Eliminating Uncertainty in Market Access: The Impact of New Bridges in Rural Nicaragua*

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Abstract

We estimate the impact of new bridges in rural Nicaraguan villages that face seasonal flooding risk. Floods unpredictably eliminate access to outside markets. We work with a partner NGO to build footbridges designed to eliminate this risk. We exploit the village selection procedure to identify a comparable set of villages, and collect household-level data before and after bridge construction. We conduct detailed household surveys within these villages and weekly telephone followups with a subset of households. In the weekly data we find that income falls during floods in the absence of a bridge. When the bridge is built, this effect is eliminated. Besides reducing the volatility of income, bridges have a level effect as income increases from households getting higher-paying jobs in outside markets. There are also effects on farming choices. Farmers store less food at home and increase spending on agricultural intermediates. In a model of risky farm investment we show that this is a rational response to lower income risk.

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1 Introduction

Agriculture is the dominant form of employment in much of the developing world. Because agriculture is land-intensive, economies with high levels of farming have low levels of spatial agglomeration. This creates a particularly important role for transportation infrastructure. Increasing integration through infrastructure development may have important productivity consequences because goods and factors may be more easily allocated across space, as studied extensively in the literature (Alder, 2013; Van Leemput, 2015; Asturias et al., 2016). In response, international organizations have spent substantially on infrastructure. The World Bank, for example, spent $24.2 billion on roads, bridges, and energy in 2014 alone.

However, transportation infrastructure has another effect that has received less attention: it increases the reliability of access to outside markets. Adverse weather, unforeseen congestion, or natural disasters can cause temporary, unpredictable increases in the cost of reaching outside markets. This increases uncertainty of wage income and consumer prices for affected households. Improved transportation infrastructure can mitigate these risks if it is resilient to these shocks, which implies that transportation actually reduces uncertainty for households.

In this paper, we study the effects of this reduction in uncertainty on households in rural Nicaragua. Each year between May and October, the Nicaraguan rainy season exposes communities in mountainous areas to the risk of flash flooding. Working with a partner NGO, we construct footbridges in these communities designed to make rivers passable even during periods of flooding. We exploit the NGO village selection procedure to identify a comparable set of villages that do not receive a bridge, and we collect multiple rounds of household-level surveys before and after the bridges are constructed.[1] We collected two types of data. First, we conducted four wide-ranging surveys in May 2014, November 2014, and November 2015, and November 2016 which cover both before and after the bridges were constructed in the first half of 2015.

[1] Our partner NGO, Bridges to Prosperity, uses a two stage selection process. First, a needs assessment determines if there is sufficient need in the village for a bridge, based on the number of people in the community, their expected level of use, and related criteria. Second, an engineering assessment determines if it is feasible to build a bridge. This is based on the topography of the land immediately around the proposed site: the resulting bridge cannot be too wide, the two sides of the river cannot be too uneven, and the river bank must have sufficient clearance over the high water mark. We compare villages where a bridge was built (having passed both assessments) to those that passed the needs assessment, but failed the feasibility assessment. We discuss this in more detail in Section 3.

These surveys cover the last dry and rainy seasons pre-bridge, along with the two main harvests post-construction.[2] These surveys include information on household composition, GPS coordinates to measure distance from bridge, agricultural information, assets, and consumption. However, flooding is a high frequency event, cutting off access for days or weeks, not entire seasons. Therefore, to capture the high frequency flood events, we also collect 70 weeks of data from July 2014 through November 2015 from a smaller group of households. These high frequency surveys cover health outcomes, labor earnings, asset purchases or sales, and crop sales, purchases, and storage over the preceding two week period.

A major challenge in this project is that bridges are expensive, and the number of projects each year is small. Our study includes fifteen villages, of which six received bridges. Therefore, in all of our empirical specifications, we must cluster at the community level and, because of the small number of clusters, apply the wild bootstrap to compute p-values. Despite these limitations, we find that bridges have both statistically and economically significant effects. Using the high frequency data we show first that periods of flooding see reductions in market income of approximately 13% in villages without bridges. However, once a village receives a bridge, this effect disappears. This is consistent with our interpretation of the bridges as a means of reducing income volatility. Second, we use the low frequency surveys to measure the longer term effects of the bridges. As in the high frequency data, we find that income rises in villages with bridges compared to those without. Moreover, the increase is concentrated in changes in income generated outside the village. The bridge also has implications for farm choices. Farmers in treated villages use substantially more fertilizer and pesticide. Consequently, crop yields increase. Finally, we see that farmers store less of their crop within their household, and sell a larger part of it in the market.

We rationalize these results with a model of farm decision making. Farmers harvest crops, which require fertilizer and labor. Fertilizer choices are set before any uncertainty is realized. In the interim periods between planting and harvesting, farmers divide their time between working on the farm or in the market to earn wages.

[2]Farmers in northern Nicaragua almost exclusively harvest during the main rainy season that ends in November. Therefore, the surveys were conducted just after the main harvest in 2014, 2015, and 2016, along with the minor dry season harvest in May 2014.

However, both types of labor are subject to shocks. These shocks may be driven by floods: heavy rains affect both the farmer's marginal product on the farm and her ability to earn wages in a spot labor market. A bridge then eliminates the left tail of potential labor market wage realizations. We show that this has two effects in the model. First, farmers invest more fertilizer on their crops. Second they store a smaller proportion of harvest for consumption. That is, they shift toward the riskier but higher return investment in response to greater self-insurance from the outside labor market. Indeed, we find support for both predictions in the data.[3]

1.1 Related Literature

The study of infrastructure benefits is large and varied. A recent literature has combined quantitative models with detailed data to provide evidence on the impact of trade costs and new construction (Alder, 2013; Asturias et al., 2016). More closely related are those papers who explicitly highlight the rural-urban link in their study of trade, such as Adamopoulos (2011), Gollin and Rogerson (2014), and Van Leemput (2015). They find large gains from reducing the cost of movement across regions, as firms are able to more able to specialize in their comparative advantage. However, both the high costs and benefits of infrastructure make identification difficult, as infrastructure tends to be targeted toward areas with the largest benefits. Recently, a number of important papers have taken advantage of policy changes and natural experiments to identify the effects of infrastructure development, including Suri (2011) and Donaldson (2013). Our close involvement in the actual construction of these bridges allows us to conduct detailed household-level surveys before and after construction to provide additional insight into the underlying mechanisms. An important contribution along these lines is Asher and Novosad (2016), who utilizes detailed Indian micro data to show that rural roads generate increased wage income among rural workers. Dinkelman (2011) finds electrification increases employment in South Africa, and also uses "engineering-related" identification strategy based on land gradients.

We also find an increase in income from off-farm labor, and moreover, show that

[3]We prove these results for an arbitrary distribution of the joint labor market and on-farm risk shocks, so that the results do not require us to take a stand on the the form of the distribution. In particular, any positive correlation between the two shocks is related to the quantitative magnitude of the effect, not in the theoretical direction of the farmer response.

this increases on-farm productivity. Thus, the lack of consistent labor market access seems an important barrier limiting agricultural productivity. Relatedly, Bryan et al. (2014) and Bryan and Morten (2015) also highlight constraints to the spatial allocation of labor as a component of the gap between agricultural and nonagricultural productivity, documented by Restuccia et al. (2008) and Gollin et al. (2014). We further show how constraints to off-farm labor directly translate into changes in farm investment and productivity.

2 Model

We begin with a model of farm investment. The goal here is to link high frequency flooding risk to lower frequency farm decisions that occur once a season.

The model is comprised of a continuum of infinitely-lived households that are endowed with a technology called a farm. We refer to households as farmers for simplicity throughout. Time is discrete, and is comprised of two different types of periods.

Every T periods, a farmer harvests her crops from the last season. She also chooses investment in fertilizer to be harvested T periods in the future. In those T periods between planting and harvesting, the farmer chooses how to divide time between farm and off-farm labor. Below, we formalize this idea and lay out the problem recursively.

Harvesting and Planting Every T periods, a farmer enters the "harvesting and planting" period, t^H. This involves two things: harvesting the crops planted T periods ago at $t^H - T$, and also planting the crops that will be harvested T periods from today at $t^H + T$.

In a harvesting period, a farmer enters with some resources X from the previous period, and the farm produces output Y. Using her new resources $X + Y$, she decides how much to invest in intermediates I for the next harvest, i.e "planting." The rest gets stored in the household. If a household invests I units on the farm, then T periods later, the farm will produce output according to the production function

$$Y = ZI^{\alpha}N^{1-\alpha} \tag{2.1}$$

where Z is a random shock, I is again the investment (e.g. fertilizer), and N is the stock of labor services that have been accumulated, which we detail to in the next section.

Labor Allocation Problem The second type of period are those in the interim between the planting and harvesting of crops. Once the farmer delineates resources between farm investment I and storage S, they are left with periods $t = 1, \ldots, T$ in which they must wait for the harvest to occur. During this time, a farmer affects eventual farm output by working. If she chooses to work a fraction n_t of their time on the farm at t, they contribute to the stock of labor N in the production function (2.1) through the constant elasticity of substitution aggregator

$$N = \left(\sum_{t=1}^{T} \varepsilon_t^{\frac{1}{\sigma}} n_t^{1-\frac{1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}. \tag{2.2}$$

Here, ε_t is a shock to the marginal benefit of n_t for producing output. With the time $1 - n_t$ not utilized on the farm, the household works in the spot labor market for stochastic wage w_t. The processes for these two shocks $\{\varepsilon_t\}_{t=1}^{T}$ and $\{w_t\}_{t=1}^{T}$ are arbitrary, including any correlation between the two.

2.1 Recursive Formulation

Given the timing described above, we can write the household problem recursively. Denoting s^t as the sequence of shocks from periods $1, \ldots, t$ and $\pi(s^t)$ as the probability of receiving that sequence of shocks, the value of entering a planting period with resources X is given by

$$V(X) = \max \sum_{t=1}^{T} \sum_{s^t} \pi(s^t) \beta^t u\left(c(s^t)\right) + \sum_{s^T} \pi(s^T) \beta^T V(X'(s^T))$$

subject to:

$$
\begin{aligned}
\forall s^t : c(s^t) &\leq (1 - n(s^t))w(s^t) + (1 - \delta)S(s^{t-1}) - S(s^t) \\
X &\geq S(s^0) + I \\
\forall s^T : X'(s^T) &\leq S(s^T) + Z(s^T)I^{\alpha}N(s^T)^{1-\alpha} \\
\forall s^T : N(s^T) &\leq \left(\sum_{t=1}^{T} \varepsilon(s^t)^{\frac{1}{\sigma}} n(s^t)^{1-\frac{1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \\
\forall s^t : S(s^t) &\geq 0
\end{aligned}
$$

Throughout we will assume that u is strictly increasing, strictly concave and has a positive third derivative. The choice variables c, S and n are measurable with respect to the history of shocks up to that period.[4] However, the choice of productive investment I is made in the planting period and is irreversible. Also, Z is a random shock whose realization is only known in the period when output is realized.[5]

2.2 Discussion

Before characterizing the model, we briefly digress to highlight the channels in the model that map to the data. We view flooding (or the weather that generates flooding) as the governing forces behind the shocks to the marginal product of farm labor, ε, and the outside wage, w. Intuitively, a flood eliminates the ability to access the outside labor market. In the context of the model, this is a realization of a low wage w. A bridge is then the elimination of the left tail of w realizations, which is both a decrease in variance and an increase in the mean realization. At the same time, substantial flooding may also make it more difficult for farmers to work on the farm. This would imply a positive correlation between the wage shocks w and the farm shocks ε. While the theoretical results do not depend on any relationship between w and ε, the magnitudes of the effects will be larger the more positively correlated the shocks. In the following sections, we show how changes to the distribution the shocks affect the key margins of interest: production, investment, and savings.

[4] Note also that our formulation implies that the sequences of shocks s^T are independent of one another. This assumption is not critical for the results, but simplifies exposition.

[5] An alternative model would be one in which Z becomes less and less uncertain as the period when output is realized approaches. That model is equivalent to one in which the process on ε changes over time, which is a special case of this formulation. Therefore, modeling Z as a one-time realization of uncertainty is without loss of generality.

2.3 Savings Decision

The critical decision that households make is how to divide their farm output between two types of savings: low return storage and productive investment. Storage is subject to depreciation, but is safe. Therefore, households may find it optimal to accumulate a buffer stock to help maintain consumption levels when bad shocks are realized. Investment has higher expected returns, but cannot be accessed until the following harvest period and its return is uncertain at the time when the investment is made. Therefore, if a sequence of bad shocks are realized, households may experience sharp declines in consumption.

This choice of how to allocate agricultural output can, after some manipulation of the household's first order conditions, be written as

$$(1-\delta)^T + \sum_{t=1}^{T}\sum_{s^t}(1-\delta)^{t-1}\frac{\rho(s^t)}{\sum_{s^T}\eta(s^T)} = \alpha\sum_{s^T} Z(s^T)\left(\frac{I}{N(s^T)}\right)^{\alpha-1}\frac{\eta(s^T)}{\sum_{s^T}\eta(s^T)} \quad (2.3)$$

where $\rho(s^t)$ is the Lagrange multiplier on the non-negativity constraint for storage, and

$$\eta(s^T) = \beta^T\pi(s^T)V'\left(S(s^T) + Z(s^T)I^{\alpha}N(s^T)^{1-\alpha}\right). \quad (2.4)$$

Equation (2.3) simply states that households equate the marginal value of both types of investment. The value of an additional unit of storage is that it makes the household less likely to reach its non-negativity constraint and, therefore, lose their ability to mitigate consumption losses from negative shocks. Also, if the non-negativity constraint is not binding in period T, an additional unit of storage has (depreciated) value in the following season.

The marginal value of a unit of productive investment is the expected value of its marginal product. Importantly, risk enters its marginal value explicitly as variation in the derivative of the continuing value function. For example, although previous period realizations of the wage rate w do not enter this equation explicitly, they determine the final value of storage $S(s^T)$. Likewise, the farm productivity ε realizations affect the value of both $S(s^T)$ and $N(s^T)$.

Therefore, the type and degree of risk faced by households may affect their choice to allocate savings to higher expected return (but risky) investment or low expected return (but safe) storage. Intuitively, if households have a reduction in the risk they face, they may shift their savings from storage into investment. We formalize this idea in Proposition 1.

Proposition 1. *If the variance of w decreases or expected value of w increases, then for every X, the household increases farm investment I and decreases storage $S(s^0)$*

Intuitively, the proof makes use of the fact that the main value of storage is to keep households away from the non-negativity constraint. Reaching that constraint is less likely when bad shocks are less severe or more unlikely. Both reductions in the variance of shocks and increases in the mean accomplish this, and therefore reduce the value of storage relative to investment. This links the construction of a footbridge to on-farm investment. High frequency variation in access to the labor market limits longer-horizon investment since it limits households' ability to self-insure. This increased investment has an intuitive effect on farm yield.

Corollary 1. *If the variance of w decreases or expected value of w increases, average farm yield $\mathbb{E}\Big[Z(s^T)I^{\alpha}N(s^T)^{1-\alpha}\Big]$ increases.*

We now turn to testing the predictions of this model. We lay out our empirical treatment and strategy, and then use this to test the theoretical predictions described above.

3 Background and Village Selection

Our treatment directly confronts the theoretical predictions in the last section by building footbridges in rural Northern Nicaragua. These villages are located in mountainous areas that face seasonal flooding during the rainy season each year (May to November). During these periods, streams and rivers that are usually passable on foot rise very rapidly and may stay high for days or weeks. This flooding is unpredictable in its timing or intensity. Rainfall in the same location is a poor predictor of flooding, as rains at higher altitudes may be the cause of the flooding. Moreover, this period is

also the main cropping season. Crops are planted at the beginning of the rainy season in May, and harvested in late October and early November. As in the model, the time between planting and harvesting is also the time in which the flooding shocks occur.

During these periods, some villages are cut off from access to outside markets. In particular, many villages have a river located between themselves and a larger, nearby city where agricultural markets and labor markets operate. When the river rises substantially, market access would require swimming across the river, which may be prohibitively dangerous and inhibit transportation of goods, or a long journey on foot to reach the market by another route.

We therefore investigate the impact of building footbridges that traverse these rivers. We do so by partnering with the non-governmental organization Bridges to Prosperity (B2P), that works to construct footbridges in these rural communities to solve some of the problems associated with flooding risk. Bridges to Prosperity provides engineering design, construction materials, and skilled labor to the village, as well as training in bridge maintenance. They ask members of the village to provide unskilled labor for construction, such as digging out the foundation of the bridge deck. Since a large part of the construction materials must be funded internally by Bridges to Prosperity, the number of bridges that can be constructed each year is limited.

Bridges to Prosperity takes requests from local village organizations and governments, then evaluates these requests on two sets of criteria. First, they determine whether the village has sufficient need. That is, are there enough people that live in the village and that would use the bridge to justify the expense of the project. These decisions are made by an in-country manager employed by the organization who inspects each site.

If the village passes the needs assessment, the country manager personally goes to the site to do an engineering assessment. The purpose of this assessment is to determine if a bridge can, in fact, be built at the proposed site. To be considered feasible, the required bridge cannot exceed a maximum span of 30 meters, and the banks of the river on each side must be of similar height (a differential not exceeding 3 meters). Moreover, the estimated high water mark (maximum height of the river when flooded) must be at least two meters below the proposed bridge deck. The assessment

makes other considerations as well: bridges cannot cross power lines, and they avoid building in places where the river bends (as river bends may indicate a river changing its course).

We are comparing communities that passed both the feasibility and the needs assessments, and therefore received a bridge, to those that passed the needs assessment, but failed the feasibility assessment. The second group makes for an ideal comparison group for two reasons. First, the fact that both groups have similar levels of need is crucial, as need is both unobservable and is likely to be highly correlated with the treatment effects. Second, failure of the feasibility assessment is very unlikely to be correlated with any relevant village characteristics. For observable differences, we show that villages that do and do not receive bridges are balanced.

We study a total of fifteen villages. Of these, six passed both the needs and feasibility assessments, and therefore received bridges. The other nine passed only the needs assessment and did not receive a bridge. These villages are located in the provinces of Esteli and Matagalpa in northern Nicaragua.[6]

4 Data Collection and Design Validity

4.1 Data Collected

We conducted two types of data collection. First, we conducted in-person household-level surveys with all households in each of the fifteen villages. The first such wave took place in May 2014, just as that year's rainy season was beginning. This survey was to designed to give us an early indication of balance, and also to sign households up for the high frequency survey. In this May survey, for those that agreed to participate, we conducted followups every two weeks by phone. The more critical surveys covering the main rainy season were conducted in November 2014, November 2015, and November 2016. Bridges were constructed in Spring of 2015. Therefore for all villages we observe three rainy seasons. For those that receive a bridge, we observe one rainy season without a bridge and two rainy season with a bridge. We will primarily focus on these

[6]One might be concerned that a control village may be treated if they are sufficiently close to a treatment village. That is, if the control villagers are sufficiently close to a bridge to access it. This is not the case in any of the fifteen villages. They are all sufficiently far from one another to eliminate this issue.

three surveys, though we include the May 2014 survey when we consider the validity of our identification strategy.

To collect the in-person household surveys, we employed local Nicaraguan enumerators. Our strategy was to survey all households within three kilometers of the proposed bridge site on the side of the river that was intended to be connected. In many villages, this implied a census of village households.

Participation in the first round of the survey was very high in general, with 97% of households agreeing to participate. This is true even though we offered no incentive for participation. Enumerators and participants were told that the purpose of the study was to understand the rural economy. We did not disclose our interest in the bridges because we suspected that would bias their answers, or may make them feel they are compelled to answer the survey when they would not otherwise want to participate. The number of households identified in each village varied widely, from a maximum of 80 to a minimum of 24.

Survey questions covered household composition, education, health, sources of income, consumption, farming choices (including planting, harvests, equipment and inputs), and business activities.

The second data collection was high frequency surveys. Because the floods are a high frequency and short term event, we also wanted to include these surveys to provide supporting evidence to the more detailed annual surveys and also validate the fact that flooding (and the bridge) was having an effect on income generating activities. We therefore carried out these surveys for 70 weeks, covering the rainy season before construction, along with the first dry and rainy seasons after construction. During the first wave, we solicited participation in cell phone followup interviews.

This high frequency survey covered income-generating activities, livestock purchases and sales, and food security questions over the past two weeks. We also asked individuals to predict the amount of flooding in the next two weeks to confirm the unpredictability of flooding.

4.2 Balance and Validity of Design

As discussed above, we base our analysis on a comparison of villages that pass both the needs and feasibility assessment with those that pass only the needs assessment. The identification assumption is that the features required to pass the feasibility test are independent of any relevant household or village-level statistics. Using the first two waves of data, we run the regression

$$y_{ivt} = \alpha + \beta B_v + \eta_t + \varepsilon_{ivt}$$

where $B_{vt} = 1$ if village v gets a bridge between $t = 2$ and $t = 3$. We consider a number of different outcomes, and show that households show no observable differences across the two groups. Table 1 produces the results, and we find no difference across households in build and no-build villages.

5 High Frequency Effects of a Bridge

We begin by assessing the immediate affect of flooding and the impact of a bridge. To do so, we use the high frequency data to considering income realizations during floods. Before moving forward, two issues are worth highlighting. First, the high frequency data is not representative of the villages under study as not every individual has a cell phone. However, the households that participate are extremely close to population averages except for household head age. As one might suspect with a cell phone-based survey, those that agreed were slightly younger. The average age of a household that agreed to participate was 37 years old, compared to the average of 43 in the population as a whole. On other margins – occupation, farming, etc. – there is no statistical difference between those that participated and did not.

Second, it is an unbalanced panel of individuals as not everyone answered the phone each time. Figure 1 plots the histogram of the number of observations per household in the high frequency data. The minimum is 1, the maximum is 32 of a possible 35 weeks, and the average is 12.

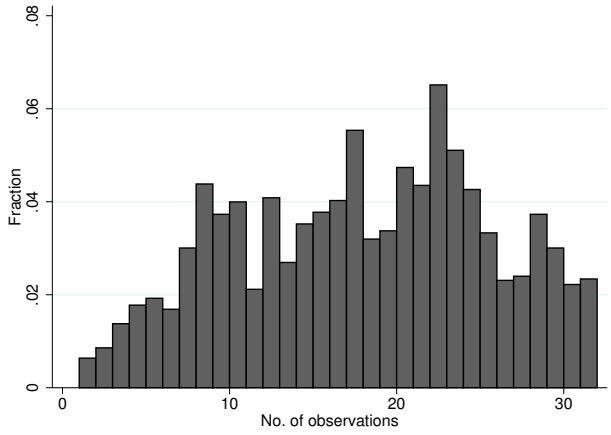
Despite these issues, the data still provides useful information on high frequency

Table 1: Pre-Bridge Differences

	Constant	Bridge
Household Composition		
HH head age	43.34***	1.39
	(0.00)	(0.18)
HH head yrs. of education	6.40***	0.33
	(0.00)	(0.22)
No. of children	1.30***	-0.03
	(0.00)	(0.70)
HH size	4.18***	0.15
	(0.00)	(0.19)
Occupational Choice		
Agricultural production	0.47***	0.01
	(0.00)	(0.76)
Off farm work	0.58***	0.03
	(0.00)	(0.54)
Total wage earnings (C$)	865.14***	46.94
	(0.00)	(0.74)
Farming		
Corn harvest	16.66***	0.43
	(0.00)	(0.88)
Bean harvest	12.09***	-1.79
	(0.00)	(0.26)
Plant corn?	0.17***	0.01
	(0.00)	(0.62)
Plant beans?	0.16***	-0.03
	(0.00)	(0.23)

p-values in parentheses. Here, we do not cluster the standard errors as to give the model the greatest chance of finding a difference between the two groups.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Figure 1: Number of Observations per Household



outcomes. To assess the impact of flooding, we run regressions of the form

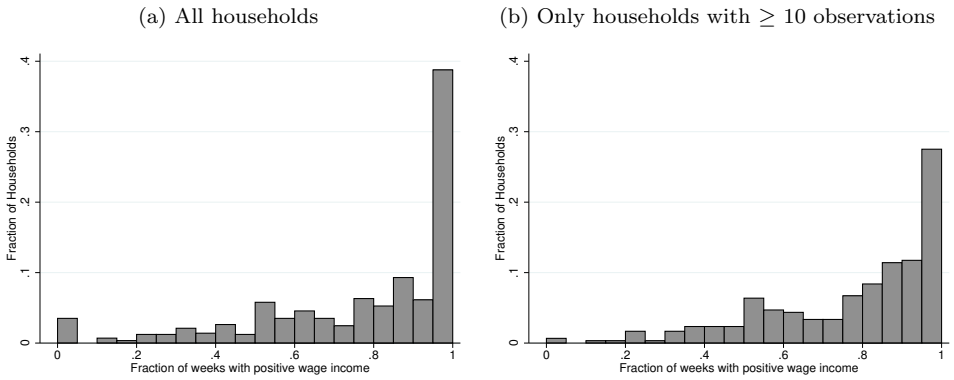
$$y_{ivt} = \alpha + \beta B_{vt} + \gamma\Big(B_{vt} \times F_{vt}\Big) + \theta\Big(NB_{vt} \times F_{vt}\Big) + \eta_t + \delta_i + \varepsilon_{ivt}. \tag{5.1}$$

The variable $B_{vt} = 1$ if village v has a bridge in week t, while $NB_{vt} = 1 - B_{vt}$ is the "no bridge" variable. The variable $F_{vt} = 1$ if village v is flooded at week t, while η_t and δ_i are week and individual fixed effects. Throughout, we use a wild bootstrap cluster at the village level.

5.1 Changes in Income Realizations

We begin by considering changes in income. First, labor income is ubiquitous even among farming households. Figure 2 plots the share of weeks each household receives positive labor market income. Indeed, despite the fact that about half of households farm some kind of crop, most are also active in the labor market.

Figure 2: Fraction of weeks with labor market income



We therefore ask how income realizations change during flooding episodes, and how the bridge changes the results. For this, we use regression (5.1). We use two measures of income: amount earned in the past two weeks and an indicator equal to one if no income was earned.

Table 2 illustrates the effects of flooding on contemporaneous income realizations. First, having a bridge in the absence of a flood does not increase income relative to households in villages without a bridge. This is shown by the insignificant effect on the

Table 2: Effects of Flooding on Income

	Household Income	Household Income	No Income Earned	No Income Earned
Flood × No Bridge	-69.949	-141.518*	0.052	0.070**
	(0.487)	(0.097)	(0.214)	(0.041)
Flood × Bridge	169.560	65.453	-0.091***	-0.038*
	(0.195)	(0.592)	(0.004)	(0.082)
Bridge	57.815	186.278**	0.060*	0.061*
	(0.750)	(0.033)	(0.091)	(0.082)
Constant	1236.573***		0.182*	
	(0.000)		(0.059)	
Observations	6756	6756	6756	6756
Individual F.E.	N	Y	N	Y
Week F.E.	Y	Y	Y	Y

p-values in parentheses computed using the wild cluster bootstrap-t with 1000 simulations, clustered at the village level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

bridge variable. However, when there is a flood, this changes. Income drops by C$142 ($p = 0.097$) during a flood in the absence of a bridge, a decrease of 11 percent of its no-flood baseline. This effect is not present in villages with a bridge. While a bridge increases average off-farm earnings by C$186 (p = 0.033), a flood has no statistical effect on the average household income realization. That is, the flood has no effect on average income realizations in the presence of a bridge, but a negative effect without one.

The same pattern holds when one considers the fraction of people who earn no income in the preceding two weeks. The likelihood of earning no income increases by 7 percentage points ($p = 0.041$) when a flood occurs in villages without a bridge. In villages with a bridge, the fraction is 0.21 regardless of whether or not there is a flood. This seems the critical margin that the bridge affects. Figure 3 plots the density of income realizations before and after bridge construction, both during periods of no flooding (left panel) and during flooding (right panel). The critical difference is the drop in zero income realizations during floods, suggesting that the bridge limits the inability to access labor markets during a flood.

5.2 Food Security

Sometimes households are not allowed to buy as much of a staple crop as they desire. This occurs when vendors are worried about running out of stock. Table 3 shows

Figure 3: Density of Income Realizations

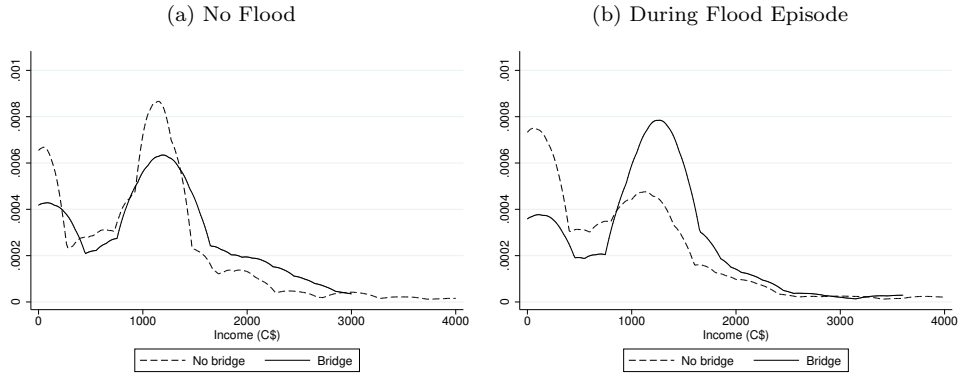


Table 3: Food Rationing During Floods

	Corn Rationed	Corn Rationed	Bean Rationed	Bean Rationed
Flood × No Bridge	0.125***	0.110**	0.142***	0.147***
	(0.000)	(0.013)	(0.000)	(0.002)
Flood × Bridge	0.000	0.014	-0.004	0.027
	(0.876)	(0.760)	(0.308)	(0.525)
Bridge	-0.104***	-0.052	-0.117***	-0.051*
	(0.004)	(0.033)	(0.004)	(0.069)
Constant	0.108***		0.126***	
	(0.000)		(0.000)	
Individual and Week F.E.	No	Yes	No	Yes
Observations	6250	6250	6250	6250

p-values in parentheses computed using the wild cluster bootstrap-t with 1000 simulations, clustered at the village level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

that this behavior is concentrated in flooding episodes. This may occur because food vendors want to prevent a "run" on the food supply when future access to food is uncertain. Once a village has a bridge, this rationing ends abruptly. For instance, there are no observations of households being rationed in corn purchases in any village that has a bridge. Moreover, the frequency of bean and rice rationing is also greatly mitigated by a bridge. This is consistent with less worry about access to food during flooding times, because households and food vendors are able to access outside food supplies when they are necessary.

5.3 Discussion and Relation to Model

Taken together, the results highlight that critical margins required for the theory posed in Section 2 also hold in the data. First, flooding shocks lower income. Second, a bridge mitigates the negative effect on income and also increases food security. Given the model assumptions confirmed here, the model predicts that these high frequency events translate into lower frequency changes on the farm. Namely, an increase in farm investment and a decrease in storage of crops. We next turn to assess whether these outcomes hold in the data.

6 On-Farm Imapct

We next turn to on-farm effects of generated by consistent access to labor markets. These results are derived from four larger, in-person surveys conducted between 2014 and 2016. We run two regressions

$$y_{ivt} = \alpha + \beta B_{vt} + \eta_t + \delta_i + \varepsilon_{ivt} \tag{6.1}$$

$$y_{ivt} = \alpha + \beta\Big(B_{vt} \times (1 - D_{ivt})\Big) + \gamma\Big(B_{vt} \times D_{ivt}\Big) + \theta D_{ivt} + \eta_t + \delta_i + \varepsilon_{ivt} \tag{6.2}$$

Again, $B_{vt} = 1$ if village v has a bridge at time t. In the second regression, we also interact the bridge indicator with a distance indicator D_{ivt}. Using GPS coordinates and either realized bridge location (in the case of build sites) or the best potential bridge site (in the case of no-build sites), $D_{ivt} = 1$ if household i is above the median village-specific as-the-crow-flies distance to the bridge location. All outcome variables are trimmed of their top and bottom 1 percent of values, and we again use the wild bootstrap-t to take into account the small number of clusters.

6.1 Off-Farm Income

Before turning to the effects on farm decisions, we first confirm that the bridge increases off-farm income, as we found in the high frequency data.

First, regression one in Table 4 shows that total wage income rises by C$265 ($p = 0.044$) in households in build villages relative to those in no-build villages. Moreover,

Table 4: Effects on Market Income, by Source

	Total Income		Outside Village		Inside Village	
	(1)	(2)	(3)	(4)	(5)	(6)
Build	265.162**		295.631***		-53.066	
	(0.044)		(0.000)		(0.680)	
Build × Near		314.479**		381.185***		-101.980
		(0.043)		(0.001)		(0.391)
Build × Far		213.334		219.358***		-1.575
		(0.172)		(0.001)		(0.992)
Baseline mean of dep. variable	590.330	590.330	294.232	294.232	222.829	222.829
Observations	917	917	919	919	916	916
Time F.E.	Y	Y	Y	Y	Y	Y
Household F.E.	Y	Y	Y	Y	Y	Y

p-value in parentheses computed using the wild cluster bootstrap-t with 1000 simulations, clustered at the village level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

from regressions three and five, this change is entirely driven by changes outside the village – that is, across the river. This is consistent with the high frequency result on the relevance of the bridge only in the presence of flooding constraints. Since within-village earnings are not subject to same flood risk as outside-village income activities, we do not see the same treatment effect. Regressions two, four, and six provide the same regressions, except the bridge indicator is interacted with distance.

6.2 Farm Investment in Intermediate Inputs

We next turn to farm investment, with results presented in Table 5. We consider intermediate input (fertilizer plus pesticide) expenditures, and also the two components individually. First, regression one shows total intermediates increase by an average of C$645 ($p = 0.054$) for households in build villages relative to no-build villages. When we decompose households into near versus far, we find that in build villages, those closer to the bridge increase their fertilizer spending by C$1092 ($p = 0.003$) relative to a statistically insignificant C$284 ($p = 0.406$) for those farther than median distance. Regressions three through six consider fertilizer with pesticide expenditures separately. Here, we see a similar pattern. Households in build villages increase fertilizer expenditures by C$437 ($p = 0.029$). Again, however, this effect is driven by those nearest the bridge site. They increase fertilizer expenditures by C$586 ($p = 0.015$), and we can indeed reject the null at 5 percent among this subset of households. There is an

economically and statistically smaller effect on pesticides, which increase by C$154 ($p = 0.424$) in response to the bridge. However, like the other inputs, the increase is driven primarily by those closest to the bridge, who increase spending by C$324 ($p = 0.075$).

Table 5: Farm Input Usage

	Intermediate Spending		Fertilizer Spending		Pesticide Spending	
	(1)	(2)	(3)	(4)	(5)	(6)
Build	645.182*		436.584**		153.564	
	(0.054)		(0.029)		(0.424)	
Build × Near		1091.613***		585.932**		323.647*
		(0.003)		(0.015)		(0.075)
Build × Far		283.158		322.930		22.189
		(0.406)		(0.145)		(0.926)
Baseline mean of dep. variable	906.026	906.026	596.991	596.991	337.343	337.343
Observations	917	917	919	919	916	916
Time F.E.	Y	Y	Y	Y	Y	Y
Household F.E.	Y	Y	Y	Y	Y	Y

p-value in parentheses computed using the wild cluster bootstrap-t with 1000 simulations, clustered at the village level. Total intermediates are fertilizer plus pesticide spending. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

6.3 Planting Decisions and Yields

Since farm investment increases, we next turn to planting decisions and yield. We begin by looking at planting decisions, where we consider staple crops corn and beans along with the main cash crop in Northern Nicaragua, coffee.[7] The outcome variable here is an indicator equal to one if the crop is planted (not necessarily harvested), and the results are in Table 6.

We find no evidence of a shift to cash crops, though we do find some evidence of more households planting staple crops, especially beans. We therefore next consider changes in yields for corn and beans, where yield is measured as total quintales harvested per manzana (about 1.73 acres). The results are in Table 7. We find a substantial increase in corn yields from 10.39 in no-build villages to 24.80 ($p = 0.063$) in build villages, for an increase of 139 percent. When we distinguish near versus far households, we see large increases in both groups, though the latter is less precise. Turning to beans, we also find an increase in yield, though only in the farther

[7] We considered other cash crops as well, and find similar results to coffee.

Table 6: Planting Decisions

	Corn		Beans		Coffee	
	(1)	(2)	(3)	(4)	(5)	(6)
Build	-0.006		0.084		0.006	
	(0.945)		(0.272)		(0.742)	
Build × Near		0.0560		0.073		0.012
		(0.524)		(0.275)		(0.697)
Build × Far		-0.059		0.117		-0.001
		(0.422)		(0.201)		(0.944)
Baseline mean of dep. variable	0.221	0.221	0.256	0.256	0.016	0.016
Observations	917	917	919	919	916	916
Time F.E.	Y	Y	Y	Y	Y	Y
Household F.E.	Y	Y	Y	Y	Y	Y

p-value in parentheses computed using the wild cluster bootstrap-t with 1000 simulations, clustered at the village level. Total intermediates are fertilizer plus pesticide spending. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

households from the bridge site.

Table 7: Farm Yield

	Corn Yield		Bean Yield	
	(1)	(2)	(3)	(4)
Build	14.411*		3.155*	
	(0.063)		(0.056)	
Build × Near		12.725*		1.827
		(0.072)		(0.440)
Build × Far		15.521		4.380**
		(0.115)		(0.019)
Baseline mean of dep. variable	10.385	10.385	5.238	5.238
Observations	917	917	919	919
Time F.E.	Y	Y	Y	Y
Household F.E.	Y	Y	Y	Y

p-values in parentheses computed using the wild cluster bootstrap-t with 1000 simulations, clustered at the village level.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

6.4 Savings Decisions

Consistent with the model developed in Section 2, households have both higher off-farm income and invest more on their farms. The last prediction of the model is that households decrease the amount of crop stored in the household. This is the main form of savings in these rural villages. To define storage, we asked first about the amount harvested of each crop. We then asked what part was sold, used to pay debt, gifted, or given as land payment. We define storage as the fraction of the harvest not distributed, as this is the correct model counterpart. That is, harvest net of sales, debt payments, gifts, and land payments.[8] Table 8 shows how bridges affect the savings behavior of farmers.

Table 8: Farm Savings Choices

	Fraction Corn Saved		Fraction Beans Saved	
	(1)	(2)	(3)	(4)
Build	-0.085**		-0.088**	
	(0.041)		(0.035)	
Build × Near		-0.093		-0.092
		(0.109)		(0.122)
Build × Far		-0.080**		-0.085*
		(0.025)		(0.077)
Baseline mean of dep. variable	0.937	0.937	0.927	0.927
Observations	917	917	919	919
Time F.E.	Y	Y	Y	Y
Household F.E.	Y	Y	Y	Y

p-values in parentheses computed using the wild cluster bootstrap-t with 1000 simulations, clustered at the village level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Consistent with the model, farmers store a significantly smaller proportion of their harvest. In build villages, farmers in build villages save 9 percentage points less of both corn harvest ($p = 0.04$) and bean harvest ($p = 0.035$).

[8] In the Appendix we present the results when we define storage as the amount of each crop currently held in the household. The results are quite similar. However, this measure is net of any already-consumed harvest and thus is not the total measure of harvest stored. For this reason, we prefer the in-text measure of storage.

7 Alternative Explanations

7.1 Prices of Inputs and Outputs

An alternative explanation for these results is that prices change. Input prices may become cheaper as the cost of trade declines, or alternatively output prices may increase if bargaining power with intermediaries increases. Both of these are unlikely given the villages under consideration, as the flooding risk is temporary. However, changes in prices underlie many studies of permanent changes in trade costs, so we therefore we assess its relevance here. Table 9 shows the prices of fertilizer and pesticide, and we find no evidence that prices go down.

Table 9: Fertilizer and Pesticide Prices

	Fertilizer Price		Pesticide Price	
	(1)	(2)	(3)	(4)
Build	0.01		-0.00	
	(0.16)		(1.00)	
Build × Near		0.01*		0.02
		(0.08)		(0.90)
Build × Far		0.00		-0.02
		(0.66)		(0.50)
Far		-0.00		0.00
		(0.98)		(1.00)
Constant	0.05***	0.05***	0.08***	0.08***
	(0.00)	(0.00)	(0.00)	(0.00)
Observations	926	926	926	926

p-values in parentheses computed using the wild cluster bootstrap-t with 1000 simulations, clustered at the village level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Alternatively, prices for crop sales could change in response to a bridge. This could be a response to better bargaining power with intermediaries, for example. Table 10 considers the sale price of corn and beans, and finds no evidence of differential price changes.

The lack of any change to input or output prices is consistent with the fact that the

Table 10: Harvest Sale Prices

	Corn Price		Bean Price	
	(1)	(2)	(3)	(4)
Build	-36.44		-45.96	
	(0.32)		(0.92)	
Build × Near		-51.32		67.55
		(0.24)		(0.78)
Build × Far		-32.79		-149.76
		(0.42)		(0.36)
Far		-40.80		108.36
		(0.34)		(1.00)
Constant	176.07***	204.63***	916.87***	874.03***
	(0.00)	(0.00)	(0.00)	(0.00)
Observations	926	926	926	926

p-values in parentheses computed using the wild cluster bootstrap-t with 1000 simulations, clustered at the village level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

flooding is generally short-lived. To the extent that input purchases can be delayed or output stored for a week or two during a flood episode, it is unlikely that the bridge would have an affect on prices.

7.2 Household Debt

We also consider other savings and borrowing technologies. Less than one percent of household observations have a bank account, so saving cash in a bank is not a margin on which these households adjust.

We also consider debt positions in the household, including to banks, businesses or any other institutions or individuals. Table 11 provides evidence on total outstanding debt levels, along with indicators for outstanding debt to different institutions. We provide the results for the triple-difference results from regression (6.2), but the results from regression (6.1) show a similar lack of effect. Regression one is the total household debt outstanding in córdobas. While households do make use of debt markets, there is no evidence that the bridge has any affect. Regressions two, three, and four are

indicators equal to one if a household has any outstanding debt, to a bank or financial institution, business (usually the local store), or any other person. Again, there is no movement either into or out of debt in response to the bridge. Though not presented here, replacing these regressions with debt amounts shows the same result.

Table 11: Household Debt

	Total Outstanding Debt	Any outstanding?		
		Bank	Business	Other
	(1)	(2)	(3)	(4)
Build × Near	-156.61	-0.02	0.02	-0.01
	(0.54)	(0.60)	(0.88)	(0.78)
Build × Far	-84.88	-0.01	-0.01	0.01
	(0.78)	(0.72)	(0.78)	(0.72)
Far	73.59	0.02	-0.03	-0.03
	(0.60)	(0.62)	(0.22)	(0.26)
Constant	1143.26***	0.14***	0.31***	0.31***
	(0.00)	(0.00)	(0.00)	(0.00)
Observations	926	926	926	926

p-values in parentheses computed using the wild cluster bootstrap-t with 1000 simulations, clustered at the village level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

8 Conclusion

We consider the impact of new footbridges in rural Northern Nicaragua. The villages that we study are subject to sporadic seasonal flooding that cuts off households from local markets, which include trading areas, schools, and hospitals. Working with an NGO partner, we construct footbridges to link these villages back to markets, and use the small but critical engineering requirements to identify the effect. Despite the fact that we construct only 6 bridges in 15 villages, we identify a number of important changes among households. First, the bridge eliminates any change in income realizations during floods. Farmers therefore increase fertilizer and pesticide investment and yields. Moreover, they store less food in their households. Lastly, we show that these predictions are consistent with a model in which households self-insure through off-farm labor. Intuitively, this smoothing channel allows them to shift savings

out of high-cost storage of crops and into more productive on-farm investments.

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A More Results

Current Storage Table 12 shows storage levels using a direct measure of storage. The measure of storage used here is

$$\frac{\text{Current Quantity Stored in Household}}{\text{Total Quantity Harvested}}.$$

This measure does not measure the total amount of harvest stored, as some was consumed prior to the survey wave. Nevertheless, the results are similar to those in the main text.

Table 12: Farm Savings Choices

	Fraction Corn Saved		Fraction Beans Saved	
	(1)	(2)	(3)	(4)
Build	-0.10*		-0.10*	
	(0.08)		(0.06)	
Build × Near		-0.12*		-0.12**
		(0.10)		(0.04)
Build × Far		-0.08		-0.08
		(0.38)		(0.24)
Far		-0.01		0.00
		(0.94)		(0.90)
Constant	0.85***	0.85***	0.90***	0.90***
	(0.00)	(0.00)	(0.00)	(0.00)
Observations	926	926	926	926

p-values in parentheses computed using the wild cluster bootstrap-t with 1000 simulations, clustered at the village level.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$