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The fruits (and vegetables) of crime: Protection from theft and agricultural development☆

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ABSTRACT

Fear of crime is a concern in developing countries where rule of law is imperfectly enforced. I use a cluster-randomized field experiment in Kenya to show that reducing fear of theft allows small-scale farmers to adjust their planting and time use decisions, as well as increasing crop yields. I randomly allocated subsidized watchmen to farmers in Kenya, reducing their perceived risk of theft. Farmers offered watchmen were 14 p.p. more likely to have crops they grew for the first time or grew on more land as a result of improved security, sold more crops off-farm, and their farm output per acre was larger by 15% of the control mean. The intervention had positive security spillovers, and led to fewer angry disputes among neighbours. Despite these benefits, this intervention is not profitable for an individual farmer, suggesting a potential role for collective security interventions.

1. Introduction

In contexts with imperfect rule of law, crime inflicts a significant welfare loss (Soares, 2015; Fafchamps and Minten, 2009)[1] and imposes economic costs, with firms diverting labour towards security (Besley and Mueller, 2018), and farmers investing in relationships (Schechter, 2007) to reduce risk of theft.[2] Fear of theft also impacts other business decisions, such as merchants keeping suboptimally low stock to reduce vulnerability (Butinda et al., 2020). For smallholding farmers in developing countries, the indirect cost of insecurity against crime may be particularly significant if it distorts their cropping decisions and time allocation. Improved farm security may also have significant long-run effects by empowering farmers to shift to profitable market-oriented activities, and the eventual transformation of rural economies. Finally, it is important to understand whether, given these potential benefits, farm security is optimally provided by individual action, or if there is a case for collective intervention.

I explore the impact of improved protection of small-scale farms against crime using a field experiment in rural Migori, Kenya where rainfed subsistence agriculture is the primary economic activity. I randomly improved farm protection by allocating security among nearly six hundred farmers across seventy-six villages, in order to identify how farmers adjust production in response to reduced fear of crime. I matched farmers in randomly selected treatment villages with watchmen from the Maasai ethnic group, who have a reputation as competent security,[3] and heavily subsidized their wages for guarding farms during the 2018/2019 short rains season. This intervention allows me to assess

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[1] See also Fafchamps and Moser (2003) who document the relationship between isolation and insecurity in Madagascar, and show that crime increases with distance to urban centres. See also Alvazzi del Frate (1998) for a general review of crime in the developing world. See Besley et al. (2015) for the consequences of broader lawlessness.

[2] See also Jayadev and Bowles (2006) for a discussion of guard labour.

[3] There are several reasons why this particular group is perceived to be highly effective security in Kenya, which I outline in Section 3.2. These reasons are, however, not the focus of this paper and this intervention was chosen simply to be effective and appropriate to the experiment context.

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the impact of farm security on perceived ex-ante theft risk, ex-post self-reported theft, and reported changes to cropping patterns, time use, and off-farm crop sales, as well as estimating the impact on crop yields. I also assess the externalities of the intervention through reduced conflict and crime and, finally, whether this particular intervention is individually profitable for farmers.

To understand how improved farm protection impacts agricultural production, we must first note several key features of the setting. The first is that not all crops are perceived to be a target for theft. Secondly, time use is an important production decision, and farmers believe they can deter theft by spending more time around a plot. This may lead to productivity losses if farmers are discouraged from leaving their farm, or if the incentive to guard certain crops causes them to decrease time spent on less theft-prone crops. Finally, beliefs are crucial, as farmers make decisions based on expectations of theft in off-equilibrium states of the world they have not experienced, rather than on their own experiences.

The intervention had substantial take-up and successfully reduced fears of crime. Eighty-six percent of farmers in the intervention group matched to subsidized watchmen chose to hire them. This improved perceived farm security, and in particular, reduced perceived ex-ante risk of farm theft from growing crops that were high-value or different from those grown by others nearby. The impact on perceived security of these crops is significantly larger than the impact on commonly-grown crops. Intervention group farmers also reported lower ex-post theft experienced during the experiment.

I find that improved security allowed farmers to change the crops they grew and the way they used their time. The intervention group were fourteen percentage points (*p.p*) more likely than the control group to report reallocating land to crops where farm security was a relevant concern. In addition, intervention group farmers reported changes to their time use, and were twelve *p.p* more likely to report increasing time spent off-farm and ten *p.p* more likely to report increased crop sales to off-farm markets. These outcomes show that fear of crime causes farmers to adjust their cropping patterns and time use.

I also find that the intervention increased the productivity of farmers in the short-run, driven primarily by crops not expected to be at great risk of theft. The value of agricultural yield, measured as the value of farm output per acre using a single price for each crop, was approximately fifteen percent higher for the intervention group than the control group. I then decompose yields by crop characteristics perceived to be related to theft risk, and show that this yield increase is driven by crops that were expected to be less vulnerable to theft. I propose mechanisms that explain this effect, consistent with other work showing improved security allows reallocation of labour from vulnerable to less-vulnerable plots (Goldstein et al., 2018; Agyei-Holmes et al., 2020).

Having established the benefits of improved protection against theft, I then examine how this intervention impacts other nearby farmers through conflict and crime displacement. Improved farm security reduced suspicion and conflict within the village. Intervention group farmers were less suspicious of opportunistic theft when they were away from their farm. Treated farmers were half as likely as control farmers to have had any disputes with their neighbours relating to them interfering on their farms. These were not all mild disputes, and the intervention group had less than half as many such disputes as the control group with neighbours involving threats or violence.

Next I explore the displacement of crime, and find no evidence that this intervention displaced crime to nearby control villages, and moreover, find beneficial security spillovers within-village. This supplementary analysis is, however, not the main focus of the experiment design and so the spillover analysis may not be sufficiently powered for geographic spillovers.

Given the benefits of the intervention, I then examine whether it is individually optimal for farmers. Low baseline take-up is, by revealed preference, a strong indicator that individual adoption is not optimal. This is consistent with estimates of the individual cost-benefit where the intervention only breaks even with implausible valuation of non-monetary benefits. This, along with positive spillovers, suggests a collective action problem or potential beneficial policy intervention.

In this paper I identify an aspect of institutions that is an under-explored constraint on agricultural development. The security of land tenure is significant for agricultural productivity (Goldstein and Udry, 2008; Goldstein et al., 2015) and labour supply away from the home (de Janvry et al., 2015). Field (2007) shows the same is true for urban tenure security. Similarly, Hornbeck (2010) shows that fencing leads to increased investment in land improvements. Building on evidence of direct deterrence by firms (Besley and Mueller, 2018; Jayadev and Bowles, 2006) and farmers (Schechter, 2007), I show that property protection influences economic behaviour. Evidence from developed countries also shows that crime impacts behaviour (Cullen and Levitt, 1999; Linden and Rockoff, 2008; Hamermesh, 1999; Janke et al., 2013).

There is a vast literature on technology adoption, much of which focuses on learning (Conley and Udry 2010, BenYishay and Mobarak 2018, Foster and Rosenzweig 1995). I build on this work by identifying fear of theft as a constraint to technological adoption. A significant literature explores other means of improving farm income, including inputs (Duflo et al., 2011; Suri, 2011; Beaman et al., 2013), and market imperfections (Bergquist, 2016; Burke et al., 2018). I build on this influential literature by identifying an institutional constraint to agricultural productivity where fear of crime distorts production decisions.

I find that this intervention had beneficial spillovers through reduced conflict, while there is no evidence of displacement of insecurity to the control group. This is consistent with the literature showing that insecure land claims are a source of disputes (Blattman et al., 2014; Hartman et al., 2018), but differs from other work on place-based crime interventions where significant displacement occurs (Gonzalez-Navarro, 2013; Blattman et al., 2021).

2. Background

2.1. Agricultural practices

Agriculture in Migori, Kenya (see maps in Figures A1 and A2) is primarily small-scale, subsistence, rainfed agriculture. There are two main farming periods, with planting for the long rains season beginning in March and planting for the short rains season beginning in September. As shown in Fig. 1, maize cultivation is ubiquitous, while beans, cassava and sweet potatoes are also very common. Irrigation is uncommon and most agricultural labour is manual, apart from renting of oxen and ploughs for ploughing and land preparation. The division of labour in agriculture varies across households, with men generally doing manual labour such as ploughing, with tasks such as planting, weeding, harvesting, and threshing falling mostly to women. The typical household is about eight people, including children. Polygamy is fairly common, where some households are run by women who often make cropping decisions.

Tobacco and sugarcane are the most common cash crops, produced in cooperation with local companies, who provide inputs and technical services on loans repaid at harvest. This harvest is sold only to the processing plants and has limited direct consumption value for households.

Farms in Migori are not heavily secured and fencing is rare, other than for a small yard around the compound containing living quarters for the household. While the boundaries of farms are not heavily secured, they are clearly demarcated. The boundaries between plots grown by different households are usually indicated by a natural border

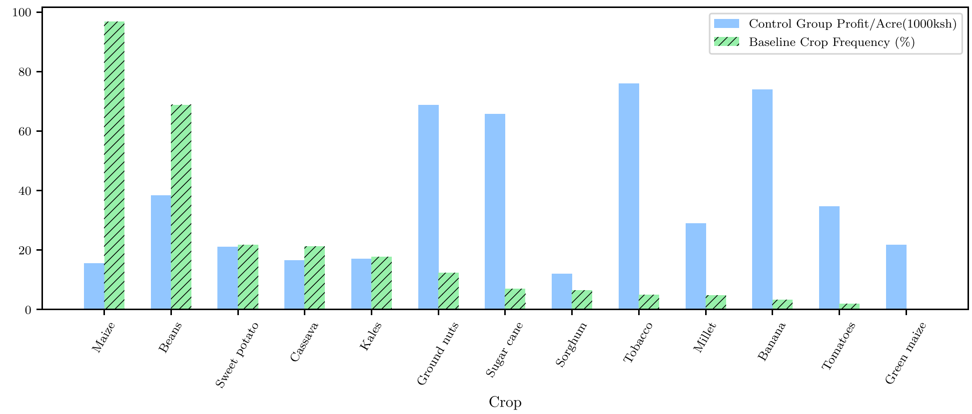

Fig. 1. Crop frequency & yields.
Description: This figure shows the profits per acre of different crops, in order of crop frequency.
Data: Profits are from the control group at endline, Crop Frequency is from the control group at baseline.

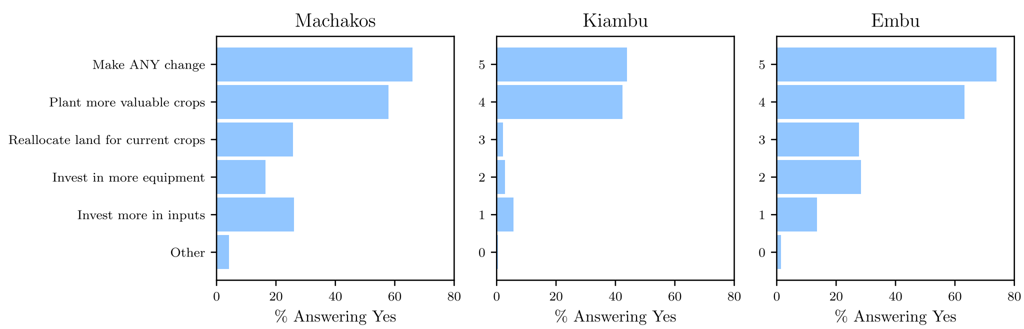

Fig. 2. External validity & security changes.
Description: This figure shows that the hypothetical changes farmers would make if their farms were secured are similar across Kenya. This is evidence that the results of this project likely generalize to small-scale farmers in three other counties in Kenya.
Source: Endline survey for an irrigation project run with other smallholding farmers in Kenya. (Dyer and Shapiro, 2022).

such as a river or man-made features such as a planted hedgerow, or a footpath or road.[4]

Most crops grown in Migori, other than cash crops are consumed locally by households, so any theft from farms has high immediate utility for consumption or resale. This consumption value is highest for crops harvested off-cycle with the maize harvest when food is plentiful. The most common place to sell crops (other than cash crops sold exclusively to processing companies) is at the farm gate, either directly to local consumers or to middlemen. The most common off-farm market for crops is for the farmer to take their crops to sell at local markets. Where the farmer can commit to spending time off-farm regularly, they can arrange to supply ingredients for lunch programs at nearby schools, health clinics or other institutions.

As shown in Fig. 1, the cropping decisions of farmers show missed opportunities to improve income by cultivating profitable crops. Qualitative information from unstructured interviews at baseline suggests that fears of crop theft constrain cropping decisions. In Fig. 2 I show survey evidence that smallholder farmers across Kenya have similar security concerns about adopting more profitable crops.

It is a common belief among farmers that certain types of crops are most likely to be targeted by thieves. Crops that are valuable (high price per kilogramme), easily picked (lower minutes to harvest per kg), with a long harvest window (greater opportunity for theft), which are available before the main staple (maize) and directly consumable or easily sold, are the most likely targets for theft.[5] In Fig. 3 I show the crops that were most often listed as being theft constrained, using data from a piloting survey with a sample of comparable smallholding farmers. These results are consistent with the perception that crime is mostly targeted towards a specific type of higher value, less common, more easily stolen, and more easily sold or consumed crops, with the top five crops identified as being constrained by theft being tomatoes, melons, kale, cabbage and spinach. These perceived theft-risky crops all share the characteristics of being easily picked with a long harvest window, making them highly conducive to crimes of opportunity. Theft is also perceived to be particularly focused on those who undertake new or different activities which may act as a constraint on farmers who seek to experiment and adopt new technology on their own.[6] While these beliefs may be incorrect, they may still shape farmers' decisionmaking.

2.2. Perceptions of theft

In the study context, farmers do not have access to detailed information on crime and cases of theft, but hold beliefs about the nature of theft that guide their decisionmaking. Theft is perceived to be primarily a crime of opportunity, with potential thieves from within the village stealing crops when the opportunity arises. In Fig. 4, I show that the

[4] This information comes from interviews with local agricultural expert informants and focus groups with participants. See Figure A4 in the Appendix for a typical boundary of a plot.

[5] These characteristics relating to perceived theft risk were all pre-registered. This is also consistent with the qualitative information on theft expectations and crops perceived to be 'stealable' in Schechter (2007).

[6] I discuss this feature of beliefs in more detail with suggestive empirical evidence in Appendix F.

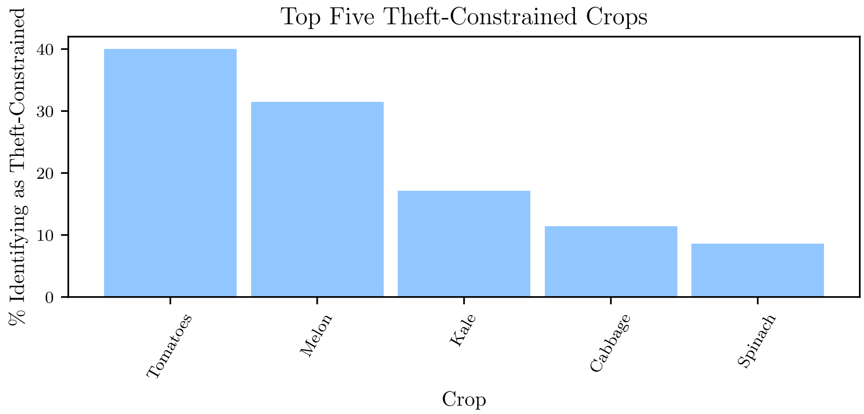

Fig. 3. Theft-constrained crops.
Description: This graph reports the frequency of a particular crop being listed as a crop farmers would like to grow, or grow more of, but do not due to security concerns.
Source: Piloting survey of comparable farmers. The sample size is 104, and these farmers were not included in the final project.

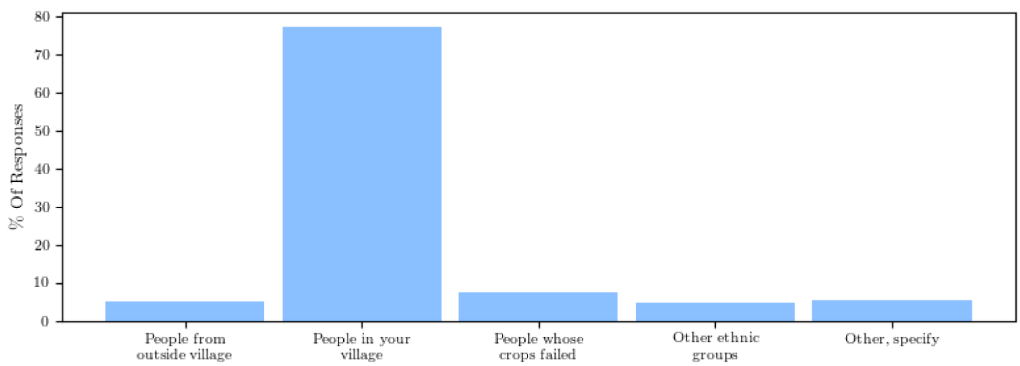

Fig. 4. Expected thief types. Description: This figure shows that farmers overwhelmingly expect that thieves from their farm will come from within their own village.
Source: Baseline survey with respondents.

people from within the village are overwhelmingly seen as the most likely perpetrators of theft.

2.3. Enforcement mechanisms for property crime

Existing enforcement mechanisms in the context of this experiment are imperfect and are consistent with the prevalent fears of crime. There are three main causes of ineffectiveness that I discuss here. One major imperfection in the ability of farmers to effectively punish thieves is that farmers are not confident of being able to identify who is stealing from their farms. In Fig. 5 below, I show that just under half of respondents agreed that they would be able to identify the culprit if they experienced theft from their farm. The formal institution responsible for property crime in rural areas is the local chief, with the support of village elders, but they are not perceived to be entirely effective. In Fig. 5, I show that more than a third of respondents are not confident that their chief would successfully punish the perpetrator if they brought forward a theft case. There is also a social cost to making accusations about other villagers. Again in Fig. 5, I show that half of respondents agree their social standing would be damaged by making accusations about another villager. Taken together, these weaknesses in enforcement mechanisms lead to a perception that farms are weakly secured against crime. This leaves an institutional gap that can be filled by a trustworthy non-state alternative. I next explain the design of the experiment, using exactly this type of non-state actor.

3. Experiment design

I now describe the details of the experiment design, including the sample and the intervention, and explain the rationale for choices made. This project has been approved by the University of Toronto Research Ethics Board, Protocol #3416. This experiment was pre-registered with the AEA RCT web registry, with RCT-ID AEARCTR-0002692.

3.1. Sample

The sample of farmers for this experiment was drawn from the field networks of the Kenyan Agricultural and Livestock Research Organization (KALRO) in Migori county. The local KALRO affiliate in Migori County is the organization Community Action for Rural Development (CARD) who maintains connections with farmers through the grassroots Farmer Research Network (FRN) which empowers farmers to undertake grassroots research projects where the community chooses research topics. This region was selected for lack of ethnic hostility towards Maasai as well as proximity to Maasailand, meaning transport is feasible.[7] Migori was not selected for its agricultural potential, and the conditions in the region are roughly typical of Kenya. The agricultural conditions

[7] See map of recruitment meetings in Figures A3. One especially important factor was that both regions were on the same side of the political divides in Kenya at this time. Groups in Migori and Maasailand are both strongly pro-opposition which was crucial given the ongoing post-election tension in Kenya. These tensions flared up in particular just at the time of watchmen recruitment, with opposition leader Raila Odinga unofficially inaugurating himself as the 'People's President' and the subsequent detention and deportation of lawyer and key opposition figure Miguna Miguna. (see news articles https://www.bbc.com/news/world-africa-42870292 and https://www.bbc.com/news/world-africa-42973169, accessed August 21, 2019.)

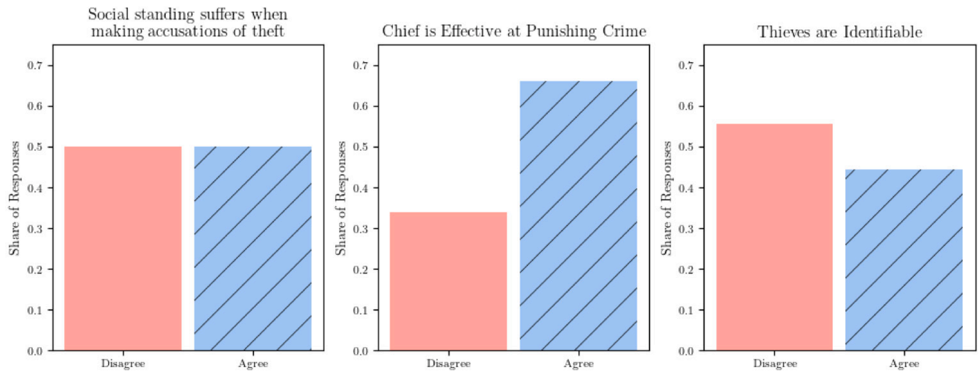

Fig. 5. Imperfect enforcement mechanisms.
Description: This figure shows the perceived prevalence of three factors that make local protection against property crime ineffective.
Source: Endline survey with respondents.

in Migori allow for planting of some horticultural crops in addition to local staples, and the selected sub-counties are a reasonable distance from Migori town and other urban centres, giving an opportunity for farmers to seek off-farm employment and crop markets during this planting season.

Recruitment for this project targeted a sample of roughly ten farmers per village and a total of 600 farmers in the core sample. This sample was recruited using the farmer networks maintained by the Kenya Agriculture and Livestock Research Organization (KALRO). This recruitment procedure was designed to mimic the standard mobilization procedures used by KALRO in their regular agricultural extension programming and did not indicate the nature of the project. After villages in three sub-counties (Suna East, Suna West and Uriri) near Migori town were identified, information meetings explaining the intervention and discussing and answering questions about the project were conducted with leadership of the farmers' group and other community members in each village. Ten interested farmers were selected from each village, who were then invited to a session where they signed consent forms and baseline data was collected.[8] The final eligible sample recruited was 585 respondents in 76 villages. The consent and baseline survey sessions with individual farmers took place from May 29th to June 6th, 2018.

3.2. Intervention

The intervention implemented in this experiment was matching farming households to high-quality, trusted Maasai watchmen at a heavily subsidized rate. The total wage paid to watchmen for the 6-week duration of the project was 14,200 Kenya Shillings, in addition to approximately 3000 Kenya Shillings of transport allowance.[9] The farmers paid 250 Kenya Shillings per week in wages, meaning that the subsidy was approximately 90% of the wages. There are two reasons why Maasai watchmen are particularly effective in this context.[10] The first is that they are outsiders in the sample farming communities, where differences in dress and language/accent make this outsider status obvious. In this regard, the availability of outsiders acting as security for divided landholdings is similar to the rise of the Sicilian mafia, as outlined by Bandiera (2003).[11] This outsider status improves perceived effectiveness because farmers have concerns that locally-hired watchmen within the villages may be more likely to collude with potential thieves or have a greater social cost of confronting them. This is consistent with the evidence presented in Fisman et al. (2017) and Jakiela and Ozier (2015) showing that there is significant social pressure to share within group, and that this pressure can be alleviated by hiring outsider agents. Ethnic stereotypes also mean that the Maasai in particular are perceived to be particularly effective at protecting property. The Maasai are a traditionally pastoralist ethnic group in Kenya, and this perceived effectiveness as guards is largely driven by the norms that evolve among pastoralist groups required to protect livestock herds, which are a highly mobile and stealable form of wealth. This persistent effect of pastoralism on behaviour is documented in Grosjean (2014) and Michalopoulos et al. (2016). I show suggestive evidence (in Figure A5) that both the outsider effect and the Maasai stereotype effects lead to increased self-reported willingness to pay for watchmen.[12]

The choice of watchmen as the security intervention for this project was motivated by the fact that many other security interventions (such as fencing) would include a significant element of improved security

[8] Some logistical issues arose which impacted turnout from some villages at the consent sessions, such as clashes with a local market day or funeral. My local partner was uncomfortable with over-inviting people to information sessions given the cost and inconvenience to farmers from coming to sessions, and a particularly prescient concern was potential resentment from invited respondents whose villages were assigned to treatment but who were not included and were not matched with a subsidized watchman.

[9] I consider the transport subsidy separately here as during the implementation period there was an unexpected police crackdown on informal *matatu* minibuses that would normally be used for transport, and more expensive coaches needed to be chartered from Easycoach, meaning these transport costs are much larger than normal.

[10] This is an example of cooperation among farmers and pastoralist groups, which is consistent with historically common relationships of mutual benefit. As described in McGuirk and Nunn (2021), the relationship between pastoralists and farmers under normal weather conditions is generally symbiotic under seasonal migration where land is used in different seasons by different groups with grazing in the dry season and cultivation in the wet. This relationship has often broken down as climate changes and under systems of unequal representation and the farmer–herder relationship is now often characterized by conflict.

[11] In that context, Bandiera (2003) shows that there is a non Pareto optimal equilibrium where it is rational for landowners to hire security, even though it makes all worse off. This result depends heavily on negative externalities of shifting crime to other unprotected landowners. Additionally there are negative externalities since (even prior to forming an organized mafia) there were few guard groups in each area which gave them significant power. In this project, I do not find evidence of strong enough spillovers to suggest this result is likely in this context, though it is possible that in the long-term collusion occurs among guard groups.

[12] These figures should be taken as suggestive evidence, however, given that these self-reported willingness to pay figures were collected at endline, when farmers were aware the Maasai had been specifically selected as outsider watchmen for this project.

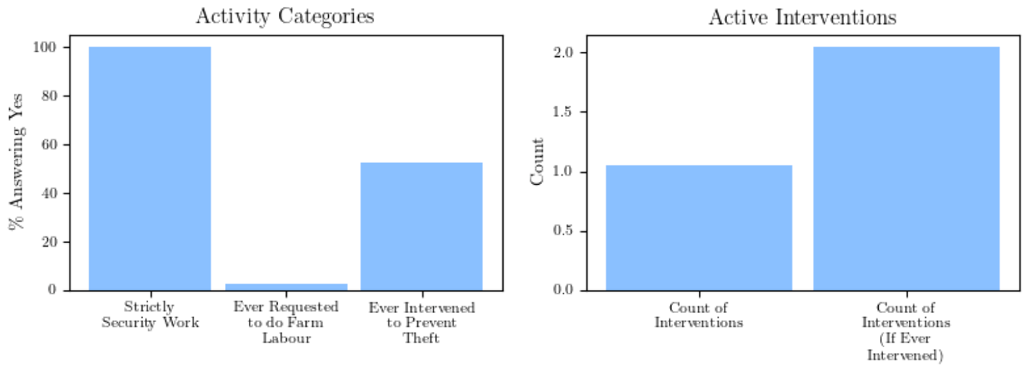

Fig. 6. Watchmen activity during experiment. Description: This figure shows that watchmen did primarily security work during their deployment, as intended. *Source:* Survey with sample of watchmen as they finished their employment and prepared to return to Narok.

of land tenure in addition to security from crime and theft. A fencing intervention, for example, would first require demarcation and clarification of exact boundaries and the status of land to be fenced, which in itself would have a strong effect on land tenure which is well known to impact agricultural decisionmaking, while for this project the goal was to isolate variation in farm security.

The intention of this intervention was to cause variation in the security of farms during the short rains season, beginning with planting in August. Watchmen were recruited with the assistance of partners from the Maasai Education Research and Conservation Centre (MERC) in Maasailand in January and early February of 2018. One potential issue with this design was that the subsidized watchmen might end up working as non-security farm labour on the farm. To prevent this from happening, farmers were informed that watchmen would be doing strictly security work, so they would not have been expecting extra farm labour when making their cropping decisions, except via the mechanism of reduced time they must themselves spend protecting their farms. Additionally, Maasai watchmen coordinators checked in with them during their deployment to make sure they were not being misused. As I show below in Fig. 6, a post-deployment survey of watchmen as they were preparing to leave Migori shows that their work was, as intended, focused on improving the security of the farm and not acting as subsidized farm labour.

For this study to successfully test whether cropping decisions are influenced by security, it was crucial that farmers were credibly informed of their treatment status. For this reason, the intervention included three separate attempts to inform them. First, farmers received phone calls from Busara Centre staff informing them of their status, and informing treated farmers to expect a call from a watchman. Second, the watchman coordinator ensured that all watchmen called their matched farmer during the assigned time frame. The watchman coordinator also verified that they had successfully communicated with the matched farmer, arranging for interpreters who could translate into local languages where the watchman and farmer struggled to communicate in Swahili. Finally, the local farmer coordinators followed up with farmers after these first two attempts to confirm that they knew their status, and to inform the watchman coordinator if any treated farmers had not yet spoken with their assigned watchman. All three of these rounds of information occurred by early July, allowing a generous amount of time for farmers to consider cropping decisions and adjust their inputs and potentially learn about new crops they might want to plant. A piloting survey on planting behaviour confirmed that cropping decisions are fixed approximately one month before planting begins, so this timing of information by the beginning of July was appropriate for planting in early September. The wage rate paid by farmers and the subsidy were uniform across the sample and set in advance. The duration of the treatment was also set at a uniform six weeks of watchman employment, at a time and duration chosen by farmers to coincide with when they anticipate their crops will be at risk.

A potential risk for the success of this intervention was that the Maasai watchmen would feel uncomfortable being in a new area or would end up working for households other than the treatment household they had been assigned to. To avoid issues, three additional Maasai coordinators were deployed to Migori a week prior to the first deployment of watchmen to farms, to prepare the farmers, greet the watchmen as they arrived and direct them to reach their assigned farming households. This process relied heavily on a network of local farmer coordinators. To ensure I had the logistical capacity to place watchmen correctly, I used the network of KALRO's local partner. By working with this local partner, I worked with a farmer coordinator familiar in all the sample villages, a team of local coordinators each covering a few villages, who themselves had a lead farmer in each village. This deep network successfully placed watchmen with the correct households and, working with the three Maasai coordinators, were able to help all watchmen find accommodation. These Maasai coordinators remained in Migori for the duration of the study, to help watchmen with any minor issues that arose and to check that the watchmen were strictly being asked by the farmers to do security work to ensure that the intervention did not unintentionally provide subsidized farm labour.

4. Data sources

For this project I used a number of data sources, outlined below. The most important source of data for analysis of my main results was survey data collected at baseline and at endline. I supplemented these surveys with data from a local agricultural expert on the objective characteristics of crops. I also used qualitative data to inform the design of the experiment and surveys, as well as to suggest hypotheses for analysis.

4.1. Survey data

I collected survey data (using a questionnaire written in English and translated into Swahili) at baseline, before farmers were informed of their treatment status. At baseline I collected data on the type of crops grown and land allocated to these crops, along with self-reported perceptions of theft risk, willingness to pay for watchmen, trust, and attitudes towards local institutions.

Endline data collection, after watchmen had finished working and the main harvest was completed, included the same data on cropping decisions and land allocations as well as their reasons for making changes, self-reported perceptions of theft risk, willingness to pay for watchmen, trust, and attitudes towards local institutions, as had been collected in the baseline survey.[13] Endline surveys also collected additional data that was not collected at baseline, on time use, local conflict and actual theft cases. This is partially driven by post-baseline, pre-endline focus groups which suggested these additional hypotheses to be tested.

Both rounds of survey data collected from farmers were implemented on tablet computers by a team of survey enumerators fluent in English and Swahili and also having knowledge of local languages where questions needed to be explained. Respondents came to central locations in each of the three study sub-counties where the baseline surveys were conducted privately by trained and experienced enumerators. Endline data was collected by household visits using local guides and farmer coordinators to locate sample households. Backchecks were implemented for a subset of this sample to check the accuracy of the data. To design the project and supplement this survey data, I collected detailed qualitative data through focus groups with participants. I also use data on crop characteristics and background information on agriculture in Migori compiled by my local agricultural expert and farmer coordinator. I now describe the data collected in more detail, explain how I construct the main variables of interest, and show how I use these to answer my research questions. After endline surveys were completed the enumerator used the tablet GPS coordinates to record household position. In Appendix C I explain the exact survey questions used and the construction of all variables used in Section 6 where I discuss results.

A number of the outcomes collected in the survey data for this project are in the form of questions asking respondents about changes they have made in the past year. Due to data limitations and the discovery of new hypotheses prior to endline data collections, the baseline data did not cover all of these outcomes, so the survey asked respondents about changes. This does, however, mean that these outcomes carry the caveat that they are more sensitive to potential experimenter demand effects. Where possible, this was mitigated by having the questions/options of interest included in broader batteries of questions about behaviour changes and were not listed first on multiple choice lists, but the possibility of experimenter demand does remain.

4.2. Crop characteristics data

I collected data on the objective characteristics of crops in order to classify them based on their risk of theft. These characteristics were those identified in the qualitative data and are consistent with the crops identified as being most at risk of theft in the pilot surveys. This data was compiled prior to endline survey data collection by the local farmer coordinator. The crop characteristics of interest are

- Time To Harvest One Kilogramme
- Consumed Locally (as opposed to being sold only to processors)
- Length of Maturity Window

5. Empirical strategy

In keeping with qualitative evidence, I use the crop characteristics data above and split crops into three categories by perceived risk of theft. First, are those with characteristics that make them *high theft risk* crops, those that have *low expected theft*, and crops that are of *low utility to thieves.*[14] I will therefore look at outcomes at the farm-level as well as disaggregating to look at outcomes for different types of crop separately. For these regressions, I consider the aggregate value of production at the farm-level, restricting to each category of crops.[15]

In this paper I implement a randomized field experiment, so the empirical strategy is straightforward. All main results in this paper are Intent-to-Treat (ITT) estimates where differences between those assigned to the matched group and those assigned to the non-matched group, regardless of whether they actually hired a watchman or not, are the outcomes of interest.

Where I have both baseline and endline data, I use a differences-in-differences strategy, as in the following specification:

$$\begin{aligned} Y_{i,v,t,s} = \;& \beta_0 + \beta_1 \text{Intervention}_v \cdot \text{Endline}_t \\ &+ \beta_2 \text{Intervention}_v + \beta_3 \text{Endline}_t + \mathbf{\Gamma}_s + \epsilon_{i,v} \end{aligned} \tag{1}$$

where Intervention_v is a binary variable indicating a respondent is in a village where farmers were matched with watchmen and Endline_t is an indicator variable for an endline observation. The variable of interest in this specification is β_1, the effect of being in the group matched with watchmen at endline. The only controls are randomization strata fixed effects (vector $\mathbf{\Gamma}_s$), and standard errors are clustered at the village level. I also estimate an ANCOVA specification as discussed in McKenzie (2012) but as I pre-registered the differences-in-differences specification I report those results as the main estimates.

Where I only have endline data, I use a simple regression comparing those matched with watchmen with the non-matched group, as in the following specification:

$$Y_{i,v,s} = \beta_0 + \beta_1 \text{Intervention}_v + \mathbf{\Gamma}_s + \epsilon_{i,v} \tag{2}$$

The variable of interest in this specification is β_1, the effect of being in the group matched with watchmen. The only controls are randomization strata fixed effects (vector $\mathbf{\Gamma}_s$), and standard errors are clustered at the village level.

I correct for multiple hypothesis testing on my main pre-registered outcome indices, reporting False Discovery Rate and Family-Wise Error Rate p-values.

5.1. Spillovers

In secondary analysis I test for cross-village spillovers in perceived security from watchman-matched villages to the households in the closest non-matched villages. This was, however, not the primary intention of the experiment design, and so the variation in distance between near and far control villages is only powered to detect large effects. This analysis uses the following specification:

$$\begin{aligned} Y_{i,v,t,s} = \;& \beta_0 + \beta_1 \text{Intervention}_v \cdot \text{Endline}_t + \beta_2 \text{Near Matched}_v \cdot \text{Endline}_t \\ &+ \beta_3 \text{Intervention}_v + \beta_4 \text{Near Matched}_v + \beta_5 \text{Endline}_t + \mathbf{\Gamma}_s + \epsilon_{i,v} \end{aligned} \tag{3}$$

[13] Furthermore, many of these outcomes were added post-baseline based on focus groups, which implies that participants were not simply providing answers that they thought the research team wanted to hear as respondents were unlikely to know the goal of the research from interaction at baseline.

[14] First, I designate crops that are not consumed directly by households (tobacco and sugarcane) and ubiquitous crops (maize) as low utility for thieves as these are unlikely to be targets of theft. The remaining potential crops are then split into High Expected Theft and Low Expected Theft crops. High Expected Theft are defined as the potential crops above median in an Opportunity for Theft Index defined over potential crops as increasing in the Length of Harvest Window, and decreasing in Minutes Required to Harvest one Kilogramme. Low Expected Theft Crops are defined as those below median for potential crops in this Opportunity for Theft Index.

[15] In Appendix B I outline a model based on Goldstein et al. (2018) of agricultural production, labour allocation, across high and low theft-risk in response to an improvement to farm security. The main contribution of this model is to show that the impact of improved farm security on labour allocation is ambiguous as labour on high theft-risk crops plays a dual role as guard labour as well as improving production.

Table 1
Baseline balance.

Category	Variable	Mean	Intervention group	
			Diff	Std. Err
Farm Characteristics	Female Farm Manager[a]	.344	−.008	.0396
	Acres Owned[b]	2.334	.228	.145
	Acres Rented[b]	.387	.0469	057
	Acres Farmed	2.147	.109	.121
Theft	Frequency of Local Crop Theft	3.75	−.096	.105
	Willingness to Pay for Watchman[b,d]	284	−5	23
	Low Farm Security[a]	.764	.051	.036
	High Risk if Growing High Value Crops[a]	.691	−.0158	.039
	High Risk if Growing Different Crops[a]	.682	−.018	.039
Nonfarm Econ	Has Off-Farm Enterprise[a]	.337	−.014	.040
	Has Off-Farm Employment[a]	.156	−.019	.030
Gifts	Gave Neighbours Gifts[a]	.833	−.005	.030
	Value of Gifts to Neighbours[b,c]	226	−166 *	100
Ethnic Identity	Ethnic Theft Stereotype[a]	.390	.030	.042
	Strength of Ethnic Identity	3.606	.038	.076
Trust	Neighbours	3.156	.028	.106
	Non-Neighbours in Village	2.858	.015	.108
	Strangers	2.489	−.002	.103
	Chief	4.014	−.039	.074
	Other Ethnic Groups	3.232	−.025	.106
Institutions	Legitimacy Formal Punishment	4.385	.071	.071
	Chief Competence in Providing Security	4.093	−.008	.081
Crop Choice	Number of Crops Grown	2.896	−.064	.110
	Any Experimentation[a]	.188	−.007	.033
	Number of New Crops Grown	.225	−.002	.044
Theft-Risky Crops	Weighted Mean Theft Riskiness	−1.411	−.037	.045
	Land Allocated to Theft Prone Crops[b]	.171	−.028	.029
	Land Allocated Highly Theft Prone[b]	.153	−.026	.027
	Land Allocated to New Crops[b]	.188	−.005	.041

[a]Binary variable, equal to 1 if true, 0 if not.
[b]Variable winsored for the top 2.5%.
[c]Variable winsored for the top 5%.
[d]Variable is in Kenya Shillings (KES), at 100 KES ≈ 1 USD.
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. One of 29 variables (∼3.5%) is significant at the 10% level, consistent with random chance.

where Near Matched$_v$, is a binary variable equal to one for non-matched households that are below the median distance (among non-matched households) to the centroid of a watchman-matched village.

I also look for within-village spillovers using a small convenience sample of farmers nearby those in the core sample who were only asked a small number of questions about perceived security. The specification for this sample is straightforward:

$$Y_{i,v} = \beta_0 + \beta_1 \text{Intervention}_v + \epsilon_{i,v} \quad (4)$$

6. Results

In this section I start by establishing that randomization created balanced watchman-intervention and control groups. I then show that the intervention was successful, before demonstrating that this intervention had direct economic benefits. Agricultural yields were higher for the intervention group than the control group, mostly driven by crops with low expected theft. Matched farmers changed their economic behaviour in response to this improvement in security. I then show evidence of positive externalities through security spillovers and reduced conflict among neighbours. Finally, I show that the intervention is not individually profitable.

6.1. Intervention implementation

First, I show that clustered village-level randomization successfully created comparable intervention and control groups of farmers. In Table 1, I present summary statistics and test for differences between matched and non-matched at baseline, covering categories such as farm size, baseline fear of theft and farm security and participation in non-farm economic activity. I also test for differences in gift-giving among neighbours, ethnic identity, trust, attitudes towards institutions, and the type of crops farmers grow. Of 29 variables only one difference (∼3.5%) is statistically significant at the 10% level, consistent with random chance.[16] I therefore find no evidence to suggest significant imbalance between the matched and non-matched groups.

I then show that the experimental intervention had high take-up and successfully improved the security of farms. In Table 2, I show that intervention group farmers were 72 percentage points (*p.p.*) more likely to have hired a watchman, corresponding to roughly one more month (3.76 weeks) during which their farm was protected. Among the intervention group, 87% hired watchmen, but there was some noncompliance on the part of the control group, 15% of whom hired watchmen, compared to the baseline period when no farmers in the sample had hired watchmen. In Table 2 I also show that the intervention had a positive effect on perceived farm security. Farmers in the matched group were 39 *p.p.* less likely to report that their farms had low security, and 26 *p.p.* less likely to anticipate a high risk of theft from growing

16 A conventional joint test, where the treatment indicator is regressed on all covariates does reject the null hypothesis of orthogonal treatment assignment when including all baseline covariates, randomization strata dummies, and clustering errors at the village level. As noted by Hansen and Bowers (2008), when the number of covariates is large relative to the number of clusters, this conventional asymptotic test is prone to spuriously rejecting balance. An asymptotic joint test without clustering errors has a p-value of 0.8841 and does not reject the null. Using the randomization inference test in Heß (2017), where treatment is randomly reassigned to generate an empirical CDF of the joint test statistic, finds that 820 of 1000 resampled draws of treatment assignment have more extreme joint test statistics for a pvalue of 0.82 in a 95% confidence interval from 0.79 to 0.84, and therefore does not reject the null hypothesis of orthogonal treatment assignment. Additionally, in Tables A1 and A2 I control for all baseline covariates and show that the main results are not qualitatively different.

Table 2
Security manipulation check.

Outcome variable	(1) Hired Watchman[a]	(2) Weeks hired watchman	(3) Low Farm Security[a]	(4) Theft risk: High value[a]
Intervention x Endline[a]	0.716	3.757	−0.394	−0.262
	(0.040)***	(0.274)***	(0.067)***	(0.076)***
Intervention[a]	−0.002	−0.005	0.053	−0.005
	(0.008)	(0.041)	(0.040)	(0.049)
Endline[a]	0.153	0.557	−0.114	−0.094
	(0.026)***	(0.108)***	(0.043)***	(0.053)*
Num. Observations	1,153	1,153	1,154	1,154
Control Mean	0.08	0.28	0.69	0.65
Full Sample Baseline Median	0.00	0.00	1.00	1.00

[a]Binary variable, equal to 1 if true, 0 if not.
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.
Standard Errors clustered at the village level in parentheses below estimates. Controls for all specifications: Randomization strata fixed effects. Intervention is an indicator variable for assignment to the treated group who were matched to a watchman offering farm security at the subsidized rate. Column 1 is a binary variable indicating whether the farm had a watchman at all during the study season. Column 2 is the number of weeks during this season the watchman was working, equal to zero where the farm did not have a watchman. Column 3 is a binary indicator of whether the respondent perceived their farm to have low security, constructed as being equal to one if the respondent selected four or five on a five-point scale and zero otherwise. Column 4 is a similarly binarized variable indicating whether the respondent perceived they would have faced a high degree of theft risk if they had planted high-value crops this season. In Table A5 I show there is an effect on theft risk of other crops, but that the effect of the intervention on reducing the security risk from growing high-value or uncommon crops is significantly stronger than for crops similar to those grown by others.

high value crops.[17] Taken together these estimates show that watchmen and non-state actors can successfully improve the perceived security of farms, and reduce the perceived risk of growing high-value crops.

The intervention also reduced the amount of ex-post self-reported farm theft during the intervention. In Table A3, I show that matched farmers were 32 *p.p.* less likely to report experiencing any theft, and 37 *p.p.* more likely to report that theft decreased from last year. This is a surprising result, as farm theft was mostly anticipated in response to farmers changing their behaviour and was not seen as common under the status quo. It is important to note, however, that perceptions of theft may not be accurate and may be driven by feelings of security.

6.2. Direct economic benefits

I now provide evidence that imperfect farm security and crime are a significant burden on the economic activity of small-scale farmers. I first analyse the impact on agricultural production, then on economic behaviour using direct reports of different economic decisions at endline and self-reported changes made by farmers during the intervention season.

6.2.1. Agricultural yields & income

I first show that this intervention has an effect on the value of agricultural output, and show that the pattern of these yield gains does not follow the ex-ante expectations of farmers, as the largest increase is for crops where little theft was anticipated. I show in Appendix B that this is consistent with a simple model (based on Goldstein et al., 2018) where labour serves a dual purpose as security and in production, and may be reallocated to low theft-risk crops when security improves. In Table 3 I present the results of the security intervention on value of agricultural output per acre. In Column 1, I show that matched farmers had higher total income per acre from agricultural production when including all crops grown by farmers.[18] In Columns 2 through 4 I decompose the increase in value of production per acre by crop characteristics related to perceived theft risk. For each of these columns, I compute total value of output for all crops in the relevant category, divided by the land used to grow those crops.[19] As described in Section 4.2, I first separate out the crops which have the lowest utility for potential thieves. I then split the remaining crops into high- and low-expected theft risk based on objective crop characteristics.[20] The results here show the strongest treatment effect is actually driven by the crops which are perceived to be the *least* vulnerable to an opportunistic theft. In Column 2, I find that the security effect on value per acre of low expected theft crops is approximately 8400 KES, more than five times greater than the coefficient on high expected theft crops, displayed in Column 3 which is approximately 1400 KES. This is evidence that theft risk imposed a productivity cost on crops that were perceived not to be a security concern. This yield effect could be explained by theft of the low perceived theft-risk crops that was prevented by having security, which would imply that farmers had incorrect beliefs about which crops were being stolen. A more likely explanation is that in the unsecured case there is reallocation

[17] In Supplementary Table A4, I show that this effect on perceived security holds with various other measures of perceived farm security and vulnerability to opportunistic theft. In Table A5 I look further at the effect of security on different type of crops. I find that the intervention had the strongest effect on crops that were *high-value* or *different* from crops commonly grown by others, and that the intervention effect on a high risk of theft for crops that were *similar* to those grown by other farmers nearby was insignificant. This difference is robust to a number of alternate specifications and is consistent with the belief that theft primarily targets *off-equilibrium* activities and that this belief – whether correct or not – distorts production decisions. This is consistent with suggestive evidence in Figure A6 in Appendix F where experimentation is perceived to be riskier if undertaken on one's own.

[18] As described in Appendix C.0.4, I use a constant price across all farmers (the median price across all markets by crop) to estimate the value of production for each crop. The observed value of production per acre is therefore driven by yield per acre of each crop and crop composition. In Table A6 I show an effect on yield per acre at the crop-level, meaning that the aggregate effect on value of production by acre is heavily driven by an increase in yield holding composition constant. The pattern at the crop-level is again driven by the low expected theft crops, with Cassava having the strongest effect.

[19] In these specifications, I split the sample and estimate separately by crop-category. To look in more detail at within-farm reallocation, I also present results in Table A7 at the farmer-crop level with controls for crop or crop-category fixed effects, as well as strata, village, or individual fixed effects. These results are mostly insignificant but are consistent with the split-sample results.

[20] I separate crops into these categories as follows. First, I designate crops that are not consumed directly by households (tobacco and sugarcane) and ubiquitous crops (maize) as Low Utility for Potential Thieves as these are unlikely to be targets of theft. The remaining crops are then split into *high* expected theft crops and *low* expected theft crops. High Expected Theft Crops are defined as the potential crops above median in an Opportunity for Theft Index defined over potential crops as increasing in the Length of Harvest Window, and decreasing in Minutes Required to Harvest one Kilogramme. Low Expected Theft Crops are defined as those below median for potential crops in this Opportunity for Theft Index.

Table 3
Value of crop production per acre.

Outcome var		Crop disaggregation		
	(1) Total income per acre[a,b]	(2) Low expected theft[a,b]	(3) High expected theft[a,b]	(4) Low utility to potential thieves[a,b]
Intervention[a]	5,002	8,421	1,444	2,837
	(2,798)*	(3,816)**	(4,714)	(2,614)
H_0: (2) - (3) = 0, [p-value]			[0.202]	
Num. Observations	568	460	186	498
Control Mean	30,694	35,500	29,714	26,110
Control Median	21,853	21,196	13,437	18,750

[a]Variable winsored at the highest 2.5% level.

[b]Variable is in Kenya Shillings (KES), at 100 KES ≈ 1 USD.

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Standard Errors clustered at the village level in parentheses below estimates. Controls for all specifications: Randomization strata fixed effects. Intervention is an indicator variable for assignment to the treated group who were matched to a watchman offering farm security at the subsidized rate. In each column the sample is farmers who grew that type of crop, restricted as per the cleaning process to crops with at least 25 yield observations across the sample at endline, where the crop's land allocation is at least 0.25% of a given farm's total land allocation this season. Individual farm yields are winsored by crop at the highest 2.5%. Using these per-acre yields, total output is generated by multiplying cleaned yield by reported acres allocated to the crop, and total value of output is generated by multiplying this output by the median self-reported sale price (across all farmers and markets) by crop. In Column 1, total value per acre is generated by taking the sum of the value of all crops (constructed as described above) divided by the sum of land allocated to all included crops, where allocated land share is at least 2.5% and with at least 25 observations. In Columns 2–4 I aggregate production separately by crop categories defined by objective characteristics. First, I designate crops that are not consumed directly by households (Tobacco and Sugarcane) and ubiquitous crops (Maize) as Low Utility to Potential Thieves as these are unlikely to be targets of theft. The treatment effect on value of production for these crops is reported in Column 4. The remaining potential crops are then split into High Expected Thefts and Low Expected theft crops. High Expected Theft are defined as the potential crops above median in an Opportunity for Theft Index defined over potential crops as increasing in the Length of Harvest Window, and decreasing in Minutes Required to Harvest one Kilogramme. Low Expected Theft Crops are defined as those below median for potential crops in this Opportunity for Theft Index. I test whether I can reject the null hypothesis that the treatment effect is the same for Low Expected Theft and High Expected Theft (Columns 2 and 3) and report the pvalue in square brackets in Column 3.

See Table A6 for a breakdown of these yield effects to the crop level. I show that there are significant results at the crop level, which suggests that these aggregated categories are at least partly driven by improved output per unit of land and not simply by reallocation. See Table D1 for robustness to variation in data cleaning procedure.

of labour towards securing the more theft-prone crops stolen.[21] The intervention would therefore allow more labour to be allocated to the less theft-prone crops, leading to increased yields.

6.2.2. Economic behaviour

I now show that the experimental manipulation to farm security, described above, led to significant self-reported changes in the production, time use and investment decisions made by farmers.[22] Table 4 estimates the regression model in Eq. (2) with the different self-reported behavioural changes as the outcomes. This table in some sense approximates a panel data specification as it reports changes in behaviour. Of course, as these are self-reported changes at endline, the potential for experimenter demand bias is an important caveat here. I show that farmers in the intervention group changed their cropping decisions, spent more time away from the farm and shifted from renting assets into buying assets. In Column 1 I show that intervention group farmers were 14 *p.p.* more likely to report that they grew any crops that were a) crops planted for the first time due to relaxed security constraints or b) previously grown crops where they expanded planted area due to relaxed security constraints.[23] I also show that the pattern of changes in cropping decisions at the crop-level is significant for crops whose characteristics are consistent with security as a constraint to planting decisions.[24] In Column 2 I show that the share of land newly allocated to security-constrained crops (using the same self-reported construction as in Column 1) is 9 *p.p.* higher for the matched group. These magnitudes are also likely an underestimate of the true long-run level distortion in desired crop choice. In this experiment farmers made their cropping decisions at the beginning of the season, before their watchman had begun working and before they had observed their effectiveness. This is consistent with there being fixed costs to adopting new crops, suggesting that these results from a single-season intervention are a lower-bound on change in cropping patterns.

I also show that this intervention improved the ability of farmers to access opportunities away from their farms. In Columns 3 and 4 of Table 4 I show that farmers in the intervention group are 11.9 *p.p.* more likely to report that they spent more time off-farm and 10.4*p.p.* more likely to report that they increased their off-farm sales of crops in the treated season relative to previous short rainy seasons. This is consistent with the crop-level data in Table A14 where I show that farmers in the intervention group were significantly more likely to have had any off-farm sales of tomatoes and kale than control group farmers growing these crops.

I also investigate whether farmers responded to the intervention by adjusting investment decisions. I show in Columns 5 and 6 of

[21] Information on time use and labour allocation is at the farm-season level and was not collected at the crop-level. For this reason, I use input spending as the best possible proxy in the data for labour allocation. The results on input spending are suggestive of labour being reallocated to low expected theft crops. In Table A8 I show that the only crop with a statistically significant treatment effect on fertilizer application is Cassava, where fertilizer use was significantly larger for the intervention group. This is consistent with qualitative information indicating that improved security relaxed constraints on time, consistent with this mechanism.

[22] See Supplementary Table A9 for the pre-registered outcome indices. In this Table 1 test for effects on the indices representing the main dimensions of agricultural decisionmaking using the more conservative Differences-in-Differences specification and the ANCOVA specification as discussed in McKenzie (2012). These results are significant and robust to the use of p-values corrected for multiple hypothesis testing, using Family-Wise Error Rate and False Discovery Rate methods. See Supplementary Tables A10, A11 and A12 for results with these indices broken down into individual components.

[23] Experimenter demand effects are unlikely for these outcomes, as the question asking for their reason for changing crops did not specifically mention watchmen, and asked about security more generally. In addition, this was not the first item on the list of multiple choice options to avoid order effects. Finally, the pattern of crop-level results are consistent with these self-reported outcomes.

[24] I show in Table A13 the cropwise results, and identify the crops where the intervention group was significantly more likely to grow for the first time or on increased land. The intervention impact was significant at the 1% level and largest (as a share of the control mean) for kale and tomatoes, the two crops most commonly identified as theft-constrained, with the intervention group being more than three times as likely as the control group to start growing or increase land to tomatoes. In terms of raw levels of increased reallocation, beans and maize had the largest difference between intervention and control. This is not surprising, as these are the most common crops and those where the adjustment costs would be the lowest.

Table 4
Self-reported economic behaviour change.

Outcome var	Cropping patterns		Time use		Investment	
	(1) Any Security Crops[a]	(2) Share Land Change Security[1]	(3) Spent More Time Off-Farm[a]	(4) Sold More Crops Off-Farm[a]	(5) Bought Farm Assets[a]	(6) Rented Farm Assets[a]
Panel A: Linear Model Intervention[a]	0.139	0.091	0.119	0.104	0.115	−0.067
	(0.054)**	(0.030)***	(0.032)***	(0.045)**	(0.045)**	(0.036)*
Num. Observations	577	574	577	577	576	576
Control Mean	0.18	0.07	0.16	0.13	0.19	0.24
Panel B: Logit Model, Average Partial Effects Intervention[a]	0.134	0.125	0.114	0.100	0.111	−0.068
	(0.049)***	(0.049)***	(0.027)***	(0.040)**	(0.041)***	(0.037)*
Num. Observations	577	574	577	577	576	576
Control Mean	0.18	0.07	0.16	0.13	0.19	0.24

[a]Binary variable, equal to 1 if true, 0 if not.
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.
Standard Errors clustered at the village level in parentheses below estimates. Controls for all specifications: Randomization strata fixed effects. Intervention is an indicator variable for assignment to the treated group who were matched to a watchman offering farm security at the subsidized rate. The outcomes in this table were only recorded at endline, so the Intervention variable is the treatment coefficient of interest. The outcome in Column 1 is a binary variable indicating whether any crops the farmer grew in the season of interest are crops they started growing or to which they increased their land allocation due to improved security. For a crop-wise analysis of which crops the intervention group were more likely to start growing or grow on increased land, please see Table A13. Column 2 is the share of land between zero and one recording the sum of the share of land allocated to new crops and land additionally allocated to crops as a result of improved security. Column 3 is a binary self-reported indicator of whether the farmer spent more time off-farm this season than in the same season last year. Column 4 is a binary self-reported indicator of whether the farmer sold more crops off-farm this season than in the same season last year. I show in Table A14 that this result holds at the crop-level using more standard outcomes for high theft-risk crops like tomatoes and kale. Column 6 is a binary self-reported indicator of whether the farmers bought any new farm assets this year. Column 5 is a binary self-reported indicator of whether the farmers rented any new farm assets this year. A table of the treatment effect on asset buying and renting broken down by asset categories is included in Table A15.

Table 4 that matched farmers were 12 *p.p.* more likely to have bought farm assets, and 7 *p.p.* less likely to have rented assets this season against non-matched means of 19% and 24%, respectively. In isolation this is an unexpected result, as the assets with the strongest observed treatment effects are, as shown in Table A15), long-term assets whose returns will not be realized during the treatment period. This outcome is consistent with farmers reinvesting a windfall from increased agricultural yields, as suggested by post-endline focus groups, similar to the results in Gertler et al. (2012), where farmers reinvested a cash transfer.

The results above are based on self-reported measures of changes to economic behaviour, which may be subject to experimenter demand effects. For this reason, I also test for differences in reported economic behaviour using the categorization of crops by objective categories. In Table 5 I explore three key behaviours: land use, input use, and marketing decisions. Looking first at conditional land allocation (restricting to farmers who grew any crops in that category) farmers in the intervention group used 0.167 more acres of land for high-risk crops. This coefficient is significantly different than that for the low theft-risk crops, which is negative, and this difference is significant at the 5% level. Looking at the total unconditional area, the effect is smaller and not significant, but is still positive for high-risk and negative for low-risk. This is consistent with (though not significant evidence for) the assertion that farmers with greater security grew more high theft-risk crops but driven largely by the intensive margin which is unsurprising for a short-term intervention. I find no significant effect of the intervention in terms of total input use or input intensity. The greater precision in Table 4 may be explained by the fact that specification is in some sense a panel data specification, though demand effects remain a potential caveat with self-reported changes. Consistent with other evidence in the paper, however, the point estimate of the intervention effect on input intensity for high-risk crops is large and negative, and the test of equality for the intervention coefficient on high-risk crops and on low risk crops is marginally insignificant (pvalue = 0.128). This is consistent with the mechanism of farmers with security spending less time on each unit of land used to grow high theft-risk crops.[25] For the objective measures of crops being sold off-farm, I look at the mean (within-farmer) of dummy variables indicating whether each crop in that category was sold off-farm and whether the farmer sold any crops off-farm by category. For both outcomes, the results show farmers selling more of their high theft-risk crops off-farm, though these are also not statistically significant.

6.3. Intervention externalities

Taken together, the above results show that security has a significant effect on the economic behaviour and outcomes of directly treated farmers. I now consider externalities of the intervention, and how other nearby farmers were impacted by reducing tensions among neighbours and security spillovers within- and across-villages.

6.3.1. Local conflict and greivances

Improved security significantly reduces the level of local suspicion and conflict related to interference on farms between matched farmers and their neighbours.[26] I first establish whether the watchman intervention reduced the degree to which farmers suspect neighbours and strangers of taking the chance to steal while the farmer is away from the farm. In Column 1 of Table 6 I show that matched farmers were 27 *p.p.* less likely to be highly suspicious of their neighbours interfering when they were away from their farm against a control mean of 60%. In Column 2, I show that matched farmers are a similar 21 *p.p.* less likely

[25] In these specifications, I split the sample and estimate separately by crop-category. To look in more detail at within-farm reallocation, I also present results in Table A16 at the farmer-crop level with controls for crop or crop-category fixed effects, as well as strata, village, or individual fixed effects. The result is only statistically significant in one specification, but all are consistent with this split-sample outcome.

[26] In Supplementary Table A17, I test for gift-giving behaviour among neighbours and find no significant effect on gifts given or received. The fact that the result from Schechter (2007) is not present here is likely explained by the fact that farmers in this context do not seem to have as much information on who is committing theft, which would reduce the value of preventative gift-giving. Another explanation is that the long-run nature of relational capital as response to theft would not be changed by a short-run intervention.

Table 5
Economic behaviour change by crop category.

(a) Land use

Outcome var	Total (conditional) area		Total area	
	(1) Low-Risk	(2) High-Risk	(3) Low-Risk	(4) High-Risk
Intervention	−0.090	0.167	−0.041	0.039
	(0.073)	(0.100)*	(0.065)	(0.040)
H_0: $\beta_{\text{High Risk}} - \beta_{\text{Low Risk}} = 0$, [p-value]		[0.013]		[0.289]
Control Mean	1.087	0.622	0.867	0.211
Control Median	1.000	0.500	0.500	0.000
Num. Observations	460	186	568	568

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.
Standard Errors clustered at the village level in parentheses below estimates. In this table observations are at the farmer crop-category level, where we aggregate all crops in each of the Low Theft-Risk, High Theft-Risk and Low Theft Utility categories. I restrict to major crops, meaning those that account for at least 2.% of a farmer's planted land and that are grown by at least 25 farmers in the sample. For Columns 1–3 I consider conditional area, meaning that these observations are only included where the farmer grew any crops in this category. In Columns 4–6 I consider total area by category, where the outcome is zero for farmers who do not grow crops in that category. The additional pvalue reported is for a test of equality of the *Intervention* coefficient for High-Risk and Low-Risk crop categories.

(b) Input use

Outcome var	Input intensity		Total input use	
	(1) Low-Risk	(2) High-Risk	(3) Low-Risk	(4) High-Risk
Intervention	363	−1,774	39	114
	(409)	(1,497)	(332)	(458)
H_0: $\beta_{\text{High Risk}} - \beta_{\text{Low Risk}} = 0$, [p-value]		[0.128]		[0.882]
Control Mean	2,866	7,242	2,628	2,608
Control Median	1,732	3,542	1,650	1,525
Num. Observations	460	186	460	186

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.
Standard Errors clustered at the village level in parentheses below estimates. In this table observations are at the farmer crop-category level, where we aggregate all crops in each of the Low Theft-Risk, High Theft-Risk and Low Theft Utility categories. I restrict to major crops, meaning those that account for at least 2.% of a farmer's planted land and that are grown by at least 25 farmers in the sample. For Columns 1–3 I consider conditional area, meaning that these observations are only included where the farmer grew any crops in this category. In Columns 4–6 I consider total area by category, where the outcome is zero for farmers who do not grow crops in that category. The additional pvalue reported is for a test of equality of the *Intervention* coefficient for High-Risk and Low-Risk crop categories.

(c) Off-farm sales

Outcome var	Share crops sold off-farm		Any crops sold off-farm	
	(1) Low-Risk	(2) High-Risk	(3) Low-Risk	(4) High-Risk
Intervention	−0.002	0.078	−0.016	0.085
	(0.042)	(0.067)	(0.046)	(0.068)
H_0: $\beta_{\text{High Risk}} - \beta_{\text{Low Risk}} = 0$, [p-value]		[0.235]		[0.149]
Control Mean	0.406	0.390	0.500	0.412
Control Median	0.167	0.000	0.500	0.000
Num. Observations	456	186	456	186

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.
Standard Errors clustered at the village level in parentheses below estimates. In this table observations are at the farmer crop-category level, where we aggregate all crops in each of the Low Theft-Risk, High Theft-Risk and Low Theft Utility categories. I restrict to major crops, meaning those that account for at least 2.% of a farmer's planted land and that are grown by at least 25 farmers in the sample. For Columns 1–3 I consider conditional area, meaning that these observations are only included where the farmer grew any crops in this category. In Columns 4–6 I consider total area by category, where the outcome is zero for farmers who do not grow crops in that category. The additional pvalue reported is for a test of equality of the *Intervention* coefficient for High-Risk and Low-Risk crop categories.

to have high suspicion of strangers interfering when they are away from their farm, against a control mean of 54%. This reduction in suspicion of both groups as a result of security shows that both well-known and unknown actors are suspected of theft.

The security intervention also reduced actual conflict and disputes among neighbours. In Column 3 of Table 6 I show that matched farmers were 14 *p.p.* less likely to have any unexpressed grievances due to their neighbours interfering on their farm, a reduction of approximately half the control mean of 27%. As described in Section 2.3, formal remedies are perceived to be ineffective, informal direct remedies involve social costs and in general there is not perfect information on who is responsible for theft. The effect of watchmen on silent grievances shows that

Table 6
Local suspicion and conflict.

Outcome var	Suspicious of opportunistic interference by:		Neighbour Conflict		
	(1) Neighbours[a]	(2) Strangers[a]	(3) Unexpressed Grievances[a]	(4) Disputes last month	(5) Angry Disputes last month
Intervention[a]	−0.272	−0.208	−0.107	−0.465	−0.322
	(0.045)***	(0.046)***	(0.047)**	(0.148)***	(0.123)**
Num. Observations	576	576	576	576	576
Non-matched Mean	0.60	0.54	0.27	0.98	0.61

[a]Binary variable, equal to 1 if true, 0 if not.

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Standard Errors clustered at the village level in parentheses below estimates. Controls for all specifications: Randomization strata fixed effects. Intervention is an indicator variable for assignment to the treated group who were matched to a watchman offering farm security at the subsidized rate. Column 1 is a binary indicator for the farmer responding with a four or five on a five-point scale in agreement to the statement *"In the last month before harvest I was worried my neighbours would interfere with my farm if I wasn't there"*. Column 2 is a binary indicator for the farmer responding with a four or five on a five-point scale in agreement to the statement *"In the last month before harvest I was worried strangers would interfere with my farm if I wasn't there"*. Column 3 is a binary variable equal to one if the respondent answered Yes to the question *"In the last month before harvest, did you have grievances with your neighbours where you didn't bother confronting them or bringing it to the authorities?"* Column 4 is an integer count of disputes in the last month before harvest, in response to the question *"In the last month before harvesting, did you have disputes with your neighbours about interference on your farm? How many times in the last month before harvesting?"* where the count of disputes is coded as zero if the respondent answered No to the first question. Column 5 is the integer count of how many of these disputes were angry, in response to the question *"How many of these disputes involved some form of threat or aggression?"*.

some combination of these three factors leads to a significant amount of farm interference among neighbours that is not addressed. This result shows that there is a significant amount of property crime which is not addressed due the costs of enforcement, but which is not viewed as acceptable redistribution.

Despite the evident costs of dealing with disputes over property crime informally, disputes among neighbours over their interference on farms are quite common, but were significantly reduced by improved security.[27] Matched farmers reported 0.6 fewer disputes over farm interference by their neighbours in the last month before harvest, a reduction of approximately 60% of the average of 1.0 dispute for the non-matched group. More importantly, these are not simply mild disputes being averted. The matched group of farmers had 0.39 fewer disputes in the last month prior to harvest involving some form of threat or aggression, again a decrease of roughly sixty percent of the control mean of 0.61 angry disputes.[28] This reduction in conflict speaks to the broader social welfare from interventions to improve security. In particular, it raises the question of whether theft is a form of socially sanctioned transfer to the less well-off.[29] Taken together these results suggest that if theft is a system of redistribution, it is one that comes with significant negative externalities through grievances and conflict.

6.3.2. Security spillovers

In this section I explore potential spillover effects, across- and within-villages. First, I test for spillovers from intervention villages to the nearest control villages, using the specification described in Eq. (3). I present the results in Table A22 and show that there is no significant effect of the intervention on the nearest control villages. This result must be taken with the caveat that this study was not designed to identify geographic spillovers. It is possible that the non-result in this specification is driven by insufficient variation in proximity to treated villages among the control group.

In addition, I use responses from the convenience sample of nearby farmers to test for spillovers within villages. I ask these respondents the same questions on self-reported theft experienced during the last season, and for perceived changes in the level of theft. I present these results in Table A23 and show a significant improvement for nearby farmers within the intervention villages. Spillover farmers in treated villages were significantly less likely to report having experienced any theft from their farm during the treatment season, and were significantly more likely to report that theft had decreased relative to the previous season. This does not mean that there was no displacement of crime within the village outside the range from which the convenience sample were drawn, but is instead evidence only of local positive spillovers.

6.4. Cost-benefit analysis

Thus far I have shown that the intervention had economic benefits for farmers through increased yields and relaxed constraints on economic behaviour. I also find no evidence for displacement of insecurity from treated villages to nearby control villages, in addition to positive within-village externalities through reduced disputes. Given these benefits, I now explore whether these interventions are optimal for farmers to undertake individually. In Table 7 I look at whether the yield gains outlined above justify the cost of hiring a watchman. As the intervention also had non-monetary benefits, such as reduced conflict with neighbours, I also back out what the implied willingness to pay for each serious neighbour dispute would have to be in order for these to make the cost-benefit break even. Using the per acre yield gain and the mean number of farmed acres, I find that the cost of this intervention is larger than the increase in value of agricultural production. The cost-benefit would only then break even with each individual aggressive dispute being valued at approximately fifteen percent of the mean value of harvest for an acre of farmed land, which suggests that it is unlikely that the social benefits are sufficient to justify the cost of the intervention for an individual farmer. This suggests that these interventions are too expensive for a single small-scale farmer, and that farmers at baseline were behaving rationally by not hiring security prior to this experiment.

The implication of these findings is that weak rule of law and insecurity of property are significant constraints to farmers but that,

[27] In Supplementary Table A18, I test for an effect on trust, and find no evidence that this reduction in suspicion and conflict is matched by an increase in trust among watchman-matched farmers. The results do strongly indicate a large across-the-board reduction in trust from baseline to endline. Given the large decrease in trust across all categories, in Supplementary Table A19 I test for effects on *relative* trust by dividing the trust for any one category by the respondent's mean trust in that period. Again, the results for relative trust do not show an effect between matched an non-matched, but the pattern of baseline-endline differences is more informative. Relative trust within-village increased significantly for both Neighbours and Non-Neighbours, but decreased for Other Ethnic Groups and the local Chief. This decrease in trust in the Chief is consistent with the results in Supplementary Table A20 where I show that a number of measures of attitudes towards local formal institutions decreased across-the-board from baseline to endline.

[28] This effect on disputes could also potentially be explained by the fact that neighbours may be less willing to start an argument with a farmer who has a watchman for their farm, though this would not explain the reduction in suspicion among treated farmers.

[29] In Table A21 I find no evidence that farmers in the treated group have different attitudes towards theft than those in the control group. This suggests that there is no disruption of local norms regarding the acceptability of theft in the intervention group relative to the control group.

Table 7
Intervention cost-benefit.

		Output effects for mean farmed area	
		TOT Estimate of Intervention Effect on Yield $\sim 15{,}000$ KSH[a]	TOT Estimate of Intervention Effect on Profit $\sim 12{,}300$[b]
Watchman Wages	Wages paid during experimental intervention $\sim 18{,}000$ KSH	−3,000 KSH [−16.7%]	−5,700 KSH [−31.7%]
	Expected wages paid to a local watchman $\sim 12{,}000$ KSH[c]	3,000 KSH [16.7%]	300 KSH [2.5%]
Valuation of non-monetary benefits	Minimum WTP per dispute for intervention to break even[d]	5,555 KSH	10,555 KSH
	WTP per Dispute as Share of Harvest/Acre[e]	15.9%	30%

[a]This estimate of the Treatment on Treated effect is generated by scaling the ITT Treatment Effect on Revenue per Acre by take-up differential and mean farmed area.

$$\text{TOT Treatment Effect} = \frac{\text{ITT Estimate}}{\text{Take-Up Rate}} \cdot \text{Mean Farmed Acres} = \frac{5002}{0.716} \cdot 2.15 \simeq 15{,}000\text{KSH}$$

[b]Generated by scaling ITT Treatment Effect on Profit per Acre by take-up differential and mean farmed area.

$$\text{TOT Treatment Effect} = \frac{\text{ITT Estimate}}{\text{Take-Up Rate}} \cdot \text{Mean Farmed Acres} = \frac{4,100}{0.716} \cdot 2.15 \simeq 12,300\text{KSH}$$

[c]Cost for six weeks of hiring a local watchman, at wages of approximately 2000 KSH per week. This figure is derived from survey data and local informants.

[d]To back-out the implied minimum Willingness-to-Pay to avoid an angry dispute, I use the estimate from Column 5 of Table 6, and divide by the take-up rate:

$$\text{TOT Treatment Effect} = \frac{\text{ITT Estimate}}{\text{Take-Up Rate}} = \frac{-0.386}{0.716} \simeq 0.54$$

which means the Treated on the Treated effect was 0.54 angry disputes avoided. I then divide the return gap in the panel above by this TOT measure of angry disputes avoided to get the required WTP per dispute.

[e]To decide whether the implied valuation of avoided conflict is reasonable, I express it as a percentage of the mean value of per-acre yield, which was approximately 35,000 KSH for the control group.

given the beneficial externalities and the individual cost-benefit, this is a challenge that is best addressed through collective action. These results do not therefore indicate that farmers are leaving money on the table by not hiring security. As such, these results should be taken as suggestive evidence in support of policy interventions to improve the rule of law on a collective basis.

7. Robustness checks

One potential unintentional impact of the intervention was to interfere with the functioning of other local institutions. In particular, if local chiefs changed their security activities in response to the presence of watchmen, this may generate significant unintended effects. I test for this in Table A24 and find little evidence of an effect of the intervention on security behaviour by chiefs. This suggests that the intervention did not have any unintended effects through an institutional response.

8. Conclusion

In this paper I use a randomized field experiment to show that insecurity of farms against crime constrains agricultural development. The intervention of matching farmers with subsidized watchmen significantly reduced anticipated theft, particularly for activities that were different from the norm. Farmers matched with watchmen changed their cropping patterns to grow more high theft-risk crops, spent more time away from their farm and sold more crops at off-farm markets. In addition, matched farmers received increased agricultural yields, unexpectedly driven by low theft-risk crops. Improved security also significantly reduced local conflict and suspicion among neighbours. These results show that fear of crime causes productivity costs for agricultural production through novel mechanisms. The learning documented here motivates further work to understand the formation of beliefs by farmers and to explore the costs of risk of crime. Given the impact of this short-term intervention and results suggestive of long-run effects and potential positive externalities, this topic merits further research.

CRediT authorship contribution statement

Julian Dyer: Conceptualization, Methodology, Project administration, Formal analysis, Investigation, Writing – original draft, Writing – review & editing.

Data availability

Data will be made available on request.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jdeveco.2023.103109.

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