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Better together? Group incentives and the demand for prevention[☆]

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ABSTRACT

In a field experiment with 400 groups of informal entrepreneurs in El Salvador, we compare the impact of group incentives (linked to compliance of all members) to equivalent individual ones to encourage cardiovascular check-ups. We test two incentive designs: small rewards and lotteries. Group incentives are as effective as individual ones at increasing demand for prevention, but, unlike individual incentives, they fail to target those with potentially higher health risks. The equal effectiveness of group incentives is linked to more communication, coordination between members and, to some extent, peer pressure. These social dynamics contribute to reduce uncertainty about other group members' decisions and enhance the perceived net benefit of prevention. Although the preventive check-ups do not induce short-term lifestyle changes, they substantially increase the detection of new risk factors, making all incentives highly cost-effective interventions in this population.

1. Introduction

Every year, millions of people in low- and middle-income countries die of diseases that could be prevented by the use of simple products, early screening and treatment.[1] Low demand of preventive care is partly due to the direct and indirect costs that individuals face to access services (Thornton 2008, Banerjee et al., 2010). It may also be driven by behavioral factors, such as inaccurate beliefs about the benefits of prevention (Baicker et al., 2015), or self-control problems which prevent people from following through with their intentions (O'Donoghue and Rabin 2001). While financial incentives that reward individuals for adopting specific behaviors have been an effective tool to overcome some of these barriers, behavioral barriers often persist (Thornton 2008, Banerjee et al., 2010; Okeke and Abubakar 2020, Banerjee et al., 2021). Meanwhile, recognizing that social forces can be motivating drivers for individuals, a growing interest has emerged to understand if interventions can use social interactions to encourage the adoption of healthy behaviors (Karing 2018; Breza and Chandrasekhar 2019).

In this paper, we compare incentives conditional on group behavior (hereafter "group incentives") to equivalent incentives conditional on individual behavior. We partner with a micro-finance institution (MFI) in El Salvador and offer a voucher for a free cardiovascular disease (CVD) check-up to members of 400 loan groups. We incentivize voucher use by randomizing loan groups to individual incentives (linked to individual behavior), group incentives (linked to the behavior of all group members) or no incentive (control).

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[1] Insecticide-treated bed nets and water chlorination dramatically reduce the incidence of infectious diseases such as malaria or diarrhea, while non-communicable diseases such as diabetes, hypertension, and even certain cancers can be easily treated or managed if they are detected early through preventive screening.

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We implement two different designs for group and individual incentives. In the first design (*cash reward*), the individual (group) incentive is a small monetary reward paid after the individual (all group members) completes the preventive check-up. In the second design (*lottery*), all individuals (groups) are informed that at the end of the study period, some individuals (groups) will be randomly chosen and earn a large prize provided they (all group members) have done the check-up. We design the incentives to ensure that the expected reward is the same across all treatment arms (USD5), from an individual standpoint (provided that all members complete the check-up in group incentive treatments).

At first glance, group incentives should be less effective than equivalent individual ones. This is because, in our design, payment of a group incentive not only depends on the individual's behavior but also on the probability that all other group members comply with the desired behavior. If there is any uncertainty about others' behavior, the perceived value of the incentive is lower. A group incentive is also less valuable than an individual one if a complying individual must wait until the last group member uses the targeted service to receive the incentive –as is the case with group cash rewards. On the other hand, group incentives could trigger social dynamics leading to two effects: reducing uncertainty about others' behaviors and increasing the net benefit of the check-up. Group conditionality may incite people to communicate more with other group members to ascertain their intentions or decisions. It could also increase collective planning to foster accountability or eliminate a delay between the check-up and incentive payment. Beyond lowering uncertainty, such social dynamics could create additional benefits. Increased communication could lead to knowledge transfer about the benefits of prevention, while social coordination could lower the behavioral costs of a visit. Group incentives could also create social benefits for compliers, from conformity to a norm or altruism to help fellow members win an incentive. Overall, whether social effects can compensate, or surpass, the negative effects of uncertainty in collective behavior, and for whom, is an open empirical question.

We first find that incentives more than double the demand for prevention. Individual and group incentives are statistically equally effective, increasing the take-up rate by 17 percentage points (pp) and 22pp respectively. In the form of *cash rewards* their effect is similar ($p = 0.865$), but in the form of *lotteries*, group incentives marginally outperform individual ones, increasing the demand by 23pp versus 12pp ($p = 0.063$). Next, we find that individual incentives, not group ones, are effective at targeting individuals with higher health needs (people with higher baseline CVD risk and those who have done preventive visits before). The lack of targeting of group incentives, not necessarily problematic for CVD screening, is consistent with the collective conditionality that encourages everyone to do the check-up.

Using the random allocation to incentives as an instrument, we demonstrate that preventive check-ups increase the detection of new risk factors by 47pp but do not induce significant behavior or lifestyle changes in the short term. Since group incentives are only paid when all members complete the check-up, they appear less costly than individual ones (USD23.8 versus USD32 per new diagnosis), although this difference is not significant. Incentivizing CVD screening in this population is highly cost-effective, at USD487 per disability-adjusted life-year (DALY) averted for group incentives and USD608 for individual ones.

Finally, we identify communication and group coordination as key mechanisms in group incentives, with peer pressure playing a more minor role. These social dynamics not only help reduce uncertainty about the behavior of others, but they also produce social benefits (e.g. knowledge transfer, social commitments etc.) that contribute to increase the demand for prevention. In the case of group lotteries, these benefits outweigh the drawbacks of the collective conditionality.

Our paper contributes to three strands of literature. First, it adds to the empirical literature on group incentives. Economists have studied group incentives that aim to improve the performance of workers who jointly contribute to an output, and emphasized the benefits of social connections.[2] Direct comparisons of team and individual performance pay schemes have shown that both can improve performance equally (Muralidharan and Sundararaman 2011, Fryer Roland, Levitt et al., 2022).[3] Another relevant economics literature compares individual and group liability lending in microfinance, where group members can borrow again only if all members repay their loans. Despite the theoretical benefits of social connections to address information asymmetry in credit contracts, empirical evidence on the superiority of group lending is mixed (Carpena et al., 2013; Giné and Karlan 2014, Attanasio et al., 2015). Finally, our study adds to the few health experiments testing if group incentives can boost the adoption of healthy behaviors (Haisley et al., 2012; Kullgren et al., 2013; Halpern et al., 2015; Patel et al., 2016; White et al., 2020). Only two experiments have compared group incentives to equivalent individual ones, and both use sharp incentives where all members must comply with the desired behavior (Patel et al., 2016; White et al., 2020).[4] White et al. (2020) find that incentives in groups of two are less effective at reducing smoking than individuals ones, while Patel, Asch et al. (2016) find that both designs equally increase physical activity in groups of four. There are several unique features in the design and analysis of our experiment. First, we study the uptake of a preventive health service, where social effects may be weaker than for behaviors such as smoking or physical activity. Second, we introduce team incentives in groups of different sizes. Finally, we conduct a cost-effectiveness analysis to test the potential efficiency gains of sharp group incentives.[5]

Second, we contribute to the literature studying the role of social dynamics on individuals' behaviors. Seminal US studies have shown that health behaviors such as smoking (Christakis and Fowler 2008) or alcohol consumption (Rosenquist et al., 2010) spread through social networks. Research in low-income settings has also highlighted the role of social learning and peers in acquiring information or adopting new health technologies (Kremer and Miguel 2007; Oster and Thornton 2012; Dupas 2014). Our study more closely relates to empirical research testing interventions that mobilize social networks to encourage desirable behaviors in LMICs. Examples include peer monitoring to increase savings (Kast et al., 2018; Breza and Chandrasekhar 2019), targeting key individuals to spread information (Beaman et al., 2021) or signaling to others the adoption of healthy behaviors (Karing and Naguib 2018; Karing 2024). We use group incentives, a strategy only used once as a way to harness existing social connections to encourage health

[2] Examples include empirical studies of team performance pay in private firms (Bandiera et al., 2013; Friebel et al., 2017; Delfgaauw et al., 2021), public administrations (Burgess et al., 2010; Burgess et al., 2017), or schools (Lavy 2002; Muralidharan and Sundararaman 2011; Imberman and Lovenheim 2015).

[3] The central empirical question in the comparison of team and individual incentives is whether the benefits of worker coordination and peer monitoring outweigh the downsides of lower reward salience and free riding (Holmstrom 1982). In our application, there is no need for group member coordination to achieve the desired output and no concern of free riding.

[4] Haisley et al. (2012) find that a group incentives (80% based on individual behavior, 20% on group behavior) outperform individual incentives, but the two differ in structure and rewards (group lottery vs. individual cash, cash prize vs. grocery voucher, and larger rewards in the group treatment. Kullgren et al. (2013) find that group incentives for weight loss are more effective than individual ones, likely due to larger rewards (a $500 bonus shared between those who comply in groups of five or fewer, compared to a $100 individual incentive).

[5] White et al. (2013) analyzed the cost-effectiveness of the combination of group incentive, text reminders and commitment device against a control group that received no incentive.

investment (Patel et al., 2016), and never in a lower-income setting.[6] Ours is also the first study to explore the nature of social dynamics activated by group incentives and how they can encourage the demand for health prevention.

Finally, we add to the literature on the demand for healthcare in low-income settings, and more specifically the demand for preventive screening, a key pre-condition to the detection and successful treatment for many diseases that remain asymptomatic for long periods of time. A few experimental studies have looked how the price of a test (Okeke et al., 2013; Li et al., 2020), information avoidance (Li et al., 2020), peer referral (Goldberg et al., 2023) and access to treatment (Okeke et al., 2013; Wilson 2016) can influence the demand for disease screening. Other studies have shown how small financial incentives (Thornton 2008) or SMS messages (Wagstaff et al., 2019) can effectively reduce the diagnosis "dropout" (the failure of tested individuals to collect their test results). We add to this experimental literature in several ways. We examine the impact of small financial incentives on *both* initial testing and diagnostic dropout. Our analysis of the role of social effects brings new evidence suggesting that behavioral barriers contribute to low demand for free screening. Finally, to our knowledge, this is the first experimental study evaluating alternative strategies to encourage screening of CVD risk factors. Given the burden of CVD deaths is, this is a first-order priority in LMICs.

2. Background

2.1. CVDs and preventive care

In 2019, an estimated 17.9 million people died from CVDs, representing 32% of all global deaths and surpassing deaths due to infectious diseases, nutritional deficiencies, and maternal and perinatal conditions combined (Murray et al., 2020). Three quarters of these deaths occurred in low- and middle-income countries. Because people often fail to access services to detect the risk factors for CVDs or detect them in the early stages of the disease, people in low- and middle-income countries die at younger ages from CVDs, often in their most productive years.

The main pathological process behind the development of CVDs, called atherosclerosis, is influenced by several risk factors: tobacco use, an unhealthy diet, and physical inactivity, which together result in obesity, elevated blood pressure (hypertension), abnormal blood lipids (dyslipidemia), and elevated blood glucose (diabetes). Continuous exposure to these risk factors causes CVD to become worse. This can then result in the narrowing of blood vessels and obstruction of blood flow to vital organs, such as the heart and the brain, causing, respectively, heart attacks or strokes, which often leads to death or severe disability.

Despite the fact that CVD-related deaths are widespread, many can be prevented through timely and sustained lifestyle interventions and, when needed, the use of effective drug treatment to manage diagnosed risk factors such as hypertension, high cholesterol, or diabetes (World Health Organization 2007). Evidence-based recommendations on how to manage individuals requires detecting risk factors, but because those can remain asymptomatic for a long time (Bovet et al., 2015), many people remain undiagnosed and untreated, particularly in disadvantaged groups and in low- and middle-income countries (Chow et al., 2013; Ataklte et al., 2015). For this reason, the World Health Organization (WHO) recommends opportunistic and routine screening by health care providers, especially in the presence of observable risk factors (e.g., obesity). Once a risk factor is detected, regular monitoring is necessary. For lower-risk individuals, annual check-ups are recommended, while higher-risk individuals should have routine appointments every three months.

2.2. Study setting

This study was conducted in El Salvador, a lower-middle-income country in Central America, where deaths from CVDs account for about a third of mortality (Barceló et al., 2011). Efforts in recent decades to reduce mortality from CVDs have remained ineffective (Ordunez et al., 2015), mainly because of the combination of the high incidence of CVD risk factors[7] and low access to preventive services, particularly among the poorest segments of the population, which limits both early detection and effective monitoring (World Health Organization 2018). In El Salvador, 70% of the population receive health services from the public sector. To enhance access to these health services, including better monitoring and detection of non-communicable diseases, the government introduced a major reform in 2009 that increased coverage through a network of primary care units and abolished user fees at the point of care. Nevertheless, indirect costs and quality issues—long waiting times, medication shortages—remain considerable barriers in the public sector (Carrillo et al., 2020; Sánchez et al., 2020).

This study was developed in collaboration with ASEI, a MFI that operates in El Salvador and provides loans to more than 23,000 local micro-entrepreneurs through a network of 11 agencies in urban and rural areas. Having identified hypertension, diabetes, and obesity as some of the main health problems of its clients, ASEI encourage them to invest in preventive care. In 2014, they organized a text messaging campaign raising awareness about CVD risks and encouraging routine preventive medical visits. In 2018 and 2019, ASEI opened a clinic next to its agencies in San Salvador and Soyapango, allowing all clients to receive free medical consultations and medicines. As consultations at the clinics remained low, we partnered with ASEI to explore new ways to encourage the uptake of preventive CVD check-ups.

Participants were recruited amongst group loan members of ASEI at their agency in Soyapango. ASEI offers two types of group credits, for which members are jointly liable: Grupos Solidarios (GS) and Bancos Comunales (BC). In an urban area such as Soyapango, most groups are GS,[8] which are smaller in size (3–7 members compared to at least 7 members for BC). BC clients are required to meet weekly with a staff of the MFI to receive support and financial literacy education. GS members have no similar requirement to meet but in practice they do, as the group must send someone to the agency every week to repay the installment (this person can change from one week to another). To be offered a group credit, at least three individuals must approach the MFI and apply together. As a result, group members typically know each other well (in our data participants declare being friends with 86% of other members), and often live or work near each other. If things go well with the loan repayment, it is also common for groups to re-apply for a credit together.

3. Experimental procedures and design

3.1. Recruitment and randomization procedures

Between September 2019 and January 2020, all groups that came for a new loan disbursement were invited to participate in the study. We used the fact that, to avoid over-crowding of their premises, the MFI gives any group a dedicated time slot on the day of their loan disbursement, when all members must be present. We made sure that this allotted time slot was long enough to allow a group to take part in our study recruitment and do the necessary paperwork for the loan disbursement. When a group arrived at the agency, they were invited to

[6] White et al. (2020) test group incentives in Thailand in a context where members had no prior connection. They suggest that the absence of existing social links could explain the lower impact of group incentives compared to individual ones.

[7] Estimates suggest that in 2015 almost 40% of adults suffered from hypertension, 25% were obese, and 12% had diabetes (Ministerio de Salud/Instituto Nacional, 2015).

[8] Less than 9% of our sample is in a BC.

take part in the study by the research team. Any group receiving a group loan was eligible for the study as long as at least three individual members were willing to participate. There was no restriction of age or health status.

Once at least three members of the group agreed to take part, enumerators administered a short baseline survey to each member individually. At the end of the baseline survey, each respondent was given a voucher to access a free health check-up within two months. The preventive check-up consisted of two parts. First, a blood test was to be undertaken at a local laboratory to obtain measures of three key CVD biomarkers (glucose, total cholesterol, and high-density lipoprotein cholesterol). Second, after the blood test was processed, usually the next day, the lab transmitted the results to the MFI clinic where the individual had to make an appointment with a doctor to obtain the results. As is common in El Salvador, respondents were told that regardless of the test results, neither the lab nor the clinic would phone participants to communicate their results. In fact, the lab and clinic staff had specific instructions to tell participants that results would only be communicated to them by the doctor in a specific consultation.[9] The consultation would focus on discussing their CVD risk factors, lifestyle and dietary habits, and the potential need for medical treatment. Overall, the check-up represented a high-quality healthcare service, estimated at USD38.[10]

After all members of a group had completed the baseline survey and received a voucher, they attended a short talk, covering basic health information on the prevalence of CVDs in El Salvador, their causes and potential consequences, and the benefits of regular preventive controls (early detection and treatment, monitoring).

At the end of the talk, the field supervisor randomized the group to one of five conditions described below, following a pre-specified sequence generated before the start of fieldwork to produce a blocked stratified randomization list – an approach often adopted in clinical trials.[11] Unlike a simple spot randomization, this method allowed us to stratify the randomization across three strata that accounted for the type and size of the loan groups.[12] Upon recruitment of the group, the field supervisor had time to determine to which stratum the group belonged, select the appropriate list and allocate the group to the next available slot on that list.[13] Because groups were recruited sequentially, and there was only ever one group at any one point handled by the research team, there was no ambiguity about treatment assignment. To prevent any manipulation of the allocation of groups to treatment arms, the MFI staff were all blinded to the randomization sequence.

3.2. Experimental design

All groups received detailed information about the voucher, including conditions of use. Depending on the treatment arm to which they had been allocated, they were informed about any incentive offered for completing the full check-up[14]: no incentive (control), an individual cash reward, a group cash reward, an individual lottery, or a group lottery (see the experimental design in Fig. 1):

In the control arm, participants received no incentive to do the free medical check-up.

In both cash reward arms, participants could earn USD5 for doing the full check-up – more than enough to cover the travel costs of two return trips needed to do the blood exam and the consultation separately, but a small fraction (less than 10%) of the average daily sales income of these informal entrepreneurs.[15] In the *individual cash reward* arm, individuals would receive the reward immediately after the medical consultation. In the *group cash reward* arm, groups of N members were given a reward worth N × USD5, received after the last member had completed the full check-up. Hence, unless all group members did their consultation at the same time, there would be a delay between the moment the first member of the group completed the medical consultation and when they received the incentive.

In both lottery arms, participants had a 5% chance of winning USD100 if they completed the full check-up, a prize representing 16% of the average individual loan amount (USD632). In the *individual lottery* arm, individuals were informed that out of the 400 individuals expected to be part of this treatment arm, 20 would be drawn at the end of the study period.[16] A lottery winner who had completed the check-up would receive USD100, but would get nothing if they had not done the full check-up.[17] In the *group lottery* arm, a group of N members could win a prize worth N × USD100. Groups were informed that, four of the 80 groups randomized to this treatment arm would be drawn in a lottery at the end of the study period.[18] Similarly to the individual lottery, the prize would only be paid to a winning group if *all* members of the group completed the full check-up (blood test and medical consultation).

Assuming a group splits the group reward evenly between group members,[19] from an individual standpoint the value of the incentive is the same for group and individual incentives (USD5), as long as, in the group treatment, all members comply with the conditionality. The latter point is the key difference between group and individual incentives: if anyone defaults in the group treatment, no one earns anything. This stringent condition eliminates concerns of free-riding and only leaves open the role of social effects, which we describe further in Section 4. It is also consistent with the WHO objective of opportunistic screening and monitoring check-ups, where the objective is to encourage everyone to attend screenings.

Note that the timing of the payment is not held constant across treatments for three reasons. First, to keep salient the main difference between group and individual incentives linked to a one-off decision,

[9] This information was also given to participants at baseline when they received the voucher. As a result, the two components of the check-up were only valuable in combination since individual blood tests could only be obtained from the clinic.

[10] In the private sector, a similar blood test would be charged approximately USD16 for the blood test, and a consultation with a medical doctor would cost USD22.

[11] We used a web-based randomization tool routinely used in clinical trials to produce the randomization sequence list (https://www.sealedenvelope.com/).

[12] There were three randomization strata: small group (GS with 3–4 members); large group type 1 (GS with 5–7 members); large group type 2 (BC, which always include at least 7 members). We used three random sequences, one per stratum.

[13] We verified daily that no allocation error occurred.

[14] Anyone could ask questions to clarify any information, and each person received a leaflet providing a summary of all the information received orally. The voucher itself clearly indicated the key information, including its expiry date, the services offered, and relevant incentives. Appendix Figure A1 shows an example of the five types of vouchers used.

[15] The average cost of a round trip from home is approximately USD0.70, while the average daily sale income of participants is USD45.

[16] Because enrolled groups were on average smaller than expected, only 331 individuals were part of this treatment arm and entered the individual lottery. Hence the true probability of winning conditional on completing the take-up was 20 out of 331, or 6% (0.0604). Since participants were only ever aware of the 5% expected probability (20 out of 400), the discrepancies between arms are trivial and would not have affected individual decisions.

[17] This amount is far from substantial and would not provide winners an opportunity to improve their status (Friedman and Savage 1948). However, it remains significant and highly valuable, equivalent to about a quarter of the average loan requested by an individual to the MFI.

[18] Only 79 groups ended up being allocated to the group lottery arm, leading to a probability of 0.0506.

[19] To our knowledge, an unequal split never happened.

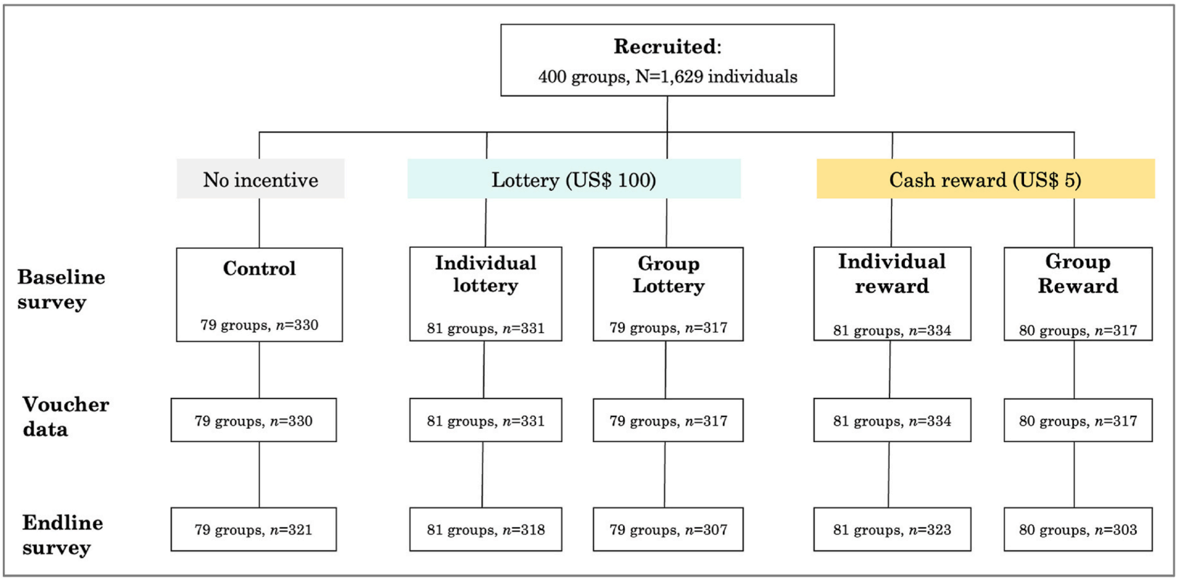

Fig. 1. Experimental design.

which is that the individual incentive can be earned immediately after task completion while it may not be the case with a group incentive. In other words, the group conditionality is driving the potential difference in the timing of the payment between the individual and group cash rewards. Second, we decided against delaying the payment of individual cash bonuses to the end of the study period (at the same time as the lottery) to maintain the policy relevant and external validity of this intervention (small cash incentives are never paid with long delays). Third, and directly linked to the second reason, delaying the payment of a small incentive would likely and artificially have weakened its effectiveness.

4. Conceptual framework

To understand the expected effects of the different incentives in our experiment, we develop a simple model of the demand for the preventive check-up.

In the absence of any intervention (control group), individuals gain $U_C = \delta_i^T h_i - C_i$ from completing the preventive check-up, where h_i, are the future health benefits from the check-up relative to no check-up, discounted by a factor δ_i^T and C_i is the cost of doing the check-up, which encompass both pecuniary and non-pecuniary costs. Consider now a program which introduces a bonus payoff for completing the preventive check-up, in the form of individual or group reward. With individual rewards, individual i earns a pecuniary benefit $r > 0$ immediately after completing the check-up or nothing if they do not do the check-up. With group rewards, the payment is made only when all members of their group have also completed the check-up. We define p_j as the probability that individual i assigns to all other group members completing the check-up, and δ_i^ε the factor by which she discounts the reward, with $\varepsilon \geq 0$ the time at which the last member of the group completes the check-up.[20] The utility derived by individual i when undertaking the check-up is therefore $U_{IR} = \delta_i^T h_i + r - C_i$ with an individual reward and $U_{GR} = \delta_i^T h_i + \delta_i^\varepsilon p_j r - C_i$ with a group reward.

Following this, one can expect the demand for prevention to be highest with the individual reward, followed by the group reward and the control group: $U_{IR} > U_{GR} > U_C$ because $r > \delta_i^\varepsilon p_j r > 0$. The higher expected effectiveness of the individual reward compared to the group reward is driven by two sources of uncertainty in group incentives which reduce the perceived value of the reward: (1) whether fellow members will complete or not ($p_j \leq 1$) and (2) how long the group completion occurs after individual i's own check-up ($\delta_i^\varepsilon < 1$ if $\varepsilon > 0$). Similarly, if the incentive for completing a check-up takes the form of a lottery with payout R received at time $t = \tau$, the utility for an individual lottery is $U_{IL} = \delta_i^T h_i + \delta_i^\tau E[R] - C_i$ and for a group lottery: $U_{GL} = \delta_i^T h_i + \delta_i^\tau p_j E[R] - C_i$. Whilst in this case uncertainty about the timing of group completion is irrelevant, we still expect the demand for prevention to be higher with individual lotteries because of the uncertainty about fellow members' behavior ($p_j \leq 1$).

In this simple framework, group incentives cannot be *more* effective than individual ones. They can only be equally effective if individual i believes or knows that other members of the group will do the check-up ($p_j = 1$) and, in the case of cash rewards, if she completes at the same time as the last group member to eliminate any payment delay ($\delta_i^\varepsilon = 1$). This could occur if individual i talks to other members and ascertains that they intend to do the check-up, and perhaps make the visit together with the last completing member(s), ensuring that $\varepsilon = 0$. In other words, to be as effective as individual ones, group incentives require some interactions between group members.

Building on such interactions, we can enrich the basic model and introduce the possibility that an individual derives non-pecuniary benefits from doing the check-up through social effects ($\sigma_i \geq 0$). We remain agnostic about the nature of these social benefits, which can be an increase in the perceived health benefit of prevention h_i produced by knowledge transfer (as individuals seek to persuade fellow members of the utility of doing the check-up to increase p_j); increased individual utility from social preferences (e.g. altruism to help others earn money, satisfaction to conform to a group norm or behavior), or a reduction in non-pecuniary costs C_i (e.g. reducing behavioral barriers by making planning easier (Rogers et al., 2015). If these social benefits are large enough compared to the uncertainty of others' behavior ($\sigma_i > r\left(1 - \delta_i^\varepsilon p_j\right)$), group incentives could be more effective than individual ones.

In sum, the model clarifies that the uncertainty linked to other members' behaviors, as well as the difference in payment timing (for rewards), are two reasons to expect take-up to be higher with individual incentives. However, the group conditionality may activate social dynamics that could not only reduce uncertainty about others' behaviors

[20] Note that $\varepsilon \ll T$ because the reward is earned in the near future (at most three months), while health benefits are in the distant future.

but also induce net social benefits. If those are large enough, group incentives can be more powerful than individual ones.

5. Data and empirical approach

5.1. Data and attrition

Baseline survey. The baseline survey covered demographics and socio-economic characteristics, basic health measures (heigh, weight, and blood pressure taken as the average of three separate measures), individual preferences (risk and time), relationships with other members of the group, and questions about known diagnoses of the main CVD risk factors (hypertension, diabetes, obesity, and high cholesterol). We combined demographic (gender and age) and health characteristics (obesity, blood pressure, diabetes) to estimate an individual-specific 10-year CVD mortality risk by following the Globorisk algorithm (Hajifathalian et al., 2015).

Voucher data. For everyone enrolled in the study, we have detailed data from the voucher use, including whether and when an individual used their voucher to do the blood test at the lab and whether and when they went to the subsequent medical consultation. We also know whether an individual requested their blood results from the clinic without doing a medical consultation.

Endline survey. We planned to conduct face-to-face interviews with all respondents from our baseline survey, but the COVID-19 epidemic and the stringent lockdown measures introduced in El Salvador at the end of March 2020 forced us to conduct the interviews by phone instead.[21] The endline interview was designed to identify the ways in which the incentives had worked and to capture the potential benefits of prevention. The phone interview had to be short, so it only included four main modules: health-related behaviors and outcomes, information received during the CVD consultation, group interactions, and reasons for not using the voucher.

Despite the challenging circumstances of the endline survey, we were able to reach 96.5% of the baseline participants.[22] Appendix Table A1 shows that attrition rate was not different across treatment arms and Appendix Table A2 presents tests showing that attrition was balanced across treatment arms (Ghanem et al., 2023).

5.2. Sample characteristics and balance

Table A3 reports summary statistics and balance checks for the characteristics of individuals (Panel A) and groups (Panel B). Panel A shows that 84.7% of study participants are women, aged 43.5 on average, with limited education (60.2% have no or basic education), and 53.8% live under the poverty line. In general, study participants are not in good health. Overall, 46.8% have been diagnosed with hypertension, high cholesterol, or diabetes, but nearly half of them (49.5%) remain untreated.[23] Many participants also have undiagnosed health issues: our baseline measures indicate that 30.3% (59.5%) suffer from hypertension (obesity) but 38.3% (66.8%) of those remain undiagnosed. Combining health outcomes with individual characteristics (age, sex, smoking status), we find that nearly 15.7% of the population has a medium or high CVD mortality risk.[24] Usage of services is generally high, with an average of 1.1 visits to a healthcare facility in the past three months. However, use of preventive care is low with only 14.8% of participants ever doing a preventive visit. Loan groups are relatively small, with an average of four members (Panel B)[25] and appear close-knit: individuals report being friends with most other members (86%) and interacting on a weekly basis with nearly all (94%).

The balance checks indicate that all characteristics are balanced across treatments, except for one variable (being under treatment for diabetes), which is expected to happen by chance.

5.3. Empirical strategy

To evaluate the effect of group incentives, we first pool the voucher use in the two group versus two individual arms. We estimate regressions of the following form:

$$y_{ig} = \alpha + \beta_1 Individual_g + \beta_2 Group_g + Z_g^{\prime}\zeta + \varepsilon_{ig}, \tag{1}$$

where y_{ig} is an indicator variable reflecting the take-up decision for individual i in loan group g. The binary variables $Individual_g$ and $Group_g$ indicate whether group g was randomly assigned to an individual incentive arm or a group incentive arm, and coefficients β_1 and β_2 capture the impact of each type of incentive. We include a vector of stratification variables Z_g. Standard errors are clustered at the loan-group level, the unit of randomization.

Next, we evaluate separately the individual effect of the four incentive designs, estimating regressions of the following form:

$$y_{ig} = \alpha + \beta_{11} I\_cash_g + \beta_{21} G\_cash_g + \beta_{12} I\_lott_g + \beta_{22} G\_lott_g + Z_g^{\prime}\zeta + \varepsilon_{ig}, \tag{2}$$

where I_cash_g, G_cash_g, I_lott_g, and G_lott_g are binary variables indicating whether group g was randomized to the individual cash reward, group cash reward, individual lottery, or group lottery treatment arm, respectively. The coefficients β_{11}, β_{21}, β_{12}, and β_{22} capture each incentive's impact. While the above specifications reflect our experimental design, the results are robust to alternative specifications including individual controls or by the double LASSO procedure of Belloni et al. (2014) – see Table A4. In addition, for each specification, we report sharpened q-values adjusting for testing multiple hypotheses using the false-discovery-rate methodology presented by Benjamini et al. (2006) and Anderson (2008).[26] Following Hess (2017), we also report randomization inference p-values based on 2000 permutations.

6. Results

6.1. Effect of incentives on check-up completion

Our main outcome of interest is whether an individual completed the preventive check-up. Table 1 presents the pooled impact of individual and group incentives, while Table 2 shows the disaggregated results, by incentive type. Against a low take-up in the control group (15.5% of individuals do the free medical check-up), incentives significantly increase the demand for prevention by 16.8 pp for individual incentives and 21.7 pp for group ones (Table 1), a difference that is not statistically

[21] While the start of the pandemic disturbed the endline survey, use of the vouchers was not because the last voucher expired by the middle of March and before any restrictions or curfews were implemented.

[22] Of all baseline participants, 0.86% refused to respond and 2.64% could not be reached despite multiple attempts and contacts with their fellow group members. To increase survey participation, individuals were entered into a lottery to win vouchers worth USD50 to spend at a local grocery store chain.

[23] Of those diagnosed with hypertension, diabetes, and high cholesterol, respectively 31.6%, 19.6% and 67% remain untreated.

[24] Medium risk corresponds to a 10%–20% probability of dying from a CVD within 10 years; a high risk corresponds to a probability greater than 20%.

[25] Appendix Figure A2 shows the distribution of group sizes.

[26] We calculate the number of hypotheses tested separately for the pooled or disaggregated results. For example, if we test 3 outcomes, there are 6 hypotheses in the pooled analysis (3 outcomes and 2 coefficients), and 12 hypotheses in the disaggregated analysis (3 outcomes and 4 coefficients).

Table 1
Pooled impact of incentives on the demand for prevention.

	(1)	(2)	(3)
	Completed the screening	Did the blood test	Dropped after blood test
Individual incentive	0.168	0.134	−0.191
	(0.036)	(0.038)	(0.061)
	[<0.001]	[<0.001]	[0.001]
	{0.001}	{0.003}	{<0.001}
Group incentive	0.217	0.205	−0.153
	(0.041)	(0.043)	(0.063)
	[<0.001]	[<0.001]	[0.003]
	{<0.001}	{<0.001}	{0.004}
P-value for group vs. individual incentives	0.260	0.106	0.183
Control mean	0.155	0.206	0.750
# of teams	400	400	400
# of individuals	1629	1629	555

Notes: Table presents OLS estimates. The dependent variables in columns 1 to 3 are binary indicators of whether an individual completed the full CVD preventive check-up (blood exam and medical consultation), whether an individual completed the blood exam, and whether an individual completed the medical consultation conditional on having completed the blood exam. The samples in columns 1 and 2 include all individuals, while column 3 only includes individuals who completed the blood test. All models include randomization strata fixed effects. Standard errors are clustered at the group level and reported in parenthesis. False-discovery rate corrected q-values based on Benjamini et al. (2006) and Anderson (2008) are presented in square brackets and randomized inference p-values following Hess (2017) using 2000 permutations are presented in curly brackets.

significant ($p = 0.260$).[27] When incentives are designed as a lottery (Table 2), group incentives are more effective than individual ones, increasing the take-up by 22.8 pp versus 12.0 pp for individual lotteries ($p = 0.063$). In the form of small cash rewards, individual and group incentives increase the demand for prevention by a similar amount (respectively by 21.6 and 20.5 pp, $p = 0.865$). Group rewards perform as well as individual ones *despite* the difference in timing to receive the monetary incentive –immediately after the consultation for individual arm relative to an average delay of 4.5 days in the group arm (see Appendix Figure A3 for the distribution of waiting time between own appointment and receipt of reward).[28]

Overall, as highlighted in our model, the fact that individual incentives are not more effective than group ones suggests the existence of social dynamics that compensate for the uncertainty of other members' behaviors, and in the case of cash rewards, delayed payment. Meanwhile, the greater effectiveness of group lotteries over individual ones provides empirical evidence that they create especially large social benefits, perhaps the "*secondary social effects*" identified in the gambling literature when individuals play the lottery with friends (Beckert and Lutter 2012).

Next, we explore whether incentives work by attracting more individuals to complete the check-up (column 2) or by reducing the diagnosis dropout (the proportion of individuals who, conditional on going to the lab, do not go to the clinic, column 3). Three results emerge. First, all incentives significantly increase the share of individuals initiating the 2-step process, respectively by 65% and 100% for individual and group incentives. This effect appears marginally stronger for group incentives ($p = 0.106$), a difference driven by lotteries that confirms

Table 2
Disaggregated impact of incentives on the demand for prevention.

	(1)	(2)	(3)
	Completed the screening	Did the blood test	Dropped after blood test
Individual Reward	0.216	0.170	−0.224
	(0.046)	(0.047)	(0.060)
	[<0.001]	[0.001]	[0.001]
	{<0.001}	{0.002}	{<0.001}
Group Reward	0.205	0.188	−0.160
	(0.055)	(0.057)	(0.066)
	[0.001]	[0.001]	[0.007]
	{<0.001}	{0.001}	{0.006}
Individual Lottery	0.120	0.099	−0.149
	(0.042)	(0.047)	(0.068)
	[0.003]	[0.012]	[0.011]
	{0.009}	{0.035}	{0.025}
Group Lottery	0.228	0.221	−0.146
	(0.052)	(0.053)	(0.066)
	[<0.001]	[<0.001]	[0.011]
	{<0.001}	{<0.001}	{0.015}
P-value for group vs. individual reward	0.865	0.770	0.061
P-value for group vs. individual lottery	0.063	0.039	0.951
Control mean	0.155	0.206	0.750
# of teams	400	400	400
# of individuals	1629	1629	555

Notes: Table presents OLS estimates. The dependent variables in columns 1 to 3 are binary indicators of whether an individual completed the full CVD preventive check-up (blood exam and medical consultation), whether an individual completed the blood exam, and whether an individual completed the medical consultation conditional on having completed the blood exam. The samples in columns 1 and 2 include all individuals, while column 3 only includes individuals who completed the blood test. All models include randomization strata fixed effects. Standard errors are clustered at the group level and reported in parenthesis. False-discovery rate corrected q-values based on Benjamini et al. (2006) and Anderson (2008) are presented in square brackets and randomized inference p-values following Hess (2017) using 2000 permutations are presented in curly brackets.

their large social benefits.[29] Second, there is a large diagnostic dropout in the control group (25% of those doing the blood test fail to go to the clinic to obtain and discuss their results)[30] that is significantly reduced by all incentives. This effect is strongest with individual cash rewards which reduce the dropout rate to only 2.6% (versus 9%–10.4% for other incentives). Since it is the only treatment where individuals earn a reward immediately after the consultation, the result suggests that individuals otherwise renounce the second visit because they update upwards the cost of the visit following the first step.

6.2. Heterogeneous effects

A key question for a policy subsidizing health service use is whether it targets those with higher needs. In our context, we first consider two potential measures of health needs to investigate the targeting effects of incentives: (i) an objective CVD risk score used in the medical literature based on demographic and health information collected at baseline, and (ii) a subjective measure of health needs, in the form of self-reported prior use of preventive care. In addition, given evidence on the role of

[27] Additional analysis also finds no difference between group and individual incentives in terms of the timing of the check-up completion (see Appendix C).

[28] In groups in the group reward arm where all members completed the check-up, 50.6% of members did not have to wait for receiving their reward because they completed the check-up on the day of the group completion. The average waiting time of individuals who waited at least one day (meaning they did not complete on the day of the group completion) was 5.9 days.

[29] For cash rewards, the take-up of the blood test is 37.7% for the individual variant and 39.4% for the group one. For lotteries, this is 30.5% and 42.6%, respectively.

[30] Unlike in the case of repeat vaccinations, we can rule out the idea that individuals do not value (or understand the value of) the follow-up visit, as the utility derived from doing a blood test without getting the result seems very limited since all participants knew they would only learn their results by going in person to the clinic.

indirect costs as a barrier for prevention (Thornton 2008), we divide people depending on whether they face above or below median indirect costs to do the check-up.[31] For each measure, we explore whether incentives differentially encourage individuals with higher needs (costs). Table 3 presents the pooled results, with column headings listing the interacted variable. Disaggregated results are shown in Appendix Table A5.[32]

We find that individual incentives, but not group incentives, have a targeting effect and encourage uptake of individuals with higher health needs. Individual incentives increase the uptake of people with above-median CVD risk by 10pp (Table 3, column 1). Take-up of the preventive check-up is also 16.7pp higher for those who have used preventive services before in the individual incentive arms (Table 3, column 2). These effects are driven by the individual cash reward arm (see Appendix Table A5). However, there is no evidence that individual incentives encourage more those facing higher indirect costs (Table 3, column 3).

Table 3
Heterogeneous effects of incentives.

	Above median CVD risk	Used preventive care before	Above median opportunity cost
	(1)	(2)	(3)
II: Individual incentives	0.116	0.144	0.211
	(0.041)	(0.036)	(0.045)
	[0.006]	[<0.001]	[<0.001]
	{0.009}	{0.001}	{<0.001}
GI: Group incentives	0.203	0.212	0.257
	(0.050)	(0.043)	(0.050)
	[<0.001]	[<0.001]	[<0.001]
	{0.003}	{<0.001}	{<0.001}
Interacted variable	0.005	−0.130	−0.001
	(0.034)	(0.033)	(0.037)
	[0.334]	[<0.001]	[0.352]
	{0.908}	{0.005}	{0.985}
II × Interacted variable	0.108	0.167	−0.088
	(0.051)	(0.061)	(0.051)
	[0.029]	[0.007]	[0.064]
	{<0.001}	{<0.001}	{0.017}
GI × Interacted variable	0.025	0.035	−0.081
	(0.052)	(0.067)	(0.054)
	[0.241]	[0.241]	[0.079]
	{<0.001}	{0.011}	{0.003}
Main effect: P-value for group vs. individual incentives	0.084	0.124	0.372
Interaction: P-value for group vs. individual incentives	0.134	0.090	0.890
Control mean	0.155	0.155	0.155
# of teams	400	400	400
# of individuals	1629	1629	1629

Notes: Table presents OLS estimates. The dependent variables in columns 1 to 3 is a binary indicator of whether an individual completed the full CVD preventive check-up (blood exam and medical consultation). Column 1–3 report heterogeneous results using: (1) above the median CVD risk; (2) whether the respondent had ever gone to a preventive consultation before; and (3) above median opportunity costs complete the full CVD preventive check-up. All models include randomization strata fixed effects. Standard errors are clustered at the group level and reported in parenthesis. False-discovery rate corrected q-values based on Benjamini et al. (2006) and Anderson (2008) are presented in square brackets and randomized inference p-values following Hess (2017) using 2000 permutations are presented in curly brackets.

Overall, these results imply that group incentives are inadequate to encourage individuals with higher (health or economic) needs. This poor targeting seems like the price to pay for encouraging *all* group members, regardless of their characteristics, to comply with a certain behavior.[33]

Does it mean that group incentives lead to over-inclusion and therefore a waste of resources? Not necessarily, for two reasons. First, past use of preventive care may be an imperfect measure of health needs. Instead, it could capture the fact that some individuals have better information about the value of prevention, leading to higher perceived value of and demand for prevention.[34] Encouraging equally those with different levels of information may therefore be a desirable policy goal. Second, in the case of CVD check-ups, universal screening may be a desirable policy objective –and indeed one recommended by the WHO– as there are several problems associated with targeted screening for CVD (Capewell 2008, Feigin et al., 2020).[35] One of them relates to the inability of CVD risk scoring system, such as the one we use to proxy health needs, to identify accurately individual risks. In our sample, 47% of individuals who do the blood test and have a below-median CVD risk measure have at least one risk factor newly diagnosed by the test.[36] Targeting only higher risk individuals according to this metric could therefore lead to under-diagnosing many at-risk individuals.

7. Impact of check-ups and cost-effectiveness of incentives

7.1. *Effects of preventive check-ups*

The next question of interest is whether the check-up then leads to the detection of new CVD risk factors, or increases individuals' knowledge and healthy behaviors. To estimate the impact of the check-up, we use information collected at endline and use the random assignment to the four incentive groups as instruments. Appendix Table A7 shows that all results are robust to an alternative specification recommended in the presence of several instruments (Keane and Neal 2023) and Appendix Table A8 presents the intention-to-treat (ITT) effects.

The results of the IV estimates, reported in Table 4, show that check-ups lead detecting new risk factors but not to significant behavior change. Screenings increase the probability that an individual knows they suffer from a previously unknown risk factor increases by more than 47 pp ($p < 0.001$). This is a substantial benefit, especially given that the screening was offered to a population where 47% had already been diagnosed with at least one risk factor. There is suggestive evidence that individuals' attitudes and behaviors improve a little, though changes are

[31] We compute a composite cost measure faced by individuals by adding the transport costs to reach the clinic and income lost due to the trips taken. To calculate the latter, we combine the time taken (transport time plus an estimated 10 min for the blood test or consultation) with the average daily revenues from an individual's economic activity.

[32] Appendix Table A6 confirms that results are robust to including controls.

[33] In our sample, all members complete the check-up in 26% of groups randomized to group incentives, against only 10% of groups with individual incentives (Appendix Figure A4).

[34] 73% of those who have done a preventive consultation before know the symptoms of hypertension and diabetes, against 65% for those who have not used preventive services before ($p = 0.01$).

[35] A first concern is that a targeted screening approach may exclude individuals with low to moderate risk who account for the vast majority (80%) of stroke and heart attack cases. Second, labeling individuals as "low risk" can lead to false reassurance and reduced motivation to control risk factors, particularly in young people with high relative risk but low absolute risk due to their age. Finally, CVD risk scoring systems that do not account for major behavioral risk factors (except smoking) and blood test results identifying key risk factors may be relatively inaccurate for estimating actual patients' risk– a problem we mention in our manuscript as limiting the effectiveness of such targeted strategy in detecting and managing patient risks.

[36] This proportion is not driven by the fact that this is a high-risk population. If we consider individuals who did the blood test and were identified as having a low CVD risk at baseline, 43% have a new risk factor diagnosed by the test.

Table 4
Effects of preventive check-up (IV estimation).

	Diagnosis	Knowledge	Attitude towards behavior change		Healthy behaviors					
	Diagnosed with new risk factor	Believes has medium/high risk of developing CVD	Willing to change habits to improve health	Believes CVD risk factors cannot be changed	# of days eating fast food	# of days eating fruits or vegetables	# of days drinking SSBs	Smoking	Health activation index	# of tickets for healthy lottery prize
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
CVD check-up	0.472	0.091	0.160	−0.050	0.054	0.540	−0.807	0.020	0.022	0.965
	(0.080)	(0.147)	(0.113)	(0.122)	(0.469)	(0.551)	(0.670)	(0.054)	(0.640)	(0.686)
Strata FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Interview week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control mean	0.076	0.582	0.788	0.249	1.713	5.427	2.352	0.034	−0.040	7.191
CGW F-test	15.147	13.762	14.388	14.388	14.388	14.388	14.388	13.400	14.388	14.252
Observations	1629	1493	1572	1572	1572	1572	1572	1538	1572	1571

Notes: Table presents 2SLS estimates with standard errors in parenthesis and all four treatment group dummies as instrumental variables for completing the full medical check-up. The dependent variable is a binary indicator whether an individual completed the full CVD preventive check-up (blood exam and medical consultation). Dependent variables are defined as follows: Column 1 presents whether the individual has been diagnosed with at least one CVD risk factor in the follow up survey; Column 2 is a binary dependent variable whether the individual perceives their risk of developing CVD to be medium or high; Column 3 is a binary indicator whether the individual was willing to change their habits to improve their health; Column 4 is a binary variable whether the respondent believes something can be done to improve CVD risk factors; Column 5 is a continuous measure of the number of days in the last week in which the respondent ate fast food; Column 6 is a continuous measure of the number of days in the last week in which the respondent ate either fruits or vegetables; Column 7 is a continuous of the number of days in the last week in which the respondent consumed sugar sweetened beverages; Column 8 is a binary indicator whether the respondent smokes at follow up, Column 9 is a health activation index constructed using principal component analysis and Column 10 is a continuous measure ranging from 0 to 10 on how many tickets they choose for the health lottery prize. All specifications include randomization strata fixed effects. Individual controls include a binary indicator whether the individual is over the age of 50, gender, a binary indicator for whether the individual has basic education or higher, 10-year CVD mortality risk at baseline, BMI at baseline, self-reported average daily earnings, and self-reported opportunity cost of travelling to the clinic.

not statistically significant. There is no evidence that check-ups increase the proportion of individuals believing they have a medium to high risk of developing a CVD event (column 2) or reporting a positive attitude toward behavior change (column 3–4). Healthy diets do not improve much: there is no reduction in the consumption of fast food or sugar-sweetened beverages, and no significant increase in the consumption of fruits or vegetables more often.[37] To limit concerns about the validity of self-reported measures, we implemented an incentivized raffle where individuals had to choose between investing in healthy or unhealthy food.[38] We find borderline evidence that individuals who completed the check-up invest more in healthy food, choosing on average one more ticket for the raffle to win healthy food ($p = 0.126$).

The limited impact of the preventive check-up is not due to poor quality of the consultation, as respondents generally remembered the key topics of CVD prevention discussed by the doctor (see Fig. A5 in Appendix). However, it is unclear to what extent patients paid attention to the information they received. For example, only 30.6% correctly remembered their own level of CVD risk (see Appendix Figure A6).[39] Overall, these null results echo the modest behavioral benefits of similar preventive screening (Deutekom et al., 2011), especially in the short term.

7.2. Cost-effectiveness of incentives

This section assesses the relative cost and cost-effectiveness of the different incentive schemes. We present a simple cost-effectiveness analysis in Table 5. Column 1 presents the treatment effects on the average cost per person.[40] Using treatment effects on completed screenings (Column 2) and diagnoses of a new risk factor (Column 4), we then calculate respectively the cost per screening (Column 3) and the cost per new risk factor diagnosis (Column 5).

The results show that, although group incentives appear to cost less on average, driven by the collective payment conditionality,[41] these differences are not statistically significant (Column 1). Equally, the cost per additional check-up with group incentives (USD10.6) is not statistically lower than for individual incentives (USD14.9) (Column 3), and neither is the cost per new diagnosed risk factor (Column 5: USD23.8 for group incentives versus USD32 for individual incentives). Overall, the

[37] In our pre-registration plan, outcomes included measures of physical activity and treatment adherence. However, the change to telephone interviews imposed by the COVID-19 pandemic led us to drop these outcomes to shorten the survey. Considering the null results on the other health outcomes measured, we would not expect to have found significant effects on these other measures.

[38] Participants could allocate nine tickets between two different raffles: in one, they could win $50 to spend on pizzas and in the other they could win $50 to spend on vegetables and fruits. We consider the number of tickets allocated to the healthy tombola as a measure of their willingness to invest in their health. This choice also mimics real-life trade-offs that individuals may have to make, deciding whether to invest more in healthy food at the expense of unhealthy one.

[39] Depending on their blood test results and characteristics, the doctor during the consultation told patients whether they had with a low, medium, or high risk of mortality within the next 10 years.

[40] The total costs per arm are presented in detail in Appendix Table A9, while the number of screenings and new diagnoses per arm are presented in Appendix Table A10. Costs include payment of the blood test at the lab and the incentives to individuals or groups. We exclude the cost of clinic staff because it is sensitive to the scale of the prevention program and specific decisions around staffing at the clinic. During the study, ASEI hired a full-time doctor to receive all participants coming for their medical consultation due to concerns that a large influx of patients would disrupt the normal functioning of the clinic and the provision of other services. In practice, the daily flow of patients could have easily been handled by a part-time doctor.

[41] For example, in the group cash reward arm, only 72% of compliers in the group cash reward arm receive the US5 incentive, since not all groups completed.

Table 5
Cost effectiveness of completed check-up and new diagnosis.

		Preventive checkup		Diagnosis	
	Cost per person	Completed check-up	Cost per check-up	New diagnosis	Cost per new diagnosis
	(1)	(2)	(3)	(4)	(5)
Panel A: Pooled incentive designs					
Individual incentive	2.506	0.168	14.908	0.078	32.019
	(0.459)	(0.036)	(4.184)	(0.023)	(11.084)
Group incentive	2.301	0.217	10.623	0.097	23.788
	(0.712)	(0.041)	(3.865)	(0.025)	(9.583)
P-value for group vs. individual incentives	0.803	0.260	0.452	0.493	0.575
Panel B: Disaggregated incentive designs					
Individual reward	2.707	0.216	12.557	0.112	24.201
	(0.411)	(0.046)	(3.280)	(0.031)	(7.627)
Group reward	2.238	0.205	10.919	0.079	28.248
	(0.510)	(0.055)	(3.840)	(0.031)	(12.939)
Individual lottery	2.304	0.120	19.163	0.044	51.904
	(0.801)	(0.042)	(9.494)	(0.026)	(35.816)
Group Lottery	2.364	0.228	10.357	0.114	20.695
	(1.315)	(0.052)	(6.226)	(0.033)	(12.935)
P-value for group vs. individual reward	0.454	0.865	0.746	0.403	0.788
P-value for group vs. individual lottery	0.969	0.063	0.438	0.056	0.413
Control Mean	1.030	0.155	0.150	0.076	0.074
N	1629	1629		1629	

Notes: Columns 1,2 and 4 present OLS estimates with standard errors clustered at the group level in parenthesis. The dependent variable in column 1 is the amount paid to the participant, the outcomes in columns 2 and 4 are binary outcomes of whether an individual completed a check-up or whether they were given a new risk factor diagnosis. Columns 3 and 4 are the cost per completed check-up and cost per new diagnosis respectively. Standard errors in columns 3 and 5 are calculated using the delta method. Values in table represent the average ratio and standard errors of the ration distribution are presented in parenthesis. All models include randomization strata fixed effects.

cost savings produced by group incentives are not large enough to lead to significant efficiency gains.

To go one step further, we estimate the cost per disability-adjusted life-years (DALYs) averted, a generic measure used by governments to compare the cost-effectiveness of health interventions. We first assume that an individual diagnosed with a particular risk factor avoids a CVD death when she manages her risk factor with an effective medical treatment. This happens with a probability well studied in the medical literature (see Appendix F for more details). Next, following Kremer et al. (2011) and Berry et al. (2020), we relate the CVD deaths avoided to DALYs averted by using estimates from the Global Burden of Disease in Salvador (Global Burden of Disease Collaborative Network 2020). Because this analysis largely depends on the probability of effective management, itself driven by the type of risk factor diagnosed, we compute three scenarios: an upper-bound scenario where all individuals are diagnosed with diabetes, the risk factor with the highest probability of effective management; a lower-bound scenario where all new diagnoses made have the lowest management probability (hypertension), and an average scenario where we compute a composite management probability following individuals' actual diagnosed risks. The results, presented in Appendix Figure F1, suggest that group incentives could be more cost-effective than individual ones, at USD487 versus USD608 per DALY averted in our average scenario. These results should be interpret with caution as they do not account for parameter uncertainty.[42] These costs per DALY are much lower than the thresholds used by policy-makers of one to three times the annual per capita GDP at purchasing power parity (Hutubessy et al., 2003) —USD9,402 for El Salvador at the time of our study— indicating that all incentives are cost-effective.

Note that our previous result of an absence of impact of the screening on behavior change is not at odds with the idea that a fraction of individuals will initiate and adhere to medical treatment, because behavior change is most critical to reduce potential risks amongst individuals below the thresholds of diagnosis (e.g. pre-hypertension, pre-diabetes, elevated cholesterol), not for adherence to medical treatment (WHO 2013). Nevertheless, we further test the robustness of our results to a range of values for the probability of appropriate risk management. The sensitivity analysis, presented in Appendix Figure F3 and F4, shows that incentives are no longer cost-effective for unrealistically low values of effective management (less than 10% of diagnosed individuals, compared to 32%–52% in our central scenario).

8. Mechanisms

In this section we examine the mechanisms through which incentives operate, especially to explain how group incentives can be as effective as individual ones. We investigate three channels that can help reduce uncertainty about others' behaviors within a group, as well as promote social benefits: communication, collective action and peer effects. For each mechanism, we use several measures and construct a summary index using a standardized inverse-covariance weighted average of

Table 6
Mechanisms – Pooled incentives.

	Communication index	Collective action index	Peer effects index
	(1)	(2)	(3)
Individual incentive	0.135	0.256	0.137
	(0.081)	(0.078)	(0.082)
	[0.033]	[0.002]	[0.033]
	{0.145}	{0.004}	{0.074}
Group incentive	0.463	0.578	0.222
	(0.086)	(0.091)	(0.081)
	[<0.001]	[<0.001]	[0.005]
	{<0.001}	{<0.001}	{0.003}
P-value for group vs. individual incentives	<0.001	<0.001	0.131
Control mean	−0.234	−0.330	−0.142
# of teams	400	400	400
# of individuals	1586	1629	1572

Notes: Table presents OLS estimates. The outcomes in columns 1, 2 and 3 are standardized weighted indices for each category (Anderson, 2008). The communication index combines whether the individual talked about using the voucher with another group member, if they heard from other members about their screening experience and a knowledge rating of other members screening status. All models include randomization strata fixed effects. Standard errors are clustered at the group level and reported in parenthesis. False-discovery rate corrected q-values based on Benjamini et al. (2006) and Anderson (2008) are presented in square brackets and randomized inference p-values following Hess (2017) using 2000 permutations are presented in curly brackets.

[42] Accounting for uncertainty would have required making further assumptions about parameters uncertainty that did not seem straightforward. The disaggregated results, presented in Appendix Figure F2, show the marginal cost per DALY averted ranges from USD390 with group lotteries to USD1,581 with individual ones.

outcomes (Anderson 2008). The impact of pooled incentives on each index is presented in Table 6 (pooled incentives). Appendix Table A11 presents the disaggregated results and Appendix Table A12 shows the results for the sub-components of each index.[43]

8.1. Communication

We compute a communication index based on three outcomes: prevalence of self-reported communication to others (about using the voucher and doing the visit); prevalence of communication from others (about a fellow member's use of the voucher) and a measure of the effectiveness of communication. For the latter, we asked each respondent at endline whether other group members had completed the check-up or not. Checking those responses against voucher use allows us to compute an individual knowledge score (the share of fellow members whose decisions are accurately known to an individual).

The results (column 1, Table 6) show that communication increases significantly more with group incentives compared to individual ones ($p < 0.001$). Looking at the index sub-components (Appendix Table A12), this result is driven by the prevalence as well as the effectiveness of communication. Only group incentives increase the share of people talking to others about the voucher (by 7.9 pp) and there is suggestive evidence that communication from others is also higher with group incentives than individual ones (14.5 pp versus 8.3 pp, $p = 0.129$). But the largest effect of group incentives comes from the increased effectiveness of communication. Against a relatively low level of knowledge in the control group (37%), group incentives significantly improve the knowledge of others' decisions by 21 pp while individual incentives have no effect ($p < 0.001$). Could this knowledge be mechanically driven by the payment conditionality, with people simply deducing others' compliance after receiving the group incentive? We show this is not the case as knowledge is higher with group incentives, whether a group has completed or not (see Appendix Table A15 and Appendix Figure A7).

Together, these results provide strong evidence that group incentives increase the quantity and quality of communication. This is not only an effective mechanism to reduce information asymmetry within a group and uncertainty about others' behaviors, but it can also promote knowledge transfer if individuals discuss the reasons or benefits of doing the visit – unfortunately, we did not specifically ask about the focus of those discussions.

8.2. Collective action

Next, we explore if group incentives encouraged more collective action through three outcomes. First, we ask participants if they planned with others to go to the lab or the clinic. Then, we use time-stamp data of the lab and clinic visits to construct two more objective measures, one for each type of visit. We assume that an individual coordinated with someone in their group if their visit to the lab (or clinic) occurred on the same day as at least one fellow group member.[44]

The results show that group incentives increase collective action significantly more individual ones (Table 6 column 2, $p < 0.001$). Results of the different components highlight that the impact of group incentives on self-reported planning is nearly twice as large as the effect of individual incentives (a 23.9 pp vs. 12.4 pp increase, $p = 0.001$), and three times as large for actual coordination.[45]

Collective action can serve several purposes only relevant to group incentives. It helps monitor fellow group members' behaviors. In the case of group cash rewards, going to the clinic at the same time as the last non-complier(s) ensures there is no delay between one's visit and incentive payment.[46] By triggering these mechanisms, group incentives may also reduce behavioral barriers, by creating a social commitment mechanism or making planning easier (Rogers et al., 2015).

8.3. Peer effects

Finally, we explore the role of peer effects through two channels: peer pressure and role modelling. We construct a peer pressure index composed of two outcomes: the share of respondents who say they reminded or motivated others to use the voucher, and the share that *were* reminded or motivated by others. The results (Table 6 column 3) provide marginal evidence that group incentives increase peer reminders more than individual incentives ($p = 0.131$). Is peer pressure more persuasive in the presence of group incentives? We find evidence suggesting that it is the case (Appendix Figure A8), as the share of people who do the check-up and say they were reminded by others is higher with group incentives (85% vs. against 77% with individual incentives, $p = 0.008$).[47]

We also investigate peer effects through the potential influence of 'first movers' – the first individuals to undertake the check-up in a group. If they act as role models, we could expect the 'first movers' in successful groups (those where all members complete the check-up) to have specific characteristics: for example, be the chosen leader of the group or be healthier. We find no evidence that it is the case (see Appendix Table A18).

Overall, these results provide limited evidence that group incentives activate stronger peer effects than individual incentives. We only find that group conditionality may make reminders more persuasive, an effect that could be driven by the mechanisms previously identified (increased communication and coordination between members), but also by the existence of social preferences such as guilt.

8.4. Alternative mechanisms

In this section, we rule out four alternative mechanisms of social effects that have been identified in the literature.

Social cover against stigma. Stigma has been shown to contribute to low demand for CVD prevention and treatment (Rai et al., 2020). In the context of jointly liable lending groups, individuals could also fear that consulting a doctor without visible symptoms might worry other members about their capacity to repay their loan and jeopardize their chance of future loans. In this context, group incentives might work by providing "a social cover" for doing the check-up (Thornton 2008, Goldberg et al., 2023).

We provide two pieces of evidence against this mechanism. First, only indirect costs are predictors of screening uptake in the control group (see Appendix Table A19). If social stigma existed, we would

[43] Tables A13 and A14 show how the results presented in Appendix Table A12, and disaggregated ones, are robust to the inclusion of additional controls.

[44] Using two more stringent definitions of coordination, the effect of group incentives is even stronger (Appendix Table A16).

[45] The difference in magnitude is driven by the fact that self-reported coordination appears over-estimated compared to actual coordination. 40% of individuals in the control group report to have coordinated, but in practice, only 8.5% of individuals coordinated their visit to the lab and 2.7% to the clinic.

[46] Appendix Table A17 shows the breakdown of all coordination events observed. It shows that 72% of all coordination events at the clinic that lead to immediate completion of the group occur with group incentives.

[47] Peer pressure effectiveness could work through a supply- or demand-side effect. On the one hand, those providing encouragement could be more persuasive or insistent due to self-interest motives. On the other hand, those receiving encouragement could be more susceptible to them because of other-regarding concerns.

instead expect those with observable risks (e.g. obese individuals, those over 50 years old) to be less likely to do the check-up in the absence of any incentive. Second, recall from Section 6.2 that group incentives were not more effective at targeting people with higher health needs. If group incentives provided an effective social cover from stigma, we would expect the opposite finding.

Social norms. Studies have identified the influence of peers in health decisions, showing how behaviors such as obesity (Christakis and Fowler 2007), smoking (Christakis and Fowler 2008) or alcohol consumption (Rosenquist et al., 2010) can diffuse or diminish in social networks, depending on the prevailing social norm. Individuals in groups where a majority of members have visibly more unhealthy habits might be less concerned about their health (Prina and Royer 2014), and therefore less likely to seek preventive care. We find some evidence of this in the control group, where 12.4% of individuals do the check-up if they belong to a group where a majority of members are obese, against 22.7% in other groups ($p = 0.019$). If group incentives tackle unhealthy social norms, their effect should be concentrated in individuals belonging to groups where 'unhealthy' is the prevailing norm, such as those where a majority of members are obese. The results, presented in Appendix Table A20, show evidence that *all* incentives, not just group ones, act by counteracting this norm, with their effect mostly concentrated in groups where most members are obese. If anything, group incentives are marginally more effective in groups where obesity is less prevalent.

Social networks. Group incentives could also work by harnessing the structure of social networks. This idea supported by studies showing that contagion of health behaviors is stronger in tighter social networks (Christakis and Fowler 2013). In our context, we would expect a greater impact of group incentives in smaller groups or closer-knit groups. Yet, we fail to find supporting evidence of differential effects according to the size of groups, group clustering or group strength (see Appendix D), although this could be due to a relative lack of heterogeneity in the characteristics of social networks in our sample.

Overcoming present bias. One of the reasons for low take-up of the screening could be that individuals are impatient and discount the future benefits of prevention. Social or financial incentives could help overcome such present-bias preferences (Aggarwal et al., 2020). We find no evidence supporting the notion that more impatient people respond differently to incentives (see Appendix E). However, this result should be interpreted with caution as our measure of time preferences was based on hypothetical questions (Falk et al., 2018), and are therefore not incentive compatible. The strong effectiveness of the individual small cash reward, the only one paid immediately after the consultation, provides suggestive evidence that present bias might play a role in low screening demand.

9. Conclusion

In a randomized trial with informal workers in El Salvador, we sought to increase the demand for prevention and compared the use of incentives conditional on collective or individual behavior. Incentives doubled the demand for a cardiovascular check-up. Group incentives were as effective as individual ones at increasing uptake, thanks to a range of social dynamics – from increased communication to coordination and peer pressure. Because the preventive check-ups led to substantial increase in the detection of new risk factors in our sample, all incentives were highly cost-effective interventions.

Our results may not necessarily generalize to other settings. First, several contextual characteristics may have boosted the effectiveness of group incentives. Participants were familiar with the concept of joint liability. Pre-existing links may also have facilitated the social interactions we identified, although other studies show that group incentives can be effective in exogenously formed groups (Babcock et al., 2015), including to encourage healthy behaviors (Haisley et al., 2012; Kullgren et al., 2013; Patel et al., 2016). Our results remain relevant to the many settings that have existing social groups, such as informal savings clubs (e.g. Rotating Savings and Credit Associations in Africa or Tandas in Latin America), farmer cooperatives, burial societies, or women self-help groups (Díaz-Martin et al., 2022).

Another concern is whether our results hold for different preventive care services. The CVD screening offered here had three characteristics that are worth noting as they may have impacted behaviors. First, it was free, although this is not unusual and indeed in line with WHO guidelines to reduce the burden of CVDs (World Health Organization 2013). Second, it included a blood test that may have made it particularly appealing – although this benefit was outweighed by the cost of the two visits required by the test. Third, potential treatment for CVDs are both easily accessible and free in our setting. Had this not been the case, the demand for screening and impact of incentives would probably be lower (Okeke et al., 2013). Beyond CVD screening, our findings may be most relevant to the demand for screening of diseases where individuals are asymptomatic (e.g. cancer, HIV, trachoma).

What do these results mean for the factors that drive the demand for prevention and strategies to increase it? Our findings are consistent with two interpretations, that are not necessarily mutually exclusive. On the one hand, the impact of small individual incentives implies that people may under-estimate the benefits of screening. On the other hand, the equally large impact of uncertain group incentives and the mechanisms through which they operate suggests that small behavioral costs prevent many individuals from investing in their health.[48] Overall, our findings suggest that information campaigns educating populations about the benefits of early detection are necessary but probably insufficient to increase screening uptake. They also suggest that encouraging CVD screening through small incentives in high-risk populations is likely to yield large long-term benefits.

Further research on understanding the potential application and performance of group incentives would be valuable. Our study suggests at least two directions. One question is whether group incentives would be as effective as individual ones for repeated incentivized behaviors. With multiple decisions incentivized, individuals who comply the first time but do not receive payment due to fellow group members' failure to comply may revise downwards their expectations about others completing the next time. This updating would lead to a diminishing impact of group incentives over time. A second question relates to the context in which group incentives could be most relevant and able to leverage social dynamics. Using group incentives to increase the demand for CVD screening may not have been the most relevant application. Instead, they could be more appropriate, and perhaps more effective, to motivate the demand for preventive services that naturally yield positive externalities, such as vaccines or HIV screening.

CRediT authorship contribution statement

Mylène Lagarde: Writing – review & editing, Writing – original draft, Supervision, Project administration, Methodology, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Carlos Riumallo Herl:** Writing – review & editing, Visualization, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

[48] At endline, 91% of people who had *not* used their voucher said they had wanted to use it but failed to.

Data availability

Data will be made available on request.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jdeveco.2024.103365.

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