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

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Abstract

We estimate the impact that consistent access to outside markets has on income, savings and investment decisions in village economies. We study rural Nicaraguan villages that experience unpredictable flash floods that cut them off from outside food, labor and product markets for days or weeks at a time. We build bridges that eliminate this risk. Identification exploits variation in river bank characteristics that preclude bridge construction in some villages, despite similar need for a bridge. We collect detailed annual household surveys over three years and conduct weekly telephone followups with a subset of households for sixty-four weeks, including both before and after construction. Floods decrease labor market income by 18 percent when no bridge is present. Bridges eliminate this effect. Despite the fact that output prices do not change, fertilizer spending and village wages both increase with a bridge, while inducing workers to shift to jobs outside the village. We show that our results are all consistent with the predictions of a general equilibrium model in which farm investment is risky and the labor market can be used to smooth shocks.

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1 Introduction

The majority of households in the developing world live in rural areas where productivity is particularly low (Gollin, Lagakos and Waugh, 2014). One channel affecting rural productivity is the poor integration between farm and non-farm labor markets. This poor integration is particularly important in rural areas, as households commonly have multiple income streams from both farming and labor markets (Foster and Rosenzweig, 2007). Integrating these markets may therefore have large effects, both by allowing individuals to take advantage of higher wages outside their village (Bryan, Chowdhury and Mobarak, 2014; Bryan and Morten, 2015), but also its potential spillovers into agricultural decisions.

In this paper, we directly study the impact of connecting rural Nicaraguan villages to markets and show that it has sizable effects on household wage earnings, farm investment decisions, and savings. We build footbridges that connect villages to markets during seasonal flash flooding, which routinely and unpredictably eliminates access to outside food, product, and labor markets.[1] We conduct household-level surveys the year before the bridges are constructed and for two years after. In addition, to understand the contemporaneous impact of flooding on household outcomes, we collect 64 weeks of data from a subset of households. This allows us to focus on multiple margins affected by improved outside market access, such as labor market outcomes and agricultural production choices.

Our identification strategy is based on the fact that many villages need bridges, but construction is infeasible for some villages due to the characteristics of the river beds that they aim to cross. Because these rivers are typically distant from the houses and farmland of the village (the average village household is 1.5 kilometers from the potential bridge site), the failure to pass the engineering assessment is orthogonal to any relevant household or village characteristics. We verify this by showing that baseline characteristics are balanced across villages that do and do not fulfill the engineering requirements, which we detail in Section 2.

A major barrier to studying transportation infrastructure as an intervention is the high cost of construction. Flash floods produce a powerful torrent of water that would destroy any bridge that is poorly designed or built with inadequate materials. The

[1] This issue is considered a major rural development hurdle by both international policy organizations and citizens of Nicaragua (World Bank, 2008*a*). More broadly, seasonal flooding or monsoons in the tropics have long been discussed as a contributor to poverty. See Kamarck (1973) for an early study on agriculture and health issues in the tropics.

bridges we construct therefore require high engineering standards, and each bridge costs approximately $40,000. Because of the high cost involved, our study includes household-level data from only 15 villages. We therefore apply the wild bootstrap cluster-t procedure from Cameron, Gelbach and Miller (2008) throughout. We provide a number of robustness checks to the clustering procedure using randomized inference (Fisher, 1935) and also vary the main regression specification. The results are robust.

Despite the small number of clusters, we find economically and statistically significant effects on household labor market earnings and agricultural decisions. We first use 64 weeks of high frequency data to study the contemporaneous impact of flooding on household income. In the absence of a bridge, floods depress labor market earnings by 18 percent and an increase in the probability of reporting no income. When a bridge is constructed, both of these effects disappear. Floods therefore generate uncertain access to labor markets, and a bridge eliminates this uncertainty.

We also find that labor market income increases in non-flood periods once a bridge is constructed. To understand this effect, we turn to our in-depth annual surveys to study the composition of wage earnings. First, we verify that average wage income is 30 percent higher in villages with a bridge than in those without.[2] Second, we provide details on the mechanisms generating this increase, which are different for men and women. Men shift their time from relatively low paying jobs in the village to higher paying jobs outside the village, and, in addition, wages increase for jobs inside the village. Because the outside market wage is unchanged, this implies that the male wages inside and outside the village converge in response to a bridge. This result is consistent with general equilibrium effects found in Mobarak and Rosenzweig (2014) and Akram, Chowdhury and Mobarak (2016), who find changes in wages in response to increased agricultural investment and rural emigration respectively. It further implies that even those workers who do continue to work in the village village benefit from the bridge, as they take advantage of the higher village wage. Unlike men, we find a significant increase in labor force participation among women, and these new entrants almost exclusively take up jobs outside the village. Correspondingly, we find no changes in female wages in or outside the village.[3]

[2] These annual surveys are conducted after the rainy season has ended, so this higher income is not due to contemporaneous flooding. They should be interpreted as harvest-time labor market earnings.

[3] It is important to note that the vast majority of men who work within the village work in farming, while almost no women work in farming. Therefore, if female labor is not a substitute for male labor, then the increase in the returns to male labor within the village does not imply an increase in the returns to female labor.

We next study how bridges influence farm investment decisions. There is reason to suspect the two are closely related. We use our high frequency data to show that essentially all households, even those that primarily farm, work off-farm at least some of the time. We find that farmers spend nearly 60 percent more on intermediate inputs (fertilizer and pesticide) in response to a bridge. We find that yields increase as well, but are statistically insignificant, consistent with the fact that harvests are subject to substantial shocks after investment.[4] One possible explanation for these results is that bridges decrease trade costs, which causes farm output prices to increase within the villages. We find no evidence of changes in crop prices.[5]

To understand the interaction between off-farm labor market access and investment decisions, we build a dynamic general equilibrium model of households that that both farm and work off-farm. The basic structure of the model is similar to that used to motivate formal rainfall insurance programs, including Mobarak and Rosenzweig (2014) and Karlan et al. (2014) among others. We expand on the ideas in those models to formally take into account the temporal nature of agricultural decisions, and allow for interaction between high frequency shocks and low frequency investment decisions and off-farm labor by cultivators. In the model, farmers make irreversible fertilizer investment decisions that take time to pay off and are subject to shocks (e.g. weather) that are unknown at the time of investment. In the interim, farmers have the choice of working on-farm to increase their eventual yield, or to earn wage income by working off-farm. However, households are subject to an aggregate shock that affects their ability to access the outside labor market, which formalizes the notion of a flood in the model.

Motivated by our empirical results, we interpret a bridge as a reduction in both the mean and variance of this shock. That is, while the river may still flood, it not longer limits the ability to access the outside labor market. This allows farmers to more easily overcome risk associated with fertilizer investment. We show theoretically that with uninterrupted market access, households use off-farm labor to smooth consumption if

[4] It is worth emphasizing that while the effects are large, the treatment is also very expensive ($40,000 each), so these effects are not as outsized as they may seem at first glance. We compute an average return on investment of 14 percent. So although the benefits are large, the returns are not implausibly high given the large costs of bridge construction. See Section 7 for more details.

[5] Changes in output prices are *a priori* unlikely in our context, and our result is not a general statement about trade costs and infrastructure. To the extent that goods are storable over the relatively short flooding period, we are unlikely to see a decrease in the spatial dispersion of output prices. Instead, we wish to highlight that even absent such effects, the overall impact is still large, which suggests that rural infrastructure development has broader potential benefits than those implied by only a decrease in goods price dispersion.

negative shocks are realized. Moreover, they become richer as market access is more consistently available. All else equal, both of these channels decrease the consumption risk associated with increased investment, and thus increase fertilizer expenditures.

However, this partial equilibrium result need not hold in general equilibrium, as the village wage also increases. This lowers demand for farm labor, which decreases the marginal product of fertilizer and puts downward pressure on investment. The overall change in fertilizer expenditures thus depends on the relative magnitudes of these two equilibrium effects. We show that the second effect dominates if households are sufficiently poor, as we would expect in rural Nicaraguan villages. Indeed, the fact that we see fertilizer use increase implies that the distortions facing households are sufficiently large to dominate the fact that labor prices increase within the village.

A critical result of the model mechanism is that savings should decrease in response to a bridge. In the absence of a bridge, farmers keep a large share of their harvest in storage as a buffer stock to smooth consumption in the face of negative shocks. Intuitively then, a bridge acts as a substitute consumption smoothing technology. Households are able to store less harvest once they have access to smoothing from the labor market, and instead redirect those resources toward fertilizer investment. We test this result in our data and find support. Agricultural storage among farmers decreases from 90 percent of harvest to 80 percent of harvest in response to a bridge. Moreover, there is a strong negative correlation between changes in fertilizer expenditures and crop storage. These results are consistent with our interpretation of the bridge as a risk-smoothing technology that changes the savings and investment decisions of farmers by giving them access to a better outside option if negative agricultural shocks are realized. The availability to smooth income *ex post* implies that it is optimal to make larger investment in the relatively high return agricultural intermediates *ex ante*.

1.1 Related Literature

Our work relates closely to work on the spatial distribution of labor, including Bryan, Chowdhury and Mobarak (2014), Bryan and Morten (2015), and Akram, Chowdhury and Mobarak (2016). Because off-farm work is an important component of rural income and potentially mitigates risk (Kochar, 1999; Foster and Rosenzweig, 2007), we contribute to this literature by assessing how this (mis-)allocation of labor affects local agricultural production, and how decreasing the cost of labor market access changes production. Similarly, Jayachandran (2006) and Fink, Jack and Masiye (2014) show how labor can be used to move resources over time in the absence of other formal savings markets that make this possible in developed countries.

Our intervention is also related to a growing literature on the benefits of new infrastructure, such as Casaburi, Glennerster and Suri (2013), Donaldson (2013), Allen and Arkolakis (2016), Asturias, Garcia-Santana and Ramos (2016), and Alder (2017). Adamopoulos (2011), Gollin and Rogerson (2014), Sotelo (2016), and Van Leemput (2016) have a similar focus, but explicitly highlight rural-urban links. These papers all focus on the ability of infrastructure to allow easier movement of goods across space. Allen and Atkin (2016) show that the ability to adjust risk-production profiles in response to lower trade costs amplifies the gains from lower internal trade costs among Indian farmers. We focus on two margins not covered by these papers. First, we show that the ability to more easily move people across space provides additional benefits and the effects are potentially quite large. Second, these papers all focus on the first moment of trade costs, while we show that variation in trade costs can also have important implications for investment.

Lastly, Asher and Novosad (2016) and Shamdasani (2016) show that a large-scale Indian roads program hastens structural transformation, thus moving workers off farms. Dinkelman (2011) finds similar results from electrifying rural South Africa. These papers that show the importance of labor movement in response to large-scale infrastructure development, and are complimentary to our work. Our involvement with planning and construction allows us to collect detailed micro data to investigate the underlying mechanisms in a way that is difficult with administrative data. The trade-off, of course, is that we must operate at a smaller scale than these projects. Nevertheless, we do find some changes in prices (wages, in particular). It is worth noting, however, that while our data allows us to provide more detailed evidence on the benefits of new infrastructure, our results are almost certainly an incomplete accounting of the aggregate impact of scaling such an intervention.

2 Background

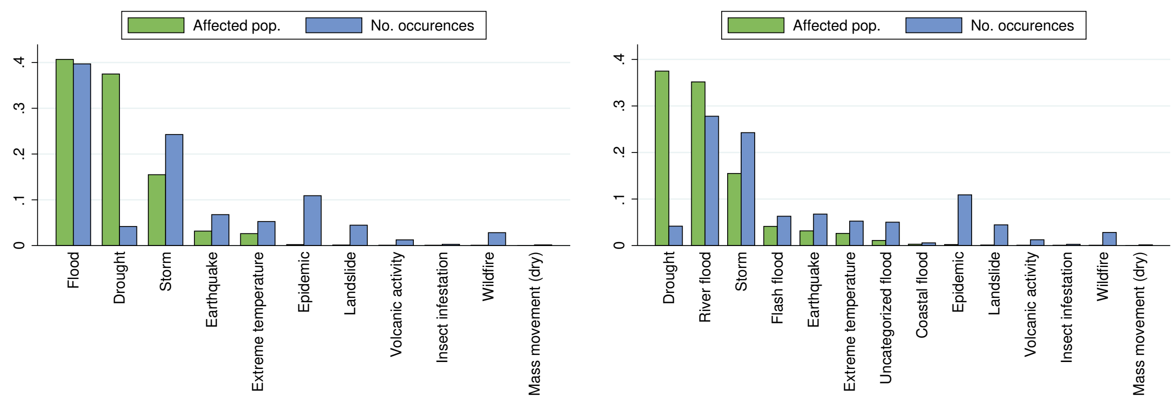
2.1 Flooding Risk

According to EM-DAT (2017), over 40 percent of people affected by disasters worldwide since 2000 are affected by flooding. Of that, nearly all are due to river floods, as shown in Figure 1.[6]

Figure 1: World Disasters (2000-2016)

(a) Different Disaster Types

(b) Finer Decomposition of *Flood*



In Nicaragua, both policy makers and residents cite flooding and the resulting isolation as a critical development constraint (World Bank, 2008*a*). The villages in our sample are located in mountainous areas that face seasonal flooding during the rainy season each year between May and November. This overlaps with the main cropping season as crops are planted in late May and harvested in November.

During the rainy season, floods cause stream and river beds that are usually passable on foot to rise very rapidly and stay high for days or weeks. This flooding is unpredictable in its timing or intensity. Rainfall in the same location is not necessarily a good predictor of flooding, as rains at higher altitudes may be the cause of the flooding, which is a feature of flooding in other parts of the world as well (e.g. Guiteras, Jina and Mobarak, 2015, in Bangladesh). During the baseline rainy season, the average village is flooded for at least one day in 45 percent of the two-week periods we observe it. Over the whole rainy season, this amounts to 2.25 days of flooding

[6] A disaster is included in the EM-DAT (2017) dataset if it meets one of the following conditions: 10 or more dead, 100 or more people affected, declaration of state of emergency, or a call for international assistance.

every two weeks, but the intensity varies. Conditional on flooding, the average flood lasts for 5 days, but ranges from less than a day to 9 days (the ninetieth percentile). During these periods, villages are cut off from access to outside markets.

It is important to emphasize that floods are intense torrents of water and not just villages situated next to rivers. Thus, crossing the river by swimming or any other methods entails substantial risk of injury or death.[7] These floods therefore usually generate prohibitively dangerous crossing conditions or a long journey on foot to reach the market by another route. For our purposes, we interpret a flood as a very substantial increase in the cost of reaching outside markets.

During dry periods, river beds in our sample are universally crossable on foot. Appendix E shows the main dry time river crossing at a number of sites from the study. As can be seen from the photos, the river beds are generally dry when not flooded, or, at most, only require wading in shallow water to cross. Moreover, these villages are not located on deep ravines that make crossing difficult during dry times. This is important for the interpretation of our results, and contrasts this context from standard issues around transportation infrastructure that is used to generate a constant reduction in transportation costs, as in recent work by Adamopoulos (2011), Gollin and Rogerson (2014), and Sotelo (2016).[8]

2.2 Economic Activity in Rural Nicaragua

Economic activity in rural Nicaragua is made up of both farming and off-farm wage work.

Crop Cultivation At baseline, 51 percent of households farm some crop. Of those households, 47 percent grow beans and 41 percent grow maize. The next most prevalent crop is sorghum (8 percent). The key cash crops in the region are tobacco and coffee, as Northern Nicaragua climate and geography are well suited for both. However, tobacco and coffee are almost exclusively confined to large plantations. Only 3 percent of households in our sample grow coffee at baseline, while less than one percent grow tobacco. As we discuss below, coffee and tobacco jobs (picking, sorting, etc.) are an important source of off-farm wage work. The modal use of staple crop

[7] We are aware of at least two people (one on horseback) in our sample that died trying to cross flooded rivers during the last survey wave.

[8] Importantly, the mechanism underlying effects in these models is convergence in the prices of goods across markets. We find no evidence of effects on the prices of goods, which confirms that those channels are inoperative in our context.

harvest is home consumption. Over 90 percent of maize and bean harvest is either consumed immediately or stored for future household consumption. The majority of those who sold crops either sell in the outside market (58 percent) or to middlemen who buy in the village and export to other markets (38 percent). Only 4 percent sell to local stores in the same village.

Fertilizer is used by 73 percent of all farming households. While for a developing country this is a relatively high prevalence of fertilizer, fertilizer expenditures are only 16 percent of total harvest value. This share is not quite as low as the poorest African countries, but substantially lower than developed countries (Restuccia, Yang and Zhu, 2008).

The Labor Market We use bi-weekly data collected from households in our sample to show that nearly all households receive labor market income at some point.[9] Figure 2 is a histogram counting the share of weeks each household receives positive labor market income. Despite the fact that 51 percent of households farm at baseline, most are also active in the labor market some of the time. When we rank households by the share of periods we observe positive income, even the fifth percentile household receives labor market income in 21 percent of the periods we observe it.[10] Households are almost never entirely specialized in farming, suggesting potential for a relationship between the labor market and on-farm outcomes, which we study in later sections.

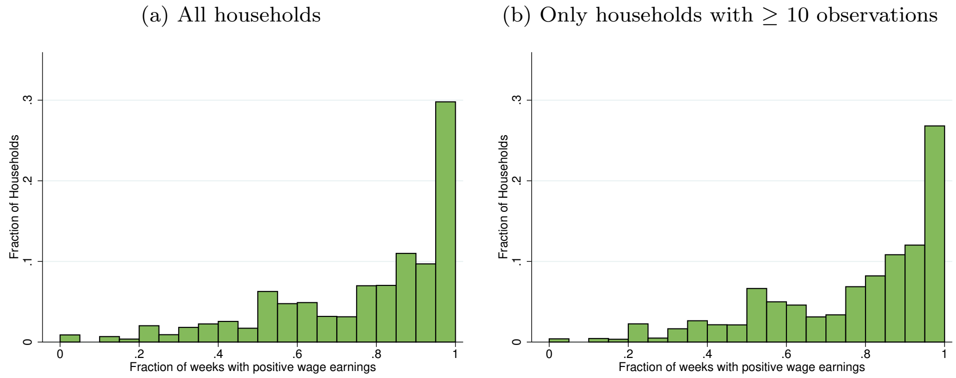
Jobs held by village members are made up of those inside the villages (62 percent) and those employed in the outside markets (38 percent). The latter are at risk of being inaccessible during a flood. Connected markets have between 10,000 and 20,000 people, compared to 150 to 400 people in the small villages we study, so these villages make up only a small fraction of the labor supplied outside the village. Outside-village jobs also pay more on average. There is a 30 percent daily wage premium for men outside the village and an even larger 70 percent daily wage premium for women, though women are employed at a much lower rate.

In both cases, jobs are primarily on short term contracts, operated in spot markets. At baseline, 80 percent of primary jobs held were on short-term (less than one week)

[9] We discuss data collection in Section 3.

[10] This is a cell phone-based survey. Therefore, one possibility is that survey non-response is correlated with realizations of zero income, thus biasing our results toward observing positive income. This would be the case if heavy rains strongly reduced cell coverage, for example. In Appendix C.2 we show that there is no relationship between flooding and the likelihood of response to surveys. Moreover, we take an extreme stance and assume every missed call implies zero income. This naturally affects the intensive margin of periods with income, but not the extensive margin. Therefore, the results are robust to even the most conservative possible assumptions on response rates.

Figure 2: Fraction of weeks with labor market income



contracts. This differs somewhat depending on job location. In the village labor market, 90 percent of all jobs held are short-term, while outside the village 64 percent of jobs are short-term. The majority of jobs in the village relate to farming. Ninety-two percent of jobs held within the village are short-term hired farmhands, while the rest are employed in various other occupations (e.g., clothes washers, teachers, brick makers, carpenters). The modal job outside the village is also farming-related, though typically on large farms producing cash crops. Thirty-five percent work in tobacco or coffee plantations. Workers in outside markets cross the river bed to reach the market town where trucks pick up workers to bring them to work. Workers are then dropped off at the same location at the end of the day. Thus, the market towns are important staging points for this work. The remaining jobs that account for at least 5 percent of outside market workers are teachers (9 percent), carpenters (9 percent), manufacturing workers (7 percent), brick layers (7 percent), cigar rollers (6 percent), and maids (5 percent).

3 Intervention, Data Collection, and Identification Strategy

3.1 Intervention

The bridges we build traverse potentially flooded river beds, thus allowing village members consistent access to outside markets. We partner with Bridges to Prosperity (B2P), a non-governmental organization that specializes in building bridges in rural communities around the world. B2P provides engineering design, construction materials, and skilled labor to the village. Bridges are designed by a lab of civil engineers in the United States in consultation with local field coordinators, who are also engineers. Bridges cannot be crossed by cars, but can support horses, livestock, and motorcycles. A bridge that can survive multiple rainy season requires durable, expensive materials and a sufficiently sophisticated design to overcome issues of rising water levels, soil erosion, and other risks that face infrastructure.

B2P 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. This assessment is made based on the number of people that live in the village, the likelihood that the bridge would be used, proximity to outside markets and available alternatives.

If the village passes the needs assessment, the country manager conducts an engineering assessment. The purpose of this assessment is to determine if a bridge can be built at the proposed site that would be capable of withstanding a flash flood. To be considered feasible, the required bridge cannot exceed a maximum span of 100 meters, and the crests of the river bed on each side must be of similar height (a differential not exceeding 3 meters). Moreover, evidence of soil erosion is used to estimate water height during a flood. The estimated high water mark must be at least two meters below the proposed bridge deck.[11]

We compare villages 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, the characteristics of the river bed are unlikely to be correlated with any relevant village characteristics. We show that villages that do and do not receive bridges are balanced on their observable characteristics in Table 1.

Because of the bridges each cost $40,000, the number of bridges that can be funded is limited.[12] 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

[11]Note that the optimal place to build a bridge need not be the optimal place to cross on foot. See Appendix E for on-foot crossing locations.

[12]We discuss cost-effectiveness in Section 7. The internal rate of return to the bridge is 14 percent.

provinces of Estelí and Matagalpa in northern Nicaragua.[13]

3.2 Data Collected

We collect two types of data. 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 only to collect GPS coordinates from households and sign them up for the high frequency survey. The data used in our analysis comes from surveys conducted at the end of the main rainy season, in November 2014, November 2015, and November 2016. Bridges were constructed in early 2015. Therefore for all villages we have surveys from three years. For those that receive a bridge, we observe one survey without a bridge and two surveys with a bridge. We refer to these survey waves at $t = 0, 1, 2$.

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 all village households. The number of households identified in each village varied widely, from a maximum of 80 to a minimum of 24, with an average household size of 4.2. Participation in the first round of the survey was very high in general, with 97 percent 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 this would bias their answers, or may make them feel they are compelled to answer the survey when they would not otherwise choose to participate.

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

The second component of our data is biweekly follow-up surveys conducted by phone with a subset of households. Because floods are high frequency and short term events, this data shows the contemporaneous effect that flooding has on households. We carried out these surveys for 64 weeks, covering the rainy season before construction, along with the first dry and rainy seasons after construction. Each household was called every two weeks and asked questions about the previous two weeks, so that

[13] The villages are far from one another, so there is no risk that the households in a control village could use the bridge in a treatment village.

the maximum number of responses per household is 32. This high frequency survey covered income-generating activities, livestock purchases and sales, and food security questions over the past two weeks.

3.3 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. Identification requires that the features required to pass the feasibility test are independent of any relevant household or village-level statistics. To test that these villages are comparable, we run the regression

$$y_{iv} = \alpha + \beta B_v + \varepsilon_{iv}$$

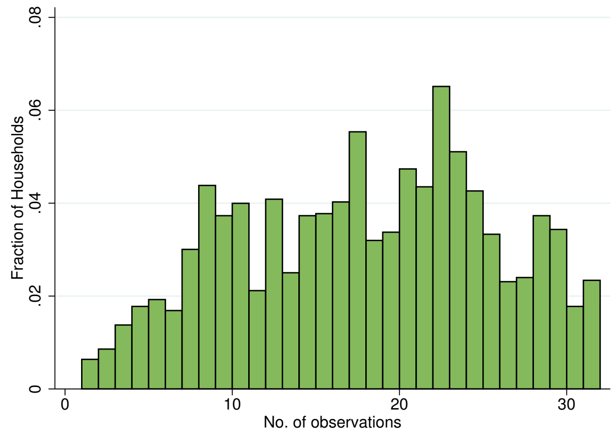
on the baseline data, where $B_v = 1$ if village v gets a bridge between $t = 0$ and $t = 1$. We consider a number of different outcomes, and show that households show no observable differences across the two groups. Table 1 produces the results, and we find no difference across households in build and no-build villages.

3.4 High Frequency Sample Selection

Because the high frequency data was collected by phone, two issues are worth highlighting before turning to the results. First, the high frequency data is not representative of the villages under study as not every individual has a cell phone. Table 11 in Appendix C.1 shows how high frequency respondents compare to the overall populations in the study. As one may suspect with a cell phone-based survey, respondents tend to be younger (the average household head is six years younger) and slightly more educated (one additional year of schooling). However, there are no other statistically significant differences between households participating in the phone survey and those that do not, such as wage income or farming outcomes. Moreover, within the high frequency sample, there are no statistical differences between those in villages that receive a bridge and those that do not except for household head age.

The second issue is that the survey is an unbalanced panel as not everyone answered the phone each time. Figure 3 plots the histogram of the number of observations per household in the high frequency data. The minimum is 1, the maximum is 32, and the average is 12. The maximum possible is also 32, as each village is surveyed biweekly.

Figure 3: Number of Observations per Household



4 Empirics: Labor Market Earnings

We begin by showing that labor market earnings respond positively to the introduction of a bridge.

4.1 Labor Market Earnings and Floods

We first estimate the relationship between floods and labor market earnings. In the high frequency data, we observe how realize labor earnings depend on contemporaneous flooding in villages without a bridge. Moreover, by interacting an indicator variable for a bridge being present with flooding, we estimate how the relationship between income and flooding changes once the bridge is built. We include household and time fixed effects to control for constant characteristics of households, and for seasonal variation in earnings. Our empirical specification in the high frequency data is:

$$y_{ivt} = \eta_t + \delta_i + \beta B_{vt} + \gamma \Big(B_{vt} \times F_{vt} \Big) + \theta \Big(NB_{vt} \times F_{vt} \Big) + \varepsilon_{ivt}. \tag{4.1}$$

The variable $B_{vt} = 1$ if village v has a bridge in week t, while $NB_{vt} = 1 - B_{vt}$. 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. P-values are again computed using the wild bootstrap cluster-t where clustering occurs at the village level. We use two measures of income in regression

(4.1): earnings in the past two weeks, and an indicator equal to one if no income was earned. Table 4 illustrates the effects of flooding on contemporaneous income realizations.

When bridges are absent, flooding has a strong effect on labor market outcomes. The decline in labor market earnings is $C\$143.6$ ($p = 0.034$), which is 18% of mean earnings.[14] Moreover, the propensity to earn no labor market income increases by 7 percent ($p = 0.040$) from a mean of 24.9 percent. However, when a bridge is built the effect on income disappears. In villages with a bridge, flooding is associated with an insignificant increase in income of \$5.1 ($p = 0.874$), and the propensity to report no income actually goes down by 3.8 percent ($p = 0.048$).[15] Figure 4 plots the density of income realizations in villages without a bridge (left panel) and with a bridge (right panel) during periods of flooding and no flooding.

Figure 4: Density of Income Realizations

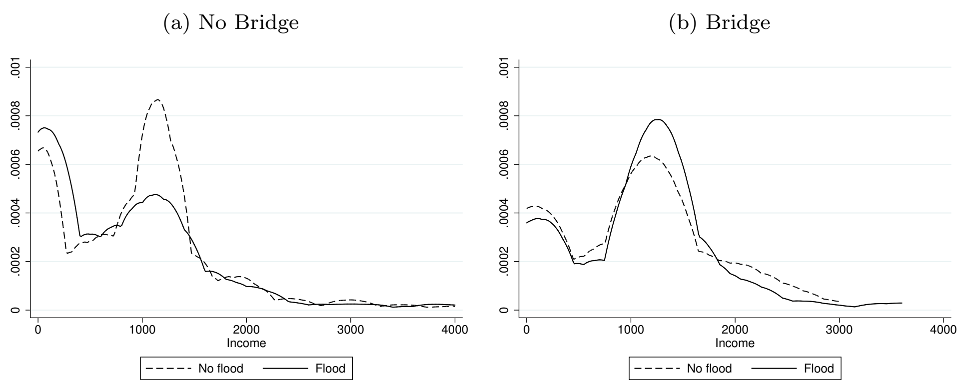


Figure notes: Figure 4a includes all village-weeks without a bridge, including those villages that eventually receive a bridge. Figure 4b includes all village-weeks post-construction.

Finally, it is notable that bridges increase income even in the absence of the flood. That is, during a non-flooded week, villagers with a bridge earn an average of C\$159 ($p = 0.004$) more. Since the bridge is intended to connect the village to outside markets during floods, it is surprising that it has any effect outside of flooding periods. We explore the cause of this finding in depth using the detailed annual data in Section

[14] The Nicaraguan currency is the córdoba, denoted C\$. The exchange rate is approximately C\$29 = 1 USD.

[15] We do not attempt to explain the association between flooding and zero reported income in villages with bridges. It is possible that it arises from general equilibrium effects: during floods many workers from many villages are all unable to get to work, which forces employers in outside labor markets to offer higher wages. However, we see no corroborating increase in labor earnings during floods. In the high frequency data we do not have enough specific information to explore what causes this. This result does not affect our explanation of the mechanisms discussed in later sections.

4.3 and find that a bridge causes workers to switch to jobs outside the village. The income gains, therefore, extend beyond just flooding periods. The bridges both smooth income during flood shocks, but also increases the average income level of households.

4.2 Do households substitute intertemporally?

The results in Section 4.1 show that flooding is associated with decreases in earnings during a flood. If a household cannot access the labor market in a given week, they can potentially recoup their lost earnings by increasing earnings in the next (un-flooded) week. However, this need not be the case if on-farm labor productivity shocks are highly correlated with non-farm labor productivity shocks. This would imply that the marginal product of on-farm labor would be high at exactly the time at which control households would wish to increase off-farm labor, thus dampening any effect.[16] We can test for these responses in our high frequency data by including lags in the earnings regression. We therefore run a regression similar to (4.1), but include lags as well

$$y_{ivt} = \beta_0+\beta_1 B_{vt}+\beta_2 F_{vt}+\beta_3(B_{vt}\times F_{vt})+\beta_4 B_{v,t-2}+\beta_5 F_{v,t-2}+\beta_6(B_{v,t-2}\times F_{v,t-2})+\eta_t+\delta_i+\varepsilon_{ivt}. \tag{4.2}$$

$B_{vj} = 1$ if a village has a bridge at week $j \in \{t-2, t\}$ and F_{vj} is defined similarly for floods. The week and household fixed effects are η_t and δ_i. Results are in Table 5. Columns (1) and (3) reproduce the earlier results with no lags, and confirm them. Column (2) shows that the results are inconsistent with control villages responding to floods by increasing future earnings. A flood at time t decreases contemporaneous earnings at t by C\$117 ($p = 0.082$), as shown previously in Section 4.1. A flood two weeks in the past implies a statistically insignificant C\$17 decrease ($p = 0.718$), suggesting control households are not responding to past floods with increased current labor market earnings. Column (4) presents a similar result using an indicator for no income earned as the dependent variable. The returns among treatment villagers are consistent with the same theory. Households actually earn C\$126 less ($p = 0.178$) when they were flooded two weeks before, though it is not statistically significant. If anything, these results are consistent with the ability of the *treatment* villages to better adjust to shocks through utilization of the labor market.

[16] Note that endogenous responses of this sort are already allowed in the model, and thus the theoretical results are robust to them.

4.3 Earnings from Annual Surveys

In the previous sections, we showed that bridges eliminate labor market income risk during floods and also provide a benefit in non-flood periods. We next use our annual surveys to better understand these results. These surveys were conducted at the end of the rainy season from 2014 to 2016 ($t = 0, 1, 2$). Our baseline regression specification is

$$y_{ivt} = \alpha + \beta B_{vt} + \eta_t + \delta_v + \varepsilon_{ivt} \tag{4.3}$$

where $B_{vt} = 1$ if a bridge is built, η_t and δ_v are time and village fixed effects. Throughout, we use the wild bootstrap cluster-t at the village level.[17] The results are in Table 2, where we consider total earnings, and also break down the results by gender. Consistent with the previous results, labor market earnings increase by C$380 ($p = 0.098$). This is almost entirely accounted for by the C$306 increase in outside earnings ($p = 0.000$). Inside earnings decrease slightly (C$27.70), but the change is statistically insignificant ($p = 0.828$). The same results hold when one distinguishes by gender. Columns 4 and 7 show that both men and women earn more, and these increases are entirely accounted for by earnings outside the village. For both genders, earnings inside the village decrease slightly, but both treatment effects are statistically insignificant.

We use the details of employment information in the annual surveys to shed light on the mechanisms that generate these changes in earnings. Table 3 decomposes earnings by the number of household members, daily wages, and days worked. The number of men employed shift from inside to outside labor market work. The number of male household members working outside increases by 0.19 ($p = 0.000$), compared to a 0.12 person decrease ($p = 0.128$) inside the village. Combined they generate a statistically insignificant net change in the total number of males employed. Women, on the other hand, see an increase in employment. On average, households employ 0.11 ($p = 0.006$) more women in wage-earning activities. This change is equal to the number of new female entrants to the outside labor market. The number of women working outside the village increases by 0.11 ($p = 0.000$), with no change inside (0.01, $p = 0.568$). Thus, while the bridge causes men to change where they work, it induces new women into labor market activity.

[17] See Section 7 for further discussion of robustness. The results are robust to both the inclusion of household fixed effects and alternative clustering procedures.

Next, we find that male daily wages inside the village increase by C$69 ($p = 0.092$), while male wages outside the village do not change (-C$5.6, $p = 0.816$). These results are consistent with what we would predict from general equilibrium effects. Because these villages account for a small fraction of labor market activity outside their villages, an increase in the number of workers from the village has no detectable effect on market wages.[18] However, since there are fewer men working within the village, the wage in the village is rises.[19] The gap in wages between inside-village and outside-village employment, therefore, converges among men. This is shown in Figure 5, where the ratio of average wages for workers outside the village to inside the village is high in the initial survey wave ($t = 0$) and the same in build and no-build villages, then falls toward one in the villages with a bridge. In the villages without bridges, it stays flat or rises. Lastly, the total number of days worked by men in the village changes by an insignificant amount (-0.30, $p = 0.418$). Thus, those who remain in the village work more intensely at the higher wage.

Figure 5: Relative Male Wage Outside Village to Inside Village

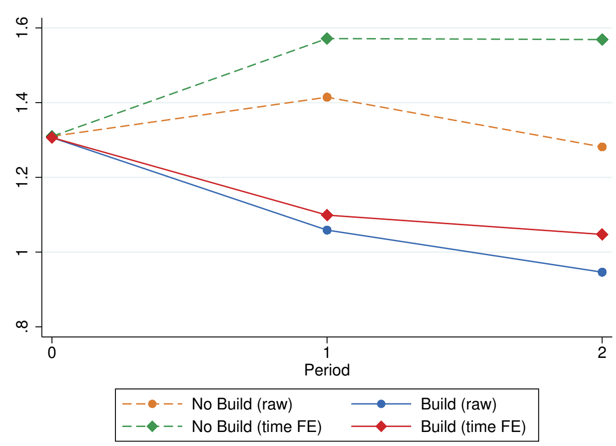


Figure notes: The raw data are simple average and the "time FE" data removes time fixed effects.

We find that the mechanisms for women are different. Neither their inside nor outside wages change, consistent with the fact that we do not find the decrease in within-village work that we do among men. We see similar changes in days worked as for men, but unlike for men, this is due to an increase in the number of women in the

[18]The market towns range in population from 10,000 to 20,000 residents. The effective labor market also includes the other villages connected to these towns. As such, it is intuitive that increased participation from a village with between 150 and 350 residents would have no detectable effect on wages.

[19]These workers moving to the outside labor market are not replaced by other workers from the outside labor market working in the village. Recall that wages outside the villages are higher than inside the villages.

labor force.

The fact that these labor market results appear even in the non-flood periods may be surprising. In our discussions with members of the treatment villages, we found two types of responses that help explain these findings. First, workers report that the choice to work outside the village without a bridge is too risky because days when flooding causes work to be inaccessible translates directly to lost labor income. As such, they view jobs outside the community as having high returns, but also a great deal of risk. Second, they explain that employers do not want to hire workers that are unable to get to work consistently. Although the majority of workers are employed on a short term basis, many workers have a set of relationships with employers that they go to as work becomes available. As such, the reputation of the worker matters, and unpredictable flooding damages the workers' reputations for reliability to get to work when they are expected to be there. The results we find are consistent with both of these effects being mitigated.

5 Model

We now present a model to generate predictions for how the labor market effects identified in the previous section link to agricultural decisions by households. The goal is to link high frequency changes in wages to longer-term agricultural outcomes, and then use these results to motivate empirical tests in the next section.

We model a village as a small open economy, in which consumption goods and farm inputs can be purchased from the larger outside economy. There is an outside labor market in which villagers can choose work at an exogenous wage, w^o. Villagers can work within the village on farms at an endogenous, market-clearing wage w^i.

Within a village, there is a continuum of infinitely-lived households that are endowed with a technology called a farm. Households can save at gross return R, which may be less than one, which we interpret as a low quality crop storage technology. Throughout, we use the terms household and farmer interchangeably. Farmers are *ex ante* heterogeneous in their ability vector $\mathbf{Z} = (Z_A, Z_L, \varphi)$, which includes their farming ability Z_A, their absolute working ability Z_L, and their comparative advantage working outside the village φ. $\mathbf{Z}$ is constant within a season, but may vary across seasons. Farmers are also subject to aggregate shocks to outside market access τ and on-farm labor productivity ε.

Outside Labor Market Households can work in the outside labor market, which pays a wage w^o per efficiency unit of time. This wage is constant over time.[20]

On-Farm Production Each household owns a farm. These farms produce output using labor and an intermediate input. The timing works as follows. Every T periods, a new season begins. At the beginning of the season, each farmer makes an irreversible intermediate input investment in their farm (e.g., fertilizer or pesticide). Output is harvested at the end of the season, T periods later. The farm technology is given by

$$Y = Z_A X^\alpha N^\gamma, \tag{5.1}$$

where Z_A is idiosyncratic farmer ability, X is the intermediate input, N is the stock of labor services that have been accumulated, and $\alpha + \gamma < 1$. Each period, the farmer employs labor on their own farm by either hiring workers within the village or by employing their own labor on-farm. The total labor services employed in their technology in period t is e_t. The stock of labor N depends on how much labor was employed in each of the T periods within a given season. We allow for the possibility that farm labor is not perfectly substitutable across time, such that the stock of labor services is:

$$N = \left(\sum_{t=1}^{T} \varepsilon_t^{\frac{1}{\sigma}} e_t^{1-\frac{1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \tag{5.2}$$

where ε_t is a village-level shock to on-farm labor productivity in a given period.

Labor Allocation Problem The last part of the problem is to decide how each farmer uses her time. She can work outside the village or inside the village. If she works outside the village, she receives $(1-\tau_t)w^o Z_L \varphi$ while working inside the village generates $w_t^i Z_L$ income. The wage w_t^i is required to clear the within-village labor market. τ is an aggregate shock that controls access to the outside market. If $\tau = 1$, the the market is inaccessible, while $\tau = 0$ implies no cost associated with accessing the market.

Each period from $t = 1, \ldots, T$, the farmer chooses which labor market she wishes

[20] To more directly close the model, one can assume the existence of a stand-in firm outside the village with production function $Y^o = AN^o$, where A is some fixed productivity term. The gross wage per efficiency unit is $w^o = A$ in any competitive equilibrium.

to work in after the stochastic access shock τ is realized. Her realized wage is $w_t = \max\{w_t^i, (1-\tau_t)w^o\varphi\}$, and total wage income is $w_t Z_L$.

5.1 Recursive Formulation

Given the model and timing described above, we can write the household problem recursively. This first requires some notation. Define $s_t = (\mathbf{Z}_1, \tau_1, \varepsilon_1, \ldots, \mathbf{Z}_t, \tau_t, \varepsilon_t) \in \mathcal{S}_t$ as one possible realization of shocks from 1,..., t, which occurs with probability $\pi(s_t)$. Since we assume $\mathbf{Z}$ is fixed between $t = 1$ and $t = T$, it is useful to define the subset of shocks that satisfy this requirement, $\widehat{\mathcal{S}}_t = \{s_t : \mathbf{Z}_{\tilde{t}} = \mathbf{Z}_1 \ \forall \text{ realizations of } \mathbf{Z}_1 \text{ and all } \tilde{t} = 1, \ldots, t\} \subset \mathcal{S}_t$ and $\widehat{\mathcal{S}}_t(\mathbf{Z_1}) = \{s_t : \mathbf{Z}_{\tilde{t}} = \mathbf{Z}_1 \ \forall \tilde{t} = 1, \ldots, t\}$.[21] With that in hand, the value of beginning a season with asset holdings A and ability $\mathbf{Z}$ is

$$V(A, \mathbf{Z}) = \max_{\{\phi, c_t, e_t, S_t \geq 0\}} \sum_{t=1}^{T} \beta^t \sum_{s_t \in \widehat{\mathcal{S}}_t(\mathbf{Z})} \pi(s_t) u(c_t(s_t)) + \beta^T \sum_{s_T \in \widehat{\mathcal{S}}_T} \pi(s_T) V(A'(s_T), \mathbf{Z}') \quad (5.3)$$

subject to:

$$\begin{aligned}
&\phi \in [0,1] \\
&S_0(s_0) = (1-\phi)A \\
&w_t(s_t) = \max\{w_t^i(s_t), \varphi(1-\tau(s_t))w^o\} \\
&c_t(s_t) = RS_{t-1}(s_{t-1}) - S_t(s_t) + w_t(s_t)Z_L - w_t^i(s_t)e(s_t) \\
&N(s_T) = \left(\sum_{t=1}^{T} \varepsilon(s_t)^{1/\sigma} e(s_t)^{1-1/\sigma} \right)^{\frac{\sigma}{\sigma-1}} \\
&A'(s_T) = S_T(s_t) + Z(\phi A)^\alpha N(s_T)^\gamma.
\end{aligned}$$

Throughout we will assume that u is strictly increasing, strictly concave and has a positive third derivative. The choice variables for consumption (c), savings (S), and labor (e) are measurable with respect to the history of shocks up to that period.[22]

This implies that farmers can adjust to shocks within the season along several different margins. For example, if a farmer receive a high τ realization, she can

[21] Also, for notational simplicity, we suppress the dependence of the problem on the aggregate state $\mu(A, \mathbf{Z})$ and its transition function $\Lambda(\mu)$.

[22] Note also that our formulation allows for arbitrary time series dependence within a season, but is i.i.d. across seasons. This assumption is not critical for the results, but simplifies exposition.

respond by drawing down their stock of savings, reducing their consumption, and adjusting their sectoral labor decisions in whatever way maximizes her continuation utility. Importantly, savings cannot be negative at any point during the season. This creates a motive to maintain a buffer stock of storage to insure against a sequence of bad shock realizations.

Farmer labor market choices follow a history-dependent cut-off rule

$$\varphi^*(s_t) = \frac{w_t^i(s_t, \mu)}{(1 - \tau(s_t))w^o}$$

such that all households with $\varphi > \varphi^*$ choose to work outside the village at time t with history s_t. On the other hand, the choice of fertilizer investment $X = \phi A$ is irreversible. Thus, this margin is not directly available for farmers to adjust in response to shocks, consistent with the theoretical motivation on formal agricultural insurance programs (Mobarak and Rosenzweig, 2014; Karlan et al., 2014).

5.2 Equilibrium

The competitive equilibrium of this economy is defined by a distribution $\mu(A, \mathbf{Z})$, a value function V, decision rules o, ϕ, c, e, S, and prices w^i and w^o such that (1) the value function V solves the household's problem given by (5.3) and the constraint set, (2) the law of motion for μ, denoted $\Lambda(\mu)$, is consistent with the shock transitions and the decision rules, and (3) the village labor market clears for all $t = 1, \ldots, T$:

$$\int_{(A,\mathbf{Z}):\varphi \leq \varphi_t^*(s^t;A,\mathbf{Z})} Z_L d\mu(A, \mathbf{Z}) = \int_{(A,\mathbf{Z})} e(s_t; A, \mathbf{Z}) d\mu(A, \mathbf{Z}) \tag{5.4}$$

5.3 Discussion: Nature of the Exercise

Before characterizing the model, it is useful to highlight how our model and analysis map to the data. Our goal is to compare two different infrastructure regimes: one without a bridge and another that mimics the introduction of a bridge. We model introduction of a bridge as a change in the distribution of τ. That is, a flood requires households to miss work or increase commuting times, which is a high τ realization in the model. Motivated by our results in the last section, we assume that a bridge decreases these costs. We model this a change in the distribution of τ such that the old distribution exhibits first order stochastic dominance over the new distribution.

We assume that both the mean and variance of τ decrease with the introduction of a bridge.

5.4 Farm Investment Decision

The critical decision that households make is how to divide their farm output between two types of savings: storage and productive investment. Storage 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 is realized, households may experience sharp declines in consumption.

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

$$R^T + \frac{\sum_t \sum_{s_t} R^t \eta(s_t)}{\sum_{s_T} \xi(s_T)} = \alpha Z_A (\phi A)^{\alpha - 1} \bar{N}^\gamma \sum_{s_T} \left(\frac{N(s_T)}{\bar{N}} \right)^\gamma \frac{\xi(s_T)}{\sum_{s_T} \xi(s_T)} \tag{5.5}$$

where $\eta(s_t)$ is the Lagrange multiplier on non-negativity of savings, and $\xi(s_t)$ is

$$\xi(s_T) = \beta^T \pi(s_T) V_1(A'(s_t), \mathbf{Z}')$$

and

$$\bar{N} = \left(\sum_{s_T} \pi(s_T) N(s_T)^\gamma \right)^{\frac{1}{\gamma}}.$$

Equation (5.5) simply states that households equate the marginal value of both types of investment. The left-hand side of (5.5) is the marginal value of savings over the course of the season. The additional unit of storage at period 0 is worth R^T at the end of the season. In addition, the value of an additional unit of storage is that it makes the household less likely to reach its non-negativity constraint on storage and, therefore, lose their ability to mitigate consumption losses from negative shocks. The right hand side of (5.5) is the marginal value of a unit of productive investment. Again, the link from investment to consumption shows up here through $\xi(s_t)$ as households weight sequences of shock realizations by their impact on the marginal value at the beginning of the subsequent season.

The intuition for a bridge's impact can also be seen in the context of equation (5.5). First, the non-negativity constraint on storage implies that households must maintain a buffer stock of savings to insure across negative shock realizations. When the household's income process becomes safer, they are less concerned about the non-negativity constraint binding, as the bridge provides a secondary smoothing technology. This frees resources to be used in investment that were formerly used as a buffer stock. Second, households are risk averse and the reduction in income risk that they face increases their willingness to substitute from safe and risky assets. All else equal, these forces imply that households shift from storage to farm investment, which we formalize in Proposition 1.

Proposition 1. *Assume $\gamma > 1 - 1/\sigma$, and suppose the process on τ changes such that $E[\tau]$ decreases or $Var[\tau]$ decreases. Then in partial equilibrium, ϕ weakly increases for every point in the state space.*

Proof. See Appendix A. ■

Note that result shows how the policy functions of households change in response to the change in the shock process, or put differently, the short-run response to a change in market access. We next ask how this result translates to general equilibrium. It is not immediate that the results of Proposition 1 will hold, as Proposition 2 shows that the village wage increases.

Proposition 2. *Under the same conditions as Proposition 1, $w^i(s_t)$ is weakly higher in every state.*

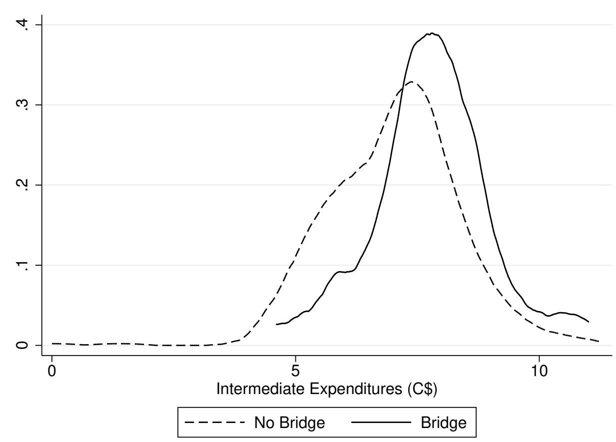
Proof. See Appendix A. ■

Intuitively, the bridge increases the returns to working outside the village compared to inside, so in general equilibrium the village wage increases to maintain market clearing in the village. The increase in wage implies the result of Proposition 1 are not generically true in general equilibrium. A higher wage implies a marginal cost for farming, and, if this effect is strong enough, may reduce the optimal scale of the farm technology and, therefore, optimal equilibrium farm investment. Which of these two effects dominates depends critically on how constrained households are. If investment increases in equilibrium, households must be sufficiently constrained that a bridge decreases the distortion by a magnitude larger than the wage increase. We next turn to testing these results empirically.

6 Empirical Impact on Agricultural Outcomes and Storage

We now examine the implications of the model empirically by estimating the effect of bridge construction on agricultural decisions of households. The results on agricultural outcomes using regression (4.3) are presented in Table 6. We first consider intermediate input (fertilizer plus pesticide) expenditures, and also the two components individually. These are columns 1-3 in Table 6. First, we see a substantial increase in intermediate expenditures. Intermediate expenditures increase by C\$659.97 ($p = 0.048$) on a baseline of C\$890. The changes are primarily accounted for by fertilizer investment, which increases by C\$383 ($p = 0.026$) compared to a statistically insignificant C\$167 ($p = 0.260$) for pesticide.[23] Figure 6 plots the density of log intermediate expenditures in villages with and without a bridge. Not only does the mean increase, but variance across households falls from 1.33 to 1.21 among those using positive amounts of fertilizer and pesticide.

Figure 6: Density of Log Intermediate Expenditures (C\$)



Columns 4–7 then consider how this increased input use translates into yields on staple crops. We look at changes in harvest for maize and beans, measured in total quintales (100 pounds) harvested.[24] Here, we find positive but mostly statistically insignificant results, consistent with the fact that farm outcomes are subject to substantial shocks after investment is made. We do find that maize yield increases by

[23]These results are for the average household, not the average household engaged in farm work, so the the total amount of intermediate inputs increases substantially in response to a bridge.

[24]In Appendix D.1, we show that there is no shift into cash crops in response to a bridge, hence our focus on staple crops here. In Nicaragua, most coffee is grown on large plantations (only 1.7 percent of households grow coffee at baseline), so this type of shift is *a priori* unlikely. Moreover, newly planted coffee trees do not produce coffee for several years.

11.90 quintales per acre ($p = 0.004$).

Panel B decomposes these results into differences between households that do and do not farm at baseline. The average effects are entirely driven by continuing farmers. That is, giving baseline farmers easier access to the labor market increases their agricultural investment, consistent with the model developed in Section 5.

The counterpart to increased investment in the model is lower savings. We therefore next consider crop storage, the key liquid savings vehicle in rural Nicaragua. Storage is defined as quantity harvested net of sales, debt payments, gifts, and land payments.[25] Any household with no crop production is given a value of zero in this regression. Table 7 shows how bridges affects savings behavior. Regressions 1 and 3 show the average effect. Farmers save about 9 percentage points less of both their maize harvest ($p = 0.014$) and their bean harvest ($p = 0.052$). Columns (2) and (4) again show that the decrease in storage is concentrated among continuing farmers, the same subgroup as those who increase investment. Among continuing farmers, we find decreases of 13 percentage points for maize ($p = 0.016$) and 17 percentage points for beans ($p = 0.056$). Among those who did not farm at baseline, we see small and statistically insignificant changes in storage rates across build and no-build villages.

Lastly, we correlate changes from baseline intermediate expenditures and with changes from baseline storage. The correlation among treatment households is -0.28 for corn storage and -0.34 for bean storage, and both are statistically significant at one percent. Consistent with the model, those who are increasing fertilizer use the most are also those decreasing their savings the most.

6.1 Heterogeneous Effects: Distance to Bridge Site

The goal of our intervention is to more easily allow households to access the market. We do so by building bridge over a (potentially flooded) river bed, but this is only one aspect of the cost of market access. It does not, for example, allow distant households to more easily reach the bridge site. Households vary substantially in their distance from the bridge. The average household at baseline is 1.5 kilometers from the bridge site, with a ninetieth and tenth percentile of 2.9 and 0.2 kilometers. To the extent that this distance increases the cost of accessing the bridge site, the estimated magnitudes

[25] In Appendix D.2 we present the results when we define storage as the amount of each crop currently held in the household, which we ask directly. The results are similar. However, "amount currently stored" is net of any already-consumed harvest and is therefore not the total measure of harvest stored. For this reason, we prefer the in-text measure of storage.

may vary within villages. We use household and bridge GPS locations to construct the straight-line distance to the bridge site for each household, normalized by the distance of the median village household. For no-build villages, the site location is defined by the most feasible spot to build a bridge. We then interact the bridge indicator B_{vt} with our distance measure D_{ivt} in regression (6.1) to measure treatment effects in the annual data,

$$y_{ivt} = \alpha + \beta B_{vt} + \gamma D_{ivt} + \theta(B_{vt} \times D_{ivt}) + \eta_t + \delta_v + \varepsilon_{ivt}. \tag{6.1}$$

The results for wage earnings, farm inputs and harvests are listed in Table 8.[26] We estimate negative and sizable interaction terms for total wage earnings, fertilizer, and pesticide expenditures, all of which are significant at 5 percent. For harvest, we find a negative effect for maize, with a p-value of $p = 0.102$ and no effect on bean harvest quantities. These results suggest that distance is a measure of the intensity of the treatment in this context, as those households very near the build site realize the greatest benefits. As such, this shows that the geographic distribution of households matters for the total effectiveness of the bridge. Villages where households are clustered close to the river bed are likely to realize higher gains than villages clustered away from it.

7 Further Discussion and Robustness

Before concluding, we discuss a number of potential alternative explanations and show that our results are robust to alternative methods of statistical inference. We discuss statistical significance and treatment effect sizes in more detail given our relatively small number of clusters. Lastly, we compute a return on investment for the intervention.

7.1 Alternative Explanations for Empirical Results

We provide a number of other results to investigate other potential channels. These results are available in Appendix D, but we briefly discus them here.

[26] In interpreting these results, it is worth noting that we did not find any households that relocated within their village at any point in the survey period. Nicaragua has weak land title rights, and most households report that they have lived in the same place since the Sandinista land reforms of the 1980s. As such, the location of households is not endogenous to bridge construction.

7.1.1 Prices Change in Agriculture

An alternative explanation for these agricultural results is that prices change. This would occur if bridge construction decreases trade costs and causes prices to converge in equilibrium, as in standard trade theories. Since the prices of staple crops are lower in farming communities than in the broader economy, this causes maize and bean prices to rise. Therefore, farmers increase agricultural inputs and yields rise. This would occur, for instance, if the village is flooded at harvest time so that the farmer is forced to sell their harvest at low prices within the village.

Our survey collects data on the realized prices of sold crops. Table 15 tests whether sale prices change for maize and beans. Prices increase by about 9 percent for maize and beans, but neither is statistically significant. The treatment effect for maize is C\$18 ($p = 0.834$) from a baseline control mean of C\$189 and the effect on bean price is C\$78 ($p = 0.646$) from a baseline control mean of C\$871.

To explain this result, recall that the floods under consideration in this context last for days or weeks, but not for a period of time such that these staple crops would experience significant spoilage. As such, although it is true that transportation costs are very high during a flood, farmers can wait for the flood to subside without significant cost and realize the outside market price for their goods.

7.1.2 Land Consolidation

One alternative theory would be that the bridge allows for land to be reallocated more productively.[27] While land transactions are rare in these villages, there do exist informal rental arrangements among households by which the amount of land that they farm can increase or decrease. This could also imply increased agricultural investment and yield, and thus be consistent with our main results. Table 16 tests whether total cropland or rentals (formal and informal) change in response to the bridge, and we find no evidence of such changes. We also test if there is any change in the total share of the population that farms. Consistent with the land use results in regression 1-3, we see only slight, statistically insignificant changes in the propensity to farm.

[27] For example, this would occur if relatively low skilled farmers move to work in the urban areas and informally rent their land to high skilled farmers.

7.2 Robustness to Clustering Procedure and Regression Framework

We also perform a number of robustness checks, which we view as especially important given the small number of clusters in this study. First, we consider a different clustering procedure. Second, we vary the regression specification by including household fixed effects. They are each discussed briefly here, with detailed results provided in Appendix B.

Clustering Procedure Even though we had only 15 villages in the study, we obtained statistically significant effects. This is less surprising in the high frequency results, as repeated measurement requires less sample size to detect effects. The low frequency data does not benefit from the same design. Here, there are two reasons why we find statistically significant effects. First, the treatment effects are large. Second, the intra-cluster correlations are relatively low. In the main empirical results, the intra-cluster correlations range from 0.002 to 0.108 with both a mean and median of 0.057. This implies that for our median dependent variable, the minimal detectable effect is roughly 69 percent higher than if the randomization were done at the household level.[28] Combined with the large average treatment effects, we are able to detect statistically significant results.

However, given the small number of clusters, we show that our results are robust to instead make statistical inferences using randomized inference. We re-run the main regressions using randomized inference based on Fisher (1935) instead of the wild bootstrap cluster-t procedure of Cameron, Gelbach and Miller (2008). Roughly, while the bootstrap procedure fixes the treatment assignment and selects random samples of the data, randomized inference fixes the data sample but randomly varies the treatment. To compute these "exact p-values," we run our main results for each of the ${}_{15}C_6 = 5005$ possible treatment realizations across villages. Defining $\mathbf{T}_j \in \mathbf{T}$ as the vector of treatment assignments across villages for assignment $j \in \{1, \ldots, 5005\}$, and $\widehat{\beta}_j(y) \in \{\widehat{\beta}_1(y), \ldots, \widehat{\beta}_{5005}(y)\}$ as the estimated treatment effect for outcome y under assignment $\mathbf{T}_j$, we compute the exact p-value for outcome y as

$$p(y) = \frac{\sum_{j=1}^{5005} \mathbb{1}\left[|\widehat{\beta}_j(y)| \geq |\widehat{\beta}_{obs}(y)|\right]}{5005}$$

[28] This calculation assumes all clusters have an average of 33.5 households per village, to simplify the exposition.

where $\widehat{\beta}_{obs}(y)$ is the estimated bridge effect for the actual treatment assignment. These are in Appendix B, and we note that the results are quite similar to the results with the wild bootstrap.

In the main body of the paper we prefer the wild bootstrap because, unlike exact p-values, it does not require that villages are i.i.d. between treatment and control. Since this is not the case here, the wild bootstrap cluster-t is the econometrically correct clustering procedure. However, given the use of permutation tests in other small-sample work (Cohen and Dupas, 2010; Bloom et al., 2013), it is still instructive to show that our results are robust.

Regression Specification As a robustness check to the regression specifications used here, we utilize the fact that we have three years of data, including observations before and after bridge construction, and estimate the main regressions with household fixed effects instead of village fixed effects. We find similar magnitudes and statistical significance for our estimates. If anything, using household fixed effects make most of the results stronger. As such, the empirical specification used in the main text seems to be a conservative choice relative to other reasonable alternatives.

7.3 Return on Investment of the Bridge

Lastly, we compute the cost-effectiveness of a bridge. Each bridge costs approximately 40,000 USD, or C$1,100,000 at an exchange rate of 0.036 USD = 1 córdoba. When computing cost-effectiveness, we focus on an earnings-only measure, as changes in harvest revenue were not uniformly statistically significant. We first compute the annualized benefit per household, which is derived from our high frequency data using changes in flooding and average time flooded. In particular, it is computed as

$$\begin{aligned}\text{Annual Effect} &= 26 \times \Big(\text{\% with flood } \times \text{Wage effect in flood weeks} \\ &\qquad + \text{ \% with no flood } \times \text{ Wage effect in no flood}\Big) \\ &= 26 \times \Big(0.095 \times 308.12 + 0.905 \times 159.42\Big) \\ &= C\$4512.21.\end{aligned}$$

On average, there are 33.5 households per village, which implies a total village benefit of C$151,152. The internal rate of return can be computed as the solution to

$$1,100,000 = \sum_{t=1}^{T} \frac{151,152}{(1+r)^t}$$

where T is the useful life of the bridge in years. Bridges to Prosperity designs bridges to last 40 years.[29] This implies that the internal rate of return is 13.67 percent. This implies that the $40,000 investment is recouped in roughly 5.5 years. Despite the high cost of the intervention, the returns are still reasonably large.

8 Conclusion

We study the impact of integrating rural villages with more urban markets. We build footbridges that eliminate the risk of unpredictable seasonal flooding. These bridges have a substantial impact on the rural economy. Bridges eliminates the decrease in contemporaneous income realizations during floods, while allowing individuals to move into better jobs. This increases income during non-flood periods as well. Second, agricultural investment in fertilizer and yields on staple crops both increase. Third, crop storage decreases. These results imply that (1) lack of consistent outside market access can have a substantial impact on long-term agricultural decisions in rural economies and (2) the benefits of infrastructure extend beyond the ability to move goods more easily across space.

We then build a model that links these results together, in which bridges facilitate consumption smoothing through more consistent labor market access, and show that it is consistent with the data. Linking these on- and off-farm channels is important for policy, given the variety of income-generating activities in rural areas (Foster and Rosenzweig, 2007; World Bank, 2008*b*). While we find no evidence of goods price changes, other work focused on larger projects (e.g. Asher and Novosad, 2016) find important implications for structural transformation and off-farm migration. An important avenue for future work is to link results like ours with larger scale projects to better discipline and understand the interaction of trade and structural transformation. One possible reason this difference is that while much of the literature at

[29] This estimate is based on internal tower corrosion rates of 25 microns per year. After 40 years, this is 1 millimeter, which no longer satisfies the design criteria for safety.

the intersection of trade and development has focused on new transportation infrastructure as a constant reduction in the cost of moving between locations, our results suggest that the second moment of trade cost shocks also matters. That is, uncertainty about the ability to access outside markets affects *ex ante* decisions. This possibility has received little attention in the context of developing countries, where this issue is likely to be the most salient.

Lastly, the annual return on investment for these bridges is 13.67 percent over the useful life of the bridge. Despite the high cost ($40,000 per bridge), this type of infrastructure is cost-effective. Understanding how to better target locations with the largest potential benefit would further increase cost-effectiveness, as there is growing acknowledgement of location-based heterogeneity in infrastructure improvements (Allen and Arkolakis, 2016).

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Main Tables for Text

Table 1: Pre-Bridge Differences

	Constant	Bridge
Flooding Intensity		
Days flooded	2.40***	-0.45
	(0.00)	(0.46)
Flood likelihood	0.47***	-0.06
	(0.00)	(0.54)
Flood length (days)	5.10***	-0.36
	(0.00)	(0.84)
Household Characteristics		
Distance to bridge site (km)	1.52***	-0.09
	(0.00)	(0.33)
HH head age	45.05***	-0.08
	(0.00)	(0.95)
HH head yrs. of education	3.43***	0.26
	(0.00)	(0.36)
No. of children	1.28***	0.04
	(0.00)	(0.68)
HH size	4.15***	0.07
	(0.00)	(0.62)
Occupational Choice		
Agricultural production	0.49***	0.05
	(0.00)	(0.26)
Off-farm work	0.57***	-0.03
	(0.00)	(0.47)
Total wage earnings (C$)	1063.80***	1.11
	(0.00)	(1.00)
Farming		
Corn harvest	2.49***	1.00
	(0.00)	(0.21)
Bean harvest	1.50***	0.26
	(0.00)	(0.26)
Plant staples (maize or beans)?	0.34***	0.03
	(0.00)	(0.45)
Fertilizer + pesticide expenditures	899.56***	99.50
	(0.00)	(0.59)
Joint F-test (linear)	0.357	
Chi-squared test (probit)	0.287	

Table notes: Flood intensity measures are from high frequency data and refer to the previous two weeks in the pre-construction rainy season. An observation in these three regressions is a community-week, while the rest are done at the household level. The F and Chi-squared tests are conducted excluding the flood intensity measures. p-values in parentheses. We do not cluster the standard errors here, as to give the regression the greatest chance of finding a statistically significant difference between the two groups.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2: Effects on Market Earnings

	All			Men			Women		
	Total	Outside	Inside	Total	Outside	Inside	Total	Outside	Inside
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Build	380.39*	306.10***	-27.70	267.09*	189.34***	-64.37	80.65*	79.21***	-7.53
	(0.098)	(0.000)	(0.828)	(0.062)	(0.006)	(0.282)	(0.082)	(0.000)	(0.790)
Control Mean, $t = 0$	1063.80	357.18	616.27	473.54	210.19	170.43	113.51	62.60	18.23
Observations	1,494	1,493	1,491	1,494	1,492	1,491	1,494	1,491	1,494
Time F.E.	Y	Y	Y	Y	Y	Y	Y	Y	Y
Village F.E.	Y	Y	Y	Y	Y	Y	Y	Y	Y
Intra-cluster correlation	0.073	0.050	0.050	0.049	0.023	0.015	0.027	0.018	0.005

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

Table 3: Decomposing Earnings Changes

Panel A: Men	No. of HH Members			Daily Wage		Days	
	Total	Outside	Inside	Outside	Inside	Outside	Inside
	(1)	(2)	(3)	(5)	(6)	(8)	(9)
Build	0.048	0.192***	-0.120	-5.63	68.57*	0.866***	-0.303
	(0.466)	(0.000)	(0.128)	(0.816)	(0.092)	(0.000)	(0.418)
Control Mean, $t = 0$	0.543	0.294	0.251	182.025	138.980	1.401	1.299
Observations	1,507	1,507	1,507	306	349	1,494	1,497
Time F.E.	Y	Y	Y	Y	Y	Y	Y
Village F.E.	Y	Y	Y	Y	Y	Y	Y
Intra-cluster correlation	0.048	0.041	0.020	0.105	0.000	0.042	0.032
Panel B: Women	No. of HH Members			Daily Wage		Days	
	Total	Outside	Inside	Outside	Inside	Outside	Inside
	(1)	(2)	(3)	(5)	(6)	(8)	(9)
Build	0.109***	0.107***	0.013	44.99	4.45	0.589***	-0.072
	(0.006)	(0.000)	(0.568)	(0.348)	(0.918)	(0.006)	(0.530)
Control Mean, $t = 0$	0.171	0.118	0.055	206.754	121.894	0.538	0.183
Observations	1,507	1,507	1,507	147	107	1,493	1,498
Time F.E.	Y	Y	Y	Y	Y	Y	Y
Village F.E.	Y	Y	Y	Y	Y	Y	Y
Intra-cluster correlation	0.043	0.021	0.019	0.035	0.061	0.019	0.003

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

Table 4: Effects of Flooding on Income

	Household Income	No Income Earned
Flood × No Bridge	-143.627**	0.070**
	(0.034)	(0.040)
Flood × Bridge	5.071	-0.038**
	(0.874)	(0.048)
Bridge	159.424***	0.061
	(0.004)	(0.110)
Control mean	783.563	0.249
Observations	6443	6756
Individual F.E.	Y	Y
Week F.E.	Y	Y
Intra-cluster correlation	0.080	0.027

Table notes: p-values computed using the wild cluster bootstrap-t with 1000 simulations are in parentheses, clustered at the village level. Control mean is average dependent variable over entire time horizon for households in villages that never receive a bridge. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Effects of Flooding on Income with Lags

	Household Income	Household Income	No Income Earned	No Income Earned
	(1)	(2)	(3)	(4)
Bridge_t	159.424**	84.029	0.061*	0.054
	(0.004)	(0.344)	(0.071)	(0.293)
Flood_t	-143.627**	-117.205*	0.070**	0.044
	(0.012)	(0.082)	(0.034)	(0.123)
$\text{Bridge}_t \times \text{Flood}_t$	148.699**	153.747***	-0.107***	-0.138***
	(0.038)	(0.000)	(0.003)	(0.000)
Bridge_{t-2}		77.443		0.023
		(0.366)		(0.728)
Flood_{t-2}		-17.401		0.005
		(0.718)		(0.854)
$\text{Bridge}_{t-2} \times \text{Flood}_{t-2}$		-125.768		0.035
		(0.178)		(0.345)
Control mean	783.563	783.563	0.249	0.249
Observations	6,443	4,295	6,756	4,589
Individual F.E.	Y	Y	Y	Y
Week F.E.	Y	Y	Y	Y
Intra-cluster correlation	0.080	0.080	0.027	0.027

Table notes: p-values computed using the wild cluster bootstrap-t with 1000 simulations are in parentheses, clustered at the village level. Control mean is average dependent variable over entire time horizon for households in villages that never receive a bridge. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 6: On-Farm Impact

Panel A: Average Farm Outcomes	Input Expenditures			Maize		Beans	
	Intermediates	Fertilizer	Pesticide	Harvest Quantity	Yield	Harvest Quantity	Yield
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Build	659.97**	383.31**	166.52	1.81	11.90***	1.02	2.19
	(0.048)	(0.026)	(0.260)	(0.202)	(0.004)	(0.172)	(0.306)
Panel B: Intensive and Extensive Margins	Input Expenditures			Maize		Beans	
	Intermediates	Fertilizer	Pesticide	Harvest Quantity	Yield	Harvest Quantity	Yield
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Build × Farm at $t = 0$	1231.48**	702.07**	315.48	4.13*	12.84***	1.58	2.23
	(0.026)	(0.022)	(0.244)	(0.080)	(0.006)	(0.124)	(0.312)
Build × No Farm at $t = 0$	-7.16	11.60	-7.96	-0.94	9.22***	0.35	2.07
	(0.958)	(0.932)	(0.918)	(0.264)	(0.008)	(0.634)	(0.342)
Control mean, $t = 0$	889.56	607.43	303.48	2.49	12.29	1.50	4.59
Observations	1,492	1,493	1,492	1,492	359	1,499	356
Time F.E.	Y	Y	Y	Y	Y	Y	Y
Village F.E.	Y	Y	Y	Y	Y	Y	Y
Intra-cluster correlation	0.068	0.051	0.071	0.073	0.097	0.108	0.059

Table notes: Farm = 1 if the household is engaged in any crop production at baseline ($t = 0$), where *No Farm = 1 - Farm*. p-values in parentheses are clustered at the village level using the wild cluster bootstrap-t with 1000 simulations. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Farm Savings Choices

	Maize		Beans	
	(1)	(2)	(3)	(4)
Build	-0.085**		-0.091*	
	(0.014)		(0.052)	
Build × Farm		-0.130		-0.172
		(0.016)**		(0.056)*
Build × No Farm		-0.032		0.007
		(0.286)		(0.824)
Control mean	0.942	0.942	0.928	0.928
Observations	1,507	1,507	1,507	1,507
Time F.E.	Y	Y	Y	Y
Village F.E.	Y	Y	Y	Y
Intra-cluster correlation	0.036	0.036	0.048	0.048

Table notes: Farm = 1 if the household is engaged in any crop production at baseline, where *No Farm = 1 - Farm*. p-values in parentheses are clustered at the village level using the wild cluster bootstrap-t with 1000 simulations. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Heterogeneous Impact by Distance

	Wage Earnings			Input Expenditures			Harvest	
	Total	Outside	Inside	Intermediates	Fertilizer	Pesticide	Maize	Beans
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Build	662.286***	466.736 ***	142.883	1232.193***	686.517**	350.105**	3.785**	0.492
	(0.002)	(0.000)	(0.362)	(0.000)	(0.012)	(0.046)	(0.026)	(0.736)
Distance	-214.142	-65.666	-117.472*	59.993	-13.073	26.109	0.233	0.365
	(0.118)	(0.464)	(0.054)	(0.526)	(0.708)	(0.516)	(0.538)	(0.324)
Build × Distance	-250.331**	-129.507	-147.734***	-455.465***	-245.193**	-140.206***	-1.649	0.478
	(0.026)	(0.116)	(0.002)	(0.002)	(0.024)	(0.002)	(0.102)	(0.468)
Control mean, $t = 0$	1063.80	357.18	616.27	889.56	607.43	303.48	2.49	1.50
Observations	1,472	1,470	1,469	1,468	1,469	1,468	1,468	1,475
Time F.E.	Y	Y	Y	Y	Y	Y	Y	Y
Village F.E.	Y	Y	Y	Y	Y	Y	Y	Y
Intra-cluster correlation	0.073	0.050	0.050	0.068	0.051	0.071	0.073	0.108

Table notes: Distance is measured as kilometers from house to bridge site, as the crow flies, normalized by median distance in the village. p-values in parentheses are clustered at the village level using the wild cluster bootstrap-t with 1000 simulations. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table of Contents for Online Appendix

A Proofs

A.1 Proof of Proposition 1

Proof. Suppose ϕ was unchanged. The realized wage $w_t(s_t)$ is weakly higher in every state.

First, we show that $e(s_t)$ is weakly higher in every state, which we guess and verify.

$$e(s_t) = \varepsilon(s_t) \left(\frac{\gamma Z_A(\phi A)^\alpha \bar{N}^{\gamma-1+\frac{1}{\sigma}}}{w_t^i(s_t)} \frac{1}{1 + \frac{\sum_t \sum_{s_t} R^{t-T}\eta(s_t)}{\sum \xi(s_T)}} \sum_{s_T : s_t \in s_T} \frac{\left(\frac{N(s_T)}{\bar{N}}\right)^{\gamma-1+\frac{1}{\sigma}} \xi(s_T)}{\sum \xi(s_T)} \right)^\sigma \tag{A.1}$$

Since only the process on τ is changing, ε is unchanged at every state. We analyze the three terms inside the parentheses separately.

If $e(s_t)$ is weakly increasing at every state, then $N(s_T)$ is weakly greater at every state. Then because $\gamma + 1/\sigma > 1$, $\bar{N}^{\gamma-1+1/\sigma}$ is weakly greater. Therefore, since ϕ and $w_t^i(s_t)$ are fixed, the first term increases. The second term is obviously increasing, as less risk implies smaller likelihood and severity of reaching the borrowing constraint.

Because V' is decreasing and convex, then when variation in $A'(s_T)$ decreases, the fall in $\xi(s_T)$ in low $A'(s_T)$ states is greater than in high $A'(s_T)$ states. Therefore, since $A'(s_T) = S(s_T) + Z_A(\phi A)^\alpha N(s_T)^\gamma$, low $N(s_T)$ states also have low $A'(s_T)$. Therefore, if we define a probability measure with mass in a given state given by $\xi(s_T)/\sum \xi(s_T)$, then when τ changes this probability measures shifts mass from relatively low $N(s_T)$ states to relatively high $N(s_T)$ states. Therefore, the third term increases. This verifies the guess, and shows that $e(s_t)$ is higher in every state.

Completing the proof uses similar arguments. First, the summation on the right hand side of equation (5.5) is higher, again, since the probability measure $\xi(s_T)/\sum \xi(s_T)$ moves mass to relatively high $N(s_T)$ states. The left hand side of (5.5) is lower because the non-negativity constraints are looser when the household faces less risk. Finally, $\bar{N}$ is greater and the other terms are unchanged.

Therefore, if ϕ is unchanged, then the left hand side of (5.5) is lower and the right hand side is greater. Since an increase in ϕ tightens non-negativity constraints on savings, the left hand side is increasing in ϕ. Also, the right hand side is unambiguously decreasing in ϕ. Therefore, if at the previous value of ϕ the left hand side is lower than the right hand side, the left hand side is increasing in ϕ, and the right hand side is decreasing in ϕ, then ϕ must increase to satisfy equation (5.5).

$\blacksquare$

A.2 Proof of Proposition 2

Proof. In the proof of Proposition 1 we showed that $e(s_t)$ is weakly greater in every state for a fixed price. Moreover, it is clear from the definition of $\varphi^*(s_t)$ that when $\tau(s_t)$ is weakly lower in every state, then $\varphi^*(s_T)$ is weakly lower in every state. Therefore, if $w^i(s_t)$ remained the same, then labor market clearing in equation 5.4 is not satisfied as the right hand side, which is labor demand, is greater while the left hand side, which is labor supply, is smaller.

The left hand side of equation 5.4 is clearly increasing in $w^i(s_t)$ as an increase in the inside wage causes $\varphi^*(s_t)$ to increase, which means the left hand side is integrating over a larger measure of positive terms causing the left hand side to increase. The proof of Proposition 1 gives the demand for labor $e(s_t)$ and shows labor demand is unambiguously decreasing in $w^i(s_t)$.

Suppose an economy faces values $\tau(s_t)$ of the trade cost in any state, and the labor market clear conditions are satisfied by $w^i(s_t)$. If the same economy instead had trade costs $\hat{\tau}(s_t)$, then at the same wages $w^i(s_t)$ now the labor supply is lower and labor demand is higher at every s_t. Since labor demand is strictly decreasing in $w^i(s_t)$ and labor supply is strictly increasing in $w^i(s_t)$, then the inside wage rate that clears the labor market in every state when the economy facing $\hat{\tau}(s_t)$ is $\hat{w}^i(s_t)$, and $\hat{w}^i(s_t) \geq w^i(s_t)$. ■

B Robustness of Main Results to Household F.E. and Clustering

Section B.1 recomputes the main results using randomized inference instead of the wild bootstrap cluster-t, while Section B.2 recomputes the main results using household fixed effects instead of village fixed effects.

B.1 Using Randomized Inference

Table 9 recomputes the main results using the randomized inference procedure detailed in Section 7.2. The p-values derived from this procedure are in brackets, while the wild bootstrap cluster-t p-values are included in parentheses for ease of comparison.

Table 9: Main Results with Randomized Inference

	Earnings			Farm Expenditures			Farm Outcomes				Storage	
	Total Earnings	Outside Earnings	Inside Earnings	Intermediates	Fertilizer	Pesticide	Maize Harvest	Maize Yield	Bean Harvest	Bean Yield	Maize	Beans
	(1)	(2)	(3)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Build	380.39	306.10	-27.70	659.97	383.31	166.52	1.81	11.90	1.02	2.19	-0.085	-0.091
	(0.090)*	(0.000)***	(0.828)	(0.048)**	(0.026)**	(0.260)	(0.202)	(0.004)***	(0.172)	(0.306)	(0.014)**	(0.052)*
	[0.042]††	[0.000]†††	[0.822]	[0.057]†	[0.085]†	[0.252]	[0.163]	[0.006]†††	[0.246]	[0.322]	[0.032]††	[0.010]††
Control Mean	1025.73	357.18	616.27	889.56	607.43	303.48	2.49	12.29	1.50	4.59	0.942	0.928
Observations	1,494	1,493	1,491	1,492	1,493	1,492	1,492	359	1,499	356	1,507	1,507
Time F.E.	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Village F.E.	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Intra-cluster correlation	0.073	0.073	0.050	0.061	0.040	0.081	0.054	0.082	0.122	0.032	0.036	0.048

Table notes: This table reports the main results using randomized inference to compute p-values. Those p-values are in brackets. For comparison, the original p-values using the wild bootstrap cluster-t are included as well, in parenthesis. p-values for the wild bootstrap cluster-t are denoted * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, while those using randomized inference are denoted †, ††, and † † †.

B.2 Using Household Fixed Effects

As a robustness check, we compare the following two regression specifications

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

The first specification includes village fixed effects (δ_v) and is the main specification in the text. As a robustness test of the specification, we re-compute the main results using household fixed effects (δ_i) instead. The results are in Table 10. We also include the main estimates and p-values from the text for ease of comparison.

Table 10: Main Results with Household Fixed Effects

	Earnings			Farm Expenditures			Farm Outcomes				Storage	
	Total Earnings	Outside Earnings	Inside Earnings	Intermediates	Fertilizer	Pesticide	Maize Harvest	Maize Yield	Bean Harvest	Bean Yield	Maize	Beans
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Village FE	380.39	306.10	-27.70	659.97	383.31	166.52	1.81	11.90	1.02	2.19	-0.085**	-0.091*
	(0.090)*	(0.000)***	(0.828)	(0.048)**	(0.026)**	(0.260)	(0.202)	(0.004)***	(0.172)	(0.306)	(0.014)	(0.052)
Household FE	307.59	295.24	-41.76	646.48	437.81	152.94	1.65	14.76	1.16	3.15	-0.085**	-0.088*
	(0.156)	(0.000)***	(0.726)	(0.012)**	(0.000)***	(0.286)	(0.238)	(0.006)***	(0.032)**	(0.012)**	(0.022)	(0.050)
Control Mean, $t = 0$	1025.73	357.18	616.27	889.56	607.43	303.48	2.49	12.29	1.50	4.59	0.942	0.928
Observations	1,494	1,493	1,491	1,492	1,493	1,492	1,492	359	1,499	356	1,507	1,507
Time F.E.	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Intra-cluster correlation	0.073	0.073	0.050	0.061	0.040	0.081	0.054	0.082	0.122	0.032	0.036	0.048

Table notes: This table reports the main regression specification using household and village fixed effects. Note that these are two separate regressions. p-values in parentheses are clustered using the wild cluster bootstrap-t with 1000 simulations. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

C High Frequency Details

This appendix covers additional results and details that are useful to understand the results of the paper. Section C.1 and C.2 cover the high frequency survey. The former discusses selection into the survey and balance, while the latter shows (1) response rates are uncorrelated with the likelihood of flooding and (2) even the most extreme assumption on missing values does not invalidate the fact that most individuals work in the labor market sometimes.

C.1 High Frequency Data Balance Checks

Table 11 shows the results from the regression

$$y_{iv} = \alpha + \beta Bridge_v + \gamma LQ_{iv} + \eta(Bridge_{iv} \times HF_{iv}) + \varepsilon_{iv}.$$

Here, y_{iv} is some outcome at baseline for household i in village v, $Bridge_v = 1$ if village v will receive a bridge, while $HF_{iv} = 1$ if household i participates in the high frequency survey.

Table 11: Pre-Bridge Differences High Frequency Data

	Constant	Bridge	High-Frequency	Interaction
Household Composition				
HH head age	47.17***	4.82**	-5.14***	-4.65**
	(0.00)	(0.02)	(0.00)	(0.05)
HH head yrs. of education	2.63***	0.70	1.03***	-0.50
	(0.00)	(0.19)	(0.00)	(0.42)
No. of children	1.06***	0.00	0.32***	-0.04
	(0.00)	(1.00)	(0.00)	(0.82)
HH size	3.81***	0.13	0.49***	0.03
	(0.00)	(0.47)	(0.00)	(0.92)
Occupational Choice				
Agricultural production	0.47***	0.02	0.04	-0.01
	(0.00)	(0.72)	(0.14)	(0.82)
Off-farm work	0.59***	0.00	0.02	0.01
	(0.00)	(0.93)	(0.56)	(0.79)
Total wage earnings (C$)	1204.68***	57.63	354.33*	-77.55
	(0.00)	(0.84)	(0.06)	(0.82)
Farming				
Corn harvest	2.21***	-1.01*	-0.66*	1.03
	(0.00)	(0.10)	(0.09)	(0.15)
Bean harvest	0.72***	-0.08	-0.11	-0.26
	(0.00)	(0.76)	(0.52)	(0.40)
Plant corn?	0.16***	0.03	0.02	-0.03
	(0.00)	(0.50)	(0.59)	(0.62)
Plant beans?	0.17***	0.01	-0.01	-0.05
	(0.00)	(0.91)	(0.72)	(0.40)

Table notes: Flood intensity measures as measured from high frequency data and refer to the previous two weeks during rainy season only. p-values in parentheses. We do no clustering procedure here as to give the regression the greatest chance of finding a statistically significant difference between the two groups.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

C.2 How high frequency survey response rates change during floods

Figure 2 in the text shows that almost all individuals in the high frequency survey use the labor market to some degree. However, our survey is biased toward finding that result if floods decrease the likelihood of answering the survey. To show that this is not the case, we run the regression

$$\mathbb{1}[answer]_{ivt} = \alpha + \beta Flood_{vt} + \eta_t + \delta_i + \varepsilon_{ivt}.$$

where $\mathbb{1}[answer]_{ivt} = 1$ if an individual answers the survey in week t, and is zero otherwise. The results are in Table 12. We find no statistically different effect of flood on the response rate, and the point estimate is small. If we remove time fixed effects we are able to generate a negative response to flooding, but again, the point estimate is quite small.

Table 12: Effect of flooding on survey response

	(1)	(2)
Flood	0.026	-0.025**
	(0.151)	(0.035)
Constant	0.580***	0.498***
	(0.000)	(0.002)
Observations	13,705	13,705
Individual F.E.	Y	Y
Week F.E.	Y	N

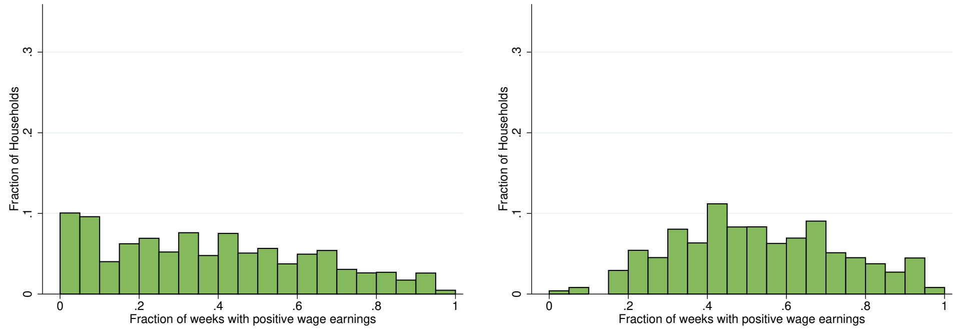
Table notes: p-values in parentheses are clustered using the wild cluster bootstrap-t with 1000 simulations. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

To further emphasize this point, Figure 7 reproduces Figure 2 in the main text with one key difference. Here, we assume that every period a household does not answer the survey, they received zero income that period. That is, we replace all missing values with zeros. This extreme assumption generates the lowest possible bound on the results driven by the unbalanced nature of the panel.

Naturally, this shifts the distribution toward zero. However, even when considering all households, the fifth percentile household still receives labor market income in 3 percent of its observations. The median household receives labor market income in

Figure 7: Fraction of weeks with labor market income

(a) All households (b) Only households with $\geq$ 10 observations



36 percent of weeks. Thus, individuals are still utilizing the labor market to varying degrees of intensity. When we condition on households that have at least ten observations, the numbers look quite similar to the text. The fifth percentile household receives labor market income in 21 percent of weeks. Thus, even under the most extreme assumptions about non-response, the labor market is still an important part of most households' income strategy.

D More Results

This appendix covers additional results and details that are useful to understand the results of the paper. Section C.1 and C.2 cover the high frequency survey. The former discusses selection into the survey and balance, while the latter shows (1) response rates are uncorrelated with the likelihood of flooding and (2) even the most extreme assumption on missing values does not invalidate the fact that most individuals work in the labor market sometimes. The latter three sections discuss robustness checks and other regressions. Sections D.1 shows no change in crop planting decisions. Section D.2 shows that using the response to the question "How much do you currently have stored in your home?" provides similar results to the storage results in the main text. Lastly, Section D.5 provides period-by-period results to show that our results are not driven by a single year.

D.1 Crop Planting Decisions

We look at planting decisions, where we consider the two key staple crops maize and beans along with the main cash crop in Northern Nicaragua, coffee. We considered other cash crops as well, and find similar results to coffee. The outcome variable here is an indicator equal to one if the crop is planted (not necessarily harvested), and the results are in Table 13.

Table 13: Planting Decisions

	Maize	Beans	Coffee
	(1)	(2)	(3)
Build	0.007	0.080	0.004
	(0.912)	(0.164)	(0.780)
Observations	1,507	1,507	1,507
Time F.E.	Y	Y	Y
Village F.E.	Y	Y	Y
Intra-cluster correlation	0.072	0.111	0.071

Table notes: p-values in parentheses are clustered using the wild cluster bootstrap-t with 1000 simulations. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

D.2 Using "current storage" as a direct measure of stored crops

Table 14 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 does not measure the total amount of harvest stored, as some was presumably consumed prior to the survey. Nevertheless, the results are similar to those in the main text. The average effect for maize storage becomes insignificant, though the magnitude (-0.113, $p = 0.124$) is still similar to that in the main text (-0.085, $p = 0.014$). Importantly, however, the same result emerges that farming households at baseline see the majority of the effect. This is consistent with both the theory and the empirical results in the text.

Table 14: Direct Measure of Farm Savings

	Maize		Beans	
	(1)	(2)	(3)	(4)
Build	-0.113		-0.084*	
	(0.124)		(0.068)	
Build × Farm		-0.210*		-0.163*
		(0.058)		(0.088)
Build × No Farm		0.005		0.011
		(0.884)		(0.728)
Observations	1,507	1,507	1,507	1,507
Time F.E.	Y	Y	Y	Y
Village F.E.	Y	Y	Y	Y
Intra-cluster correlation	0.082	0.082	0.061	0.061

Table notes: These results define savings as the response to the question "How much of crop X do you currently have stored?" p-values in parentheses are clustered using the wild cluster bootstrap-t with 1000 simulations. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

D.3 Output Prices for Sold Crops

Table 15: Output Prices

	Maize Price	Bean Price
	(1)	(2)
Build	18.183	78.012
	(0.834)	(0.646)
Control mean, $t = 0$	189.333	871.429
Observations	176	184
Time F.E.	Y	Y
Village F.E.	Y	Y
Intra-cluster correlation	0.129	0.016

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

D.4 Land Use and Farming

Table 16: Land Use and Farm Size

	Total Land Owned	Total Land Cropped	Rent out any land?	Any farming?
	(1)	(2)	(3)	(4)
Build	-0.333	-0.092	-0.018	-0.051
	(0.468)	(0.532)	(0.496)	(0.444)
Control mean, $t = 0$	2.636	1.074	0.067	0.488
Observations	1,601	1,601	1,601	1,601
Time F.E.	Y	Y	Y	Y
Village F.E.	Y	Y	Y	Y
Intra-cluster correlation	0.088	0.112	0.021	0.051

Table notes: Regressions one and two are measured in manzanas (1.73 acres), while regression three is an indicator for whether or not you rent land to someone else, including formal and informal arrangements. p-values in parentheses are clustered at the village level using the wild cluster bootstrap-t with 1000 simulations. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

D.5 Per-Period Effects

To what extent to the results hold year-by-year? We re-run the regressions as

$$
\begin{aligned}
y_{ivt} &= \alpha + \beta B_{vt} + \delta_v + \varepsilon_{ivt} \qquad \text{for t = 0,1} \\
y_{ivt} &= \alpha + \beta B_{vt} + \delta_v + \varepsilon_{ivt} \qquad \text{for t = 0,2.}
\end{aligned}
$$

Table 17 shows the main results for each period. All of the main results hold period-by-period. Total earnings from $t = 0$ to $t = 2$ is not statistically significant ($p = 0.188$), but the point estimate is still in line with the estimates at $t = 1$.

Table 17: Main Empirical Results by Period

Panel A: t=1	Earnings			Farm Expenditures			Farm Outcomes				Storage	
	Total Earnings	Outside Earnings	Inside Earnings	Intermediates	Fertilizer	Pesticide	Maize Harvest	Maize Yield	Bean Harvest	Bean Yield	Maize	Beans
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Build	404.14**	308.95***	-63.17	659.96*	378.69*	220.58	2.03	11.59***	0.56	1.01	-0.090***	-0.127**
	(0.032)	(0.000)	(0.700)	(0.094)	(0.052)	(0.266)	(0.248)	(0.008)	(0.478)	(0.702)	(0.004)	(0.012)
Control mean, $t = 0$	1025.73	357.18	616.27	612.50	405.60	176.45	1.58	9.03	0.98	3.94	0.936	0.937
Time F.E.	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Village F.E.	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Panel B: t=2	Earnings			Farm Expenditures			Farm Outcomes				Storage	
	Total Earnings	Outside Earnings	Inside Earnings	Intermediates	Fertilizer	Pesticide	Maize Harvest	Maize Yield	Bean Harvest	Bean Yield	Maize	Beans
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Build	362.62	305.08***	18.11	682.59*	415.84**	98.28	1.72	11.22**	1.62**	3.24	-0.082	-0.048
	(0.188)	(0.00)	(0.916)	(0.054)	(0.038)	(0.494)	(0.304)	(0.016)	(0.028)	(0.120)	(0.136)	(0.306)
Control mean, $t = 0$	1025.73	357.18	616.27	612.5	405.60	176.45	1.58	9.03	0.98	3.94	0.937	0.937
Time F.E.	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Village F.E.	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Table notes: This table reproduces the main results from the paper, but reports them period-by-period instead of pooled. p-values in parentheses are clustered using the wild cluster bootstrap-t with 1000 simulations. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

E Dry River Bed Crossings (Photos)

Figure 8: River Beds During Dry Times

(a)

(b)

(c)

(d)