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 fear of theft imposes pervasive indirect costs on small-scale farmers, distorting their planting and time use decisions, as well as crop yields. I randomly allocated subsidized watchmen to farmers in Kenya, reducing their perceived risk of theft. Farmers offered watchmen were 14 percentage points 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 farmers assigned watchmen reported fewer angry disputes with neighbours. Despite these benefits, this intervention isn't profitable for an individual farmer,suggesting a potential role for collective security interventions.

Keywords: crime, theft, security, agriculture, institutions, development

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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, these indirect costs 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 a 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 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

[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.

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 profitability 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 spend 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, and find that this impact on these crops is significantly higher 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 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 percentage points more likely to report increasing time spent off-farm and ten percentage points more likely to report increased crop sales to off-farm markets. [4]These outcomes show that fear of crime causes farmers to adjust their cropping patterns and time use.

[4]These aggregate results are consistent with outcomes at the crop-level.

I also find that the intervention increased the short-run productivity of farmers, 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. I first show that 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. When comparing the control villages closest to the intervention to those further away, I find no evidence of spillovers in ex-ante perceived theft risk. Similarly, I find no evidence of spillovers in ex-post self-reported theft to the nearest control villages. I do find positive effects within the village, with nearby farmers within intervention villages reporting less theft experienced during the intervention season. Together with the reduction in local conflict, this is evidence that an intervention to improve farm protection against theft had beneficial spillovers within village, and no detectable negative spillovers through displacement across villages.

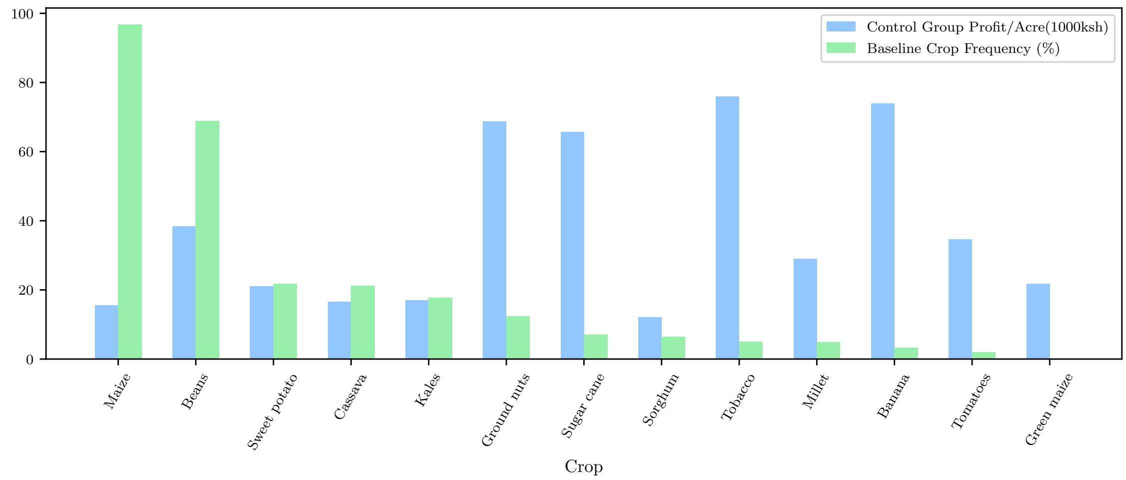
Having presented evidence that the experimental intervention improved the productivity of farms and allowed behaviour change, and the effect on nearby households and villages, I then examine whether it is individually optimal for farmers. Low baseline take-up is, by revealed preference, a strong indicator that individual adoption is not optimal. This is consistent with estimates of the individual cost-benefit the intervention that at only breaks even with implausible valuation of non-monetary benefits. This, along with positive spillovers, suggests a collective action problem or potential for beneficial policy intervention.

In this paper I identify an aspect of institutions that is an underexplored 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).

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 a less-understood institutional constraint to agricultural productivity where fear of crime distorts production decisions.

I find that this intervention had beneficial spillovers through conflict, and no evidence of displacement of crime 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., 2017).

Figure 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.

2 Background

2.1 Agricultural Practices

Agriculture in Migori is small-scale rainfed agriculture, with a large degree of subsistence agriculture, typical of Sub-Saharan Africa. 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 Figure 1, maize cultivation is ubiquitous, and is the staple for the local diet. Beans, cassava and sweet potatoes are also very common. Irrigation is uncommon in this area, 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.

Tobacco and sugarcane are the most common purely cash crops, produced in close cooperation with local sugar and tobacco companies, who provide inputs and technical services on a loan that is repaid when the farmer harvests their crop. This harvest is sold only to the processing plants at fixed prices, and has limited direct consumption value for households. These crops are attractive to some households due to the fact that they require no up-front costs for the farmer.[5] Sugarcane, in particular, tends to deplete the soil and lead to reduced yields on future harvests. In addition, the sugarcane growing cycle lasts two years, including three harvests during this time, so often leads to land being committed for a long time to crops that are of limited dirct consumption value. Tobacco also has sustainability concerns, with huge demand for firewood during post-harvest curing which leads to clearing of forests crucial to local water systems.

The typical household is usually about eight people, including children and typically one or two elderly household members. Polygamy is fairly common, where some households are run by women despite having a husband who is primarily living at a different household. In these households, the woman farmer makes decisions on cropping patterns and the division of labour between men and women becomes less distinct and the household farms plots together.

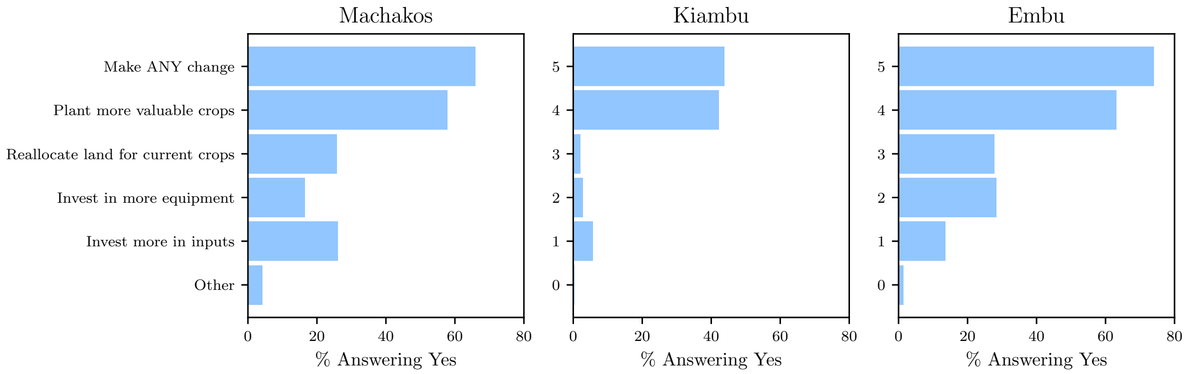
Farms in Migori are not heavily secured and fencing is rare, other than in a for a small yard around the compound containing living quarters for the household. While the boundaries of farms are not heavily secured, they are clearly demarcated. The boundaries between plots grown by different households are usually indicated by a natural border such as a river or man-made features such as a planted hedgerow, or a footpath or road.[6] See Figure A4 in the Appendix for a typical boundary of a plot. Property rights over land in Migori are a mix of individual title and land allocated through community rights.

Most crops that are grown in Migori, other than the cash crops discussed above, are consumed locally by households, which means that any theft from farms has high immediate utility as they can be consumed immediately. In particular, this consumption value is highest for crops that are harvestable off-cycle with the maize harvest. As the ubiquitous local staple, when maize is harvested food is plentiful and hunger is at its

[5]See Karlan et al. (2014) for an example of the importance of credit constraints for agricultural decisionmaking.

[6]This information comes from interviews with local agricultural expert informants and focus groups with participants.

Figure 2: External Validity & Security Changes



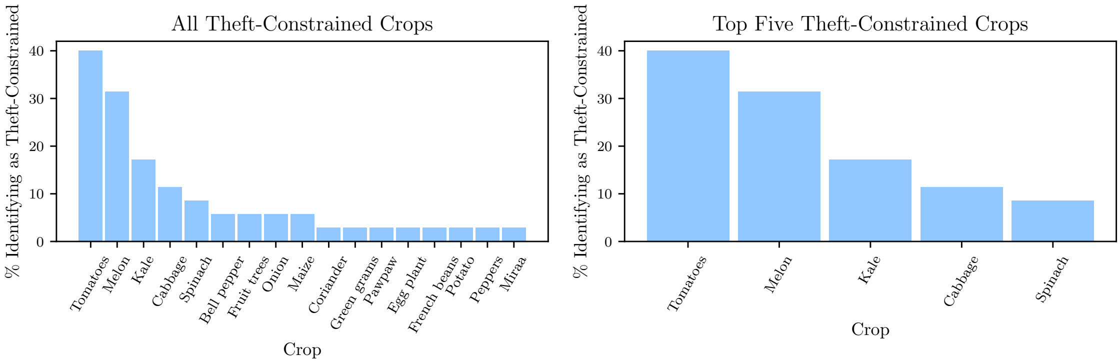
Description: This figure shows that the hypothetical changes farmers would make if their farms were secured are similar across Kenya. This is evidence that the results of this project likely generalize to small-scale farmers in three other counties in Kenya.
Data Source: Endline survey for an irrigation project run with other smallholding farmers in Kenya.(Dyer and Shapiro, 2018)

lowest. While maize is the most common carbohydrate-heavy staple, there are other crops, namely onions and tomatoes, are heavily used in local cooking and food preparation. These crops, however, are not as commonly grown among smallholder farming households, and are instead purchased at market stalls in town or from roadside kiosks in more rural areas.

While a large share of agriculture is consumed by the household, crops are also sold on a variety of markets. The most common place to sell crops is at the farm gate. Crops sold on the farm are either sold directly to local consumers, or to middlemen who then sell the crops on at local markets. As mentioned above, cash crops like sugarcane and tobacco are sold exclusively to processing companies who come collect the harvest from the farm. The most common off-farm market for crops is for the farmer to take their crops to sell at the local market centres. Where there is demand available and the farmer can commit to spending time off-farm regularly, farmers can also make other off-farm marketing arrangements. One common such arrangement is an agreement to regularly supply ingredients for lunch programs at nearby schools, health clinics or other local institutions.

As shown above in Figure 1, the cropping decisions of farmers show missed oppor-

Figure 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 don't due to security concerns.
Data Source: Piloting survey of comparable farmers.

tunities for improving income from agricultural production by adopting the cultivation of profitable crops. There is a vast literature on the topic of technology adoption, with a heavy focus on learning and information transfer. (Conley and Udry (2010), BenYishay and Mobarak (2018), Foster and Rosenzweig (1995)) Qualitative information from unstructured interviews at baseline with study participants suggests that fears of crop theft crime play a role constraining cropping decisions. This qualitative evidence is supported by quantitative evidence linking security concerns to adoption of more profitable crops. In a survey of 876 similar smallholding farmers from three other counties in Kenya (Kiambu, Machakos and Embu)[7], fifty-five percent of farmers reported that if their farm were secured by a watchman, they would change their crop allocation and plant more valuable crops. I show above, in Figure 2, that this response is relatively similar across the three different counties, suggesting that this perceived security constraint on adoption of valuable crops has external validity across Kenya and is not particular to Migori.

It is a common belief among farmers that certain types of crops are more likely to be targeted by thieves than others, with crops that are valuable (high price per kilogram), easily picked (lower minutes to harvest per kg), with a longer harvest window (greater opportunity for theft), which are available before the main staple (maize) and directly

[7]This survey was conducted as part of another RCT evaluating the effectiveness of irrigation pumps. See Dyer and Shapiro (2018)

consumable or easily sold, being the most likely targets for theft.[8] This qualitative evidence is also supported by quantitative survey evidence. In Figure 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.[9] 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. As I show above, in Figure 3, the top five crops identified as being constrained by theft are 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 additionally 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. [10]These beliefs are not based on accurate crime statistics and may not be accurate, but they are relevant here as they are the beliefs used when farmers decide on the potential risk of different types of agricultural production.

2.2 Perceptions of Theft

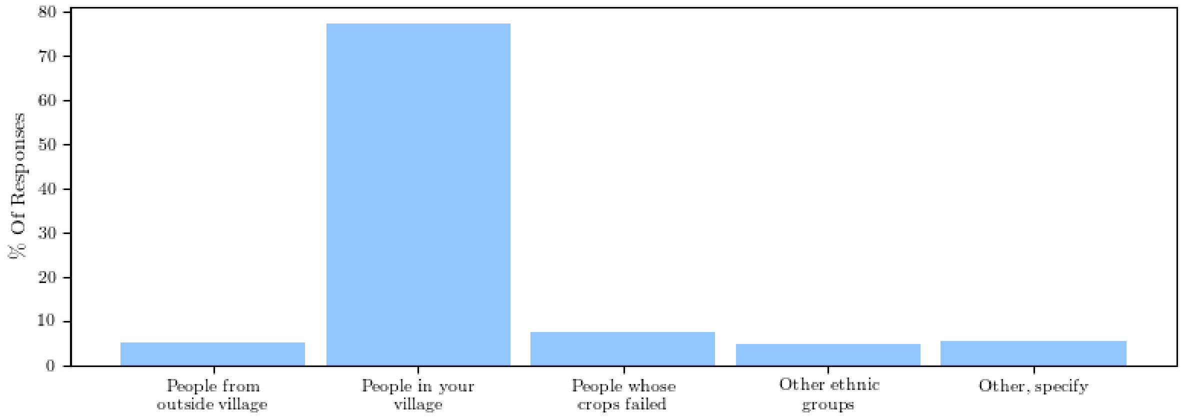
In the study context, farmers do not have access to detailed information on crime and cases of theft, but hold beliefs about the nature of theft that guide their decisionmaking. Theft is perceived to be primarily a crime of opportunity, with potential thieves from within the village stealing crops when the opportunity arises. In Figure 4, I show that the people from within the village are overwhelmingly seen as the most likely perpetrators of theft. This suggests that theft is not highly targeted across villages, but is instead concentrated among those who are nearby and have the greatest likelihood of coming

[8]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).

[9]The survey sample for this pilot survey is 104, and these farmers were not included in the final project.

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

Figure 4: Expected Thief Types



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

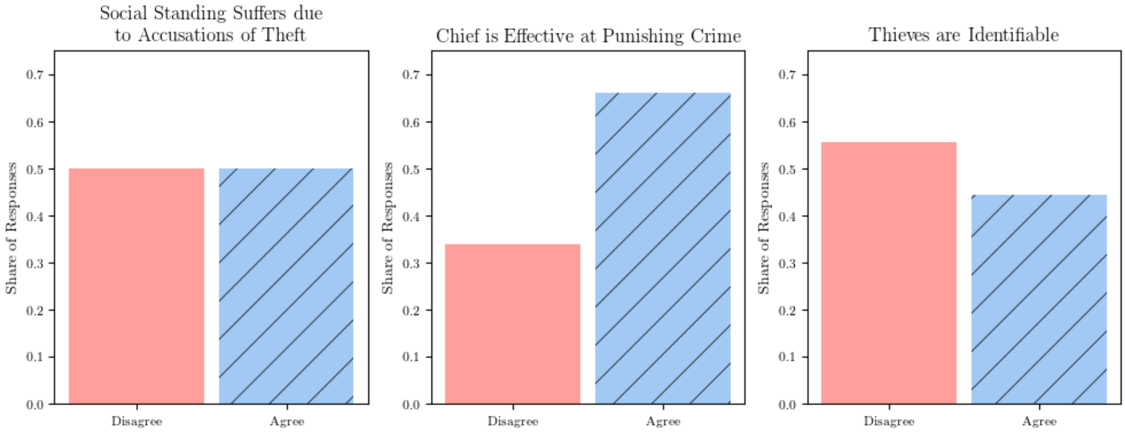
upon the farm when it is unguarded.

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 the fact that farmers are not often confident of being identify thieves from their farms. Frictions exist in existing institutions, with the added difficulty of culprits being hard to identify. In Figure 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.

State institutions in rural areas are not perceived to be particularly effective at punishing property crime. The formal institution responsible for property crime in rural areas is the combination of village elders and the local chief. The local chief is ultimately responsible for dealing with crime, where village elders are the first layer, who pass complaints along to the village chief. In Figure 5, I show that more than a third of respondents in the sample are not confident that their chief would be able to successfully punish the perpetrator if they brought a theft case to them.

Figure 5: Imperfect Enforcement Mechanisms



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

In addition to the lack of information and the ineffectiveness of local institutions, there is also a social cost to making accusations about other villagers. Again in Figure 5, I show that half of respondents agree that their social standing in their community would be damaged by making accusations about another villager.

Taken together, the fact that local institutions are perceived to be ineffective, the social cost to denunciations and the difficulty in identifying the perpetrator all explain why property is weakly secured against crime. This leaves an institutional gap that can be filled by a trustworthy non-state alternative. In the next section I explain the design of the experiment, using exactly this type of non-state actor intervention appropriate to both the context described above and the research questions I answer in this paper.

3 Experiment Design

I now describe the details of the experiment design, and explain the rationale for choices made. I first describe the sample involved in this experiment and then explain the intervention the intended effect and the tradeoff relative to other potential designs. 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 main sample of farmers for this experiment are 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.[11] Migori was not selected for its agricultural potential, and the conditions in the region are roughly typical of Kenya. The agricultural conditions 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

[11] 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.)

the intervention and discussing and answering questions about the project were conducted with leadership of the farmer's 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. [12] 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

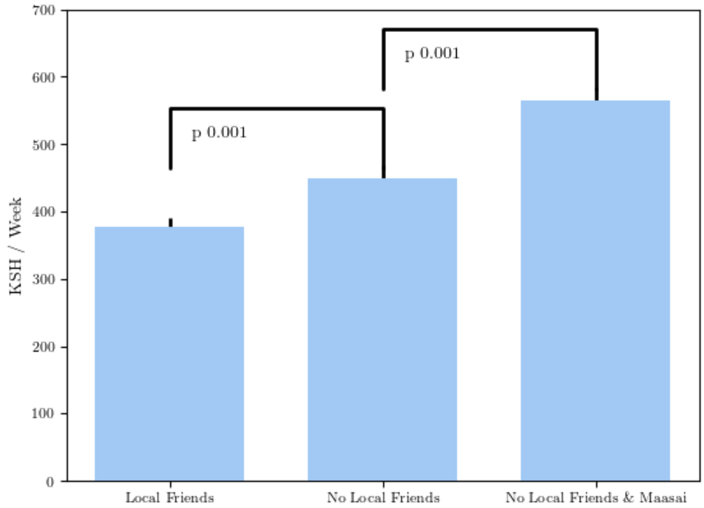
The intervention implemented in this experiment was matching farming households to high-quality, trusted Maasai watchmen at a heavily subsidized rate. There are two reasons why Maasai watchmen are particularly effective in this context. The first is that they are outsiders in the sample farming communities, where differences in dress and language/accent make this outsider status obvious. 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.[13] 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 below, in Fig-

[12]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.

[13]For further discussion of the perception of the Maasai as being effective guards, see Dyer (2016).

ure 6, suggestive evidence that both the outsider effect and the Maasai stereotype effects lead to increased self-reported willingness to pay for watchmen.[14]

Figure 6: Valuation of Watchmen



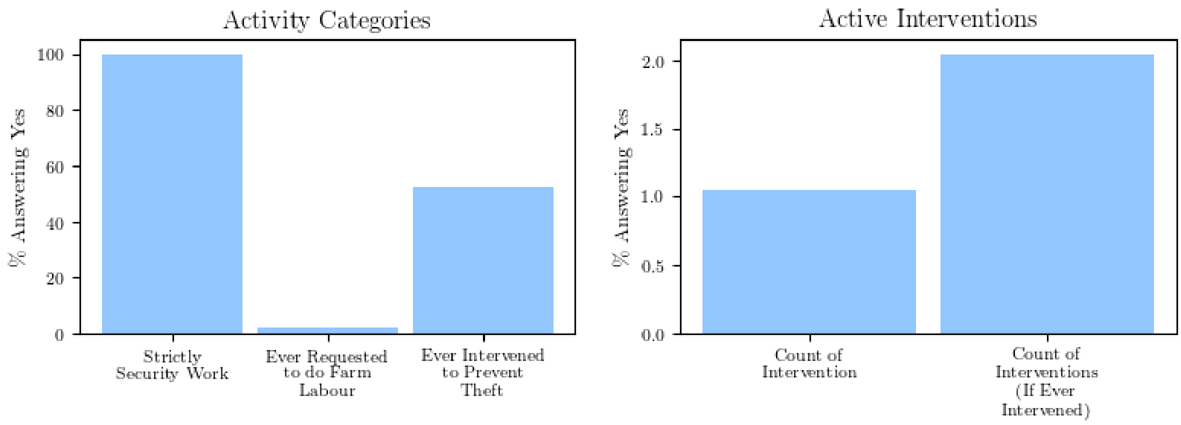
Decription: This figure shows that fear of local collusion is an important factor in valuation of security services, in addition to the Maasai cultural stereotype.
Data Source: Self-reported willingness-to-pay from endline survey.

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 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 decision-making, 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

[14]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.

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 weren't being misused. As I show below in Figure 7, 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.

Figure 7: Watchmen Activity during Experiment



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

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 are set in advance, so the treatment is uniform across the sample. 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 subsidised 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 prior to watchman assignment, and again at endline, after watchmen had finished working and the main harvest was completed. 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 (in English and translated into Swahili) at baseline, before farmers were informed of their treatment status, and again at the end of the project, after the employment of watchmen and the main harvesting period had concluded.

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 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.[15] 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

[15] Experimenter demand effects are unlikely in this case. Not only were self-reported outcomes checked where possible, respondents were unlikely to know the goal of the research. Furthermore, many outcomes were added post-baseline based on focus grouping, which implies that participants were not simply providing answers that they thought the research team wanted to hear.

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 to record household position. In Appendix C I explain the exact survey questions used and the construction of all variables used in Section 7 where I discuss results.

4.2 Focus Groups & Qualitative Data

I conducted qualitative data collection at three points during this project. First, I conducted a number of unstructured interviews with farmers prior to the baseline survey in order to explore the most important effects of property crime. These interviews were conducted in a strictly unstructured manner so as not to prime respondents with particular results I expected to observe. These interviews helped with the design of the intervention, as described in Section 3.2, by informing the use of Maasai watchmen as well as documenting beliefs regarding spillovers which motivated randomization of treatment at the village-level.

The second major round of qualitative data collection was in early January 2019, after watchmen had been deployed. At this point I spent a week conducting (with the aid of a translator) unstructured interviews with farmers, discussing their experience with security and understanding how their behaviour had changed. Again, these interviews were conducted in a strictly unstructured manner so as not to prime respondents. These interviews proved to be highly informative, and raised a number of potential outcomes where the participants had not anticipated effects at baseline, and I was able to update the endline survey and pre-registered analysis plan accordingly.

Finally, I also conducted a series of focus group discussions led by the local farmer coordinator after endline data collection had concluded and after preliminary analysis had begun. As I explain in detail in Section 7, some of the empirical results were surprising given my priors and the qualitative data collected before endline surveys. The focus groups were conducted with specific sub-samples of respondents whose responses in the endline survey could not easily be rationalized, and generated new hypotheses to test along with my pre-registered outcomes.

4.3 Crop Characteristics Data

I collected data on the objective characteristics 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 Kilogram
- Consumed Locally (as opposed to being sold only to processors)
- Length of Maturity Window

5 Conceptual Framework

To understand the mechanisms underlying the decisions of farmers, I adapt the model used by Goldstein et al. (2018) to model agricultural production, labour allocation and the security of plot tenure. In keeping with qualitative evidence, I assume there are two types of crops split by perceived risk of risk of theft: *high expected theft* crops and *low expected theft* crops. Crop type c is therefore $c \in \{H, L\}$ with a market price P_c. The production function for crops is $Q_c(l)$ where l is the labour applied to crop type c, and where $Q_c(l)$ has the usual properties $Q'_c(l) \equiv \frac{\partial Q_c(l)}{\partial l} > 0$ and $Q''_c(l) \equiv \frac{\partial^2 Q_c(l)}{\partial l^2} < 0$. I model the share of crop c yield that is not stolen as $\sigma_c(l_c, S)$ where l_c is the labour allocated to crop c and S is the quality of security on the farm and $\sigma_L(l_L, S) > \sigma_H(l_H, S)$.

Holding labour allocation fixed at $\bar{l}$, a household decides whether to cultivate high-theft crops on a given plot according to the following optimization problem:

$$\max_{c \in \{L,H\}} \Pi_c = \sigma_c(\bar{l}, S) Q_c(\bar{l}) P_c \tag{1}$$

Proposition 1. *Land allocation responds to security and improved security increases the likelihood of cultivating high theft risk crops when the impact of security on theft is stronger for the high theft risk crops:*

$$\frac{\partial \sigma_H(\bar{l}, S)}{\partial S} > \frac{\partial \sigma_L(\bar{l}, S)}{\partial S}$$

See Proof B.1 in Appendix.

For a household with labour endowment $\bar{l}$ that is growing both types of crop, they choose to allocate labour to the high theft risk crop l_H according to the following optimization problem, which the conditions on equilibrium labour allocation l_H and allows us to consider how it responds to a change in S, the security institution.

$$\max_{l_H} \Pi = \sigma_L(\bar{l} - l_H, S) \cdot Q_L(\bar{l} - l_H) \cdot P_L + \sigma_H(l_H, S) \cdot Q_H(l_H) \cdot P_H \tag{2}$$

Proposition 2. *The sign of the labour allocation response to security is ambiguous and depends on the returns to the dual roles of labour as reducing theft and increasing production. An improvement to security provision will decrease labour allocated to the high expected-theft crops if the substitution of security for guard labour dominates the increased returns to productive labour, as follows:*

$$\left| \frac{\partial^2 \sigma_H(l_H, S)}{\partial l \partial S} Q_H(l_H) P_H \right| > \left| \frac{\partial \sigma_H(l_H, S)}{\partial S} Q'_H(l_H) P_H \right| \tag{3}$$

See Proof B.2 in Appendix.

6 Empirical Strategy

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:

$$\begin{aligned} Y_{i,v,t,s} = \;& \beta_0 + \beta_1 \text{Watchman Matched}_i \cdot \text{Endline}_{i,t} \\ & + \beta_2 \text{Watchman Matched}_v + \beta_3 \text{Endline}_t + \mathbf{\Gamma}_i + \epsilon_{i,v} \end{aligned} \tag{4}$$

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 $\mathbf{\Gamma}_i$), and standard errors are clustered at the village level.

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:

$$Y_{i,v,t,s} = \beta_0 + \beta_1 \text{Watchman Matched}_i + \mathbf{\Gamma}_i + \epsilon_{i,v} \tag{5}$$

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 $\mathbf{\Gamma}_i$), 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.

6.1 Geographic Spillovers

I test for cross-village geographic spillovers in perceived security from watchman-matched villages to the closest non-matched households using the following specification:

$$\begin{aligned} Y_{i,v,t,s} = \; & \beta_0 + \beta_1 \text{Watchman Matched}_i \cdot \text{Endline}_{i,t} + \beta_2 \text{Near Matched}_i \cdot \text{Endline}_{i,t} \\ & + \beta_3 \text{Watchman Matched}_v + \beta_4 \text{Near Matched}_i + \beta_5 \text{Endline}_t + \mathbf{\Gamma}_i + \epsilon_{i,v} \end{aligned} \tag{6}$$

Here, Near Matched$_i$, is a binary variable equal to one for non-matched households that are below the median (among non-matched households) distance to the centroid of a watchman-matched village, and equal to zero for matched households and non-matched households further than the median from matched village centroids. The variable of interest in this specification, to test for a treatment effect spilling over to the nearest non-matched households, is β_2, the coefficient for the interaction term between being near matched villages (Near Matched$_i$) and the endline period (Endline$_t$).

7 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, with high take-up of subsidized watchmen and the expected improvement in the perceived security of farms against theft. Next, I demonstrate that this intervention had direct economic benefits. Matched farmers changed their economic behaviour in response to this improvement in security. Agricultural yields were also higher for the intervention group than the control group. This yield effect is mostly driven by crops with low expected theft, suggesting the most likely mechanism is reallocation of farmer effort across crops. Having shown evidence that the watchman intervention successfully secured farms against theft, and that the benefits were significant, 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, and discuss the conditions under which this intervention would be individually or collectively optimal.

7.1 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 ($\sim$ 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 among farmers in the intervention group, 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.[17] In

[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.

[17] Evidence from focus groups after endline data collection suggest that this hiring was mostly done after farmers observed the effectiveness of watchmen who had been placed with the farmers who requested the earlier deployment.

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 high value crops.[18] 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 respondents experienced during the intervention season. In Table 3, I show that matched farmers were 32 *p.p.* less likely to report experiencing any theft from their farms during the experiment. In addition, I show that they were 37 *p.p.* more likely to report that theft decreased and 15 *p.p.* less likely to report an increase in theft cases from the corresponding season 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. These results suggest that either actual farm theft had been occurring at baseline, or that farmers are poorly informed about actual theft and these perceptions of theft experiences are driven by feelings of security.[19]

7.2 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 show that improved security allowed farmers to adjust their economic behaviour. I then explore the effect on farm yields and agricultural profits.

[18]In Supplementary Table A3, I show that this effect on perceived security holds with various other measures of perceived farm security and vulnerability to opportunistic theft. In Tables A3 and A4 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.

[19]Given qualitative information at baseline, farmers did not perceive farm theft to be common, and mostly discussed theft in terms of fear of theft in case of acting differently.

7.2.1 Economic Behaviour

I now show that the experimental manipulation to farm security, described above, led to significant changes in the production, time use and investment decisions made by farmers.[20] In Table 4, 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. [21] 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.[22] 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.[23] 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.

[20]See Supplementary Table A5 for the pre-registered outcome indices. In this table I 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 A6, A7 and A8 for results with these indices broken down into individual components.

[21]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.

[22]I show in Table A9 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 are had the largest raw 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.

[23]This rises to 12.5% using the average partial effects from a logit model.

[24]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 A10 where I show that farmers in the intervention group were significantly more likely to have had any off-farm sales of Tomatoes and Kales 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 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 where the strongest treatment effect is observed are long-term assets, whose returns will not be realised during the treatment period.[25] I show below that this outcome is rationalised by a windfall from increased agricultural yields this season and anticipated future hiring of farm security.[26] This mechanism is consistent with the results in Gertler et al. (2012), where farmers reinvested a cash transfer.

[24]As shown in Figure A5, an endline survey of farmers who hired watchmen shows that crop change is by far the most frequent long-run change they would make should they continue to have farm security.

[25]I show which of the nineteen asset categories display the greatest difference in buying and renting difference between matched and non matched in Supplementary Table A11. This includes assets such as water tanks, that do not pay off in a single season.

[26]Evidence from post-endline focus groups also suggest that these assets were bought around harvest time once farmers had earned this windfall, and just before harvest where the expected additional yield was apparent. Some farmers in the focus group also reported that they bought assets after having decided that they would be hiring security in the future, and that this reduced the risk of owning valuable assets in the future.

7.2.2 Agricultural Yields & Profit

The results above establish that allocating watchmen to guard farms reduces fear of theft, actual theft and leads to changes in economic behaviour. I now show that this has an effect on the the value of agricultural output, and show that the pattern of these yield gains doesn't follow the ex-ante expectations of farmers. In Table 5 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, combining all crops grown by farmers.[27] In Columns 2 through 4 I decompose the increase in value of production per acre by crop characteristics related to perceived theft risk. As described in Section 4.3, 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.[28] 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 8,400 KES, more than five times greater than the coefficient on high expected theft crops, displayed in Column 3 which is approximately 1,400 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

[27] As described in Section 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 Supplementary Table A12 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.

[28] 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 Kilogram. Low Expected Theft Crops are defined as those below median for potential crops in this Opportunity for Theft Index.

explanation is that in the unsecured case there is reallocation of labour towards securing the more theft-prone crops stolen.[29] The intervention would therefore allow more labour to be allocated to the less theft-prone crops, leading to increased yields.

7.3 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. I show that there were positive externalities through reduced suspicion and disputes among neighbours. I also show evidence suggesting positive security spillovers within-village to nearby farmers, and do not find significant evidence of crime displacement from treated villages to the nearest control villages.

7.3.1 Local Conflict and Greivances

I now turn my attention to the social impact of improved security and show that improved security significantly reduces the level of local suspicion and conflict related to interference on farms between matched farmers and their neighbours.[30] 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

[29]While I do not have detailed crop-level information on time use and labour allocation, the results on input spending are suggestive of labour being reallocated to low expected theft crops. In Table A13 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.

[30]In Supplementary Table A14, 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.

of 60%. In Column 2, I show that matched farmers are a similar 21 *p.p.* less likely 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.

Along with this reduction in suspicion I discuss above, I now show that the security intervention 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 nearly half the control mean of 27%. The fact that the security intervention had such a significant effect on these latent grievances confirms that existing possible remedies for property crime are costly or ineffective, and not worth using in all cases. As described in Section 2.3, formal remedies are perceived to be ineffective, informal direct remedies involve social costs and in general there isn't perfect information on who is responsible for theft. The effect of watchmen on silent grievances shows that 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.[31] Matched farmers reported 0.6 fewer disputes over farm interference by their neighbours in the last month before harvest, a reduction

[31] In Supplementary Table A15, 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. This is, however, no conclusive evidence that the intervention decreased trust as there are other potential causes for this effect, such as seasonal effects or other external shocks to the entire sample. Given the large decrease in trust across all categories, in Supplementary Table A16 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 A17 where I show that a number of measures of attitudes towards local formal institutions decreased across-the-board from baseline to endline.

of approximately 60% of the average one 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. 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. In Table A18 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. 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.[32]

7.3.2 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 Equation 6. Here I split control villages into those nearest and those furthest from the treated group, and test for a significant interaction term $\beta_2 \text{Near Matched}_i \cdot \text{Endline}_{i,t}$. I present the results in Table A19 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 that same questions on self-reported theft experienced during the last season, and for perceived changes in the level of theft. I

[32]To properly evaluate the costs of crime through social local conflict would require an estimate of how much sample farmers would be willing to pay to avoid a conflict.

present these results in Table A20 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.[33]

7.4 Cost-Benefit Analysis

Thus far I have established that the intervention had significant direct economic benefits for farmers matched with watchmen, through relaxed constraints on economic behaviour and improved farm productivity. I also find no significant evidence for displacement of crime from treated villages to nearby control villages, in addition to significant positive externalities through reduced disputes and suspicion. Having shown these benefits of improved security, I now explore whether these interventions are optimal for farmers to undertake individually, or whether these findings motivate interventions in collective provision of property protection. In Table 7 I look at whether the yield gains outlined above are enough to 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 agres, 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

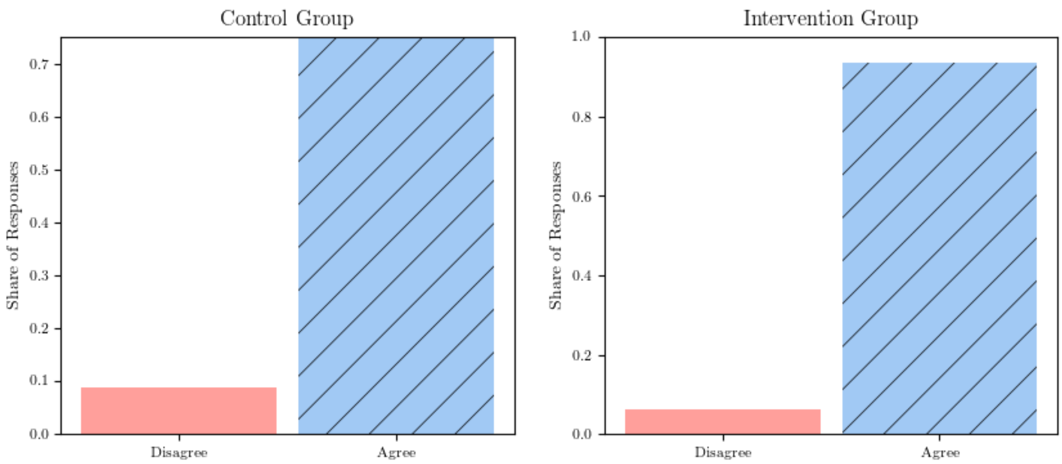
[33] These results should not be taken as evidence that there is no displacement of crime within the village - it could simply be the case that within-village displacement occurs outside the range where enumerators were easily able to find additional farmers while travelling among the core sample.

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, 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 for some reason 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.

7.5 Continuing Effects

Figure 8: Learning About Security



Description:This figure shows that both matched and non-matched groups increased their valuation of security and watchmen over the course of the project.
Data Source: Endline survey.

I document significant learning about the value of security, with more than 90% of the sample reporting they they now value security more than they did at the beginning of the treated season, as shown above in Figure 8. I directly investigate the channels by which the intervention impacted learning, and provide evidence that the pattern of learning is consistent with the surprising results on yields discussed above. In Table 8, I show that being matched with watchmen had a significant effect on numerous dimensions of self-reported learning. In Column 1, I show that the intervention group significantly increased their valuation of security, with 75% reporting that having security was more effective than they expected. In Column 2, I show that matched farmers were 8 *p.p.* more likely to have increased their valuation of security due to learning more about crop yields. In Column 3, I show that intervention group farmers were 6 *p.p.* more likely to have learned about crop prices, and as a result increased their valuation of security. In Columns 4 and 5, I show positive but insignificant evidence of treated farmers increasing their valuation of security due to learning about prices off-farm and learning about profitability of enterprise. This pattern of learning, where farmers learned about crop yields and prices, is consistent with the results I showed earlier where effects on crop yields were large and unexpected in nature.[34] In addition to direct learning by intervention group farmers, I also find significant indirect learning among the non-matched farmers. In Column 6, I show that 63% of the non-matched group reported that they had observed someone else doing well with a watchman, and now valued them more. This is consistent with the magnitude of the gains in yield, and with the unexpected stronger effect on non-opportunity theft crops. Finally, I show that the benefits observed by farmers during the intervention were significant enough to adjust their future behaviour. In Column 7, I show that approximately 55% of the matched group intend to hire a watchman in the next agricultural season (a marginally significant 7 *p.p.* greater than the non-matched mean of 49%) which is a dramatic increase from baseline when no farmers in the sample hired watchmen in the last short rain season. This is evidence of significantly updated beliefs of how their farms are impacted by theft, which suggests that short-run interventions relating to security can have long-run effects, via new information.

[34] This is consistent with the suggestive evidence from post-endline focus groups, where responses indicate that the large effects on yields was the most important piece of information learned by farmers in the non-matched group.

8 Robustness Checks

I conduct a number of robustness checks to verify the results are robust to other potential mechanisms. 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 A21 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.

9 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 actual theft and anticipated theft from engaging in different activities. I show that this improvement to farm security impacts agriculture through mechanisms that increase experimentation by farmers and allow to have greater connection to off-farm markets. Farmers matched with watchmen changed their cropping patterns, spent more time away from their farm and sold more crops at off-farm markets. In addition, matched farmers received increased agricultural yields, driven by unexpected crops. In addition, improved security 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 significant 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 success of the short-term intervention implemented in this project and the results suggestive of long-run effects, this topic merits further research.

Tables

Table 1: Baseline Balance

Category	Variable	Mean	Intervention Group	
			Diff	Std.Err
Farm Characteristics	Female Farm Manager†	.344	-.008	.0396
	Acres Owned[1]	2.334	.228	.145
	Acres Rented[1]	.387	.0469	057
	Acres Farmed	2.147	.109	.121
Theft	Frequency of Local Crop Theft	3.75	-.096	.105
	Willingness to Pay for Watchman[1,3]	284	-5	23
	Low Farm Security†	.764	.051	.036
	High Risk if Growing High Value Crops†	.691	-.0158	.039
	High Risk if Growing Different Crops†	.682	-.018	.039
Nonfarm Econ	Has Off-Farm Enterprise†	.337	-.014	.040
	Has Off-Farm Employment†	.156	-.019	.030
Gifts	Gave Neighbours Gifts†	.833	-.005	.030
	Value of Gifts to Neighbours[2,3]	226	-166 *	100
Ethnic Identity	Ethnic Theft Stereotype†	.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†	.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 [1]	.171	-.028	.029
	Land Allocated Highly Theft Prone [1]	.153	-.026	.027
	Land Allocated to New Crops [1]	.188	-.005	.041

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

Table 2: Security Manipulation Check

Outcome Variable	(1) Hired Watchman†	(2) Weeks hired watchman	(3) Low Farm Security†	(4) Theft risk: High value†
Intervention x Endline†	0.716	3.757	-0.394	-0.262
	(0.040)***	(0.274)***	(0.067)***	(0.076)***
Intervention†	-0.002	-0.005	0.053	-0.005
	(0.008)	(0.041)	(0.040)	(0.049)
Endline†	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
Non Matched Mean	0.08	0.28	0.69	0.65
Full Sample Baseline Median	0.00	0.00	1.00	1.00

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

† Binary variable, equal to 1 if true, 0 if not.

Standard Errors clustered at the village level in parentheses below estimates. Controls for all specifications: Randomization strata fixed effects. Watchman Matched 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 addition to perceived theft risk of high-value crops, there is also an effect for other categories of crops. See Table A.X in Appendix.

Table 3: Reported Farm Theft Experienced

Outcome Var	(1) Any Crop Theft†	(2) Theft Decreased†	(3) Theft Increased†
Intervention†	-0.325	0.371	-0.151
	(0.056)***	(0.048)***	(0.038)***
Num. Observations	576	576	576
Non Matched Mean	0.58	0.44	0.27

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

† Binary variable, equal to 1 if true, 0 if not.

Standard Errors clustered at the village level in parentheses below estimates. Controls for all specifications: Randomization strata fixed effects. Watchman Matched 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 Watchman Matched variable is the treatment coefficient of interest. Column 1 is a binary variable equal to one if the farmer observed any crop theft during the study season. Column 2 is a self-reported binarized outcome equal to one if observed theft experienced by the farm decreased relative to the previous season. Column 3 is a self-reported binarized outcome equal to one if observed theft experienced by the farm increased relative to the previous season. See Appendix Table AX for a specification controlling for geographic spillovers including a binary control for whether a control household was above or below the median distance to a treated village centroid.

Table 4: Economic Behaviour Change

	Cropping Patterns		Time Use		Investment	
	(1)	(2)	(3)	(4)	(5)	(6)
Outcome Var	Any Security Crops†	Share Land Change Security[1]	Spent More Time Off-Farm†	Sold More Crops Off-Farm†	Bought Farm Assets†	Rented Farm Assets†
Panel A: Linear Model						
Intervention†	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
Non Matched Mean	0.18	0.07	0.16	0.13	0.19	0.24
Panel B: Logit Model, Average Partial Effects						
Intervention†	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
Non Matched Mean	0.18	0.07	0.16	0.13	0.19	0.24

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

† Binary variable, equal to 1 if true, 0 if not.

Standard Errors clustered at the village level in parentheses below estimates.. Controls for all specifications: Randomization strata fixed effects. Watchman Matched 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 Watchman Matched 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 A9. 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. 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 Appendix Table A11.

Table 5: Value of Crop Production per Acre

Outcome Var	(1) Total Income Per Acre[1,2]	Crop Disaggregation (2) Low Expected Theft[1,2]	(3) High Expected Theft[1,2]	(4) Low Utility to Potential Thieves[1,2]
Intervention†	5,002	8,421	1,444	2,837
	(2,798)*	(3,816)**	(4,714)	(2,614)
Num. Observations	568	460	186	498
H0: (2) - (3) = 0, [p-value]			[0.202]	
Non Matched Mean	30,694	35,500	29,714	26,110
Non Matched Median	21,853	21,196	13,437	18,750

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

[1] Variable winsored at the highest 2.5% level

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

Standard Errors clustered at the village level in parentheses below estimates. Controls for all specifications: Randomization strata fixed effects. Watchman Matched 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. Value of agricultural production is constructed by restricting to crops with at least 25 observations where the crop's land allocation is at least 0.25% of the 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 market categories) 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 crops having characteristics. First, I designate crops that are not consumed directly by households (Tobacco and Sugarcane) and ubiquitous crops (Maize) as non-stealable 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 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 Kilogram. 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 A12 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.

Table 6: Local Suspicion and Conflict

Outcome Var	Suspicious of opportunistic interference by: (1) Neighbours†	(2) Strangers†	Neighbour Conflict (3) Unexpressed Grievances†	(4) Disputes last month	(5) Angry Disputes last month
Intervention†	-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

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

† Binary variable, equal to 1 if true, 0 if not.

Standard Errors clustered at the village level in parentheses below estimates. Controls for all specifications: Randomization strata fixed effects. Watchman Matched 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?".

Table 7: Intervention Cost-Benefit

		Output effects for mean farmed area	
		TOT Estimate of Intervention Effect on Yield$\sim 15,000$ KSH [1]	TOT Estimate of Intervention Effect on Profit $\sim 12,300$[2]
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[3]	3,000 KSH [16.7 %]	300 KSH [2.5%]
Valuation of non-monetary benefits	Minimum WTP per dispute for intervention to break even[4]	5,555 KSH	10,555 KSH
	WTP per Dispute as Share of Harvest/Acre[5]	15.9%	30%

[1] 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.

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

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

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

[3] Cost for six weeks of hiring a local watchman, at wages of approximately 2,000 KSH per week. This figure is derived from survey data and local informants.

[4] 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.

[5] 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.

Table 8: Learning About Security

		Value Watchmen More Because:					
Outcome Var	(1) Watchman More Effective than Expected†	(2) Learned about Crop Yields†	(3) Learned about Crop Prices†	(4) Learned about Off-Farm Prices†	(5) Learned about Enterprise Profits†	(6) Observed Others Doing Well†	(7) Next Season Hire Watchman†
Intervention†	0.464	0.085	0.055	0.013	0.022	-0.461	0.067
	(0.050)***	(0.031)***	(0.023)**	(0.014)	(0.021)	(0.044)***	(0.046)‡
Num. Observations	576	576	576	576	576	576	576
Non-matched Mean	0.29	0.03	0.02	0.02	0.06	0.63	0.49

‡ $p \leq 0.15$; * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

† Binary variable, equal to 1 if true, 0 if not.

Standard Errors clustered at the village level in parentheses below estimates. Controls for all specifications: Randomization strata fixed effects. Watchman Matched 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 whether the respondent selected "Watchmen were more effective than I previously thought" as a reason they have come to value watchmen more than at baseline. Column 2 is a binary indicator for whether the respondent selected "I learned more about how well some crops grow" as a reason for valuing security more than at the beginning of the season. Column 3 is a binary indicator for whether the respondent selected "The price for some crops was better than I expected" as a reason for valuing security more than at the beginning of the season. Column 4 is a binary indicator for whether the respondent selected "I learned that prices off-farm were much higher" as a reason for valuing security more than at the beginning of the season. Column 5 is a binary indicator for whether the respondent selected "My off-farm enterprise is more profitable than I expected." as a reason for valuing security more than at the beginning of the season. Column 6 is a binary indicator for whether the respondent selected "I saw others doing well with a watchman and now I want one" as a reason for valuing security more than at the beginning of the season. Column 7 is a binary indicator variable for whether the respondent intends to hire a farm watchman in the next season.

References

Agyei-Holmes, A., Buehren, N., Goldstein, M., Osei, R., Osei-Akoto, I. and Udry, C. (2020). *The Effects of Land Title Registration on Tenure Security, Investment and the Allocation of Productive Resources : Evidence from Ghana*, Policy Research Working Papers, The World Bank.
URL: *http://elibrary.worldbank.org/doi/book/10.1596/1813-9450-9376*

Alvazzi del Frate, A. (1998). *Victims of crime in the developing world*, United Nations Interregional Crime and Justice Reasearch Institute, Rome, Italy.

Beaman, L., Karlan, D., Thuysbaert, B. and Udry, C. (2013). Profitability of Fertilizer: Experimental Evidence from Female Rice Farmers in Mali, *American Economic Review* **103**(3): 381–386.

BenYishay, A. and Mobarak, M. (2018). Social Learning and Incentives for Experimentation and Communication, *The Review of Economic Studies* **86**(3): 976–1009.

Bergquist, L. F. (2016). Pass-Through, Competition, and Entry in Agricultural Markets: Experimental Evidence from Kenya, *Job Market Paper* .

Besley, T., Fetzer, T. and Mueller, H. (2015). The Welfare Cost of Lawlessness: Evidence from Somali Piracy, *Journal of the European Economic Association* **13**(2): 203–239.

Besley, T. and Mueller, H. (2018). Predation, Protection, and Productivity: A Firm-Level Perspective, *American Economic Journal: Macroeconomics* **10**(2): 184–221.

Blattman, C., Green, D., Ortega, D. and Tobón, S. (2017). Pushing Crime Around the Corner? Estimating Experimental Impacts of Large-Scale Security Interventions, *National Bureau of Economic Research Working Paper Series* **No. 23941**.

Blattman, C., Hartman, A. C. and Blair, R. A. (2014). How to Promote Order and Property Rights under Weak Rule of Law? An Experiment in Changing Dispute Resolution Behavior through Community Education, *American Political Science Review* **108**(1): 100–120.

Burke, M., Bergquist, L. F. and Miguel, E. (2018). Sell Low and Buy High: Arbitrage and Local Price Effects in Kenyan Markets, *The Quarterly Journal of Economics* **134**(2): 785–842.

Butinda, L. D., Lameke, A. A., Nunn, N., de la Sierra, R. S. and Winkler, M. (2020). Traditional Belief Systems and Economic Behavior: Evidence from Beer Retailers in the Eastern DRC, *Working Paper* .

Conley, T. and Udry, C. (2010). Learning about a New Technology: Pineapple in Ghana, *The American Economic Review* **100**(1): 35–69.

Cullen, J. B. and Levitt, S. D. (1999). Crime, Urban Flight, and the Consequences for Cities, *The Review of Economics and Statistics* **81**(2): 159–169.

de Janvry, A., Emerick, K., Gonzalez-Navarro, M. and Sadoulet, E. (2015). Delinking Land Rights from Land Use: Certification and Migration in Mexico, *American Economic Review* **105**(10): 3125–49.

Duflo, E., Kremer, M. and Robinson, J. (2011). Nudging Farmers to Use Fertilizer: Theory and Experimental Evidence from Kenya, *American Economic Review* **101**(6).

Dyer, J. G. (2016). Monitoring and the Maasai: Crop Theft and Institutional Legitimacy in Rural Kenya, *Unpublished Manuscript* .

Dyer, J. G. and Shapiro, J. (2018). Pumps, prosperity and household power: Experimental evidence on irrigation pumps, *Unpublished Working Paper* .

Fafchamps, M. and Minten, B. (2009). Insecurity and Welfare: Evidence from County Data, *The Journal of Development Studies* **45**(6): 831–863.

Fafchamps, M. and Moser, C. (2003). Crime, Isolation and Law Enforcement, *Journal of African Economies* **12**(4): 625–71.

Field, E. (2007). Entitled to Work: Urban Property Rights and Labor Supply in Peru*, *The Quarterly Journal of Economics* **122**(4): 1561–1602.

Fisman, R., Paravisini, D. and Vig, V. (2017). Cultural Proximity and Loan Outcomes, *American Economic Review* **107**(2): 457–92.

Foster, A. D. and Rosenzweig, M. R. (1995). Learning by Doing and Learning from Others: Human Capital and Technical Change in Agriculture, *Journal of Political Economy* **103**(6): 1176–1209.

Gertler, P. J., Martinez, S. W. and Rubio-Codina, M. (2012). Investing Cash Transfers to Raise Long-Term Living Standards, *American Economic Journal: Applied Economics* **4**(1): 164–192.

Goldstein, M., Houngbedji, K., Kondylis, F., O'Sullivan, M. and Selod, H. (2018). Formalization without certification? Experimental evidence on property rights and investment, *Journal of Development Economics* **132**: 57–74.

Goldstein, M., Houngbedji, K., Selod, H., O'Sullivan, M. and Kondylis, F. (2015). *Formalizing Rural Land Rights in West Africa: Early Evidence from a Randomized Impact Evaluation in Benin*, Policy Research Working Papers, The World Bank.

Goldstein, M. and Udry, C. (2008). The Profits of Power: Land Rights and Agricultural Investment in Ghana, *Journal of Political Economy* **116**(6): 981–1022.

Gonzalez-Navarro, M. (2013). Deterrence and Geographical Externalities in Auto Theft, *American Economic Journal: Applied Economics* **5**(4): 92–110.

Grosjean, P. (2014). A History of Violence: The Culture of Honor and Homicide in the US South, *Journal of the European Economic Association* **12**(5): 1285–1316.

Hamermesh, D. S. (1999). Crime and the Timing of Work, *Journal of Urban Economics* **45**(2): 311–330.

Hansen, B. B. and Bowers, J. (2008). Covariate Balance in Simple, Stratified and Clustered Comparative Studies, *Statistical Science* **23**(2).
URL: *https://projecteuclid.org/journals/statistical-science/volume-23/issue-2/Covariate-Balance-in-Simple-Stratified-and-Clustered-Comparative-Studies/10.1214/08-STS254.full*

Hartman, A. C., Blair, R. A. and Blattman, C. (2018). Engineering Informal Institutions: Long-run Impacts of Alternative Dispute Resolution on Violence and Property Rights in Liberia, *Working Paper 24482*, National Bureau of Economic Research.

Heß, S. (2017). Randomization inference with Stata: A guide and software, *Stata Journal* **17**(3): 630–651. Place: College Station, TX Publisher: Stata Press.
URL: *//.stata-journal.com/article.html?article=st0489*

Hornbeck, R. (2010). Barbed Wire: Property Rights and Agricultural Development, *The Quarterly Journal of Economics* **125**(2): 767–810.

Jakiela, P. and Ozier, O. (2015). Does Africa Need a Rotten Kin Theorem? Experimental Evidence from Village Economies, *The Review of Economic Studies* **83**(1): 231–268.

Janke, K., Propper, C. and Shields, M. A. (2013). Does Violent Crime Deter Physical Activity?, *IZA Discussion Papers 7545*, Institute for the Study of Labor (IZA), Bonn.

Jayadev, A. and Bowles, S. (2006). Guard labor, *Special Issue in honor of Pranab Bardhan* **79**(2): 328–348.

Karlan, D., Osei, R., Osei-Akoto, I. and Udry, C. (2014). Agricultural Decisions after Relaxing Credit and Risk Constraints, *The Quarterly Journal of Economics* **129**(2): 597–652.

Linden, L. and Rockoff, J. E. (2008). Estimates of the Impact of Crime Risk on Property Values from Megan's Laws, *The American Economic Review* **98**(3): 1103–1127.

McKenzie, D. (2012). Beyond baseline and follow-up: The case for more T in experiments, *Journal of Development Economics* **99**: 210–221.

Michalopoulos, S., Putterman, L. and Weil, D. N. (2016). The Influence of Ancestral Lifeways on Individual Economic Outcomes in Sub-Saharan Africa, *NBER Working Paper No. 21907* .

Platteau, J.-P. (2014). Redistributive pressures in sub-Saharan Africa: causes, consequences, and coping strategies, *in* E. Akyeampong, R. H. Bates, J. A. Robinson and N. Nunn (eds), *Africa's Development in Historical Perspective*, Cambridge University Press, New York.

Schechter, L. (2007). Theft, Gift-Giving, and Trustworthiness: Honesty Is Its Own Reward in Rural Paraguay, *The American Economic Review* **97**(5): 1560–1582.

Scott, J. C. (1976). *The Moral Economy of the Peasant*, Yale University Press.

Soares, R. R. (2015). Welfare costs of crime and common violence, *Journal of Economic Studies* **42**(1): 117–137.

Suri, T. (2011). Selection and Comparative Advantage in Technology Adoption, *Econometrica* **79**(1): 159–209.

A Supplementary Tables

Table A1: Economic Behaviour Change w. Baseline Controls

	Cropping Patterns		Time Use		Investment	
	(1)	(2)	(3)	(4)	(5)	(6)
Outcome Var	Any Security Crops†	Share Land Change Security[1]	Spent More Time Off-Farm†	Sold More Crops Off-Farm†	Bought Farm Assets†	Rented Farm Assets†
Watchman Matched†	0.132	0.086	0.119	0.093	0.120	-0.055
	(0.052)**	(0.028)***	(0.032)***	(0.042)**	(0.044)***	(0.036)
Baseline Controls	✓	✓	✓	✓	✓	✓
Num. Observations	569	569	569	569	569	569
Non-matched Mean	0.18	0.07	0.16	0.13	0.19	0.24
Control Median	0.00	0.00	0.00	0.00	0.00	0.00

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

† Binary variable, equal to 1 if true, 0 if not.

Standard Errors clustered at the village level in parentheses below estimates.. Controls for all specifications: Randomization strata fixed effects and full set of baseline controls. Watchman Matched 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 Watchman Matched 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. 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. 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.

Table A2: Value of Crop Production w. Baseline Controls

		Crop Disaggregation		
Outcome Var	(1) Total Income Per Acre[1,2]	(2) Low Expected Theft[1,2]	(3) High Expected Theft[1,2]	(4) Low Utility to Potential Thieves[1,2]
Watchman Matched†	4,727	8,592	2,902	2,531
	(2,806)*	(3,708)**	(6,315)	(2,740)
Baseline Controls	✓	✓	✓	✓
Num. Observations	563	455	186	493
H0: (2) - (3) = 0, pval:			0.353	
Control Mean	30,694	35,500	29,714	26,110
Control Median	21,853	21,196	13,437	18,750

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$
[1] Variable winsored at the highest 2.5% level
[2] Variable is in Kenya Shillings (KES), at 100 KES ≈ 1 USD
Standard Errors clustered at the village level in parentheses below estimates. Controls for all specifications: Randomization strata fixed effects. Watchman Matched is an indicator variable for assignment to the treated group who were matched to a watchman offering farm security at the subsidized rate. Value of agricultural production is constructed by restricting to crops with at least 25 observations where the crop's land allocation is at least 0.25% of the 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 market categories) 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 crops having characteristics. First, I designate crops that are not consumed directly by households (Tobacco and Sugarcane) and ubiquitous crops (Maize) as non-stealable 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 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 Kilogram. 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 A12 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.

Table A3: Other Measures of Perceived Security

Outcome Var	(1) High Risk if Growing Different Crops†	(2) High Risk if Growing Similar Crops†	(3) Perceived Likelihood of Theft Attempts
Intervention x Endline†	-0.256	-0.049	-0.595
	(0.075)***	(0.040)	(0.149)***
Intervention†	-0.007		
	(0.042)		
Endline†	-0.117		
	(0.059)*		
Num. Observations	1,154	577	576

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$
† Binary variable, equal to 1 if true, 0 if not.
Standard Errors clustered at the village level in parentheses below estimates. Controls for all specifications: Randomization strata fixed effects. Watchman Matched 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 respondent selected either four or five on a five point scale of theft risk if they had grown *different* crops to those around them. Column 2 isa binary variable indicating whether the respondent selected either four or five on a five point scale of theft risk if they had grown *similar* crops to those around them. Column 3 is a response on a scale from one to five on the likelihood of opportunistic theft attempts by people passing by their farm.

Table A4: Security Risk by Crop Types (Alternate Construction)

Outcome Var	(1) Security Risk of Growing High-Value Crops	(2) Security Risk of Growing Different Crops	(3) Security Risk of Growing Similar Crops
Intervention Group†	-0.599	-0.607	-0.413
	(0.118)***	(0.116)***	(0.093)***
H0: (1) - (3) = 0, pval:			0.014
H0: (2) - (3) = 0, pval:			0.007
Control Mean	0.26	0.26	0.17
Control Median	0.75	0.82	0.42
Num. Observations	576	576	576

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

† Binary variable, equal to 1 if true, 0 if not.

Standard Errors clustered at the village level in parentheses below estimates. Controls for all specifications: Randomization strata fixed effects. Watchman Matched is an indicator variable for assignment to the treated group who were matched to a watchman offering farm security at the subsidized rate. All outcomes are standardized z-score outcomes from the raw 5-point scale. Column 1 refers to perceived likelihood of theft if the farmers had grown *high-value* crops during this season. Column 2 refers to perceived likelihood of theft if the farmers had grown *different* crops than their neighbours during this season. Column 2 refers to perceived likelihood of theft if the farmers had grown *different* crops to their neighbours during this season. Column 2 refers to perceived likelihood of theft if the farmers had grown *similar* crops to their neighbours during this season.

In Column 3 below point estimates I report the p-value of the difference between Columns 1 and 3, and Column 2 and 3. These significant differences indicate that improved security had a significantly stronger effect on high-value or different crops than the crops similar to what everyone else was growing.

Table A5: Pre-Registered Outcome Indices

Outcome Var	(1) Cropping Patterns[1]	(2) Off Farm Time Use[2]	(3) Prices & Market Interaction[3]
Panel A: Diff-in-Diff Specification			
Intervention x Endline†	0.266	0.282	0.138
	(0.151)*	(0.148)*	(0.077)*
FWER p-value	[0.17]	[0.17]	[0.17]
FDR p-value	[0.19]	[0.19]	[0.19]
Intervention†	-0.024	-0.051	
	(0.097)	(0.107)	
Endline†	0.618	0.000	
	(0.092)***	(0.085)	
Control Mean	0.31	0.00	0.00
Control Median	0.04	-0.31	-0.17
Num. Observations	1,153	1,153	576
Panel B: ANCOVA (Baseline as Controls) Specification			
Intervention x Endline†	0.260	0.242	0.139
	(0.126)**	(0.081)***	(0.077)*
FWER p-value	[0.02]	[0.02]	[0.12]
FDR p-value	[0.08]	[0.01]	[0.08]
Control Mean	0.00	0.00	-0.00
Control Median	-0.11	-0.26	-0.18
Num. Observations	577	577	577

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

† Binary variable, equal to 1 if true, 0 if not.

Standard Errors clustered at the village level in parentheses below estimates. P-values for multiple hypothesis corrected tests are reported in square brackets below point estimates. FWER p-value refer to the Family-Wise Error Rate method, and FDR p-values refer to the False Discovery Rate method. Both tests computed with one thousand iterations. Controls for all specifications: Randomization strata fixed effects. Watchman Matched is an indicator variable for assignment to the treatment group. Panel A reports results using the more conservative differences-in-differences specification. Panel B reports results using the ANCOVA specification discussed in McKenzie (2012).

[1] Cropping Patterns Index. Combined index of variables indicating change in cropping patterns. See Table A6 for results for the individual component variables.

[2] Off Farm Time Use Index. Combined index of variables indicating more time spent off-farm. See Table A7 for results for the individual component variables.

[3] Prices & Market Interaction Index. Combined index of variables indicating greater market interaction for crop sales. See Table A8 for results for the individual component variables.

Table A6: Components: Cropping Patterns Index

Outcome Var	(1) New Crops Land Share	(2) Any New Crops†	(3) Theft Prone Land Share	(4) Any Theft Prone Crops†	(5) Highly Theft Prone Land Share	(6) Mean Theft Risk	(7) Land Use Change	(8) Land Share Sec. Crops	(9) Num. Sec. Crops
Intervention x Endline†	-0.006	0.028	-0.012	-0.016	-0.008	0.008	0.153	0.137	0.437
	(0.064)	(0.077)	(0.028)	(0.065)	(0.026)	(0.090)	(0.169)	(0.042)***	(0.139)***
Intervention†	0.019	-0.004	0.000	-0.019	-0.002	-0.033			
	(0.034)	(0.042)	(0.019)	(0.049)	(0.016)	(0.056)			
Endline†	0.140	0.192	0.126	0.227	0.106	0.350			
	(0.039)***	(0.048)***	(0.018)***	(0.044)***	(0.018)***	(0.057)***			
Observations	1,151	1,153	1,151	1,153	1,151	1,151	577	577	577
Non-Matched Mean	.15	.29	.14	.46	.12	-1.21	.55	.09	.26

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

† Binary variable, equal to 1 if true, 0 if not.

Standard Errors clustered at the village level in parentheses below estimates. Controls for all specifications: Randomization strata fixed effects. Watchman Matched is an indicator variable for assignment to the treated group who were matched to a watchman offering farm security at the subsidized rate.

The outcome in Column 1, New Crops Land Share, is the share of land the farmer allocated to new crops they had never grown before. In Column 2, Any New Crops, is a binary variable that records whether the farmer grew any crops they had never grown before. In Column 3, Theft-Prone Land Share, is the share of land the farmer allocated to crops classified as theft-prone, defined as crops that are above-median in the ranking of theft-riskiness measured by an index of objective characteristics. Column 4, Any Theft Prone Crops, is a binary variable that records whether the farmer grew any crops classified as theft-prone, defined as crops that are above-median in the ranking of theft-riskiness measured by an index of objective characteristics. Column 5, Highly Theft Prone Land Share, is the share of land the farmer allocated to crops classified as highly theft-prone, defined as crops that are above the seventy-fifth percentile in the ranking of theft-riskiness measured by an index of objective characteristics. Column 6, Mean Theft Risk, is the land share-weighted mean of standardized theft-riskiness scores of crops grown by the farmer. Column 7, Land Use Change, is the total percentage of baseline land that was reallocated to a different crop at endline. Column 8, Land Share to Security-Constrained Crops, is the *total* share of land allocated to crops that the farmer identified as security-constrained, which they either began growing for the first time or to which they allocated additional land, due to security. Column 9, Number of Security-Constrained Crops, is the count of crops that the farmer identified as security-constrained, which they either began growing for the first time or to which they allocated additional land, due to security.

Table A7: Components: Time Use Index

Outcome Var	(1) Any Off-Farm Enterprise†	(2) Any Off-Farm Employment†	(3) Share of Reported Time Spent Off Farm	(4) Spent More Time Off-Farm†
Intervention x Endline†	0.012	0.043	0.015	0.119
	(0.049)	(0.041)	(0.010)	(0.032)***
Intervention†	-0.017	-0.022		
	(0.045)	(0.037)		
Endline†	-0.334	-0.132		
	(0.033)***	(0.030)***		
Observations	1,153	1,153	576	577
Non-Matched Mean	.18	.1	.45	.16

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

† Binary variable, equal to 1 if true, 0 if not.

Standard Errors clustered at the village level in parentheses below estimates. Controls for all specifications: Randomization strata fixed effects. Watchman Matched is an indicator variable for assignment to the treated group who were matched to a watchman offering farm security at the subsidized rate.

In Column 1 the outcome, Any Off-Farm Enterprise, is a binary variable recording whether the farmer had any off-farm enterprise during this season. In Column 2, Any Off-Farm Employment, records whether the farmer had any off-farm employment (casual or salaried) during this season. In Column 3, Share of Reported Time Spent Off Farm, is the share of total reported time use allocated to off-farm economic and social activities. In Column 4, Spent More Time Off-Farm, is a self-reported binary variable recording whether the farmer spent more time off-farm this season than the equivalent season last year.

Table A8: Components: Prices & Market Interaction

Outcome Var	(1) Share of Harvest Sold	(2) Share of Crops Sold Off-Farm	(3) Avg. Share of Harvest Sold Off-Farm	(4) Price Premium above Mean	(5) Sold More Crops Off-Farm†
Intervention†	62.998	-0.029	-8.030	-0.618	0.104
	(82.085)	(0.032)	(7.549)	(0.627)	(0.045)**
Num. Observations	574	574	574	458	577
Non-matched Mean	80.08	.39	8.48	.47	.13
Control Median	0.56	0.33	0.25	-0.70	0.00

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

† Binary variable, equal to 1 if true, 0 if not.

Standard Errors clustered at the village level in parentheses below estimates. Controls for all specifications: Randomization strata fixed effects. Watchman Matched is an indicator variable for assignment to the treated group who were matched to a watchman offering farm security at the subsidized rate.

In Column 1 the outcome Share of Harvest Sold is the percentage (0-100) of harvest that was sold on markets as opposed to self-consumed. In Column 2, Share of Crops Sold Off-Farm measures the share of crops grown that had any sales off-farm. Column 3, Avg. Share of Harvest Sold Off-Farm, is the average percent (0-100) of harvests sold off-farm. This is computed by taking the average of share of harvest sold off-farm for each crop. Column 4 is the average price premium relative to the mean. This is computed by measuring, for each crop, the difference between mean price received by a farmer for that crop as a share of the mean. This mean deviation by crop is then averaged to generate an aggregate price premium above the mean. Column 6, Sold More Crops Off-Farm, is a binary self-reported variable asking farmers whether they had increased their off-farm sales this season relative to the equivalent season in the previous year.

Table A9: Cropwise New/Increase Treatment Effect

	Intervention Group			Summary Stats	
	Treatment Effect Point Estimate	Treatment Effect Standard Error	Treatment Effect as share of Control Mean	Control Mean	Num Observations
Beans	**.1049*** **	(.0346)	**.73**	.1437	577
Maize	**.0653***	(.0337)	**.3**	.2141	577
Kale	**.0507*** **	(.0193)	**.82**	.0616	577
Cassava	.0272	(.0184)	.44	.0616	577
Tomatoes	**.0222** **	(.0113)	**3.76**	.0059	577
Tobacco	.0193	(.0165)	.94	.0205	577
Green Maize	.0174	(.014)	1.18	.0147	577
Melon	**.014** **	(.0072)	**.**	0	577
Saga	.0138	(.0107)	1.18	.0117	577
Cabbage	.0115	(.0083)	1.95	.0059	577

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$
Controls for each specification: Randomization strata fixed effects. Standard Errors clustered at the village level.
This table presents regressions where the binary outcome is whether a respondent listed that particular crop as one where they either i) grew it for the first time or grew this variety for the first time this year or ii) increased the amount of land allocated to that crop relative to the equivalent season last year.
The two crops with the largest reallocations by raw difference between treatment and control are, Maize and Beans. This is to be expected, as they are the most common crops and hence have the lowest adjustment costs for a farmer. The other crops with a significant difference between intervention group and the control group are Kale, Tomatoes and Melons, all of which were identified in a sample of comparable farmers as being among the most theft-constrained. (See Figure 3.)

Table A10: Cropwise Off-Farm Sales Treatment Effect

	Intervention Group			Summary Stats	
	Treatment Effect Point Estimate	Treatment Effect Standard Error	Treatment Effect as share of Control Mean	Control Mean	Num Observations
Tomatoes	**.48****	(0.20)	4.8	.1	22
Crotolaria (mito)	.45	(0.31)	1.6	.29	20
Saga	.22	(0.23)	2.2	0.1	17
Kale	**.18****	(0.08)	0.69	.26	114
Tobacco	.14	(0.11)	3.5	.04	47
Soybean	.09	(0.52)	.69	.13	16
Sweet potatoes	.09	(0.12)	.35	.26	57
Cassava	.03	(0.08)	.07	.41	153
Beans	.02	(0.06)	.05	.44	362
Banana/plantain	0.00	(0.1)	0	.28	57
Maize	-.04	(0.04)	-.09	.43	489
Sugarcane	-.06	(0.06)	-2	.03	55
Millet	-.07	(0.20)	-.18	.4	42
Sorghum	-.13	(0.17)	-.65	.2	24
Groundnuts	-.13	(0.09)	-.28	.45	114
Green Maize	-.2	(0.12)	-.21	.96	40
Potato	-.31	(0.35)	-.56	.55	17

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

Controls for each specification: Randomization strata fixed effects. Standard Errors clustered at the village level.

This table presents regressions where the binary outcome is whether a respondent reported any off-farm sales (either at the local market or to some other off-farm buyer) for the given crop. The two crops with significant differences in likelihood of off-farm sales are Kale and Tomatoes. Both of these were identified in a sample of comparable farmers as being among the most theft-constrained. (See Figure 3.)

Table A11: Assets Bought & Rented

Panel A: Buying

Asset Name	Intervention	p-value	Control Mean
Water tank	.041	.042	.023
Ox-Ploughs	.04	.085	.029
Greenhouse	.037	.029	.003
Hip pump	.036	.002	0
Zero grazing unit	.032	.015	.003

Panel B: Renting

Asset Name	Intervention Effect	p-value	Control Mean
Oxen/work bulls	-.028	.118	.07
Knapsack sprayers	-.027	.045	.041
Ox-Ploughs	-.016	.614	.135
Boreholes/wells	-.013	.081	.015
Water tank	-.012	.186	.023

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

† Binary variable, equal to 1 if true, 0 if not.

Reported p-values are clustered at the village level. Controls for all specifications: Randomization strata fixed effects. Panel A reports the five asset categories with the largest absolute magnitude of treatment effect on buying, out of a total of eighteen asset categories. The outcome variable is a binary indicator variable equal to one if the respondent reported buying an asset of this category, equal to zero if the respondent did not select this asset or reported they did not buy any farm assets at all. Panel B is similar to Panel A, but reports the five asset categories with the largest absolute magnitude of treatment effect on renting.

Table A12: Cropwise Income per Acre Treatment Effect

	Intervention Group†		Crop Characteristics		
	Coefficient	Standard Error	Harvest Window	Harvesting Time	Theft of Opportunity Index
Panel A: Low Expected Theft					
Millet	16812	(10343)‡	1	10	-1.027
Groundnuts	-470	(13255)	2	10	-.879
Cassava	10054	(3772)***	4	10	-.584
Sweet potatoes	38742	(24158)‡	1	7	-.415
Beans	9406	(5560)*	1	5	-.007
Panel B: High Expected Theft					
Green Maize	-1126	(8598)	2	5	.141
Banana/plantain	94408	(99111)	3	5	.288
Kale	1657	(6469)	24	3	3.794
Panel C: Low Utility to Thieves					
Maize	1679	(1671)	1	5	.
Sugarcane	-17757	(29322)		3	.
Tobacco	17858	(26482)	12	6	.

‡ $p \leq 0.15$; * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Here I report cropwise results for value of agricultural output per farmed acre. These cropwise results are aggregated to generate the yield effects reported in Table 5.

The characteristics in the right panel show the crop characteristics that are perceived to be related to ease of theft, and thus form the breakdown of crops into the three categories I use in Table 5.

Value of agricultural production is constructed by restricting to crops with at least 25 observations where the crop's land allocation is at least 0.25% of the 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 market categories) 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 crops having characteristics. First, I designate crops that are not consumed directly by households (Tobacco and Sugarcane) and ubiquitous crops (Maize) as Low Utility to Thieves as these are unlikely to be targets of theft. The remaining potential crops are then split into High Expected Thefts and Low Expected Theft 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 Kilogram. Low Expected Theft Crops are defined as those below median for potential crops in this Opportunity for Theft Index.

Table A13: Fertilizer Spending Treatment Effect

	Intervention Group			Summary Stats	
	Treatment Effect Point Estimate	Treatment Effect Standard Error	Treatment Effect as share of Control Mean	Control Mean	Num Observations
Panel A: Fertilizer					
Millet	1557	1115.56	.17	61	42
Sugarcane	1139	1404.52	.42	4841	55
Banana/plantain	519	517.94	.32	698	57
Maize	328	245.08	.18	1697	489
Cassava	**48****	24.22	.05	0	153
Groundnuts	-88	201.99	.66	279	114
Beans	-362	275.86	.19	1325	362
Kale	-736	814.39	.37	2971	114
Green Maize	-1330	1133.58	.25	2249	40
Tobacco	-2706	6334.49	.67	13046	47

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$
Controls for each specification: Randomization strata fixed effects. Standard Errors clustered at the village level.
This table presents regressions where the outcome is intensity of spending on fertilizer for the given crop.
The only crop with a significant difference is Cassava, which is typical of the type of low expected theft crop that is largely driving the income effect. This does not directly capture whether farmers reallocated their own time and labour towards these crops, but it is suggestive evidence consistent with this mechanism.

Table A14: Neighbour Gift-Giving

	Gifts Given		Gifts Received	
Outcome Var	(1) Any Gifts Given†	(2) Size of Gifts Given[a]	(3) Received Any Gifts†	(4) Size of Gifts[a]
Intervention Group x Endline†	0.040	195	0.035	24
	(0.068)	(111)*	(0.049)	(18)
Intervention Group†	-0.006	-154		
	(0.037)	(104)		
Endline†	-0.460	-1,015		
	(0.046)***	(73)***		
Num. Observations	1,153	1,153	576	576
Non-Matched Mean	0.61	664	.	.
Full Sample Baseline Median	1.00	550	.	.

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

† Binary variable, equal to 1 if true, 0 if not.

[a] This variable is measured in Kenya Shillings (KES), at 100 KES ≈ 1 USD.

Standard Errors clustered at the village level in parentheses below estimates. Controls for all specifications: Randomization strata fixed effects. Watchman Matched is an indicator variable for assignment to the treated group who were matched to a watchman offering farm security at the subsidized rate.

The outcome in column 1 is a binary variable recording whether farmers gave any gifts (in-kind or monetary) to their neighbours. In Column 2, the outcome is the total size of these gifts given to neighbours. The outcome in Column 3 is a binary variable recording whether farmers received any gifts (in-kind or monetary) from their neighbours. Column 4 records the approximate of gifts received, with no gifts received being included as zero.

Table A15: Trust

Outcome Var	(1) Neighbours	(2) Chief	(3) Other Ethnic Groups	(4) Non Neighbours	(5) Strangers
Intervention x Endline†	0.009	0.186	-0.053	-0.032	-0.057
	(0.202)	(0.186)	(0.164)	(0.175)	(0.156)
Intervention†	0.016	-0.027	-0.033	0.002	-0.015
	(0.120)	(0.097)	(0.109)	(0.113)	(0.108)
Endline†	-0.238	-0.665	-0.646	-0.247	-0.278
	(0.139)*	(0.146)***	(0.122)***	(0.119)**	(0.091)***
Observations	1,153	1,153	1,153	1,153	1,153
Non-Matched Mean	3.03	3.69	2.93	2.74	2.37
Baseline Median	3.00	4.00	4.00	3.00	2.00

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

† Binary variable, equal to 1 if true, 0 if not.

Standard Errors clustered at the village level in parentheses below estimates. Controls for all specifications: Randomization strata fixed effects. Watchman Matched is an indicator variable for assignment to the treated group who were matched to a watchman offering farm security at the subsidized rate.

All outcomes are self-reported trust reported on a five-point scale, where a higher value indicates greater trust. The trust measure in Column 1 refers to the farmers neighbours, In Column 2 respondents report their trust in their local chief, in Column 3 respondents report their trust in other ethnic groups in their area, in Column 4 they report trust in non-neighbours within their village and Column 5 refers to strangers passing through their village.

Table A16: Relative Trust

Outcome Var	(1) Neighbours	(2) Non Neighbours	(3) Strangers	(4) Other Ethnic Groups	(5) Chief
Intervention Group x Endline†	-0.002	-0.043	-0.067	-0.064	0.175
	(0.104)	(0.090)	(0.121)	(0.084)	(0.142)
Intervention Group†	0.027	0.013	-0.003	-0.022	-0.016
	(0.063)	(0.061)	(0.078)	(0.059)	(0.092)
Endline†	0.177	0.167	0.137	-0.231	-0.250
	(0.063)***	(0.061)***	(0.086)	(0.055)***	(0.110)**
Observations	1,153	1,153	1,153	1,153	1,153
Non-Matched Mean	0.08	-0.21	-0.59	-0.02	0.74
Baseline Median	0.00	-0.20	-0.40	0.00	0.80

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

† Binary variable, equal to 1 if true, 0 if not.

Standard Errors clustered at the village level in parentheses below estimates. Controls for all specifications: Randomization strata fixed effects. Watchman Matched is an indicator variable for assignment to the treated group who were matched to a watchman offering farm security at the subsidized rate.

All outcomes are trust relative to an individual's mean trust in a given period. Each measure of self-reported trust reported on a five-point scale, where a higher value indicates greater trust. To generate the relative trust for each category in each period, I divide each trust measure by the respondent's mean trust across these five categories in that period. The trust measure in Column 1 refers to the farmers neighbours, In Column 2 respondents report their trust in non-neighbours within their village, in Column 3 respondents report their trust in strangers passing through their village, in Column 4 they report trust in other ethnic groups in their area and Column 5 refers to trust in their local chief.

Table A17: Institutional Attitudes

Outcome Var	(1) Trust in Chief	(2) Legitimacy of Formal Punishment	(3) Perceived Chief Competence
Intervention Group x Endline†	0.186	0.038	0.032
	(0.186)	(0.146)	(0.155)
Intervention Group†	-0.027	0.068	-0.011
	(0.097)	(0.083)	(0.080)
Endline†	-0.665	-0.475	-0.532
	(0.146)***	(0.090)***	(0.085)***
Num. Observations	1,153	1,153	1,153
Non-Matched Mean	3.69	4.12	3.84
Full Sample Baseline Median	4.00	5.00	4.00

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

† Binary variable, equal to 1 if true, 0 if not.

Standard Errors clustered at the village level in parentheses below estimates. Controls for all specifications: Randomization strata fixed effects. Watchman Matched 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 self-reported trust in the local chief, reported on a five-point scale where higher values indicate stronger trust. Column 2 reports agreement with the statement *"If someone does something bad to you, you should go to legal authorities instead of personal retaliation"* on a five-point scale, with 1 being Strongly Disagree and 5 being Strongly Agree. Column 2 is self-reported agreement with the statement *"My local chief has been doing a good job enforcing property rights and punishing thieves"* on a five-point scale, with 1 being Strongly Disagree and 5 being Strongly Agree.

Table A18: Crime and Theft Attitudes

Outcome Var	(1) Agree/Disagree: Theft acceptable if you need food	(2) Agree/Disagree: Theft acceptable if someone has better harvest	(3) Agree/Disagree: Theft Acceptable if someone earns much more than you
Intervention Group†	-0.062	-0.049	-0.102
	(0.096)	(0.089)	(0.089)
Num. Observations	576	576	576
Non-matched Mean	1.79	1.72	1.69
Control Median	2.00	1.00	1.00

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

† Binary variable, equal to 1 if true, 0 if not.

Standard Errors clustered at the village level in parentheses below estimates. Controls for all specifications: Randomization strata fixed effects. Watchman Matched 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 Watchman Matched variable is the treatment coefficient of interest. Column 1 records a score for agreement on a five-point scale that theft is acceptable in the hypothetical situation that you needs food. Column 2 records a score for agreement on a five-point scale that theft is acceptable in the hypothetical situation that you steal from someone who has a better harvest. Column 3 records a score for agreement on a five-point scale that theft is acceptable in the hypothetical situation that you steal from someone who earns much more than you.

Table A19: Farm Security - Spillover Check

Outcome Variable	(1) Hired Watchman†	(2) Weeks hired watchman	(3) Low Farm Security†	(4) Theft risk: High value†
Intervention x Endline†	0.700	3.697	-0.350	-0.221
	(0.048)***	(0.292)***	(0.074)***	(0.081)***
Near Intervention Village x Endline†	-0.032	-0.121	0.087	0.082
	(0.048)	(0.180)	(0.085)	(0.096)
Intervention†	-0.004	-0.079	-0.021	-0.054
	(0.012)	(0.063)	(0.044)	(0.054)
Near Intervention Village†	-0.005	-0.151	-0.151	-0.099
	(0.015)	(0.093)	(0.049)***	(0.062)
Endline†	0.169	0.617	-0.158	-0.135
	(0.037)***	(0.147)***	(0.053)***	(0.059)**
Non-Matched Mean	0.08	0.28	0.69	0.65
Full Sample Baseline Median	0.00	0.00	1.00	1.00
Num. Observations	1,153	1,153	1,153	1,153

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

† Binary variable, equal to 1 if true, 0 if not.

Standard Errors clustered at the village level in parentheses below estimates. Controls for all specifications: Randomization strata fixed effects. Watchman Matched is an indicator variable for assignment to the treated group who were matched to a watchman offering farm security at the subsidized rate. Near Treated Village indicates whether a control village was less than the median distance among control villages to a treatment village centroid. 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 addition to perceived theft risk of high-value crops, there is also an effect for other categories of crops.

Table A20: Within-Village Spillovers in Perceived Crime

Outcome Var	(1) Experienced any crop theft from farm this season†	(2)) Crop Theft Decreased Relative to Last Season†
Intervention Village x Endline†	-0.264 (0.076)***	0.354 (0.130)**
Num. Observations	65	65
Non-Matched Mean	0.95	0.39

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$
† Binary variable, equal to 1 if true, 0 if not.
Standard Errors clustered in parentheses below estimates.
This table reports within-village spillovers in self-reported crime experienced. Here, Watchman Matched x Endline indicates whether a spillover respondent lived in a treatment village. These spillover surveys were only conducted at endline while enumerators were travelling from household to household in order to conduct surveys with the main sample. This sample was constructed as a convenience sample within the village. The positive effect is suggestive that the presence of the watchmen reduced theft on other nearby farms as well as those assigned to treatment. This indicates that there was some perception that the watchmen nearby would discourage theft more broadly, even if they weren't actively protecting another farm.
This is suggestive evidence that there are returns to scale and that a watchman intervention can impact more than one farm household.

Table A21: Security Patrols by Chief

	Any Patrols in Last Month†		More than Two Patrols in Last Month†	
	(1)	(2)	(3)	(4)
Intervention Group x Endline†	-0.093	-0.111	0.028	0.019
	(0.077)	(0.077)	(0.061)	(0.060)
Intervention Group†	0.075	0.075	-0.007	-0.007
	(0.055)	(0.055)	(0.042)	(0.042)
Endline†	-0.059	-0.052	-0.068	-0.065
	(0.047)	(0.047)	(0.038)*	(0.038)*
Spillover Household†	0.006	-0.067	0.017	-0.018
	(0.053)	(0.072)	(0.044)	(0.052)
Intervention Village x Spillover Household†		0.173		0.083
		(0.091)*		(0.084)
Num. Observations	1,031	1,031	1,031	1,031
Non-Matched Mean	0.39	0.39	0.39	0.39

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

† Binary variable, equal to 1 if true, 0 if not.

Standard Errors clustered at the village level in parentheses below estimates. Controls for all specifications: Randomization strata fixed effects.

In Columns 1 and 2, the outcome is a binary variable indicating whether the respondent observed any security patrols by their local chief in the last month before harvest. In Columns 3 and 4, the outcome is a binary variable indicating more intensive patrols, whether the chief conducted at least two patrols in the last month before harvest.

B Theory Appendix

B.1 Proposition 1

Proof of Proposition 1. The optimization problem

$$\max_{c\in\{L,H\}} \Pi_c = \sigma_c(\bar{l},S)Q_c(\bar{l})P_c$$

means the farmer grows high theft risk crops if

$$\sigma_H(\bar{l},S)Q_H(\bar{l})P_H > \sigma_L(\bar{l},S)Q_L(\bar{l})P_L$$

or equivalently:

$$\frac{\sigma_H(\bar{l},S)}{\sigma_L(\bar{l},S)} > \frac{Q_L(\bar{l})P_L}{Q_H(\bar{l})P_H} \tag{7}$$

The derivative of the left-hand side is $\left(\frac{\partial\sigma_L(\bar{l},S)}{\partial S}\right)^{-2}\left[\frac{\partial\sigma_H(\bar{l},S)}{\partial S}\sigma_L(\bar{l},S) - \sigma_H(\bar{l},S)\frac{\partial\sigma_L(\bar{l},S)}{\partial S}\right]$ which is positive if

$$\frac{\partial\sigma_H(\bar{l},S)}{\partial S}\sigma_L(\bar{l},S) > \sigma_H(\bar{l},S)\frac{\partial\sigma_L(\bar{l},S)}{\partial S}$$

or

$$\frac{\partial\sigma_H(\bar{l},S)}{\partial S}/\frac{\partial\sigma_L(\bar{l},S)}{\partial S} > \frac{\sigma_H(\bar{l},S)}{\sigma_L(\bar{l},S)}$$

Since $\sigma_L(\bar{l},S) > \sigma_H(\bar{l},S)$, the condition $\frac{\partial\sigma_H(\bar{l},S)}{\partial S} > \frac{\partial\sigma_L(\bar{l},S)}{\partial S}$ means the left-hand side is increasing in S, while the right-hand side is constant. Therefore, under this condition, an increase to security increases the likelihood of a farmer choosing to grow high theft risk crops. □

B.2 Proposition 2

Proof of Proposition 2. I use the Implicit Function Theorem approach (as in Goldstein et al. (2018)) to analyse how the equilibrium labour allocation responds to changes in security provision. The program

$$\max_{l_H} \Pi = \sigma_L(\bar{l}-l_H,S)\cdot Q_L(\bar{l}-l_H)\cdot P_L + \sigma_H(l_H,S)\cdot Q_H(l_H)\cdot P_H$$

gives the following First Order Condition, with respect to l_H:

$$\begin{aligned}\Phi(l_H,S) \equiv & \frac{-\partial\sigma_L(\bar{l}-l_H,S)}{\partial l}Q_L(\bar{l}-l_H)P_L - \sigma_L(\bar{l}-l_H,S)Q_L'(\bar{l}-l_H)P_L \\ & + \frac{\partial\sigma_H(l_H,S)}{\partial l}Q_H(l_H)P_H + \sigma_H(l_H,S)Q_H'(l_H)P_H\end{aligned} \tag{8}$$

Now, applying the Implicit Function Theorem:

$$\frac{\partial \Phi(l_H, S)}{\partial S} + \frac{\partial \Phi(l_H, S)}{\partial l_H} \cdot \frac{\partial l_H}{\partial S} = 0$$

rearranging this gives:

$$\frac{\partial l_H}{\partial S} = -\frac{\frac{\partial \Phi(l_H,S)}{\partial S}}{\frac{\partial \Phi(l_H,S)}{\partial l_H}} \tag{9}$$

Assuming the Second Order Condition holds, then $\frac{\partial \Phi(l_H,S)}{\partial l_H} < 0$ so the sign of $\frac{\partial l_H}{\partial S}$ is the same as the sign of $\frac{\partial \Phi(l_H,S)}{\partial S}$, which is as follows:

$$\begin{aligned}
\frac{\partial \Phi(l_H, S)}{\partial S} &= -\frac{\partial^2 \sigma_L(\bar{l} - l_H, S)}{\partial l \partial S} Q_L(\bar{l} - l_H) P_L - \frac{\partial \sigma_L(\bar{l} - l_H, S)}{\partial S} Q'_L(\bar{l} - l_H) P_L \\
&\quad + \frac{\partial^2 \sigma_H(l_H, S)}{\partial l \partial S} Q_H(l_H) P_H + \frac{\partial \sigma_H(l_H, S)}{\partial S} Q'_H(l_H) P_H \\
&= \frac{\partial^2 \sigma_H(l_H, S)}{\partial l \partial S} Q_H(l_H) P_H - \frac{\partial^2 \sigma_L(\bar{l} - l_H, S)}{\partial l \partial S} Q_L(\bar{l} - l_H) P_L \\
&\quad + \frac{\partial \sigma_H(l_H, S)}{\partial S} Q'_H(l_H) P_H - \frac{\partial \sigma_L(\bar{l} - l_H, S)}{\partial S} Q'_L(\bar{l} - l_H) P_L
\end{aligned} \tag{10}$$

Recall: $\sigma_c(l_c, S)$ is the share of output **not** stolen given labour l_c and security provision S. It is therefore reasonable to assume that for low theft-risk crops, the impact of labour and security provision on theft of these much less vulnerable crops is significantly lower than the impact on high expected-theft crops. Therefore:

$$\frac{\partial^2 \sigma_L(\bar{l} - l_H, S)}{\partial l \partial S} Q_L(\bar{l} - l_H) P_L \ll \frac{\partial^2 \sigma_H(l_H, S)}{\partial l \partial S} Q_H(l_H) P_H$$

and

$$\frac{\partial \sigma_L(\bar{l} - l_H, S)}{\partial S} Q'_L(\bar{l} - l_H) P_L \ll \frac{\partial \sigma_H(l_H, S)}{\partial S} Q'_H(l_H) P_H \tag{11}$$

So, given the assumption that the impact of security and labour on the theft of low theft-risk crops is negligible compared to the impact on theft of high expected theft crops, we can rewrite $\frac{\partial \Phi(l_H,S)}{\partial S}$ as follows:

$$\frac{\partial \Phi(l_H, S)}{\partial S} \simeq \frac{\partial^2 \sigma_H(l_H, S)}{\partial l \partial S} Q_H(l_H) P_H + \frac{\partial \sigma_H(l_H, S)}{\partial S} Q'_H(l_H) P_H \tag{12}$$

Or in other words, we can say that an improvement to security provision S will decrease labour allocated to the high theft-risk crops if

$$\left|\frac{\partial^2\sigma_H(l_H,S)}{\partial l\partial S}Q_H(l_H)P_H\right| > \left|\frac{\partial\sigma_H(l_H,S)}{\partial S}Q'_H(l_H)P_H\right| \tag{13}$$

□

C Data Appendix

In this section I discuss the exact construction of the outcome variables in Section 7 where I discuss my main results.

C.0.1 Security & Perceived Theft Risk

I collect data in both survey rounds on past hiring of watchmen for the previous year's short rainy season, recording both the extensive margin (whether they hired a watchman) and the intensive margin (the number of weeks they were working). Exact question text *Did you have a farm watchman in this Short Rains season?* and *For how many weeks did they guard your farm?*.

I also ask farmers about their potential theft risk they would face if they planted high-value crops, if they grow different crops from everyone else, and if they grow the same crops as everyone else. These questions are all asked on a five-point Likert scale and binarized (as pre-registered) for ease of interpretation, where a response of four or five indicated perceived high risk of theft and based on the feedback of enumerators who reported that respondents had difficulty distinguishing between options four and five. The exact question text was *If in this last short rains season you planted high-value crops, how likely is it that they would have been stolen?* with response options *1 – no chance they would be stolen, 2 – small chance they would be stolen, 3 – some chance they would be stolen, 4 – high chance they would be stolen, 5 – definitely would have been stolen.*The measure for whether a farm was perceived to have low-security against theft was also collected on a five-point scale and binarized (as pre-registered) in the same way, where the question text was *How well protected was your farm this season?* with response options *1 - farm is well protected and nobody could steal, farm is mostly protected and unlikely that anybody could steal, 3 – thieves might be able to steal,4 – farm isn't very secure and thieves could probably steal, 5 – farm isn't secure and thieves could definitely steal.* In addition, I also asked an alternative phrasing of the perceived risk of theft, based on qualitative information, by asking *If in this last short rains season you planted different crops from others around you, how likely is it that they would have been stolen?* with the same options as above. I also asked at endline *If in this last short rains season you planted similar crops to others around you, how likely is it that they would have been stolen?* to see if the treatment effect was larger for different or high-value crops compared to common crops.

C.0.2 Actual Experience of Theft

In addition to data on perceived potential risk of theft depending on production decisions, I also collect self-reported data on perceptions of actual theft experienced. Respondents were asked whether they had experienced any theft from their farm during this season. Qualitative data collected at baseline suggested that the most important dimension of theft was indirect through distortions, so this data was only collected at endline. To deal with this, I also collected data on perceived *change* in theft occurrence from the corresponding season last year, with farmers being asked if theft frequency was increased, decreased or was roughly the same as last year. Exact question text was *Compared to this season last year, has theft/interference on your farm been ...* with response options *More frequent, About the same, Less frequent.*

C.0.3 Production & Time Use Decisions

To evaluate the effect of improved security on economic behaviour, I collect data on agricultural production, time use and investment decisions made by farmers. Farmers listed all crops they chose to grow this season, along with the area allocated to each crop. For some small plots farmers weren't sure of the area in acres/hectares, so were given the option to define the plot dimensions in strides or metres. For each crop, farmers also report their input spending in each of the following categories: Fertilizer, Seeds & Planting Material, Hired Labour, and Petrochemicals. To evaluate whether farmers are able to experiment more with improved security, farmers also report for each crop whether it is their first time planting that crop. If they chose to grow a new crop or increase land allocated to a crop, they were also asked to report the reason for doing so, with security being one possible option among others. Exact question text *Why did you decide to start planting {Crop Name}?* and *Why did you increase the area of {Crop Name}?* with the multiple choice options being *I received inputs for this crop, I knew my farm would be secured against interference/theft this season, I was told of a new marketing opportunity for this crop, I learned about this crop from someone, Other, Not Sure* I use these survey questions to generate the measures used in Columns 1 and 2 of Table 4, where Any Security Crops is a binary variable recording whether the respondent had any crops newly grown or grown on increased land due where they selected the response indicating that security was a constraint. Share Land Change Security, is the sum of additional land allocated to crops that were reported to have had land allocation increased as a result of security (coded as zero where mistakes in measurement of land meant the difference in allocated land between baseline and endline was negative, despite the respondent saying they increased their land allocation) and the land allocated to crops newly-grown as a result of security, as a share of total endline land used.

I also investigate whether security concerns constrain the time use of farmers, in particular their time spent away from the farm. To test this, I collect data at endline on estimated time per day spent on different types of activities, separated into time at home and away from home.[35] as follows: Time Spent on Crops, other economic activity (at home), leisure (at home), household chores, non-economic activity (away from home), marketing crops (off-farm), leisure time (away from home),other economic activity (away from home) and non-leisure social activity (faith based, community groups, etc.) off farm. To generate shares of time use, I take the sum of time spent in on-farm categories and off-farm categories, then divide by the total time use captured across all categories. This time use data was only collected at endline, as baseline interviews indicated more extensive changes such as new employment or enterprises, and it was only raised during pre-endline interviews that the intensive margin of change in time spent away from the farm. For this reason, I included self-reported binary variables asking whether farmers had spent more time away from the farm this year than in the equivalent season last year. The exact question text was *"Compared to last year's short rainy season, have you spent ... [More,About the Same, Less] time away from your farm this season?"*. I binarize this variable as equal to one if they selected *More*, and report it as an outcome in Column 3 of Table 4.

At endline, I also measure crop marketing behaviour. I asked farmers to report their harvest amount, amount sold and amount sold to each of six possible markets: On-farm to consumers, on-farm to middlemen, off-farm sales at local markets, sales to processing plants (tobacco and sugarcane) as well as options for other on-farm and other off-farm. As above, these questions were only included in endline as at baseline, qualitative interviews did not suggest marketing practices would be a margin of significant change. I therefore directly asked farmers for changes in their marketing with the exact text being *"Have you changed how much of your harvest you sell away from the farm?"* and a follow-up asking whether they increased or decreased. This variable is binarized, equal to one if they increased off-farm sales, and reported as Column 4 of Table 4.

To explore whether security influenced the investment behaviour of farmers, I also collect data on buying and renting of assets. Farmers reported if they had bought or rented any new assets this year and, if they responded that they had, were asked to list which assets they had bought or rented from a list of eighteen asset categories. The categories are as follows: *Hip pump, Motorized pump, Hose pipe, Ox-Ploughs, Oxen/work bulls, Knapsack sprayers, Wheelbarrows, Ox-carts/donkey carts, Hand carts, Zero grazing*

[35]Exact question text: *"In the last month before harvest, how much time did you spend (in minutes) during an average day on ..."*

unit, Boreholes/wells, Fishing equipment (boats, canoes, etc), Fish pond, Electric generator, Solar panel, Car battery, Greenhouse, and *Water Tank* with an option for *"Other, Specify"*. I created binarized variables reporting whether the farmer had bought or rented any assets this year, and included them as Columns 5 and 6 of Table 4.

C.0.4 Value of Agricultural Yield

To measure the value of agricultural production, I aggregate up from the yield for each crop. I first clean up the crop yields at the individual level, and restrict to observations where the farmer allocates a non-negligible amount of their land ($>$ 0.25% of their land) and where there are at least 25 yield observations for that crop. Yields are winsored within-crop at the highest 2.5%. To find a consistent price for each crop, in order to aggregate, I use the median sale price across all markets for each crop and multiply this price by the yield. These crop-level yield values are used for the cropwise regressions in Appendix Table A12. I then aggregate these crops up to the farm level by taking the weighted mean income per acre within the three categories Low Expected Theft, High Expected Theft, Low Utility to Potential Thieves. Outliers in these farm-level values are then winsored at the highest 2.5%, to generate the values used in Table 5.

C.0.5 Learning

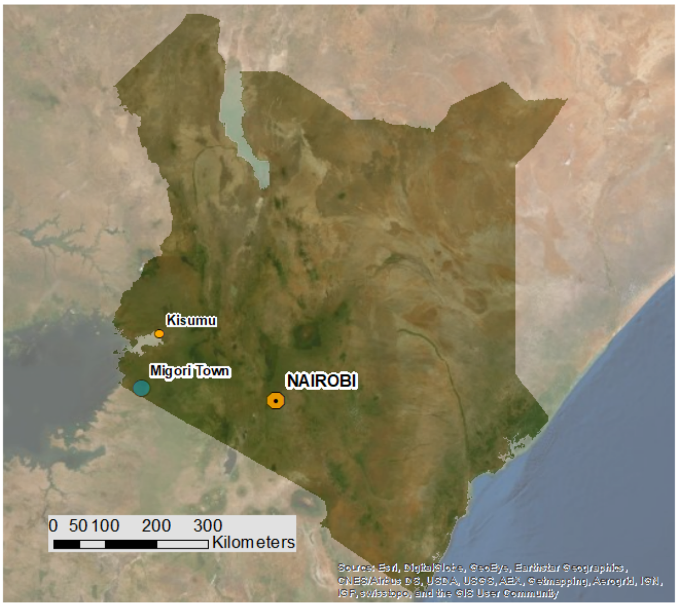
To understand whether farmers learned and in what ways they learned, I directly asked survey questions about the reasons for their updated beliefs. I fist ask whether farmers now value security more than they did at the beginning of the project. The exact text of the question was *"Have you come to value farm security / watchmen more during this season?"* As a follow-up to this question asking whether the farmers had increased their valuation of security, I then asked for reasons why they had changed their valuation. This took the form of a multiple-choice question, capturing direct learning about watchman effectiveness, learning about farm yields for different crops, learning about crop prices, learning about off-farm prices, and learning about the profits they might earn from their enterprise. This also captures direct information spillovers where non-matched farmers observed the experience of a matched farmer. Each of these options, as a binary variable equal to one if the response was selected and equal to zero if the response was not selected or the respondent reported no learning, is an outcome in Table 8.

C.0.6 Local Conflict

I now explain the details of the measures of local suspicion and conflict reported in Table 6. 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?"*.

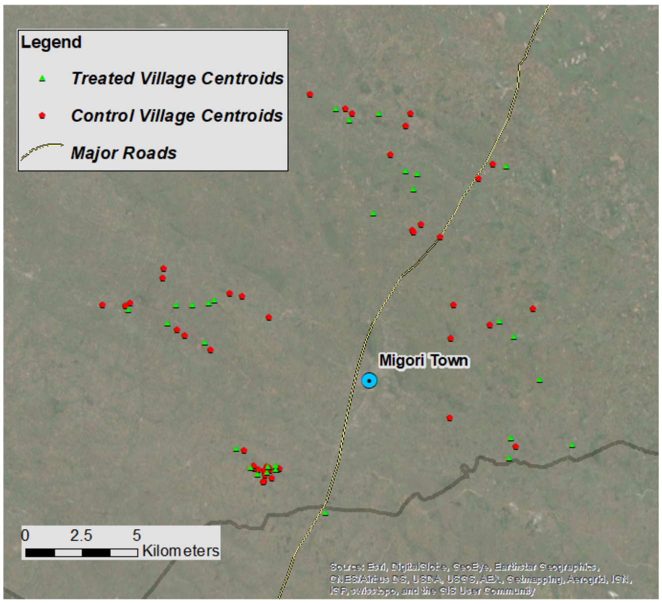
D Supplementary Figures

Figure A1: Experiment Location Within Kenya



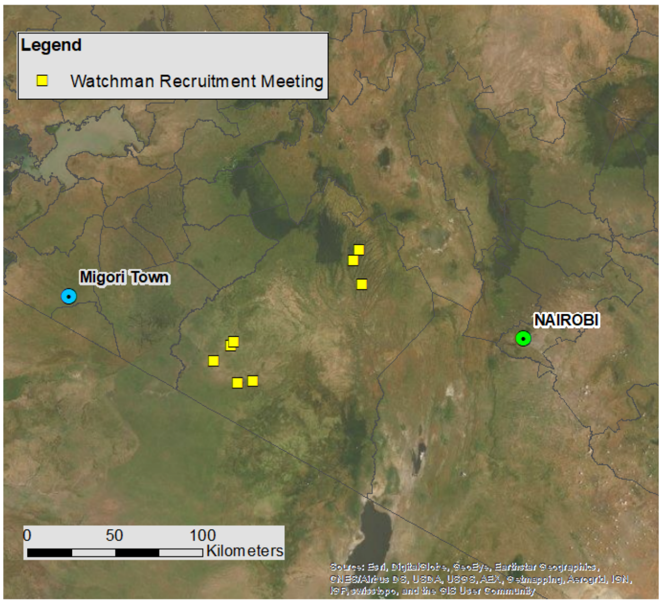
Description: Map showing experiment location (Migori) relative to nearby major population centres in Kenya.

Figure A2: Sample Villages around Migori Town



Description: This map shows the centroids of treated and control village around Migori town centre.

Figure A3: Watchman Recruitment Map

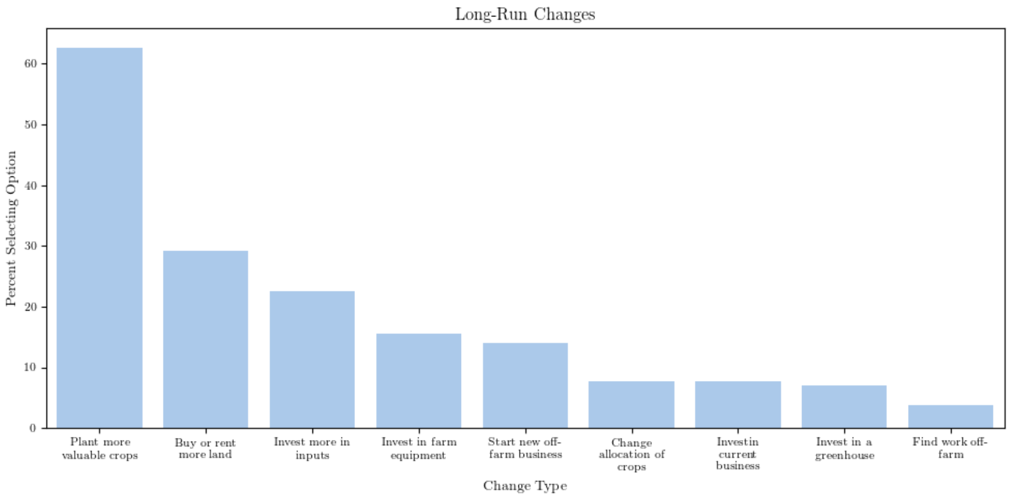


Description: This map shows the locations of watchmen recruitment meetings. Recruitment took place in the north, near the city of Narok, where underemployed young people often go looking for work, and in the south of Maasailand near the game reserves, where underemployed young people also go looking for work in the tourism sector.

Figure A4: Typical Plot Boundary

Description: This figure shows that where plots are not demarcated by a natural boundary like a river or road, they are clearly demarcated by a man-made boundary such as the hedgerow at the edge of the maize field in the photo above.
Data Source: Author's own photograph.

Figure A5: Anticipated Long-Run Behaviour Change



Description: This figure shows the responses when asking respondents who had watchmen what their long-run changes would be if they had security from now on. This is suggestive evidence of how these results would extrapolate to a longer-run intervention, and suggests that changes in crop choices would become even more important in the long-run.
Data Source: Endline survey.

E Robustness Checks on Main Results

Table D1: Value of Crop Production - Robustness to Outcome Construction

Outcome Var	(1) Total Income Per Acre[1,2]	Crop Disaggregation (2) Low Expected Theft[1,2]	(3) High Expected Theft[1,2]	(4) Low Utility to Potential Thieves[1,2]
Panel A: Raw yields, no Winsor[3]				
Intervention Group†	5,039	8,575	-52	3,766
	(3,157)	(3,908)**	(5,427)	(2,950)
Num. Observations	568	460	186	498
H0: (2) - (3) = 0, pval:			0.144	
Control Mean	31,920	36,075	31,628	26,474
Control Median	21,853	21,196	13,437	18,750
Panel B: Local informant prices[4]				
Intervention Group†	5,205	7,098	14,529	2,539
	(2,915)*	(3,507)**	(12,944)	(2,402)
Num. Observations	568	460	186	498
H0: (2) - (3) = 0, pval:			0.554	
Control Mean	34,375	33,007	65,475	27,283
Control Median	25,323	20,272	30,044	21,737
Panel C: Crops, min 50 obs[5]				
Intervention Group†	4,902	8,579	4,514	1,755
	(2,781)*	(3,858)**	(6,819)	(2,026)
Num. Observations	556	456	155	492
H0: (2) - (3) = 0, pval:			0.550	
Control Mean	29,664	36,109	31,343	22,334
Control Median	21,301	21,060	12,176	16,200
Panel D: Clean land allocation outliers[6]				
Intervention Group†	5,059	8,492	1,444	2,847
	(2,799)*	(3,824)**	(4,714)	(2,613)
Num. Observations	568	460	186	498
H0: (2) - (3) = 0, pval:			0.198	
Control Mean	30,675	35,488	29,714	26,100
Control Median	21,716	21,196	13,437	18,750

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

[1] Variable winsored at the highest 2.5% level

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

[3] This construction uses raw individual farm yields by crop, unlike Table 5 where individual farm yields are winsored by crop at the highest 2.5%. Construction of outcome for each column is otherwise identical to Table 5.

[4] This construction uses market prices sourced from local informant, unlike Table 5 each crop is priced at the median sale price. Construction of outcome for each column is otherwise identical to Table 5.

[5] This construction restricts to crops with at least 50 observations, unlike Table 5 which restricts to crops with 25 observations. Construction of outcome for each column is otherwise identical to Table 5.

[6] This construction uses land allocated to each crop, winsored the highest 2.5%, unlike Table 5 which uses raw land allocations. Construction of outcome for each column is otherwise identical to Table 5.

Table D2: Cropwise Income per Acre Treatment Effect

	Intervention Group†		Crop Characteristics		
	Coefficient	Standard Error	Harvest Window	Harvesting Time	Theft of Opportunity Index
Panel A: Low Expected Theft					
Millet	15961	(9421)*	1	10	-1.027
Groundnuts	-1327	(12653)	2	10	-.879
Cassava	9501	(3557)***	4	10	-.584
Sweet potatoes	38742	(24158)‡	1	7	-.415
Beans	9436	(5229)*	1	5	-.007
Panel B: High Expected Theft					
Green Maize	126	(7851)	2	5	.141
Banana/plantain	1388	(44863)	3	5	.288
Kale	2418	(5919)	24	3	3.794
Panel C: Low Utility to Thieves					
Maize	1288	(1492)	1	5	.
Sugarcane	-15142	(28362)		3	.
Tobacco	19894	(24892)	12	6	.

‡ $p \leq 0.15$; * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$ Yield: w5, Price: Med, Obs cutoff: 25

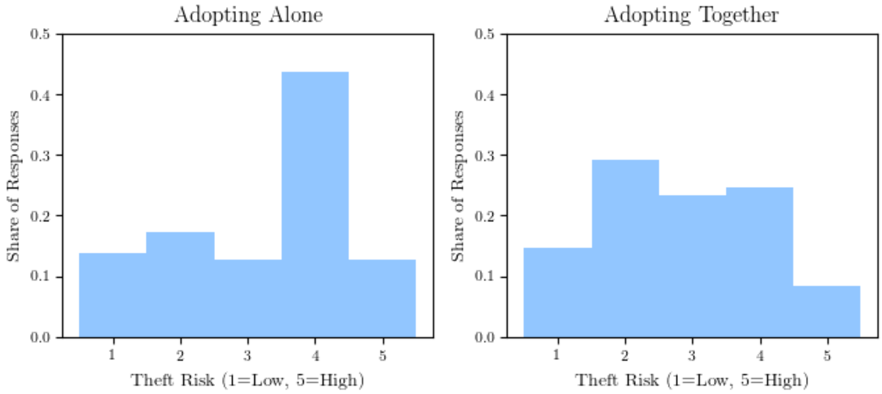
Here I report cropwise results for value of agricultural output per farmed acre. These cropwise results are similar to those in Table A12, except here I winsor the top 5% instead of the top 2.5%, to be sure that outliers are not driving the results.

The characteristics in the right panel show the crop characteristics that are perceived to be related to ease of theft, and thus form the breakdown of crops into the three categories I use in Table 5.

Value of agricultural production is constructed by restricting to crops with at least 25 observations where the crop's land allocation is at least 0.25% of the farm's total land allocation this season. Individual farm yields are winsored by crop at the highest 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 market categories) 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 crops having characteristics. First, I designate crops that are not consumed directly by households (Tobacco and Sugarcane) and ubiquitous crops (Maize) as Low Utility to 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 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 Kilogram. Low Expected Theft Crops are defined as those below median for potential crops in this Opportunity for Theft Index.

F Supplementary Descriptive Evidence

Figure A6: Theft & Experimentation



Description: This figure shows that perceived risk from being a lone adopter of new crops is significantly higher than when adopting with others.
Data Source: Baseline survey with respondents.

Theft is additionally perceived to be particularly focused on those who undertake new or different activities. This acts as a constraint on farmers who seek to experiment and adopt new technology on their own. In Figure A6, I show that the risk of theft is perceived to be significantly stronger for who adopt a new crop on their own compared to those who adopt at the same time as others. The origins of these beliefs are unclear, but it are possibly related to the 'moral economy of the peasant' as outlined in Scott (1976), where innovation and experimentation in search of greater profits is considered immoral. This morality rule is derived from an emphasis on preventing catastrophe over trying to increase expected profits. In Platteau (2014) we see a historical example of a redistributive constraint that binds for innovators. He documents how upwardly mobile individuals freed themselves from local redistributive norms by converting to Islam as an obvious signal that they had opted out of the local culture and associated reciprocal obligations. These examples are consistent with the expectations of farmers in this sample regarding how their neighbours may respond to someone who is taking risks to experiment with adoption of technology that may increase their income.