 1-9)	15.04	15.41	-0.37***	(0.02)	-18.06	284485	7309
HH owns a bicycle	0.99	1.09	-0.10***	(0.01)	-12.09	288740	7309
# Goats	2.44	3.32	-0.89***	(0.05)	-16.90	288240	7309

Notes: All variables from the 2013 member census, N=3,801 members. N=722 of these members could be matched by name to the 2009-11 panel dataset. All possible dyads in which both individuals live in the same village are constructed for the full sample (N=289,914) and for the matched subsample (N=7,301). Missing observations reflect answers of "do not know" or "not applicable". Occupation denotes an individual's primary economic activity, if engaged in multiple activities.

Table 13: Dyadic regressions – 2013 member census and matched subsample

	(1) **Full CSAE sample** Mfx / (s.e.)	(2) **Matched subsample** Mfx / (s.e.)	P-value $\beta_1 = \beta_2$
Occupation			
Same economic activity	0.086***	0.206***	0.132
	(0.008)	(0.045)	
Absolute differences			
Male	-0.053***	-0.034	0.054*
	(0.015)	(0.028)	
Female-headed household	-0.012***	-0.065***	0.034**
	(0.004)	(0.023)	
Age	-0.001***	-0.001	0.629
	(0.000)	(0.001)	
Some post-primary educ.	-0.008	-0.005	0.724
	(0.005)	(0.021)	
Literate (read & understand newspaper)	-0.013*	-0.009	0.417
	(0.0067)	(0.018)	
Father well-off in village (scale 1-5)	-0.013***	-0.025***	0.577
	(0.002)	(0.010)	
Spouse's father well-off in village (scale 1-5)	-0.013***	-0.030**	0.379
	(0.003)	(0.012)	
Household well-off in group (scale 1-9)	-0.010***	-0.020**	0.659
	(0.003)	(0.010)	
HH owns a bicycle	-0.003	0.009	0.159
	(0.003)	(0.009)	
# Goats	-0.006***	-0.012***	0.407
	(0.002)	(0.004)	
Sums	✓	✓	
Village f.e.'s	✓	✓	
Observations	219747	5878	
Pseudo R^2	0.129	0.142	
Baseline predicted probability	0.161	0.168	

Notes: *, ** and *** represent p<0.10, p<0.05 and p<0.01 respectively. All variables from the 2013 member census, N=3,801 members. N=722 of these members could be matched by name to the 2009-11 panel dataset. All possible dyads in which both individuals live in the same village are constructed for the full sample (N=289,914) and for the matched subsample (N=7,301). Missing observations reflect answers of "do not know" or "not applicable". Occupation denotes an individual's primary economic activity, if engaged in multiple activities. Reported effects are marginal effects estimated at the mean.

Table 14: Dyadic regressions – treated vs. control villages, and villages with above vs. below median number of groups

	(1) **Treated 2009** Mfx / (s.e.)	(2) **Treated 2011** Mfx / (s.e.)	(3) **> 2 groups** Mfx / (s.e.)	(4) **≤ 2 groups** Mfx / (s.e.)
Occupation				
Same economic activity	0.074***	0.139***	0.079***	0.144***
	(0.007)	(0.028)	(0.007)	(0.040)
Absolute differences				
Male	-0.056***	-0.032**	-0.052***	-0.035
	(0.014)	(0.013)	(0.014)	(0.026)
Female-headed household	-0.008*	-0.023**	-0.007*	-0.068**
	(0.005)	(0.011)	(0.004)	(0.029)
Age	-0.001***	-0.001***	-0.001***	-0.002**
	(0.000)	(0.000)	(0.000)	(0.001)
Some post-primary educ.	-0.008	-0.006	-0.007	-0.013
	(0.005)	(0.011)	(0.005)	(0.021)
Literate (read & understand newspaper)	-0.012	-0.019	-0.010	-0.049*
	(0.008)	(0.015)	(0.007)	(0.027)
Father well-off in village (scale 1-5)	-0.010***	-0.022***	-0.011***	-0.030***
	(0.002)	(0.003)	(0.001)	(0.010)
Spouse's father well-off in village (scale 1-5)	-0.010***	-0.022***	-0.011***	-0.032***
	(0.003)	(0.008)	(0.003)	(0.012)
Household well-off in group (scale 1-9)	-0.008***	-0.017***	-0.009***	-0.010
	(0.003)	(0.005)	(0.003)	(0.009)
HH owns a bicycle	-0.003	-0.001	-0.004	0.010
	(0.003)	(0.010)	(0.003)	(0.007)
# Goats	-0.004**	-0.011***	-0.005***	-0.011**
	(0.002)	(0.003)	(0.002)	(0.004)
Sums	✓	✓	✓	✓
Village f.e.'s	✓	✓	✓	✓
Observations	171738	48009	204089	15658
Pseudo R^2	0.122	0.085	0.086	0.019
LR χ^2	.	.	.	.
Prob > χ^2	.	.	.	.
Baseline predicted probability	0.217	0.206	0.141	0.494

Notes: *, ** and *** represent p<0.10, p<0.05 and p<0.01 respectively. All variables from the 2013 member census, N=3,801 members. 519 of these members were no longer active, but are included here to avoid selection bias. Results are robust to excluding these individuals, see Section 7. All possible dyads in which both individuals live in the same village are constructed, N=289,914. Missing observations reflect answers of "do not know" or "not applicable". Occupation denotes an individual's primary economic activity, if engaged in multiple activities. Reported effects are marginal effects estimated at the mean.

Table 15: Dyadic regressions – matched subsample, treated vs. control villages, and villages with above vs. below median number of groups

	(1) **Treated 2009** Mfx / (s.e.)	(2) **Treated 2011** Mfx / (s.e.)	(3) $>$ **2 groups** Mfx / (s.e.)	(4) $\leq$ **2 groups** Mfx / (s.e.)
Occupation				
Same economic activity	0.178**	0.212	0.106	0.295
	(0.087)	(0.160)	(0.067)	(0.191)
Absolute differences				
Present-biased	1.173***	0.073	0.899***	0.153
	(0.051)	(0.076)	(0.036)	(0.103)
Male	0.020	-0.014	0.001	-0.047
	(0.034)	(0.039)	(0.027)	(0.107)
Female-headed household	-0.274***	0.110	-0.136**	-0.137
	(0.061)	(0.077)	(0.054)	(0.171)
Age	-0.003	-0.014**	-0.002	-0.015***
	(0.003)	(0.006)	(0.002)	(0.006)
Some post-primary educ.	-0.045	-0.040	-0.005	-0.135*
	(0.081)	(0.069)	(0.056)	(0.072)
Literate (read & understand newspaper)	-0.028	-0.002	-0.015	-0.107
	(0.039)	(0.154)	(0.022)	(0.227)
Father well-off in village (scale 1-5)	-0.014	-0.030	-0.009	-0.048
	(0.012)	(0.035)	(0.009)	(0.034)
Spouse's father well-off in village (scale 1-5)	-0.050***	-0.007	-0.032***	-0.030
	(0.015)	(0.017)	(0.012)	(0.033)
Household well-off in group (scale 1-9)	-0.060***	0.029	-0.023	-0.085*
	(0.013)	(0.033)	(0.015)	(0.049)
HH owns a bicycle	-0.005	0.044	0.003	-0.077
	(0.034)	(0.056)	(0.022)	(0.080)
# Goats	-0.006	-0.043*	-0.010**	-0.014
	(0.006)	(0.026)	(0.005)	(0.033)
Sums	✓	✓	✓	✓
Village f.e.'s	✓	✓	✓	✓
Observations	920	372	944	348
Pseudo R^2	0.271	0.227	0.147	0.194
Baseline predicted probability	0.331	0.298	0.181	0.554

Notes: *, ** and *** represent p<0.10, p<0.05 and p<0.01 respectively. N=722 individuals are matched from the 2013 census to the 2009-11 panel data. N=383 of these individuals are matched to the longer panel survey including preference modules. All possible dyads in which both individuals live in the same village are constructed, N=7,314 for the general survey and N=1,641 for the full survey including preference modules. Missing values reflect "do not know", "not applicable", or inconsistent answers in the case of risk preferences. Time preferences are taken from the 2010 survey, wave since the 2009 wave did not include the far frame for females. Present-biased (future-biased) is a dummy equal to one if the response to the near frame is more impatient (patient) than the response to the far frame. Reported effects are marginal effects estimated at the mean.

Table 16: Dyadic regressions – 2013 member census, weighted

	(1) Matched subsample Mfx / (s.e.)
Occupation	
Same economic activity	0.098***
	(0.035)
Absolute differences	
Present-biased	0.096***
	(0.032)
Male	0.000
	(0.014)
Female-headed household	-0.094***
	(0.032)
Age	-0.004***
	(0.001)
Some post-primary educ.	-0.013
	(0.025)
Literate (read & understand newspaper)	-0.035
	(0.028)
Father well-off in village (scale 1-5)	-0.009
	(0.006)
Spouse's father well-off in village (scale 1-5)	-0.016**
	(0.007)
Household well-off in group (scale 1-9)	-0.027***
	(0.008)
HH owns a bicycle	0.008
	(0.016)
# Goats	-0.005
	(0.004)
Sums	✓
Village f.e.'s	✓
Observations	1280
Pseudo R^2	0.280
Baseline predicted probability	0.197

Notes: *, ** and *** represent p<0.10, p<0.05 and p<0.01 respectively. N=722 individuals are matched from the 2013 census to the 2009-11 panel data. N=383 of these individuals are matched to the longer panel survey including preference modules. All possible dyads in which both individuals live in the same village are constructed, N=7,314 for the general survey and N=1,641 for the full survey including preference modules. Missing values reflect "do not know", "not applicable", or inconsistent answers in the case of risk preferences. Time preferences are taken from the 2010 survey, wave since the 2009 wave did not include the far frame for females. "Present-biased" ("future-biased") is a dummy equal to one if the response to the near frame is more impatient (patient) than the response to the far frame. Reported effects are marginal effects estimated at the mean.

Table 17: Dyadic regressions – time preference measures, matched subsample, weighted

	(1) Mfx / (s.e.)	(2) Mfx / (s.e.)	(3) Mfx / (s.e.)	(4) Mfx / (s.e.)	(5) Mfx / (s.e.)
Occupation					
Same economic activity	0.098***	0.093**	0.098***	0.102***	0.097***
	(0.035)	(0.038)	(0.034)	(0.034)	(0.035)
Absolute differences					
Present-biased	0.096***		0.099***	0.097***	0.096***
	(0.032)		(0.031)	(0.030)	(0.032)
Future-biased					0.002
					(0.015)
Minimum switch-point (MK), far frame		0.000	0.001		
		(0.002)	(0.002)		
Minimum switch-point (MK), far frame		0.000	-0.001		
		(0.003)	(0.003)		
Patience above median, near frame				0.015	
				(0.017)	
Patience above median, far frame				-0.022	
				(0.016)	
Wealth & income controls (abs. diffs)	✓	✓	✓	✓	✓
Demographic controls (abs. diffs)	✓	✓	✓	✓	✓
Sums	✓	✓	✓	✓	✓
Village f.e.'s	✓	✓	✓	✓	✓
Observations	1280	1280	1280	1280	1280
Pseudo R^2	0.280	0.272	0.282	0.286	0.281
Baseline predicted probability	0.197	0.196	0.197	0.197	0.197

Notes: *, ** and *** represent p<0.10, p<0.05 and p<0.01 respectively. N=722 individuals are matched from the 2013 census to the 2009-11 panel data. N=383 of these individuals are matched to the longer panel survey including preference modules. All possible dyads in which both individuals live in the same village are constructed, N=7,314 for the general survey and N=1,641 for the full survey including preference modules. Missing values reflect "do not know", "not applicable", or inconsistent answers in the case of risk preferences. All variables presented here were measured in the 2009 wave of the panel survey, except time preferences, which are taken from the 2010 survey wave since the 2009 wave did not include the far frame for females. "Present-biased" ("future-biased") is a dummy equal to one if the response to the near frame is more impatient (patient) than the response to the far frame. Minimum switch-point is the lower bound of the interval in which the respondent switched to preferring the payment dated one month later compared to a 2000 MK payment on the earlier date. 150 MK ≈ 1 USD at the time of the 2009 and 2010 surveys. Patience above median is a dummy for having a switch-point below the median in that frame. Reported effects are marginal effects estimated at the mean.

Table 18: Dyadic regressions – effects of controls, matched subsample, weighted

	(1) Mfx / (s.e.)	(2) Mfx / (s.e.)	(3) Mfx / (s.e.)	(4) Mfx / (s.e.)	(5) Mfx / (s.e.)	(6) Mfx / (s.e.)	(7) Mfx / (s.e.)
Occupation							
Same economic activity	0.098***		0.117**	0.119**	0.088**	0.094***	0.098***
	(0.035)		(0.049)	(0.050)	(0.038)	(0.035)	(0.035)
Absolute differences							
Present-biased	0.096***	0.093***	0.052**	0.057**		0.117***	0.096***
	(0.032)	(0.028)	(0.022)	(0.023)		(0.035)	(0.031)
Risk-neutral			0.026				
			(0.036)				
Risk aversion above median				-0.020			
				(0.015)			
Ever hides money from spouse					-0.002	-0.005	
					(0.019)	(0.015)	
Female HH decision-making power (index 0-8)					0.005	0.003	
					(0.007)	(0.007)	
HH important in village decisions (scale 1-6)							-0.013
							(0.009)
HH speaks at village meetings							-0.001
							(0.012)
Wealth & income controls (abs. diffs)	✓	✓	✓	✓	✓	✓	✓
Demographic controls (abs. diffs)	✓	✓	✓	✓	✓	✓	✓
Sums	✓	✓	✓	✓	✓	✓	✓
Village f.e.'s	✓	✓	✓	✓	✓	✓	✓
Observations	1280	1280	1021	1021	969	947	1265
Pseudo R^2	0.280	0.264	0.270	0.271	0.242	0.268	0.285
Baseline predicted probability	0.197	0.191	0.189	0.189	0.193	0.197	0.194

Notes: *, ** and *** represent p<0.10, p<0.05 and p<0.01 respectively. N=722 individuals are matched from the 2013 census to the 2009-11 panel data. N=383 of these individuals are matched to the longer panel survey including preference modules. All possible dyads in which both individuals live in the same village are constructed, N=7,314 for the general survey and N=1,641 for the full survey including preference modules. Missing values reflect "do not know", "not applicable", or inconsistent answers in the case of risk preferences. All variables presented here were measured in the 2009 wave of the panel survey, except time preferences, which are taken from the 2010 survey wave since the 2009 wave did not include the far frame for females. "Present-biased" ("future-biased") is a dummy equal to one if the response to the near frame is more impatient (patient) than the response to the far frame. Risk-neutral is a dummy equal to one if the respondent prefers a 50-50 lottery to its expected value for certain, and thus could indicate risk-neutral or risk-seeking behaviour. Female HH decision-making power is constructed from questions over four types of economic decisions, scoring one if the female has some say in the decision and two if she has complete control. Reported effects are marginal effects estimated at the mean.

A.2 Testing for assortative matching using dyadic regressions

In this Appendix, we demonstrate how testing for negative or positive assortative matching in groups can be implemented using a dyadic regression. We start with a simple numerical example to illustrate the intuition behind the proposed method. We then offer various simulations to show how the method performs in various situations.

A.2.1 A simple example

Imagine a population with four individuals numbered 1 to 4. Individuals 1 and 2 are high types; 3 and 4 are low types. The difference between high and low type is 1. There are six dyads in this dataset:

Table A1. Possible dyads with difference in type

Individual 1	Individual 2	Difference in type
1	2	0
1	3	1
1	4	1
2	3	1
2	4	1
3	4	0

These four individuals can form two groups of two individuals. Since order is irrelevant, there are three possible groupings:

Table A2. Possible groupings with average differece within and across groups

Pair 1	Pair 2	Av. Diff. within groups	Av. Difference across groups
$1-2$	$3-4$	0	1
$1-3$	$2-4$	1	0.5
$1-4$	$2-3$	1	0.5

In each grouping, two of the six dyads are within groups, and four are across groups. In the first grouping, individuals are sorted by type and the difference in type for grouped dyads $1-2$ and $3-4$ is 0. As shown in Table A1, the difference across each the four ungrouped dyads is 1. In the other two groupings, the difference for within group dyads is 1 while the average difference for across group dyads is 0.5.

Now imagine that we have a data composed of N pools of four individuals grouped in pairs. Within each pool we form all possible six dyads, giving us $6N$ observations in total: $2N$ within groups and $4N$ across groups. Let d_{ijk} be the difference in type between individuals i and j in pool k. Further let $g_{ijk} = 1$ if i and j are in a group and 0 otherwise. The estimated regression is:

$$d_{ijk} = \alpha + \beta g_{ijk} + u_{ijk}$$

It immediately follows that if all groups in all pools are $1-2$ and $3-4$, regressing d_{ijk} on g_{ijk} will yield a coefficient of -1, which is the average difference within groups minus the average difference across groups. Similarly if all groups are of the form $1-3$ and $2-4$ or $1-4$ and

$2-3$, then the coefficient of $g_{\imath jk}$ will be $1-0.5=0.5$. In other words, perfect positive assorting – the first case – yields $\widehat{\beta}<0$ while negative assorting – the second case – yields $\widehat{\beta}>0$.

Let us now generalize this example to imperfect, i.e., probabilistic assorting. We consider three possible assorting rules: neutral; positive assorting; and negative assorting. Examples of assorting probabilities are shown in Table A3, each with its associated $E[d_{ijk}]$:

Table A3. Expected dyadic regression coefficient for different assorting probabilities

Pair 1	Pair 2	Neutral	$E[d_{ijk}]$	Positive	$E[d_{ijk}]$	Negative	$E[d_{ijk}]$
$1-2$	$3-4$	0.333	-0.333	0.533	-0.533	0.133	-0.133
$1-3$	$2-4$	0.333	0.167	0.233	0.117	0.433	0.217
$1-4$	$2-3$	0.333	0.167	0.233	0.117	0.433	0.217
		$E[\widehat{\beta}]=$	0	$E[\widehat{\beta}]=$	-0.3	$E[\widehat{\beta}]=$	0.3

We see that, as it should be, neutral assorting yields $E[\widehat{\beta}]=0$ while imperfect positive and negative assorting yields $E[\widehat{\beta}]$ values that are negative and positive, respectively (e.g., Fafchamps and Gubert, 2007).

The above example can be turned on its head to ask whether differences in type *predict* groupings. This is achieved by estimating a predictive regression of the form:

$$g_{ijk}=\theta+\gamma d_{ijk}+e_{ijk} \tag{2}$$

Since both β and γ capture the correlation between g_{ijk} and δ_{ijk}, it follows that the sign properties of $\widehat{\beta}$ transfer to $\widehat{\gamma}$: if similarity ot type predicts a dyad being in the same group, large differences in type will predict *not* being in a group – hence a negative $\widehat{\gamma}$.

With this transformation, the example can easily be expanded to a situation in which there are two or more dyadic variables susceptible of predict groupings. For example, imagine that individuals can also be divided into male and female. Suppose for instance that individuals match negatively on gender but positively on type, then knowing that a dyad has one male and one female of the same type predicts a higher grouping probability $E[g_{ijk}]$. If gender and type are correlated, estimating equation (2) will help disentangle the respective predictive role of gender and type. For it will let us test whether observed differences in types across pairs are a by-product from matching on gender rather than a manifestation of assorting on type.

A.2.2 Simulations

The above apparatus can be extended to groups of arbitrary size. We illustrate this with a couple of simulations below. The details of the implementation are given in the next subsection. Neutral assorting means sorting on an unobserved variable only. Positive assortative matching (PAM) is here defined as matching on both gender and type, in addition to the unobserved variable; hybrid assortative matching (HAM) is defined as negative assorting on gender but positive assorting on type and on the unobserved variable. Gender and type are uncorrelated by design. Table A4 considers small groups of 3 individuals in pools of 15; Table A4 consideres larger groups of 10 individuals in pools of 20. Both Tables illustrates how dyadic estimation correctly identifies the correct sign of the gender and type dummies – i.e., positive in case of negative assorting and vice versa.

Table A4. Dyadic estimation of simulated data – group of size 3

	Neutral	S.E.	PAM	S.E.	HAM	S.E.
Gender dif.	−0.015	0.016	−0.179***	0.010	0.074***	0.003
Type dif.	−0.003	0.010	−0.048***	0.014	−0.079***	0.015
Intercept	0.151	0.093	0.258	0.006	0.137	0.007
N.obs.	6300		6300		6300	

Table A4 notes: Size of group: 3. Number of groups per pool: 5. Number of pools: 30. PAM is positive assorting on gender and type. NAM is negative assorting on gender and positive assorting on type. Estimator is OLS with standard errors clustered by pool. Results shown are for one simulation.

Table A5. Dyadic estimation of simulated data – group of size 10

	Neutral	S.E.	PAM	S.E.	HAM	S.E.
Gender dif.	0.011	0.013	−0.285***	0.022	0.045***	0.003
Type dif.	−0.003	0.011	−0.056***	0.017	−0.186***	0.014
Intercept	0.469	0.007	0.644	0.011	0.523	0.006
N.obs.	11400		11400		10400	

Table A5 notes: Size of group: 10. Number of groups per pool: 2. Number of pools: 30. PAM is positive assorting on gender and type. NAM is negative assorting on gender and positive assorting on type. Estimator is OLS with standard errors clustered by pool. Results shown are for one simulation.

A.3 Implementation details

The simulations are implemented as follows. For each pair, we create a value of the match variable that takes three possible values: neutral V_{ij}^n; PAM V_{ij}^p; and HAM V_{ij}^h. They are calculated as follows:

$$\begin{aligned}
V_{ij}^n &= |e_i - e_j| \\
V_{ij}^p &= -|gender_i - gender_j| - 0.5|type_i - type_j| + |e_i - e_j| \\
V_{ij}^h &= |gender_i - gender_j| - 0.5|type_i - type_j| + |e_i - e_j|
\end{aligned}$$

where e_i and e_j are independent random draws from a standard normal distribution, $gender = 1$ for 55% of randomly selected individuals and $type = 1$ for 75% of randomly selected individuals. Type and gender are independently assigned.

Values are then used to calculate the aggregate value of any grouping. To find the groupings yielding the highest average value on the match, we randomly try 100 different groupings and keep the grouping with the highest aggregate value across all groups. This is done separately for each pool. In practice, most of the improvement in value is achieved after a small number of iterations, e.g., less than 10. Small incremental improvements are occasionally observed up to 50 iterations, rarely above that. We are therefore confident that the simulated groupings are arbitrarily close to 'equilibrium' groupings that would maximize aggregate payoffs within each pool.