

**Transfers, Diversification and Household Risk Strategies:
Experimental evidence with lessons for climate change adaptation¹**

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Abstract

While climate change is likely to increase weather risks in many developing countries, there is little evidence on effective policies to facilitate adaptation. This paper presents experimental evidence on a program in rural Nicaragua aimed at improving households' risk management through income diversification. The intervention targeted agricultural households exposed to weather shocks related to changes in rainfall and temperature patterns. Households received either a basic conditional cash transfer, or the same CCT plus a productive intervention: a vocational training or a productive investment grant. We identify the relative impact of each of the three packages based on randomized assignment, and analyze how impacts vary by exposure to exogenous drought shocks. The results show that both packages that included a productive intervention provided protection against drought shocks two years after the end of the program. Households that received the productive investment grant also had higher average consumption levels. The complementary interventions led to diversification of economic activities and better protection from shocks compared to both beneficiaries of the basic conditional cash transfer and control households. These results show that combining safety nets with productive interventions can help households manage future weather risks and promote longer-term program impacts.

Keywords: cash transfers, investment grant, vocational training, productive safety nets, diversification, risk management, adaptation, climate change, randomized experiment.

JEL codes: 01, D1, I3.

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1. Introduction

Poor households in developing countries are often highly exposed to risk. This can lead to high welfare costs, including large reductions in consumption and increased food insecurity. It can also hamper households' productivity and upward mobility. In many countries, safety net programs have been put in place that can help poor households with short-term relief from shocks. More recently, governments from Brazil to Ethiopia, as well as international organizations including the World Bank, OECD and UN agencies are debating how to design productive safety nets and exit strategies for existing programs that can promote resilience and opportunities beyond short-term relief (World Bank, 2012).

Climate change is likely to make these policy questions even more pertinent, as agricultural households' risk exposure could further increase through changes in weather patterns and higher weather variability. Despite frequent climatic shocks, many rural households remain specialized in subsistence agriculture. They have few opportunities for adaptation or diversification, and imperfect access to coping and risk management mechanisms. Indeed, results from empirical studies suggest limited adaptation, even in developed country settings (Schlenker and Roberts, 2009). In developing countries, the many market imperfections that poor agricultural households face are likely to further constrain their ability to adapt. While the need for policies that enhance adaptation to climate change is recognized (IPCC, 2007a; World Bank 2009), existing evidence on effective interventions to facilitate household adaptation and improve risk management remains thin.

As many climatic changes most directly affect agricultural production, policy discussions typically focus on agricultural adaptation, through development and adoption of drought and heat resistant crop varieties, shifting of planting dates, changes in crop mix, or expansion of irrigation (Lobell, et al., 2008). Empirical evidence on agricultural adaptation is starting to emerge (Fishman, 2011; Hornbeck and Keskin, 2011; Olmstead and Rhode, 2011). Social protection interventions such as safety nets are seen as complementary (IPCC, 2007a; World Bank 2009). While it has been argued that livelihood diversification might be necessary for adaptation to severe climatic changes (Howden et al, 2007), there is little empirical evidence on interventions that foster such diversification.

This paper provides experimental evidence on the impact of a pilot program that combined a traditional safety net with interventions to improve households' ex ante risk management. The program targeted agricultural households who faced increased exposure to weather shocks linked to changes in rainfall and temperature patterns. It complemented a conditional cash transfer (CCT) with a vocational training or a productive investment grant. Identification relies on the randomized assignment of the different treatment

packages, and on local weather variability that provides exogenous variation in the intensity of the shocks.

The design of the complementary interventions started from the insight that households can use a wide range of strategies to manage risks ex ante and cope with shocks ex post (Fafchamps, 2003, Dercon, 2004). It aimed to expand households' possibilities for income diversification in order to decrease reliance on coping mechanisms that might have adverse effects in the long run. Indeed, empirical evidence from many settings shows that shocks can have long-term impacts on welfare through decapitalization of productive assets or human capital (Fafchamps, Udry and Czukas, 1998; Hoddinott and Kinsey, 2001; Premand and Vakis, 2010).

Poor households with limited ability to smooth consumption ex post may have to reduce the variability of their income portfolio ex ante (Alderman and Paxson, 1992). Income smoothing can hence reduce the need to deal ex post with the realization of shocks by reducing consumption. However, such strategies may be costly if expected profits are sacrificed for lower risk (Morduch, 1995). Existing empirical evidence suggests that the implicit insurance premium related to choosing low-risk, low-return strategies can be substantial (Rosenzweig and Binswanger, 1993; Dercon, 1996).²

Many policy interventions address ex post coping, for instance, by providing short-term protection once shocks have realized. Evidence has shown that interventions such as safety nets, food aid or cash transfers can provide short-term protection against shocks (Dercon and Krishnan, 2004; Yamano et al., 2005; de Janvry et al., 2006; Skoufias, 2007). Much less evidence exists regarding policies aimed at improving households' ex ante risk strategies (Elbers, Gunning and Kinsey, 2007). A notable exception is the growing body of studies analyzing weather insurance interventions showing mixed results, in part related to low take-up (Cole et al., 2012; Cole, Giné and Vickery, 2012, Giné and Yang, 2009, Karlan et al. 2012).

This paper contributes to this literature by providing experimental evidence on an intervention aimed at improving households' ex ante risk management through income diversification in rural Nicaragua. Despite the high frequency of droughts in the study region, most households primarily depend on semi-subsistence agriculture and diversification into non-agricultural activities is limited. A one-year basic conditional cash transfer intervention provided short-term shock relief through cash, conditional on

² Dercon (1996) shows that farmers in western Tanzania who have limited options to smooth consumption ex post are more likely to grow lower return but safer crops. As a result, households pay an implicit insurance premium of up to 20 percent of their income. Rosenzweig and Binswanger (1993) show that the poorest households in semi-arid India hold a low-risk low-return portfolio and estimate that a one standard deviation decrease in weather risk would raise their average profits by up to 35 percent.

human capital investments.³ This was complemented with interventions aimed at helping households protect themselves against future shocks, by enhancing income diversification beyond agriculture. A first group of beneficiaries received a traditional CCT, a second group received a traditional CCT and a vocational training, and a third group received a traditional CCT and a productive investment grant. Households were assigned to one of the three groups based on a lottery in each treatment community. Treatment communities were themselves randomly selected, so that each of the intervention groups can also be compared to an experimental control group.

Longitudinal rainfall and temperature data show that climatic changes are affecting the main agricultural crop cycles in the study region, consistent with farmers' reports of increased variability. While on average almost two thirds of the farmers report having been affected by droughts in the year before the follow-up survey, there is substantial local variation in rainfall and temperature shocks at critical periods during the crop growth cycles. Based on insights from agronomical models, we define different weather variables that together are good predictors of self-reported shocks. Using a 2SLS approach, we then rely on this exogenous variation in shock intensity to examine how the impact of such shocks varies across the different treatment and control groups.

The results in this paper show that, two years after the end of the intervention, households eligible for the complementary interventions were better protected against the negative impact of drought shocks. In fact, for total and food consumption, as well as for income, the negative impact of increases in shock intensity is completely offset. This holds for the intervention that provided households with a productive grant to invest in a nonagricultural self-employment activity, as well as for the other complementary intervention aimed at building skills through vocational training. These results differ significantly from those of the basic CCT, indicating that the protection against shocks comes from the complementary interventions. In addition, for household eligible for the productive investment grant, there is a significant positive impact on consumption and income at average drought intensity. This intervention hence helped to both increase and smooth consumption and income.

To shed light on the mechanisms, the paper shows that the complementary interventions increased households' participation in non-agricultural activities, as well as returns from such activities. And by analyzing whether results differ depending on the shock intensity in neighboring communities, we infer that households with nonagricultural activities likely smooth their income by offering their products or services to households from communities less affected by shocks.

³ The short-run impact of the program were consistent with the safety net objective by increasing school enrollment and consumption, improving nutrition and reducing delays in early childhood cognitive development (Macours and Vakis, 2009; Macours, Schady and Vakis, 2012). Similar results have been shown for CCTs in other countries (Fiszbein and Schady, 2009).

To our knowledge, these results constitute unique evidence that productive transfers aimed at diversifying economic activities can lead to an improvement in protection from shocks beyond the end of an intervention. They demonstrate that adaptation through diversification in nonagricultural activities, rather than changes in agricultural practices directly affecting food crop production, do not have to come at the cost of higher food insecurity at the household level. This suggests that productive safety nets can help poor households adapt to increased risk due to climatic changes.

The results relate to Gertler, Martinez and Rubio-Codina (2012), who show impacts of a standard CCT program on investments in nonagricultural activities and average longer-term consumption levels. We go further by showing the separate impact of additional productive interventions, and how these impacts vary by exposure to exogenous weather shocks. We also focus on impacts after the program has ended, allowing to demonstrate benefits of the program after exit. More generally, the paper relates to recent experimental evidence on the impact of cash grants for small business development (De Mel, McKenzie and Woodruff, 2008, 2012; Blattman, Fiala and Martinez, 2011; Fafchamps et al. 2011) and vocational training (Attanasio, Kugler and Meghir, 2011).

The next section provides more details on the intervention, the experimental design and the data. Section 3 then discusses the climatic changes in the study region, and the insights from agronomical models that allow identifying meaningful exogenous variation in shocks. In section 4 we further discuss the empirical strategy and outline the main hypotheses to be tested. Section 5 presents the main results, and section 6 highlights the mechanisms by showing results on diversification of economic activities. Section 7 concludes.

2. The experimental design and data

Description of the program and the three transfer packages

The *Atención a Crisis* program was a one-year pilot implemented between November 2005 and December 2006 by the Ministry of the Family in Nicaragua.⁴ The program was implemented in six municipalities in the Northwest of Nicaragua targeted because they had been affected by a drought the previous year and had high prevalence of extreme rural poverty.⁵ To stratify, all communities in the six municipalities were

⁴ The pilot design built on the already existing and successful conditional cash transfer (CCT) model in Nicaragua *Red de Protección Social*, evaluated by Maluccio and Flores (2005).

⁵ The budget for the pilot allowed targeting 3000 households for a one-year period, which was much smaller than the population of the six municipalities. The program was therefore allocated randomly. Households were notified that available funding implied that the program would last one year, and would only cover the treatment communities. Households in the control communities did not receive any program benefits. They were notified that if there was a decision to scale up the program after the initial year, the control communities would be incorporated. People in the treatment communities understood the program was only to last for a year, and people in the control communities knew that there was a possibility they may receive the program the next year, but

grouped in blocks based on microclimates, crop mix, similarity in road access, and infrastructure.⁶ Through a lottery, to which the mayors of the municipalities were invited to attend and participate, 44 blocks were selected and half of the communities in each block were randomly assigned to treatment, and the other half to the control.

Baseline data were then collected in the 56 treatment and 50 control communities. These data were used to define households' eligibility for the program based on a proxy means test. Around 10 percent of households in treatment and control communities were ineligible for the program because their estimated baseline expenditures, as determined by the proxy means, were above the pre-defined threshold. This process resulted in the identification of 3,002 households to participate in the program. In a next step, 3.7 percent of households that had originally been deemed eligible by the proxy means were reclassified as ineligible after a process of consultation with community leaders, and a corresponding 3.7 percent that had originally been deemed ineligible were reclassified as eligible. To avoid any possibility of selection bias from these choices, we use the *original* eligibility as the intent-to-treat.

In the treatment communities, the principal caregiver in each eligible household (typically a woman) was then invited to a registration assembly, where the program objectives and various components were explained. At the end of the assembly, a second lottery took place in each community. Participation in the assemblies and lotteries was close to 100 percent.

On the basis of this lottery, all eligible households within each community were assigned to one of three treatments packages: (1) a basic CCT; (2) a basic CCT plus a scholarship for a vocational training; and (3) a basic CCT plus a productive investment grant. The cost of the second and third package was approximately the same. While the basic CCT's aim was to protect investments in human capital, the two complementary interventions aimed at strengthening households' *ex ante* risk management via income diversification in non-agricultural activities.

All selected beneficiary households received the basic CCT, which included cash transfers conditional on children's primary school and health service attendance during the one-year time period.⁷ Households received a transfer of US \$ 145 even if they did not have children. Households with children between 7 and 15 enrolled and attending primary school received an additional US \$ 90 per household and an additional US \$ 25 per child (with amounts referring to the total transfer received over the year).

they also knew it was likely to depend on the result of the national elections that were to be organized at the end of that year. In that election, the government changed and the project was not scaled up.

⁶ The grouping was based on maps and discussions with municipal technical personnel.

⁷ While the design of the basic CCT is similar to many other CCTs in Latin America, an important difference is the limited duration of one year. Most other CCTs offer more continuous income support.

In addition to the CCT, one third of the beneficiary households received a scholarship that allowed one of the adult household members to choose among a number of vocational training courses offered in the main town of the municipality. The scholarship was conditional on regular attendance to the course. The courses aimed at providing participants with new skills for income diversification outside of subsistence farming. These beneficiaries were also offered labor-market and business-skill training workshops organized in their own communities.

Finally, another third of the beneficiary households received, in addition to the basic CCT, a US \$ 200 grant for productive investments aimed at encouraging recipients to start a small non-agricultural activity. This grant was conditional on the household developing a business development plan, outlining the proposed investments in new livestock or non-agricultural income generating activities. Beneficiaries received technical assistance to develop the business plan and also participated in business-skills training workshops organized in their own communities.

Program take-up was high. More than 95 percent of all households randomized into the three treatment groups signed up for the program and took up the basic cash transfer.⁸ A small fraction of those households (less than 5 percent) did not collect the full amount of the transfer they were eligible for because they had not complied with the school enrollment and attendance requirements. Take-up of the additional benefits offered to the two groups receiving the productive packages was also high—89 percent for those with vocational training, and close to 100 percent for the productive investment grant.⁹ Contamination of the control group was negligible (one household).

Data

Baseline data for the evaluation were collected in April-May 2005. The sample includes the 3,002 eligible households in the treatment communities, and a random sample of 1,019 eligible households in the control communities. A first follow-up survey was collected in July-August 2006, nine months after the households had started receiving payments, but before the training and productive investment packages were fully implemented. A second follow-up survey was collected between August 2008 and May 2009 (henceforth referred to as 2008). At this point, households had stopped receiving transfers and any related program benefits for an average of two years. Due to implementation delays, the vocational training courses started after the first follow-up survey took place, and the productive investment grant had been

⁸ The main reason households did not take-up the program was the fact that some originally eligible households were deemed ineligible by local leaders after the initial assignment—see above. A small number of households had also migrated out of the communities after baseline. In order to avoid any selection bias, we treat all of these households as *eligible*.

⁹ About 10 percent of the business development plans was initially turned down by the ministry. These proposals were sent back to the households and virtually all of them developed a new plan after receiving technical assistance (the few exceptions being households that had migrated).

disbursed only 2 to 3 months prior to that survey. As the first follow-up survey was done too early to observe impacts on the returns to income diversification, this paper uses the second follow-up survey only.

Due to thorough tracking procedures, attrition compared to the baseline was minimal, less than 2.4 percent in 2008, and is uncorrelated with treatment status (P-value = 0.54). Differences in attrition rates between treatment groups are also very small and not significant (P-value = 0.67).

The surveys included comprehensive information on household socioeconomic status, including detailed modules for expenditures and economic activities.¹⁰ Table 1 provides descriptive statistics of some key variables at baseline. It documents particularly low levels of education (2.6 years for household heads), and a high dependency on agriculture with 90% of households involved in self-employment agriculture. About half the households are engaged in livestock activities and temporary migration. On the other hand, nonagricultural self- or wage-employment is much less prevalent.

Table 1 also establishes that the randomization resulted in balanced samples in the treatment and control communities as well as between treatment groups. Differences are generally small and the number of significant differences is not larger than expected. Considering some of the few significant differences, treatment households, and in particular those with the basic package, do seem to be more likely to engage in nonagricultural high-skilled wage work, but the shares for all groups are very small. To account for this, the impact estimates control for baseline activities. The main outcome variables (total consumption, food consumption and income) are balanced between all groups. The self-reported drought shock at baseline is also balanced. In fact, almost all households reported having been affected by drought at baseline. This is consistent with the occurrence of a major drought in 2004 in the region – the event that triggered the design of the program.

In addition to the quantitative data, qualitative work preceded each round of data collection. The qualitative work consisted of focus groups and semi-structured interviews with a wide set of beneficiaries and other local actors in treatment and control communities, and in the main town of the municipality. It also explored households' perception about weather patterns, qualitative evidence of the program's impacts, as well as issues related to program implementation (Aguilera et al., 2006).

¹⁰ The expenditure modules were taken from the 2001 Nicaragua Living Standards Measurement Study (LSMS) survey and include detailed information on various expenditure categories. For example, food expenditures include questions about 63 food items, and includes actual expenditures, home production, and food consumed outside the home. The income module was designed specifically for this study with the objective to capture all the different economic activities household members are engaged in.

The rainfall and temperature data were obtained from a gridded analysis for Nicaragua (Uribe, 2011).¹¹ The rainfall data are available for a grid of 0.075° (approximately every 8km) and are interpolated from existing weather stations (from the Nicaraguan Institute of Territorial Studies, INETER) and satellite data measured at a resolution of 0.1875° (approximately every 20km) from NARR (the North American Regional Reanalysis).¹² Temperature data are available from the same source for a grid of 0.15° (approximately every 16km). Rainfall data are available for 17 nodes across the study region. Temperature estimates are available for 8 nodes. Temperature and rainfall are mapped to communities based on the geographical location of the center of each community.

3. Changes in weather patterns, agronomical droughts and welfare losses

Climatic changes

Farmers in the study region report a high incidence of drought shocks. Despite the frequency of droughts, there is a strong dependence on self-employment agriculture, almost no irrigation, and little diversification into non-agricultural activities.¹³ When droughts occur, harvests are often completely lost. Not surprisingly then, households consider agricultural activities riskier than other type of economic activities.¹⁴ During qualitative interviews, farmers conveyed their strong perception that drought shocks had become more frequent since 1998 and that changes in weather patterns were interfering with the traditional agricultural seasons.¹⁵

Longitudinal rainfall and temperature data confirm these perceptions.¹⁶ Figure 1 presents the longest rainfall and temperature series available for the region, contrasting patterns from 1979 until 1997 with patterns from 1999 to 2008. The figure confirms significant changes in rainfall and temperature patterns, including during key months for planting and harvesting of the main crops (corn and beans). Specifically, post-1998, rainfall is lower from April to mid-May delaying the start of the first agricultural season (traditionally planting for this season starts in May and harvesting occurs in August or September).

¹¹ More precise rainfall and temperature data that captures all the variation across the microclimates in the region is unfortunately not available. Specifically, the alternative of using rainfall data from specific weather stations in the region was not feasible. Of the 11 rainfall stations located in the region, only 4 have sufficient coverage during the study period.

¹² <http://www.emc.ncep.noaa.gov/mmb/rreanl>. Interpolation is based on the Cressman method, an iterative process to correct data obtained from low reliability preliminary fields (satellite rainfall) using high-reliability observations (from weather stations) in successively shorter scanning radii around the pixel of interest.

¹³ To our knowledge, farmers did not use drought resistant varieties. Local extension agents have advocated switching to crops with different cycles that might be better suited to drought like sorghum (sorgo millón) and sesame (ajonjolí), but adoption of these crops remained very low.

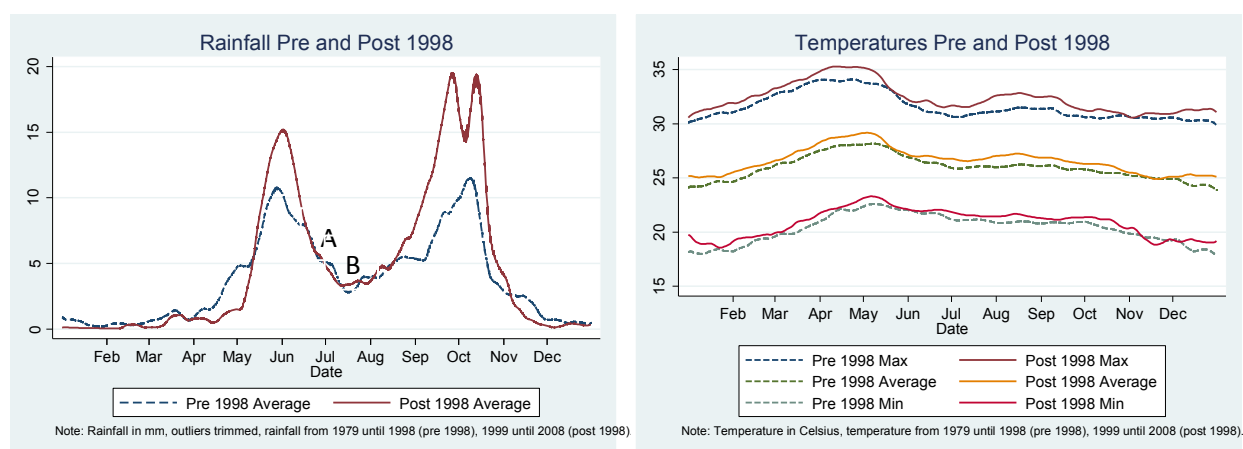
¹⁴ 93 percent of households report agricultural activities to be riskier than wage employment, and 77 percent considers it riskier than non-agricultural activities.

¹⁵ 1998 is a reference year for farmers as it was marked by hurricane Mitch, one of the largest hurricanes to ever hit the region.

¹⁶ This paper focuses on both rainfall and temperature following the empirical literature on climate change and given evidence that high temperature may have strong negative effects on yields (Schlenker and Roberts, 2009). As confirmed below, high temperatures might increase farmers' perceptions of drought.

Rainfall is also lower in November, shortening the second agricultural season (planting for this season starts mid-August and harvesting in November). As the figure suggests, changes in rainfall patterns have shortened the overall time window for the two crop cycles.¹⁷ In addition, rainfall is more irregular, with a higher incidence of heavy rainfall as well as prolonged dry spells during the cropping seasons.

Figure 1: Rainfall and Temperature Variation – Pre and Post 1998



Changes in temperature are more uniformly distributed over the year but are equally drastic. Minimum, average and maximum temperatures increased post 1998 for almost all months. The increases are substantial, with maximum temperatures being 0.4 (in November) to 1.2 (in August) degrees Celsius higher in the post 1998 period (Figure 1).¹⁸

Table 2 summarizes these changes and demonstrates that they are statistically significant.¹⁹ Maximum temperatures are almost one degree Celsius higher in the post-1998 period, and this difference is statistically significant. The number of growing degree days, a measure of heat exposure widely used to predict crop yield in the agronomical and climate change literature is also significantly higher.²⁰ While total rainfall from April to November is not significantly different (and the point estimate is even positive), the standard deviation of rainfall is higher in the post-1998 period, confirming that rainfall has become more variable. Total rainfall is significantly lower in April and the difference is large, with

¹⁷ The period from December to April is too dry for any grain or pulse production.

¹⁸ The finding of significant higher temperatures is consistent with those found in a wider set of countries and using longer time series (IPCC 2007b; Lobell, Schlenker, and Costa Roberts, 2011).

¹⁹ All estimates are based on node-level information, and include a node-fixed effect. Hence changes over time are estimated controlling for location.

²⁰ Growing degree days is the summation of a function of temperature $D(T)$ reflecting the ability of crops to absorb heat between 8 and 32 degrees Celsius, with $D(T) = 0$ for temperature lower than 8 degrees, $D(T) = T - 8$ for temperatures between 8 and 32 degrees, and $D(T) = 24$ for temperatures higher than 32 degrees (Schlenker et al. 2006).

rainfall in April in the post-1998 period at one third the earlier period's level. Rainfall in November is also lower, though not significantly so (P-value of 0.16).²¹

Agronomical droughts and welfare

Agronomical models provide insights on how the observed changes in rainfall and temperatures can affect yields. In these models, drought is not simply a function of total rainfall during the season, but is defined based on rainfall and temperatures during critical windows in the crop cycle. The exact relationship is not straightforward as many factors affect evapotranspiration and hence yields, including crop attributes, the water holding capacity of the soil, humidity, wind speed, duration of sunshine, radiation, and altitude (Doorenbos and Pruitt, 1975). In order to estimate water stress and subsequent yield loss, agronomists model crop-specific water requirements for each developmental stage (planting, vegetative growth, flowering, yield formation and ripening) and map water deficits into yield losses, for each developmental stage and for each crop. For example, while corn is relatively tolerant to water deficits during the vegetative and ripening periods, the greatest decrease in grain yields is caused by water deficits during the flowering period, which occurs 48-60 days after sowing (Urbina, 1991). The cycle for beans is shorter and flowering occurs 31-38 days after sowing.

These critical growth periods help to understand the possible consequences of the climatic changes described above. For example, Figure 1 shows that rainfall in the region (both before and after 1998) tends to dip in July before increasing again in August. This phenomenon, locally referred to as the “*canicula*”, would typically come after the flowering stage of both corn and beans, with limited damage to crop yields. However, delays in the start of the rains in May, and hence of sowing decisions, imply that the July dry period is more likely to affect crops during critical growth periods.²² Post 1998, the flowering stage for corn is more likely to occur during this low rainfall period (Figure 1, point B) as opposed to the historic norm (Figure 1, point A). The empirical strategy in this paper relies on these insights regarding the role of shocks during critical windows in the crop growth cycles.

While the figures show average trends across the study region, there is substantial variation within the region in terms of rainfall and temperature, as well as in the timing and duration of hot and dry spells. Indeed, even if the 106 communities are located in a relatively small geographical area, the area contains many different microclimates. As a consequence, in any given year, drought shocks might be more severe for some communities compared to others. We exploit this variation to shed light on the relationship

²¹ These patterns carry over when focusing on 2007-2008, the specific period covered by the survey recall period.

²² Rojas, Rodríguez and Rivas (2000) suggest that Nicaraguan farmers traditionally use five consecutive rainy days as a rule of thumb to infer when to start sowing.

between drought shocks and household welfare, and to analyze to what extent the different interventions help households adapt and protect themselves against such shocks.

Before turning to the available rainfall and temperature data, we first consider households' self-reported measures of drought, as they permit capturing more of the weather variation across the different microclimates. Given potential concerns about using self-reported drought at the household level, we use the fact that prior to randomization, neighboring communities were grouped into blocks based on local microclimates. All blocks by construction include treatment and control communities. The measure of drought shock used in this paper is therefore the share of households in each block having reported a drought shock in the last 12 months.²³ That variable has a mean of 0.61, a standard deviation of 0.15, and ranges between 0.12 and 0.95. Hence the average shock intensity is high, and there is substantial variation in shock intensity. Most of these drought shocks occurred during the first agricultural season of 2008.

As Table 3 shows, this drought measure is indeed strongly negatively correlated with household welfare in the control communities. The estimates show that, moving from the lowest (0.12) to the highest (0.95) intensity of shock implies about a 50% reduction in total consumption and about 25% in food consumption. While the magnitude of the coefficients captures the extreme change, these numbers are revealing given the wide range of shock intensity observed in the data.²⁴

To facilitate interpretation of the shock variable, and comparability with other studies, we normalize so that a value of 0 describes average incidence of shock, and the slope estimates correspond to a one standard-deviation change in drought incidence (corresponding to a 15% change in the share of households affected by a drought in a block). By construction, this shock variable is orthogonal to treatment (including each treatment package).

Still, we cannot rule out that this variable is correlated with block-level unobservables that might be driving potential heterogeneity in treatment effects. In particular, a potential concern is that the survey question asks whether income was affected by the weather shock. The variable might hence be a noisy measure of the weather shock, as it incorporates the income information. Moreover it is possible, for instance, that blocks where households tend to have a larger dependence on crop income might on average have more households reporting such shocks, but also might have reacted differently to treatment

²³ To calculate the share, self-report measures of households in the control are over-weighted with a factor three compared to those in the treatment, to account for the fact that we sample three times more households in the treatment than in the control. Calculations are based on the community where households resided in at baseline.

²⁴ These results, and the other results in the paper, are very similar when using only the average reported shocks of the control households in each block. In the main specification, we use the average of both treatment and control as only using the control might mechanically lead to smaller impacts of the drought in the treatment in case it would measure drought with less accuracy for the treatment.

than more diversified places. Our preferred specification is therefore a 2SLS estimate, in which we use the exogenous weather information to estimate the block-level average shocks in the first stage.

First-stage specification

We first explore the correlation between the block-level averages of the self-reported shocks and the weather shock variables defined based on agronomical insights. We focus on the first agricultural season of 2008, when self-reported shock data are available for all households.²⁵ The majority of all self-reported shocks in the survey refer to that season. Specifically, the start of the rainy season is defined as the first 5 days with consecutive rain and at least 15 millimeters cumulative rainfall, following Rojas, Rodríguez and Rivas (2000).²⁶ In 2008, this date varies between May 23 and June 5 and is on average 10 days later than the pre-1998 start date (and maximum 23 days later). Based on the insights regarding critical periods for evapotranspiration (see above), we define the length of the longest dry spell as the number of consecutive days without rainfall, with the last day of the spell being in the period between 15 and 60 days after the start of the season for the specific node. This corresponds to crop developmental stages with higher water requirements and yield loss potential (the flowering period for corn and the flowering and yield formation stages for beans). The duration of the longest dry spell is a measure commonly used for the dispersion of rainfall in the climate change literature (Tebaldi et al., 2006; Fishman, 2011).

As the temperature data are measured at a more aggregate level, we cannot link them to the exact start of the rains, and instead consider daily temperatures in June and July. Specifically, following the climate change literature, the number of growing degree days was calculated, and the deviation of the pre-1998 growing degree days is used in order to measure temperature shocks. A second temperature measure is the duration of the longest hot spell in June and July, where a day is defined as hot if the temperature is higher than the pixel-specific median temperature pre-1998.

There is substantial variation across the study region in these different weather measures, the reported shocks, as well as in altitude (Table 4). Altitude varies between 240 and 1494 meters, leading to differences in local climatic conditions beyond what is captured by the gridded weather measures. Variation in altitude, weather and shock measures also exists when comparing blocks in close proximity to each other. To illustrate this, Table 4 shows descriptive statistics for three groups with about equal number of households and blocks, grouped based on geographical proximity.

²⁵ For the second agricultural season, data refers to 2007 for some of the households in the sample, but to 2008 for other households, making it more difficult to map the self-reported data to the available weather data.

²⁶ Also see Doorenbos and Kassam (1979).

Table 5 shows that the length of dry spells, the degree days, and the delay in the start of the rains are indeed all positively and significantly correlated with self-reported shocks in the first season. Given the variation in altitude, and given that water evaporates faster with high temperatures when altitude is higher, we interact the temperature measures with altitude.²⁷ Columns 3 and 4 show that these interactions explain additional variation, consistent with agronomical drought models.²⁸ All variables together capture up to 65% of the variation in the self-reported shocks. This suggests that the self-reported shocks primarily capture actual variations in weather patterns across locations.

As the main regressions are estimated at the household level, the next set of columns shows the same relationship using household level data. The regression also includes a number of basic control variables at the household level. The dependent variable is the normalized block level average shock reported for the first season (column 5-6) or the last 12 months (column 7-8). These regressions confirm that the exogenous weather variables are strong predictors for the self-reported drought measures. The R-squared is up to 48 % for the reported shock intensity in the first season, and 37 % for reported shocks in the last 12 months.

4. Empirical specification and hypotheses

We estimate the following intent-to-treat household-level regressions:

$$Y = \alpha_1 T_1 + \alpha_2 T_2 + \alpha_3 T_3 + \beta S + \gamma_1 T_1 * S + \gamma_2 T_2 * S + \gamma_3 T_3 * S + \delta X + \varepsilon, \quad (1)$$

Where Y denotes household per capital consumption (total and food) or income; T_1 , T_2 and T_3 correspond to the intent-to-treat indicators taking the value of one for households randomly assigned to receive the basic CCT, the CCT plus training, and the CCT plus productive investment grant, respectively; S is a measure of the drought shock; $T_1 * S$, $T_2 * S$ and $T_3 * S$ are interaction terms between each treatment package and the drought shock; X includes an intercept, altitude, and a set of baseline control variables.²⁹ To increase precision and control for unobservables at the block-level, a second specification includes block fixed effects. In this specification β cannot be estimated but other coefficients are estimated with more precision.

²⁷ Altitude is measured using GPS at a central point in one of the communities in the block. In the household level regression, altitude refers to the altitude of the community where the household resided in 2005.

²⁸ The interaction terms suggest that hot spells are more strongly correlated with reported weather shocks at higher altitudes, as is to be expected since evaporation increases with altitudes due to low atmospheric pressure (see Allen et al., 1998). Adding interactions between altitude and dry spells does not add further explanatory power, but 2SLS results are qualitatively similar with such an alternative specification for the first stage.

²⁹ The control variables are the baseline value of the outcome variable, as well as baseline values for age, gender and literacy of the household head, the number of household members in different age groups by gender, distances to school and health center, land ownership, and dummy variables for baseline participation in different nonagricultural self- and wage employment activities.

S is the normalized block-level shock variable, taking the value of 0 at average shock intensity. Remember that average incidence of drought is high in itself (61% of households in a block reporting drought shocks). The specification in equation (1) allows separating program effects depending on the intensity of the exposure to shocks, and by treatment. α_1 , α_2 and α_3 capture the impact of the program at average shock intensity, γ_1 , γ_2 and γ_3 show how the impact of the program changes as the shock intensity increases by one-standard deviation.³⁰

We estimate equation (1) by OLS and 2SLS. For the latter, we instrument the shock variable as well as the shock variable interacted with the dummy variables for each of the treatment groups.³¹ We use the findings from section 3 to define the instruments and use the combination of instruments that result in the highest F-stat in the first stage. In particular, we use dry spells, degree days and hot spells and their interaction with altitude (as in column 7 of table 5), and include interactions of these variables with the dummy variables for each of the 3 treatment groups.³²

Given that treatment was assigned at the community level (with additional variation within the community), and shocks are measured at the block level, but instrumented with weather and altitude variables at the community level, standard errors are either clustered at the community or the block level. The F-statistics for the joint significance of the instruments are high (16.35 with clustering at the community level, and 10.21 with clustering at the block level).³³

The experimental design allows testing various hypotheses regarding the impact of each treatment and regarding differences between treatments.

(H1) First, we test whether being eligible for the productive investment grant or training interventions protects households' consumption from the negative impact of drought shocks, two years after the end of the interventions. Specifically we test whether these interventions prevent consumption from decreasing as shock intensity increases. We hypothesize that the relationship between per capita expenditures and shocks is less steep for these two treatments. Hence we hypothesize we can reject:

³⁰ Given the normalization of the shock variables the estimates of α_1 , α_2 and α_3 give the average intent-to-treat effect for each of the interventions.

³¹ The first stage allows combining the available weather information in one aggregate shock measure. Instead of estimating the impact of each weather variable separately, we use 2SLS to create an index of the available weather data in the first stage, and estimate how treatment effects differ depending on this index of weather information in the second stage.

³² All instruments capture time-variant shocks, rather than broader changes in climate. Dry spells are defined for the critical window in 2008, which itself depends on the year and location-specific start of the rainy season. The temperature variables are defined as deviations from historical average. Given these definitions, none of the weather variables used as instruments is significantly correlated to the same measures for earlier years. In an alternative specification, we use the number of hot days defined based on absolute temperatures and the length of dry spells, and all results are qualitatively similar. Results are also qualitatively similar when including the delay in the rains as extra instrument, but the F-stats are lower (given the low significance of the variable measuring the delay in the rains in column 8 in Table 5).

³³ All results are very similar when estimating the same model using Limited Information Maximum Likelihood (LIML) instead of 2SLS, further confirming there is no weak instrument problem.

$$\gamma_i = 0 \quad \text{for } i=2,3.$$

We also consider the magnitude of γ_i compared to β to infer whether the complementary interventions partially protect or completely isolate households' consumption from the negative impact of increasing drought intensity.

(H2) Second, we test whether at average shock intensity, and two years after the end of the intervention, households eligible for the productive investment grant or training have higher consumption levels than households in the control group. We hypothesize that per capita expenditures is higher for these two treatments. Hence we hypothesize we can reject

$$\alpha_i = 0 \quad \text{for } i=2,3.$$

(H3) Third, to shed light on the relative effectiveness of interventions aimed at different types of income diversification, we test whether the interventions are equally effective in limiting the negative impact of increased shock intensity on consumption. We also test whether the program impact at average shock intensity are the same for households eligible for the productive investment grant compared to the vocational training. We test the hypotheses:

$$\gamma_3 = \gamma_2 \text{ and } \alpha_3 = \alpha_2.$$

(H4) Fourth, we test whether some of the impacts could be related to the longer-term impacts of the conditional cash transfer, rather than the complementary income diversification components. To do so, we consider the impacts for the basic package only, and hypothesize we cannot reject

$$\alpha_1 = 0 \text{ and } \gamma_1 = 0.$$

We also compare the impact of the productive investment grant and training packages to the basic package, and test

$$\alpha_1 = \alpha_i \text{ and } \gamma_1 = \gamma_i \quad \text{for } i=2,3.$$

5. Impacts on consumption and income

Consumption

Table 6 presents the main results for total consumption per capita (column 1-6). The first two columns present the OLS estimates, the next four the 2SLS estimates. The first, third and fifth columns show the specification without block fixed effects, the second, fourth and sixth include block fixed effects. The point estimates are similar in both specifications, but estimates are generally more precise in the latter.

Columns 1-4 have standard errors clustered at the community level while column 5 and 6 at the block-level. P-values for tests of hypotheses H3 and H4 are reported at the bottom of the table. The discussion focuses on the 2SLS results, our preferred set of estimates.³⁴

First, the estimate of β confirms the large negative impact of weather shocks on consumption. A one standard deviation increase in shock intensity decreases consumption by 9 percent (columns 3 and 5).

Turning to hypothesis H1, the results show that both the vocational training and the productive investment grant help to protect against the negative impact of drought shocks. In particular, the estimates of the interaction effect γ_2 and γ_3 show that the vocational training and productive investment grant significantly increase consumption by 9 and 12 percent, respectively, as shock intensity increases by one standard deviation (column 4 and 6). The coefficients of the interaction terms are of the same magnitude as the shock coefficient β , indicating that both complementary interventions provide full protection against the negative effect of increased shock intensity on consumption.

With respect to hypothesis H2, the results show a strong positive and significant impact of the productive investment grant package on consumption. At average shock intensity, households that were eligible for this treatment have 8% higher consumption than control households. On the other hand, there is no significant impact of the vocational training package on consumption at average level of shocks.

Turning to hypothesis H3, the average impact is significantly higher for the productive investment grant than for the vocational training (P-value = 0.01). By contrast, the estimates of the coefficient of the interaction terms are not significantly different (P-value between 0.5 and 0.6 when testing $\gamma_3 = \gamma_2$). Households eligible for the productive investment grant have higher consumption levels at average shocks than households eligible for the vocational training, but both are equally protected against the negative impact of increased shock intensity on consumption.

Are households receiving the conditional cash transfer package also protected from shocks (hypothesis H4)? While the point estimates are positive, households eligible for the basic package do not have significantly smoother nor significantly higher average consumption compared to control households. We cannot reject that $\gamma_1 = 0$ and $\alpha_1 = 0$. Moreover, at average level of shocks, consumption is significantly lower than for households eligible for the productive investment package (P-value between 0.01 and 0.03). And the coefficient of the interaction term is significantly different compared to both productive investment grant and vocational training packages (P-value between 0.01 and 0.02). Hence, in contrast

³⁴ The point estimate of the shock variable, and consequently of the interaction effects of the shock with the treatment variables is smaller in the OLS than in the 2SLS, consistent with potential attenuation bias in the OLS related to measurement error in the shock variable.

with the complementary productive packages, the basic CCT package does not offer protection against the negative effect of shocks two years after the end of the intervention.

Taken together, these results show that the protection against shocks stems from the complementary interventions, not the basic CCT. Two years after the end of the intervention, both productive packages lead to smoother consumption and protect against the negative impact of drought shocks. In addition, households eligible for the productive investment grant also have higher average consumption compared to all other groups.

Income

The right hand side panel of Table 6 presents the main results for total income per capita. As before, the first two columns present the OLS results, the next four the 2SLS estimates. The same specifications are displayed. Here again (and as expected), weather shocks have a large effect on income in the control communities: a one standard deviation increase in shock intensity decreases per capita income by 11 percent, suggesting that income is slightly more sensitive to drought than consumption.

The results for the average effects of the different interventions and the interactions with the shock variables are very consistent with the results for consumption. Income of households eligible for either complementary intervention is protected against the negative impact of increases in shock intensity. The interaction effect (in column 10 and 12) is significant and large, indicating income is 10-11 percent higher than in the control when shock intensity increases by 1 standard deviation. The magnitude of the interaction terms suggests that both complementary interventions protect income from the negative effect of increased shock intensity. In addition, there is a positive average impact of the productive investment grant package on income, significant at 10 percent. At average shock intensity, households that were eligible for this treatment have 4 to 5 percent higher income than households in the control group. Hence the productive investment grant increases average income while also making income less sensitive to the magnitude of drought. As with the consumption results, being eligible for training does not lead to higher average income, but does lead to less variable income.

For both vocational training and productive investment grant, the coefficients of the interaction effects with shocks are similar for consumption and income, suggesting that smoother income contributes to protecting consumption from shocks. For the productive investment grant, the impact at average shock intensity is smaller for income than for consumption, indicating that the intervention contributes to higher consumption through other channels as well. For instance, beneficiary households may have resorted to inter-temporal consumption smoothing by using savings from earlier periods.

Food consumption

Table 7 presents results for food consumption to shed further light on welfare outcomes. The results indicate that the productive interventions fully compensate for shock-related reductions in food consumption. This is an important finding given that the shock directly affects the main subsistence crops and hence might have important consequences for food security. Hence, even if economic diversification may shift some of the household income portfolio away from direct production of such crops, the resulting income gains, together with consumption smoothing, allow for higher overall food consumption. Hence, at least at the household level, adaptation through changes in income strategies, rather than changes in agricultural practices themselves, does not need to come at the cost of higher food insecurity.

Notably, two years after the end of the intervention, and at average shock intensity, food consumption of households with the basic and the training package is also higher than in the control. The magnitude of the coefficients of the basic and the training package is very similar. This is consistent with a possible longer-term impact of the basic CCT, and in particular a shift of consumption towards more nutritious food, as shown in Macours, Schady and Vakis (2012), potentially driven by the social marketing regarding nutrition that was part of the program. It could in addition indicate a possible spillover effect, coming for instance from the increased local availability of certain food items through the presence of small food-related businesses started with the productive investment grant (see further).

Is there a risk premium at low shock intensity?

Finally, we explore whether there exists an implicit insurance premium. The point estimates in table 6 suggest that, at low shock intensity, control households have higher consumption than treatment households eligible for the productive investment grant. This would be consistent with households incurring an implicit cost at low shock intensity in order to smooth income at average and high shock intensity, in line with discussions in Morduch (1995) and Dercon (2006).

We therefore test whether households benefitting from the productive investment grant or training packages have significantly lower consumption and income compared to control households at very low shock intensity. Note first that the productive investment grant increased average income while also reducing income variability due to drought shocks. As a result, the overall impact of the productive investment grant is positive for almost the entire range of the shock intensity in the data. Indeed, even at shock intensities 2 standard deviations lower than average levels of shock, we only find in one specification a marginally significant (at the 10%) negative impact. Results are similar for the vocational training package (considering all specifications together P-values for $\alpha_i - 2\gamma_i = 0$ for $i=2,3$ range from 0.07

to 0.97). Hence in this context, and given the intervention, we do not find strong evidence that income smoothing at average and high shock intensity comes at the cost of lower income at low shock intensity.

6. Impacts on income diversification

The complementary interventions aimed at improving households' risk management strategies by facilitating income diversification. In particular, the productive investment grant provided financial support and (limited) technical assistance for households to start a nonagricultural self-employment activity. The vocational training intervention aimed at increasing households' skill base, to be applied either in a nonagricultural wage job, or by providing services (such as sewing or carpentry) in self-employment. The results in the previous section indicate that the average impact was higher for the grant than for the training intervention, even if the training helped reduce the negative impact of shocks on income and consumption. To better understand how eligibility for these different interventions might have led to gains in protection against drought shocks, this section analyzes impacts on economic activities. Table 8 and 9 presents results for the same 2SLS specification as before, with different variables related to nonagricultural activities as outcome variables, and with controls and block fixed effects.

Impacts on participation and returns in nonagricultural activities

Table 8 shows the impact of the three intervention packages on households' participation in different nonagricultural activities.³⁵ The table provides evidence that helps explain why the strongest impacts come from the productive investment grant. Compared to households in the control, households that were eligible for the productive investment grant are 13 percentage points more likely to engage in nonagricultural self-employment. There is no significant impact on participation in nonagricultural wage employment. The right panel of the table unpacks the impact of nonagricultural self-employment by type of activity. The productive investment grant leads to significant increases in both elaboration of food products (such as small bakeries or elaboration of cheese) and small commerce (such as corner stores or roaming sellers of cloths). These are activities for which an initial capital investment likely was important to overcome liquidity constraints and cover start-up costs (such as building an oven and buying baking material or buying stock for a store). The increases are significantly larger than for the training and the basic package. In contrast, increases in nonagricultural wage or self-employment for households eligible for the vocational training intervention are not significant. When disaggregating the self-employment

³⁵ There are no significant impacts on participation in agricultural activities, possibly because almost all households have some self-employment in agriculture, and the program is unlikely to move households completely away from agriculture.

activities, there is however a small but significant average impact on services and the interaction effect is positive for manufacturing activities.

While Table 8 establishes impacts on participation in nonagricultural self-employment, Table 9 presents different indicators of economic returns and shows how they vary by shock intensity. At average level of shock intensity, households eligible for the productive investment grant have higher profits from nonagricultural self-employment activities, and higher values from sale or self-consumption of livestock products. Impacts are not only significant but of substantial magnitude. Two years after the end of the intervention, average annual profits of nonagricultural self-employment are 603 Cordobas (about US \$30) higher than in the control while the return on livestock adds another 222 Cordobas (about US \$10). These numbers hence imply a 15 to 20 percent annual return to the household's initial investment of US \$200.

As calculating profits can be challenging for many respondents, who have low levels of education and not much prior business experience, a concern could be that the results may hide a depletion of the underlying asset base. Even so, households that were eligible for the productive investment grant still report higher levels of business assets compared to the control.³⁶ More tellingly, those with businesses expect profits to further increase in the future. Taken together, this suggests that the households that received this intervention might continue to better manage risk.

Table 9 shows no positive effects of the basic and vocational training interventions at average level of shock intensity, but the interaction term of shocks with vocational training is significant and large for nonagricultural wage employment. This suggests that the skills obtained from training might help smooth consumption and income by allowing households to obtain a wage income when shocks are particularly strong. Possibly, only then households consider it worth to overcome the transaction costs related to wage employment (which given the remoteness of the region, often implies temporary migration, or very long commutes). This would be consistent with findings of qualitative work on the reasons for the limited average impact of the training on wage employment, which indicated the short duration of the training, low labor demand, labor market imperfections and remoteness as potential factors.³⁷ Finally, Table 9 suggests that beneficiaries of the vocational training and the basic package also appear to partly offset negative impacts of shocks through positive returns to animal production.

In sum, the results above indicate that the complementary interventions helped shift households' income portfolios towards more diversification. This is particularly true for the households eligible to receive the productive investment grant. Smaller impacts on diversification are found for those eligible for training

³⁶ The difference between households with the productive investment grant package and control households is much smaller than the initial value of the productive investment grant, but it likely does not include the value of most of the livestock assets.

³⁷ Unfortunately, there is no exogenous variation in these factors, limiting the possibility to analyze their effects quantitatively.

and the basic conditional cash transfer. The latter could be due to investments of the basic cash transfer in nonagricultural activities, as in Gertler, Martinez and Rubio-Codina (2012).

Diversification and local markets

Diversification in nonagricultural activities is only likely to be an effective risk management strategy if the returns to such activities are not equally affected by the same weather shocks as agricultural production. Given the strong dependence on agriculture in the study region, the potential for income smoothing is not a priori obvious for nonagricultural activities that mostly cater to local demand. For instance, beneficiaries of the productive investment grant who diversified into nonagricultural activities and mainly supply local markets can also suffer from low demand at times of drought. By contrast, vocational training can potentially facilitate diversification since wage work is not necessarily locally based. Recall however that there is substantial variation in shocks even within the municipalities studied. This may enable households to sell their nonagricultural products to people from nearby places that are less affected by shocks.

Based on these insights, we hypothesize that the estimate of the interaction effect of the productive investment grant package will be larger when communities in neighboring blocks have low shock intensity. To test this, we calculated for each block the average estimated shock intensity in the other blocks of the same municipality.³⁸ We then split the sample based on whether the average shock intensity in the other blocks of the municipality is in the bottom or upper half of the distribution of shock intensity.

The results in table 10 show that the consumption and income smoothing results for the productive investment grant are indeed much stronger when neighboring blocks are less affected by shocks. This suggests that weather variability across communities partly explains why nonagricultural activities are less vulnerable to localized weather shocks and as such can contribute to income and consumption smoothing. In contrast, and as hypothesized, income smoothing by beneficiaries of the vocational training grant does not seem larger when shocks intensity in the rest of the municipality is lower.

A related question is whether shocks might affect the value of livestock or business assets differentially in the treatment communities compared to the control. This could happen for instance if individuals in control communities are more likely to use distress sales of animals to cope with shocks, driving down the prices of those animals. If this was to occur, shocks could create differences in asset values between treatment and control that could possibly explain part of the estimated differences in the sensitivity of income and consumption to the intensity of shocks.

³⁸ For this calculation, one municipality for which there is only one block in the sample was grouped together with the neighboring municipality. Shock intensity for each block is estimated from the combination of weather variables as in Table 4.

To analyze this possibility, we estimated whether the impact of shocks on the price of products depends on the treatment status of the community. We rely on community level information regarding prices of animals and of a number of frequently bought food and non-food items.³⁹ The prices of food and non-food items are a proxy for the value of the business assets as they are the items that typically can be commercialized within the communities. We do not find any evidence that differences in prices between treatment and control vary by the intensity of shocks. We also do not find evidence of lower prices in the treatment communities.

That said, the availability of food and non-food items in the treatment communities remains higher two years after the end of the intervention. This is consistent with the increase in small businesses, but it may create potential spill-over effects within treatment communities from the productive investment grant to households with the vocational training or basic package. As discussed, this could help explain part of the average higher food consumption in that group. While such spillover effects might cause a downward bias in the differences between treatment groups, the differences are still large and significant. Hence even if there might be spillovers, the evidence shows that the CCTs combined with productive interventions were more effective than the basic CCT in helping households protect themselves against future shocks.

7. Conclusion

This paper presents experimental evidence from a randomized control trial undertaken in rural Nicaragua. Households in the study region report an increased incidence of drought shocks. Longitudinal rainfall and temperature data confirm that climatic changes are interfering with traditional agricultural crop cycles. The self-reported shocks are highly correlated with weather data, consistent with agronomical definitions of drought. These drought shocks have large welfare effects.

In this context, we provide experimental evidence on the impact of a cash transfer program expanded to include two complementary interventions: a vocational training and a productive investment grant. The paper estimates the average impact of each package and analyzes whether these impacts differ by exposure to drought shocks, relying on the randomized assignment of the interventions and on exogenous local variation in shock intensity.

Based on follow-up data collected two years after the end of the program, we show that both complementary interventions reduce the sensitivity of consumption and income to the intensity of shocks. Being eligible for training or for the productive investment grant offsets the negative impact of drought shocks. These results differ significantly from those of households only receiving the basic CCT,

³⁹ Prices of the most commonly bought food items (12), non-food items (10) and live animals (3 types) were collected in the community survey. Based on this information, an index of standardized prices was constructed to analyze the price changes.

indicating that the protection against shocks comes from the complementary productive interventions. In addition, being eligible for the productive investment grant increases average consumption by 8 percent, and income by 4 percent. Hence the productive investment grant increases average consumption while also reducing its sensitivity to drought shocks. The basic CCT does not lead to higher or smoother consumption levels two years after the end of the transfers, even if of course it had increased consumption while the program was in place.

The productive interventions allowed households to diversify economic activities and increase participation and returns to nonagricultural and livestock activities. Households eligible for the productive investment grant are 13 percentage points more likely to be self-employed in non-agricultural activities, and have higher profits from nonagricultural self-employment. The magnitude of the impact on returns is large, amounting to a 15 to 20 percent annual return on the initial investment of US \$ 200, two years after the program ended.

Finally, the results suggest that risk management is facilitated by selling products or services to households from other communities less affected by shocks. This might have allowed drought-affected households to maintain positive returns to their nonagricultural activities. A potential caveat to these results is then that they were obtained in a context where there was substantial cross-sectional variation in the incidence of drought. Possibly this type of diversification based on nonagricultural self-employment may be less successful if a very large drought shock were to affect all households in the region at once. Productive transfers should therefore not be seen as a substitute for the need of social safety nets when low-probability shocks with very large welfare effects occur.

To our knowledge this is the first paper providing experimental evidence on an intervention that is effective in promoting income diversification to reduce vulnerability to weather shocks. As such, our results go beyond the existing literature documenting the short-term protection from cash transfers against shocks. They show that combining short-term social safety nets with productive interventions can promote sustainability of program impacts, and help households manage risk before future shocks occur. The results show that this not only can lead to smoother overall consumption, but can also protect food consumption, even if the shock directly affected the main food crops. Hence, adaptation through changes in nonagricultural activities, a possible alternative to changes in agricultural practices themselves, does not have to come at the cost of higher food insecurity. Overall, these results contribute to the ongoing debates on productive safety nets and climate change adaptation, by providing empirical evidence on an intervention that successfully targeted livelihood adaptation and helped to reduce poor households' vulnerability to weather variability.

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Table 1: Baseline characteristics and balance between treatment groups

	Mean control	Mean basic	Mean training	Mean grant	P-value T=C	P-value T1=T2=T3
Age household head	47.06	46.28	45.28	45.13	0.06*	0.16
Number of years education household head	2.58	2.64	2.61	2.74	0.56	0.60
Number of years education main beneficiary	3.20	3.22	3.09	3.17	0.84	0.62
Average number of years education among all household members	3.25	3.25	3.15	3.20	0.79	0.53
Literate household head	0.58	0.62	0.60	0.63	0.10	0.47
Male household head	0.81	0.82	0.83	0.84	0.42	0.15
Household size	5.40	5.22	5.32	5.38	0.46	0.35
Household size: 0-5 year olds	0.67	0.62	0.64	0.67	0.52	0.25
Household size: 5-14 year olds	1.52	1.53	1.58	1.57	0.49	0.70
Household size: 15-24 year olds	1.11	1.05	1.07	1.11	0.56	0.54
Household size: 25-64 year olds	1.80	1.77	1.80	1.80	0.78	0.67
Household size: 65 year and older	0.29	0.24	0.21	0.22	0.02**	0.30
Distance to school (hours)	0.30	0.26	0.27	0.24	0.16	0.02*
Distance to health center (hours)	1.20	1.12	1.14	1.12	0.62	0.75
Distance to municipal center (hours)	1.64	1.51	1.51	1.52	0.44	0.92
Size of total land owned (manzanas)	4.18	3.67	3.43	3.45	0.25	0.92
Share households owning any land	0.68	0.64	0.67	0.65	0.45	0.46
Value small livestock (Cordobas)	501	459	442	447	0.30	0.83
Value all livestock (Cordobas)	6362	4378	6136	3674	0.15	0.17
Value small livestock sold or self-consumed	376	316	352	401	0.72	0.59
Value all livestock sold or self-consumed	1298	1013	1840	829	0.81	0.26
Share households with agricultural activities	0.90	0.84	0.88	0.87	0.12	0.14
Share households with livestock activities	0.54	0.45	0.47	0.47	0.27	0.45
Share households with agricultural wage work	0.56	0.58	0.60	0.63	0.23	0.06*
Share households with nonagr. self-employment: elaboration food products	0.07	0.06	0.07	0.07	0.87	0.56
Share households with nonagr. self-employment: manufacturing	0.03	0.02	0.03	0.03	0.66	0.16
Share households with nonagr. self-employment: commerce	0.07	0.07	0.08	0.07	0.83	0.38
Share households with nonagr. self-employment: services	0.05	0.04	0.05	0.05	0.94	0.20
Share households with nonagr. low-skilled wage work	0.15	0.16	0.16	0.18	0.41	0.41
Share households with nonagr. high-skilled wage work	0.04	0.07	0.05	0.06	0.10*	0.02**
Share households with at least one member seasonally migrating	0.48	0.45	0.49	0.47	0.71	0.22
Total income p.c. (cordobas)	4371	4842	4876	4444	0.32	0.16
Food consumption p.c.(cordobas)	3537	3578	3443	3539	0.95	0.64
Total consumption p.c.(cordobas)	5291	5574	5320	5454	0.67	0.43
Log(total consumption p.c.)	8.35	8.40	8.37	8.37	0.66	0.49
Log(food consumption p.c.)	7.93	7.89	7.88	7.85	0.36	0.61
Log(total income p.c.)	8.11	8.16	8.15	8.11	0.69	0.17
Reported drought in 2005	0.96	0.96	0.96	0.95	0.35	0.56
Altitude (meters)	775	814	814	814	0.57	-

Note: P-values calculated with s.e. clustered at community level. N = 3918, sample used in the estimation, i.e. excluding the 97 baseline households not tracked back in 2008, and 5 households for whom consumption data (the main outcome variable) is missing.

Table 2: Significant changes in rainfall and temperature patterns

	Pre-1998	Post-1998	Dif	P-value diff.
Temperature				
Daily max during agricultural seasons- April to Nov. (C°)	31.58	32.41	0.83***	0.00
Daily max during June and July (C°)	31.02	31.83	0.83***	0.00
Degree days in June and July (C°)	1110	1147	37***	0.00
Rainfall				
Total rainfall during agricultural seasons - April to Nov (mm)	1310	1348	47	0.16
Standard deviation daily rainfall (April-Nov)	12	16	4.32*	0.10
Total rainfall in April (mm)	73	26	-46.83**	0.03
Total rainfall in November (mm)	62	39	-24	0.16
Start of rainy season (5 days with 15 mm cumulative rainfall)	131	141	10*	0.08

Note: P-value based on s.e. clustered by year and with pixel fixed effects. Degree days are calculated as explained in footnote 20. Start of the rainy season is defined as the number of days since Jan 1 when the first period of 5 consecutive days with 15 mm cumulative rainfall occurs. N=240 for temperature measures; N=510 for rainfall measures.

Table 3: Impact of block-level rainfall shocks in control communities

	Log consumption p.c.	
	Total	Food
Share households reporting drought (in block)	-0.558*** (0.175)	-0.288** (0.129)
Number of observations	994	994
R2	0.028	0.008

Note: *** p<0.01, ** p<0.05, * p<0.1; s.e. clustered by community in parentheses

Table 4: Descriptive statistics: Variation in weather variables and shock measures

	Mean	sd	min	max
<u>All: 3918 households; 44 blocks</u>				
Altitude	804	308	240	1494
Number of days delay in start rains (compared to pre-1998 median start day)	10	7	-9	23
Longest dry spell: consecutive dry days in 15-60 days after start wet season	5	1	3	7
Degree days in June and July, as deviation from pre-98 average	12	7	-8	29
Longest hot spell: consecutive days in June-July with temperature higher than median pre-1998 daily temp.	6	1	5	8
Share of households reporting drought shock (first season)	0.35	0.15	0.03	0.69
Share of households reporting drought shock (last 12 months)	0.61	0.15	0.12	0.95
<u>Municipality Pueblo Nuevo: 1455 households; 16 blocks</u>				
Altitude	813	181	598	1234
Number of days delay in start rains (compared to pre-1998 median start day)	11	6	-9	16
Longest dry spell: consecutive dry days in 15-60 days after start wet season	4	1	3	7
Degree days in June and July, as deviation from pre-98 average	11	1	10	13
Longest hot spell: consecutive days in June-July with temperature higher than median pre-1998 daily temp.	6	0	6	6
Share of households reporting drought shock (first season)	0.25	0.10	0.03	0.43
Share of households reporting drought shock (last 12 months)	0.52	0.15	0.12	0.73
<u>Municipalities: San Lucas and Las Sabanas: 1254 households; 14 blocks</u>				
Altitude	1034	250	323	1494
Number of days delay in start rains (compared to pre-1998 median start day)	9	7	1	17
Longest dry spell: consecutive dry days in 15-60 days after start wet season	6	1	3	7
Degree days in June and July, as deviation from pre-98 average	7	7	-8	15
Longest hot spell: consecutive days in June-July with temperature higher than median pre-1998 daily temp.	6	1	6	8
Share of households reporting drought shock (first season)	0.33	0.10	0.12	0.49
Share of households reporting drought shock (last 12 months)	0.61	0.10	0.33	0.75
<u>Municipalities: SJ Cusmapa, San Francisco, Cinco Pinos: 1209 households; 14 blocks</u>				
Altitude	555	292	240	1286
Number of days delay in start rains (compared to pre-1998 median start day)	10	7	4	23
Longest dry spell: consecutive dry days in 15-60 days after start wet season	5	0	5	6
Degree days in June and July, as deviation from pre-98 average	19	5	13	29
Longest hot spell: consecutive days in June-July with temperature higher than median pre-1998 daily temp.	7	1	5	8
Share of households reporting drought shock (first season)	0.50	0.14	0.22	0.69
Share of households reporting drought shock (last 12 months)	0.73	0.14	0.51	0.95

Table 5: Relationship between weather variables in first season and self-reported drought intensity

	BLOCK LEVEL REGRESSION				HOUSEHOLD LEVEL REGRESSION			
	Drought in first season				Drought in first season		Drought in last 12 months	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Length longest dry spell	0.430*** (0.12)	0.500*** (0.11)	0.247** (0.11)	0.305** (0.11)	0.296*** (0.086)	0.367*** (0.081)	0.296*** (0.082)	0.280*** (0.087)
Number of days delay of rains		0.0530*** (0.019)		0.0262 (0.019)		0.0354** (0.014)		-0.0080 (0.017)
Number of degree days	0.0773*** (0.019)	0.0867*** (0.018)	0.122 (0.10)	0.104 (0.10)	0.141** (0.070)	0.135* (0.068)	0.0652 (0.098)	0.0665 (0.098)
Length longest hot spell	-0.0779 (0.19)	-0.249 (0.18)	-2.000*** (0.54)	-1.783*** (0.55)	-1.231*** (0.25)	-1.051*** (0.26)	-1.215*** (0.37)	-1.256*** (0.39)
Altitude*number of degree days			-0.0000 (0.0001)	0.0000 (0.0001)	-0.0000 (0.0001)	-0.0000 (0.0001)	-0.0000 (0.0001)	-0.0000 (0.0001)
Altitude*length longest hot spell			0.0037*** (0.0009)	0.0031*** (0.0010)	0.0019*** (0.0004)	0.0014*** (0.0005)	0.0017*** (0.0006)	0.0019** (0.0007)
Altitude			-0.0230*** (0.0050)	-0.0199*** (0.0054)	-0.0109*** (0.0018)	-0.0079*** (0.0022)	-0.0112*** (0.0026)	-0.0118*** (0.0033)
Observations	44	44	44	44	3918	3918	3918	3918
R-squared	0.40	0.50	0.63	0.65	0.43	0.48	0.37	0.37

Note: *** p<0.01, ** p<0.05, * p<0.1; for household-level regression: s.e. clustered by community (in parentheses); For definition of weather variables, see table 4. Drought intensity measures normalized the share of households in block reporting drought shock. Household level regression includes controls for age, gender and literacy of the household head, number of household members in different age groups by gender, land ownership, participation in different nonagricultural self- and wage employment activities, distances to school and health center.

Table 6: Impact of shocks on consumption and income with different treatments

		Log(total consumption per capita)						Log(per capital income)					
		OLS		2SLS		2SLS		OLS		2SLS		2SLS	
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
CCT + Grant (T3)	$\alpha 3$	0.0837*** (0.026)	0.0833*** (0.023)	0.0845*** (0.027)	0.0837*** (0.024)	0.0845*** (0.026)	0.0837*** (0.030)	0.0456 (0.034)	0.0385 (0.026)	0.0542* (0.033)	0.0436* (0.026)	0.0542* (0.028)	0.0436 (0.032)
CCT + Training (T2)	$\alpha 2$	0.0307 (0.028)	0.0276 (0.022)	0.0320 (0.030)	0.0277 (0.023)	0.0320 (0.025)	0.0277 (0.028)	0.0044 (0.035)	-0.0048 (0.025)	0.0075 (0.034)	-0.0050 (0.026)	0.0075 (0.026)	-0.0050 (0.030)
CCT (T1)	$\alpha 1$	0.0224 (0.029)	0.0206 (0.023)	0.0251 (0.032)	0.0221 (0.025)	0.0251 (0.025)	0.0221 (0.027)	-0.0015 (0.034)	-0.0095 (0.025)	-0.0078 (0.035)	-0.0195 (0.026)	-0.0078 (0.024)	-0.0195 (0.026)
Shock	β	-0.0393** (0.019)		-0.0869** (0.038)		-0.0869** (0.039)		-0.088*** (0.022)		-0.110*** (0.040)		-0.110** (0.042)	
Shock*T3	$\gamma 3$	0.0373 (0.026)	0.0392* (0.023)	0.0851* (0.048)	0.122*** (0.041)	0.0851* (0.045)	0.122** (0.050)	0.0137 (0.031)	0.0171 (0.024)	0.0776 (0.056)	0.112** (0.046)	0.0776 (0.054)	0.112* (0.057)
Shock*T2	$\gamma 2$	0.0297 (0.029)	0.0290 (0.023)	0.0615 (0.046)	0.0897** (0.038)	0.0615 (0.042)	0.0897* (0.046)	-0.0066 (0.034)	-0.0025 (0.024)	0.0732 (0.060)	0.1000** (0.049)	0.0732 (0.056)	0.1000* (0.056)
Shock*T1	$\gamma 1$	0.00182 (0.031)	0.00372 (0.024)	-0.0221 (0.047)	0.0114 (0.036)	-0.0221 (0.039)	0.0114 (0.039)	0.0006 (0.034)	0.0048 (0.024)	-0.0086 (0.052)	0.0241 (0.044)	-0.0086 (0.044)	0.0241 (0.045)
Level of clustering		com.	com.	com.	com.	block	block	com.	com.	com.	com.	block	block
Block F.E.		No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations		3918	3918	3918	3918	3918	3918	3892	3892	3892	3892	3892	3892
R-squared		0.28	0.32					0.16	0.21				
H3: P-value $\alpha 3=\alpha 2$		0.011**	0.007***	0.013**	0.008***	0.015**	0.010**	0.127	0.109	0.079*	0.066*	0.085*	0.071*
P-value $\gamma 3=\gamma 2$		0.693	0.597	0.600	0.471	0.609	0.480	0.424	0.439	0.939	0.835	0.940	0.835
H4: P-value $\alpha 3=\alpha 1$		0.009***	0.007***	0.017**	0.015**	0.025**	0.021**	0.019**	0.013**	0.005***	0.004***	0.009***	0.007***
P-value $\gamma 3=\gamma 1$		0.100*	0.096*	0.018**	0.015**	0.024**	0.020**	0.487	0.505	0.053*	0.049**	0.062*	0.057*
P-value $\alpha 2=\alpha 1$		0.654	0.706	0.733	0.779	0.713	0.758	0.811	0.852	0.591	0.608	0.596	0.611
P-value $\gamma 2=\gamma 1$		0.090*	0.119	0.007***	0.009***	0.007***	0.008***	0.739	0.738	0.198	0.212	0.200	0.214

Note: *** p<0.01, ** p<0.05, * p<0.1; s.e. in parentheses. All regressions including hh level controls (see note table 5). Income trimmed for 1% highest outliers.

Table 7: Impact of shocks on food and nonfood consumption with different treatments

		Log(total food consumption per capita)					
		OLS		2SLS		2SLS	
		(1)	(2)	(3)	(4)	(5)	(6)
CCT + Grant (T3)	α_3	0.0967*** (0.028)	0.0927*** (0.026)	0.105*** (0.025)	0.102*** (0.025)	0.105*** (0.024)	0.102*** (0.029)
CCT + Training (T2)	α_2	0.0519* (0.030)	0.0481* (0.025)	0.0530* (0.027)	0.0488** (0.023)	0.0530** (0.026)	0.0488* (0.028)
CCT (T1)	α_1	0.0540 (0.033)	0.0515* (0.028)	0.0481 (0.032)	0.0449* (0.026)	0.0481* (0.025)	0.0449* (0.027)
Shock	β	-0.0467** (0.019)		-0.0742** (0.033)		-0.0742** (0.031)	
Shock*T3	γ_3	0.0170 (0.027)	0.0217 (0.028)	0.0901* (0.049)	0.120*** (0.045)	0.0901* (0.048)	0.120** (0.054)
Shock*T2	γ_2	0.0102 (0.032)	0.0150 (0.028)	0.0617 (0.046)	0.0851** (0.042)	0.0617 (0.046)	0.0851 (0.051)
Shock*T1	γ_1	-0.0004 (0.035)	0.0049 (0.030)	-0.0098 (0.048)	0.0163 (0.040)	-0.0098 (0.041)	0.0163 (0.042)
Level of clustering		com.	com.	com.	com.	block	block
Block F.E.		No	Yes	No	Yes	No	Yes
Observations		3918	3918	3918	3918	3918	3918
R-squared		0.04	0.08				
H3: P-value $\alpha_3=\alpha_2$		0.075*	0.072*	0.024**	0.020**	0.029**	0.025**
P-value $\gamma_3=\gamma_2$		0.797	0.802	0.570	0.485	0.579	0.496
H4: P-value $\alpha_3=\alpha_1$		0.116	0.128	0.037**	0.039**	0.047**	0.049**
P-value $\gamma_3=\gamma_1$		0.519	0.534	0.059*	0.052*	0.067*	0.059*
P-value $\alpha_2=\alpha_1$		0.917	0.863	0.824	0.861	0.803	0.843
P-value $\gamma_2=\gamma_1$		0.572	0.596	0.029**	0.031**	0.025**	0.026**

Note: *** p<0.01, ** p<0.05, * p<0.1; s.e. in parentheses. All regressions including hh level controls (see note table 5).

Table 8: Impact on households' participation in nonagricultural economic activities

		Non-agriculture wage employment	Non-agriculture self-employment	By type of nonagricultural self-employment			
				Elaboration	Manufacturing	Commerce	Services
CCT + Grant (T3)	$\alpha 3$	-0.0211 (0.023)	0.126*** (0.021)	0.0634*** (0.017)	0.0051 (0.010)	0.107*** (0.014)	0.0108 (0.015)
CCT + Training (T2)	$\alpha 2$	0.0177 (0.024)	0.0383* (0.021)	0.0170 (0.017)	0.0109 (0.010)	0.0104 (0.011)	0.0341** (0.013)
CCT (T1)	$\alpha 1$	0.0221 (0.022)	0.0396* (0.021)	0.0256 (0.017)	0.0028 (0.010)	0.0291** (0.014)	0.0325** (0.014)
Shock*T3	$\gamma 3$	0.0444 (0.043)	-0.0678 (0.051)	0.0110 (0.033)	0.0162 (0.021)	-0.0130 (0.029)	-0.0684** (0.032)
Shock*T2	$\gamma 2$	0.0539 (0.043)	0.0026 (0.045)	-0.0236 (0.030)	0.0490** (0.021)	-0.0124 (0.025)	-0.0244 (0.032)
Shock*T1	$\gamma 1$	0.0361 (0.046)	-0.0357 (0.049)	-0.0194 (0.030)	0.0113 (0.022)	-0.0078 (0.030)	-0.0353 (0.032)
Mean in control		0.358	0.381	0.207	0.039	0.138	0.105
R-squared		0.14	0.11	0.08	0.09	0.14	0.06

Note: *** p<0.01, ** p<0.05, * p<0.1; s.e. clustered by community. 2SLS estimates, including all hh controls and block F.E. n = 3918

Table 9: Impacts of shocks on different indicators of economic returns and sustainability

		Nonagricultural wage income	Profits of nonagricultural business	Value livestock sold or self-consumed	Value business assets	Exp. increase in profits in 12 months
CCT + Grant (T3)	$\alpha 3$	-242.4 (351)	602.8*** (160)	221.8*** (46.1)	235.3*** (81.6)	164.2*** (63.5)
CCT + Training (T2)	$\alpha 2$	-166.0 (332)	-296.9* (158)	-33.57 (38.5)	-17.80 (90.2)	-56.88 (54.8)
CCT (T1)	$\alpha 1$	-148.8 (340)	98.51 (167)	-2.519 (40.9)	-92.68 (99.9)	72.44 (65.4)
Shock*T3	$\gamma 3$	263.4 (699)	-282.5 (310)	38.81 (80.9)	3.391 (161)	-126.0 (156)
Shock*T2	$\gamma 2$	1282* (714)	87.46 (313)	129.5* (67.9)	-18.94 (148)	1.669 (115)
Shock*T1	$\gamma 1$	684.7 (662)	-247.5 (273)	120.3* (66.1)	307.5 (192)	-64.22 (130)
Mean in control		2201	1579	836	606	345
Observations		3879	3878	3880	3882	1204
R-squared		0.22	0.13	0.08	0.10	0.08

Note: *** p<0.01, ** p<0.05, * p<0.1; s.e. clustered by community in parentheses; Dependent variables trimmed for 1% highest outliers. Expected increase in profits. 2SLS estimates, including all hh controls and block F.E. only for those with nonagricultural self-employment.

Table 10: Impact on consumption and income, by shock intensity in other blocks from the same municipality

		Log(total consumption per capita)				Log(per capital income)			
		Low shock intensity in rest muni (1)	High shock intensity in rest muni (2)	Low shock intensity in rest muni (3)	High shock intensity in rest muni (4)	Low shock intensity in rest muni (5)	High shock intensity in rest muni (6)	Low shock intensity in rest muni (7)	High shock intensity in rest muni (8)
CCT + Grant (T3)	α_3	0.131*** (0.040)	0.0588* (0.034)	0.142*** (0.030)	0.0566 (0.038)	0.0706 (0.046)	0.0848** (0.037)	0.0588* (0.033)	0.0588 (0.036)
CCT + Training (T2)	α_2	0.0459 (0.036)	0.0110 (0.043)	0.0507* (0.026)	0.00417 (0.036)	0.000164 (0.048)	0.0328 (0.046)	-0.0126 (0.033)	0.00894 (0.038)
CCT (T1)	α_1	0.0444 (0.034)	0.0336 (0.039)	0.0526* (0.027)	0.00861 (0.036)	-0.0111 (0.047)	0.0357 (0.043)	-0.0265 (0.032)	0.00980 (0.038)
Shock	β	-0.0367 (0.041)	-0.0573 (0.040)			-0.0261 (0.049)	-0.0541 (0.043)		
Shock*T3	γ_3	0.266*** (0.064)	0.0632 (0.043)	0.239*** (0.054)	0.107** (0.042)	0.212** (0.095)	0.0233 (0.044)	0.188** (0.085)	0.0655* (0.037)
Shock*T2	γ_2	0.0498 (0.089)	0.0328 (0.053)	0.0626 (0.056)	0.0812* (0.043)	0.0830 (0.084)	0.0225 (0.057)	0.0706 (0.073)	0.0654 (0.042)
Shock*T1	γ_1	0.0751 (0.086)	-0.0278 (0.044)	0.0823 (0.062)	0.0197 (0.040)	0.135 (0.095)	-0.0159 (0.046)	0.114 (0.075)	0.0285 (0.037)
Block F.E.	no	no	no	yes	yes	no	no	yes	yes
Observations		2031	1887	2031	1887	2022	1870	2022	1870

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors clustered by community (in parentheses). All regressions include hh level controls