Seeding the Seeds: Role of Social Structure in Agricultural Technology Diffusion

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August 2, 2022

Exploiting the two-stage randomized introduction of flood resistant seeds in rural Odisha, India, we find that the local social structure (the jati caste system) has a significant influence on diffusion of the technology. First, modest overall differences in adoption between treated and control villages is largely explained by the substantial heterogeneity in village-level jati fractionalization. Second, we find immediate diffusion among non-recipient farmers in the same jati groups as the initial, treated recipients and lower diffusion among lower status jatis. These findings highlight the limitations of randomized introduction of technology in a context of weak markets and closed social structures. (*JEL* O33, Q12)

1 Introduction

A long-standing puzzle in development economics is that technologies proven to be useful frequently have low rates of adoption, which remain low over long periods of time. Recent literature documents substantial costs due to delays in adoption - for example, Gollin et al. (2021) estimate a loss equal to 17% of global GDP for every 10 years delay in adoption of green revolution technologies (i.e., high-yielding varieties of cereal crops).

In the context of poorly developed markets for inputs and outputs, as is the case in much of the developing world, farmers tend to rely on social networks and informal arrangements rather than markets (Foster and Rosenzweig 2010; Jack 2013; de Janvry et al. 2017). Governments can play a large role in bridging this gap but are limited by capacity constraints

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(Chatterjee and Kapur 2017). Given this context, the equilibrium levels of technology adoption are importantly a function of village social structures (Emerick 2018; Rao and Shenoy 2021).

In this paper, we study the adoption of a flood-tolerant paddy variety (Swarna Sub-1) over five years, covering the entire population of non-recipient farmers in 126 villages across two rural districts in Odisha, India. We conduct a census of the universe of non-recipient farmers in the experimental and control villages from Emerick et al. (2016) up to four years after introducing the technology in 2011. In this prior study, villages were randomly assigned, stratified by the corresponding administrative sub-district (block), to receiving the new seed variety and status quo. In the treated villages, the intervention provided 5-kilogram minikits of the new seed variety to a random sample of $\approx$ five farmers per village.

We present three key results. First, exogenous introduction of the technology generates a modest effect on the subsequent diffusion among the non-recipient farmer population in treated villages relative to control. Measuring across the universe of non-recipient farmers, we estimate a 23% difference in diffusion rates as the long-run impact of exogenous, external introduction of a profitable technology. Additionally, the total village area under cultivation with the new seed variety is nearly two times higher (0.8 acres more) in treated villages relative to control. These effects are consistent with slightly higher farmer-to-farmer sharing of seeds within the experimental villages. The key highlight of this result is that the control villages lag treated villages by at least 1-2 years in reaching the same level of adoption of the new seed variety, which has important welfare consequences. Further, this modest effect masks substantial heterogeneity that forms our second key result.

Second, we find substantial differences based on the presence of many distinct jati groups (endogamous kinship groups) at the village level. Specifically, we note that villages with a lesser number of distinct jatis, after accounting for village size, experience higher immediate adoption (8-9 percentage points higher relative to similar control villages), which persists over time. This important heterogeneity based on predetermined jati compositions of the villages highlights critical constraints posed by local social structures in adopting beneficial technology.

Third, farmers are more likely to adopt if at least one farmer from their own jati received a minikit during the 2011 intervention. Further, adoption increases over time among farmers within similar social status jati groups as the modal jati of initial recipients, whereas farmers belonging to jatis of lower social status relative to initial recipients experience lower adoption in the early years. These results unpack the heterogeneity in village-level treatment effects, suggesting that jati networks are plausibly important barriers to farmer-to-farmer sharing of information and technology.

These differences by farmer jati affiliation are stark even though the initial recipients were randomly selected and the jati groups across the social hierarchy were equally likely to receive minikits in 2011. This is in a context where farmers from lower status jati groups (SC and ST) are more likely to experience flooding events over the study period, and therefore, for whom the technology is particularly beneficial. This suggests that random initial introduction of technology could have distributional implications, at least in the initial years. While the gap may reduce or converge over time, these delays could have substantial welfare consequences as documented in Gollin et al. (2021).

This paper contributes to three sets of literature. First, we show that social networks play a considerable role in technology diffusion in a context where markets are poorly developed. This paper connects a vast literature on the economics of identity groups (Akerlof and Kranton 2000; Banerjee and Munshi 2004; Miguel and Gugerty 2005; Anderson 2011; Lowes et al. 2015; Fisman et al. 2017; Emerick 2018; Oh 2021) with the literature on social networks and technology adoption (Beaman and Magruder 2012; Banerjee et al. 2013).

Second, this paper shows that the structure of jati networks is plausibly an important barrier to adoption.[1] In this regard, this paper is consistent with Duflo et al. (2011), Suri (2011), and Beaman et al. (2021), documenting significant heterogeneity in farmer-level technology adoption decisions. We extend this literature by exploiting experimental variation in villages and farmers that first received the technology on subsequent adoption decisions across the universe of non-recipient paddy farmers over the long run. We highlight that technology diffuses quickly in villages with fewer jati goups, generating persistently higher adoption in such villages over time. On the other hand, having more groups attenuates the advantages of external introduction of a profitable technology.

Third, this paper contributes to the literature on targeting by local communities/social networks (Alatas et al. 2012; Beaman et al. 2021; Banerjee et al. 2021). We find that introducing seeds to a random group of farmers generates more adoption among same jati groups as initial recipients but delays diffusion from higher status recipients to lower status non-recipients. This suggests that targeting considering the underlying social network structure is important to increase adoption rates, and that random seeding may miss equity considerations as it may limit diffusion to underprivileged groups.

The rest of the paper is as follows. Section 2 discusses the context and data. Section 3 reports on overall diffusion of the technology. Sections 4 presents the results based on village-level jati fractionalization and farmer-level differences in jati affiliation. Section 5 concludes.

[1] Demand for the technology was demonstrated through a door-to-door sales intervention in a similar context documented in Emerick (2018).

2 Context and Data

This study is a follow-up to the original research (Emerick et al. 2016) that examined the impact of flood-tolerant Swarna Sub-1 (SS1) paddy variety using a two-stage cluster randomized trial. A random sample of five farmers from each of the 64 (of 128) experimental villages (which were randomly assigned to receiving the intervention) were each provided with 5-kg minikits of SS1 seeds in 2011.

This earlier study documented that the new seed variety was profitable and substantially increased yields when plots sown with the seed variety experienced flooding for up to two weeks. The study showed that the increase in yields was primarily due to farmers' production choices when faced with lower down-side risk guaranteed by the technology. Given that the technology induces behavioral response in farmers, the next question to examine is how the technology diffuses among non-recipient paddy farmers over time. The context provides a good opportunity to understand the subsequent diffusion process in the absence of widespread availability of the seed variety in local agricultural input markets.[2]

We returned to 126 out of 128 study villages during the main growing season in 2015 to assess adoption across all paddy farmers in the study villages.[3] We first obtained a list of all paddy-growing households from the local ward members (elected representatives), who were knowledgable about the village residents and their occupation. Following the listing exercise, we approached farmers door-to-door and administered a short survey noting their use of different paddy varieties for each of the growing seasons between 2011 and 2015. To aid recall, we started with the most recent season first and followed past seasons in decreasing order. We used specific events as props to enable recollection pertaining to particular seasons.[4] We also asked additional production-related questions including total area cultivated and area under SS1, and reasons for not adopting SS1. In addition, we collected basic demographic details including jati (sub-caste), education levels, poverty status, and the number of household members. Since we planned to cover all farmers in the study village, we kept the survey instrument relatively short.

We focus on the cultivation outcomes of SS1 paddy variety among all paddy farmers in these villages that didn't receive a seed minikit in the 2011 study. On average, there are 66 non-recipient farmers per village (SD 26), forming a sample of 8796 non-recipients across the study villages. The largest village has 140 non-recipient farmers, and the smallest 20.

[2] Although the government seed centers at the block-level (already at a large distance from a village) claimed to stock the variety around similar timeline as our study, we heard many anecdotes regarding how seeds were rarely available for purchase for an average farmer unless one had strong contacts with the store officials.

[3] 2 villages were unreachable due to excessive flooding.

[4] For example, 2013 was the year of the Phailin cyclone, which we used as a benchmark for recall.

Table A.1 shows the summary statistics using the census data. Importantly, the population consists mainly of paddy farmers (98% cultivate paddy), with close to 50% cultivating the Swarna variety. SS1 is a modified variety of Swarna, with the additional feature of flood tolerance. Therefore, ex-ante, one would expect Swarna growers to switch to SS1.

The average farmer is small, cultivating less than 3 acres of land during the main agricultural season (Kharif). Those that cultivate SS1, cultivate over a smaller area relative to total cultivated area. As the source of SS1, farmers are more likely to mention other farmers as the main source relative to seed centers or markets. Further, they are more likely to report obtaining the seeds from someone outside their village rather than someone within their village.

Finally and importantly, there are many endogamous kinship or jati (also known as sub-castes) groups, corresponding to different varnas (social classification of Hindu society as per Manusmriti, a prominent Hindu religious text), in the study villages. About 11% of farmers belong to dalit and adivasi groups, recognized as scheduled caste (SC) and scheduled tribes (ST) by the Constitution of India. About 5% and 2% of farmers belong to brahmin (priests) and kshatriya (warrior) varnas, respectively. Though small in terms of population, these two varnas occupy influential positions in local social networks and are privileged. Members of this community usually serve as priests or local leaders in addition to their occupation in farming, are more educated than other jati groups, and/or are better connected to those with salaried jobs outside their village. In contrast, jatis belonging to Scheduled Caste and Scheduled Tribe (SC/ST) categories are socially and economically oppressed. They typically serve as agricultural laborers and are engaged in subsistence farming. The rest of the population - about 80% - belongs to lower status varnas (termed as "Backward Castes") compared to brahmin and kshatriya varnas but higher status compared to SC/ST. Two jati groups are particularly important in this context, both in terms of their population share as well as their social mobility in Odisha. These are Khandayat and Gola jatis that constitute about 50% of the population and have higher levels of education relative to other lower status jati groups (Mitra 2021). Finally, remaining jatis are grouped as the Other Backward Caste (OBC) category constituting the remaining quarter of the population.[5]

3 Overall Diffusion and Heterogeneity by Flood-Exposure

In this section we analyze the evolution of farmers' cultivation choice of Swarna Sub-1 over 5 main cultivation seasons among non-recipient farmers across treated and control villages,

[5]The terms SC/ST and OBC are umbrella categories comprising many jatis within them and composed of various endogamous partitions within. Farmers from Khandayat and Gola jatis have significantly higher levels of education compared to SC/ST or OBC groups in our data.

following the initial, 2-stage experimental variation in the distribution of seeds. Because the technology is particularly beneficial in flood-prone areas, we examine its potential heterogenous diffusion by degree of flood exposure. We exploit the fact that the initial set of villages as well as the initial set of farmers were randomly selected from a sample of flood-prone villages in the Balasore and Bhadrak districts of Odisha. We use this initial assignment of villages to receive the seed technology through the external intervention as the main identifying variation to examine adoption among non-recipient farmers over 2011-2015.

We use Intent-to-Treat (ITT) analysis using village (v) treatment status dummy as the main explanatory variable and either farmer-level (i) or village-level yearly outcomes, including: (a) farmer's decision to cultivate SS1, (b) total village area under SS1, and (c) seed exchange from another farmer within the village, all denoted by y_{ivt}. We define the dummy $Treat_v$ to take on the value 1 if a village received the intervention in 2011 and 0 if it did not. We account for block b fixed effects, which was the geographic strata used for randomization. We examine the treatment effects by each calendar year within our study period using the following specification:

$$y_{ivt} = \beta_t Treat_v + \delta_t + \delta_b + \epsilon_{ivt} \tag{1}$$

We use $t = 2011$ as the base year in the regression specifications, so that $\delta_t, t > 2011$ is the mean outcome in control group in year t relative to 2011. β_t is the difference in the mean outcome in treated villages relative to control group for the same year t. For inference, we cluster the standard errors by village, which is the unit of treatment assignment.

The above specification enables us to estimate the dynamic average treatment effect (ATE) in the study sample over 5 years following the initial intervention. We also examine the above specification using treatment intensity - fraction of paddy farmers who initially received seed minikits - to measure a dose-response style effect.[6]

Measuring Flood Exposure We categorize farmers as high-flood exposure if their household location experiences 2 or more days of flooding during the main cultivation seasons over the study period (i.e., 2011-2015). We classify a day during the cultivation season as a flood day if the distance between the farmer household coordinates and the nearest flood polygon (as per flood product generated from LANCE-MODIS satellite data) is less than 1 km.[7]

[6] Figure A.1 shows that the treatment intensity varies from a very small fraction to a quarter of all paddy farmers.

[7] We also test for distance cut-offs at 2 km to test for sensitivity to any measurement error in the calculation. We note that 90% of farmers are 5 or fewer kms away from the closest flooded area and therefore use 1 km as our preferred distance threshold. Since the entire study area is at sea-level or below, elevation is not an important dimension for consideration in measuring flood exposure.

Figure A.2 shows the distribution of the number of flood days over the study period as well as the number of cultivation seasons/years recording at least one flood event. Our definition of flood exposure classifies about 50% of the farmers as experiencing some flooding during the study period. The higher distance cut-off classifies an even larger fraction of the sample as high risk since the overall study location is within low-elevation districts in coastal Odisha.

Our definition of flood-exposure is motivated by two facts: (a) damage caused by flooding is steep going from no flooding to experiencing at least one day of flooding, and (b) keeping the distance threshold small (but large enough to minimize measurement error) since the entire study region is already low-lying. Further, measuring flooding based on distance from household location is a useful metric because farmers usually store their seeds and grain in their houses, and therefore flooding affects farmers' ability to carry forward seeds for cultivation in subsequent seasons.[8]

We estimate the following heterogeneous treatment effect specification with interaction terms based on farmer classification as high flood exposure (flood < 1 km).

$$y_{ivt} = \gamma_t^f HiFlood_{iv} \text{ x } Treat_v + \phi_t^f Treat_v + \alpha_t^f HiFlood_{iv} + \delta_t + \delta_b + \epsilon_{ivt} \tag{2}$$

The subscripts denote units as described above. $HiFlood_{iv}$ is a dummy variable that takes the value 1 if a farmer's household GPS coordinates are within 1 km from the closest flood layer, for at least 2 days, during 2011-2015 (we also estimate the same specification where $HiFlood_{iv}$ is defined using 2 km threshold). The main coefficient of interest is γ_t^f, which is the mean outcome among high flood exposure farmers in treated villages relative to low exposure farmers in treated villages in year t. γ_t^f can also be interpreted as the differential outcome between similarly high-risk farmers in the control group.

Table 1 reports the result on overall diffusion. We notice only a modest and statistically insignificant increase in adoption of the new variety in treated villages relative to control (Column 1). Treated villages have a few more farmers cultivating SS1, and this difference remains stable over time, particularly in the later years (see Figure A.5). In aggregate, slightly more than 10% of the paddy farmers adopt SS1 and the adoption rate appears to plateau in both treated and control villages during the study period. This difference corresponds to a modest but statistically insignificant difference of 23% relative to the control group.

Column 2 reports the differences in village-level total area under SS1 cultivation. While both treated and control villages start with similar areas - less than 5% area -under SS1 in

[8] In fact, losing seeds to floods is often cited as one of the reasons why someone didn't cultivate SS1 in any given year as shown in Figure A.3.

2011, the difference almost doubles in the later years (is statistically significant in 2014), with treated villages cultivating almost one additional acre. Though the gap slightly reduces in 2015 and is no longer statistically significant, the difference is similar to that in 2014. Since we regress village-level area under cultivation on treatment and year dummies, we weight the regressions by the underlying village size.

Finally, Column 3 suggests that these differences in cultivation decision and area indicate farmer-to-farmer diffusion of seeds within treated villages, seen in the form of substantial differences in citing another village farmer as the seed source. Recall that we asked respondents about the source of SS1 seeds in our survey. We specifically asked whether the source was any farmer within their village. We find that at least 10-15% of adopters' report receiving seeds from someone within their village in the control group. This share is substantially higher in treated villages relative to control. In the early years, this difference is 23 percentage points. In 2015, this reduces to 8 percentage points but is still economically and statistically significant.

One plausible reason for the modest effect on average could be treatment intensity. Note that we seed up to 5 farmers during the 2011 intervention. Depending on village size, which is orthogonal to the intervention due to randomization, the treatment could be less intensive in large villages. We continue to find similar differences in adoption and area under cultivation if we take this variation in treatment intensity into account (see Table A.3).

Examining farmer-level heterogeneity by flood-exposure, we find suggestive evidence that the external intervention reaches those with higher flood exposure over time relative to status quo. This is reassuring since the technology mainly reduces the downside risk of flood-exposure on yields. Figure A.6 (and Column 1 of Table A.4) depicts the diffusion curves in treated and control villages by farmer flooding exposure. Panels A and C present diffusion among high flood-exposure farmers (at 1 and 2 km cut-offs, respectively) whereas Panels B and C depict diffusion among low-exposure farmers in treated and control villages.

The results on area and seed exchange (Columns 2-3 Table A.4) along with the delay in differential adoption question whether random initial seeding reaches those more likely to benefit from the technology relative to status quo. Could there be gains from trade within a village that aren't currently being exploited? When asked for reasons for not cultivating the new variety, most farmers reported non-availability or lack of information as among the main reasons (see Figure A.3). We examine jati networks as a plausible barrier to information exchanges and trade between farmers, that we discuss in the next section.

4 Jati as an Impediment to Trade

Jatis in India are endogamous kinship groups, with close social ties between members of a jati both within and across villages. The sample villages in our study vary in their jati composition, with some villages being more homogenous with a small number of jatis whereas others are a composite of multiple jatis. Figure A.4 shows the distribution of the number of distinct jatis and the associated ethnolinguistic fractionalization index of the sample villages.

We examine both heterogeneous treatment effects by village-level jati fractionalization as well as the effect of farmer-level jati affiliation following exogenous variation in the jati identities of initial recipients, motivated by a growing literature on identity as a potential barrier to gainful trade (Anderson 2011; Emerick 2018). This design attempts to: a) identify whether there is significant heterogeneity by the structure of local social networks, and b) whether individual-level affiliations to specific groups explain the differences in technology adoption.

Village-Level Jati Fractionalization To address a), we define measures of jati-based village-level fractionalization based on the number of distinct jatis in a village. A village is more fractionalized if it has more than 6 distinct jatis. As an alternate measure, we also categorize villages based on the inverse Herfindahl-Hirschman Index (called Ethno-Linguistic Fractionalization or ELF in the relevant literature), constructed as $1 - \sum_j s_j^2$ where s_j is the population share of jati j within a village. We categorize villages as those with high fractionalization if their index is above 0.6.[9] The cut-offs to define fractionalization using either of the measures roughly map to each other. Specifically, we estimate the following heterogeneous treatment effect specification with additional interaction terms based on the extent of fractionalization.

$$y_{ivt} = \gamma_t^J LessFrac_v \text{ x } Treat_v + \phi_t^J Treat_v + \alpha_t^J LessFrac_v + \delta_t + \delta_b + \epsilon_{ivt} \tag{3}$$

The subscripts denote units as described above. $LessFrac_v$ is a dummy variable that takes the value 1 if the number of distinct jatis in a village is less than 6 as our preferred measure of fractionalization (we also estimate the same specification where $LessFrac_v$ denotes village fractionalization based on ELF ≤ 0.6). The main coefficient of interest is γ_t^J, which is the differential impact of the treatment in less fractionalized villages relative to more fractionalized villages. When using the number of jatis as a measure of fractionalization, we

[9] Industrial Organization literature uses 0.6 as a cut-off to define an industry as an oligopoly if few firms have more than 60% of the market share. In the case defining fractionalization based on ethnic divisions, $1 - \sum_j s_j^2 > 0.6$ implies presence of many different ethnic groups.

control for village size in both treated and control villages to account for any imbalances in village size due to empirical realization of the random assignment.

Figure 1 depicts a clear pattern using raw means on the adoption decision, suggesting that any differential patterns in technology diffusion between treated and control villages plausibly arises due to the extent of fractionalization. Less fractionalized treated villages experience a head-start in adoption that persists and plausibly increases over time. On the other hand, we observe no differential diffusion across fractional villages. These differences in raw means are similar using either way of constructing the fractionalization measure. We verify whether these patterns are visible as heterogenous treatment effects by estimating Equation 3. Note that we control for village sizes in both treated and control villages when using the number of jatis as a measure of fractionalization.

Table 2 reports both ϕ_t and γ_t from Equation 3, where γ_t presents the differential treatment outcome in less fractionalized villages relative to more fractionalized villages as well as less fractionalized control villages. The coefficients suggest a strong positive effect of greater jati homogeneity on adoption, implying that external introduction of technology generates immediate diffusion among non-recipient farmers in the same village compared to the diffusion process seen in more fractionalized treated villages. This gap in adoption among non-recipient farmers persists over time.

Though noisily estimated, the effects on area cultivated in fewer jati treated villages is positive albeit not statistically significant. The magnitude for 2015 suggests that the area under the crop is two-thirds more relative to more fractionalized treated villages (see Columns 2 Table 2). Finally, these effects are consistent with more seed exchanges between farmers within treated villages with greater jati homogeneity (Columns 3 Table 2). These exchanges are also more likely to occur early in the timeline.

The subsections below help pin down whether the observed village-level heterogeneous effects by jati fractionalization are due to information and seed trade primarily between farmers within jati-groups rather than across groups.

Jati Identity We exploit the second stage of the initial randomization, i.e., at the farmer-level, that generates exogenous variation in which jati groups initially received the seed technology in 2011. While the probability of receiving the initial endowment of seeds is similar across the various jati groups, the extent of flood exposure is markedly different between the lowest status jati groups (SC/ST), which face higher exposure, compared to higher status groups that either face no significant exposure or face lower exposure (see Table A.2). This suggests that the technology provides social protection particularly to the vulnerable groups that are more likely to experience flooding.We cannot rule out whether other jati groups could face flood risk in the future and therefore, their interest in trying out the new variety may indeed be efficiency-enhancing in the long run. However, the realized flood events suggest that there are at least short-term efficiency gains in trading seeds with lower status groups.

We estimate the following specification, examining the differences in outcomes based on whether anyone from a farmer's own jati network received a seed minikit in 2011. In villages with more jatis than the number of kit recipients, it is possible that no farmer from some jatis received a kit whereas villages with fewer jatis could experience multiple kit recipients within the same jati. In view of the fact that villages were also randomized, jati-level compositions are exogenous to the intensity of external introduction of new seed technology, and therefore enables us to estimate the causal effect of jati-network affiliations.

$$y_{ivt} = \beta_t^1 \mathbb{1}(Kit > 0)_{iv} + \beta_t^0 Treat_v + \delta_t + \delta_b + \epsilon_{ivt} \tag{4}$$

$\mathbb{1}(Kit > 0)_{iv}$ is an indicator variable that takes value 1 if at least one from farmer i's own jati network received a seed minikit in 2011. β_t^0 is the treatment effect in year t when no one from the farmer's own jati network initially received the kit in 2011 and β_t^1 is the additional effect if at least one received the kit.

If we fail to reject $\beta_t^0 = 0$ but reject $\beta_t^1 = 0$, then we can infer that the diffusion process mainly occurs within and not between jati networks in year t. We cluster standard errors by village, the more aggregate strata of treatment assignment, which helps account for serial correlation between farmers across jati groups within the same village. We also examine the robustness of the hypothesis tests by clustering at the jati-group level since jati is the main unit of randomization within this research design.

We find that adoption increases if at least one initial seed recipient belonged to one's own jati group (Column 1 Table 3). In fact, in the initial years (2011-2012), almost all diffusion occurred within jati networks, whereas we observe some between-jati diffusion in later years (although not statistically significant). Consistently, we also observe an increase in area under cultivation (Column 2 Table 3) and there is more seed sharing within jati networks (Column 3 Table 3). While we fail to reject $\beta_t^0 = 0$ for adoption and area under cultivation, we do record farmers reporting receiving seed from other farmers in treated villages even when no one from their own jati group initially received minikits. However, having at least one own-jati recipient magnifies the reported seed exchanges in the first and last year of the study period.[10]

[10]The results are qualitatively similar when we examine the marginal effect based on the number of initial kit recipients rather than the binary indicator.

Diffusion Across Jati Social Hierarchy In addition to the multiplicity of jati groups that follow greater economic and social interactions within rather than between such groups, there is also a hierarchy in the relative status of these groups based on their varna status briefly discussed in Section 2. We codify jati ranks based on a jati's relative status in the social hierarchy in Odisha. Jatis belonging to brahmin and kshatriya jatis (mapping to the same *varnas*) wield enormous social, political, and economic power. We rank these two jatis as 1 and 2, respectively. We rank Khandayat and Gola/Gopal jatis as 3. As noted earlier, these two are dominant jati groups in Odisha, both in terms of their respective population sizes as well as having experienced significant social mobility over the past decades. All other jati groups belonging to the OBC category are ranked 4, whereas jati groups belonging to Scheduled Caste and Scheduled Tribe (SC/ST) are ranked 5. We examine the technology adoption outcomes among farmers within treated villages based on the ranks of their own jati groups relative to that of the modal jati group of initial recipients. Mainly, we examine outcomes for farmers belonging to jatis of the same rank, those belonging to jatis of relatively higher rank than the modal recipient, and those belonging to relatively lower rank than the modal recipient (since rank is coarser than jati groups, multiple jatis can belong to the same rank).[11]

$$\begin{aligned} y_{it(v\in Treat)} &= \beta_t^l \mathbb{1}(RecipLower)_{i(v\in Treat)} + \beta_t^h \mathbb{1}(RecipHigher)_{i(v\in Treat)} \\ &+ \beta_t^s + \delta_b + \epsilon_{it(v\in Treat)} \end{aligned} \tag{5}$$

β_t^s provides the average rate of adoption in year t among non-recipient farmers belonging to the same jati group as the modal recipient. The coefficients β_t^h and β_t^l correspond to the treatment effect if a farmer's jati group is lower or higher than that of the modal recipient, respectively. Both the magnitude and direction of these effects are important as they provide important information on how the relative status of jati groups matters. Note that because the specification is estimated only within the subsample of treated villages, the year fixed effect incorporates the leave-out group of similarly ranked farmers as that of the modal recipient.

Table 4 presents the estimates from Equation 5 by relative jati rank. As before, the dependent variable in Column 1 is seed adoption. Focusing on non-recipient farmers from similarly ranked jati groups as the modal recipient, we clearly note a diffusion process, with adoption rates increasing over the previous year. Surprisingly, there is no differential diffusion among farmers belonging to jati groups that are relatively higher in social status compared

[11] We focus on the modal jati of recipients since there are at most 5 initial recipients within each village. In the event of multiple modes, we select the lowest ranked jati of initial recipients.

to the modal recipient farmer. In contrast, we note a modest reduction in adoption among farmers belonging to relatively lower ranked groups, at least in the initial years. That is, we note diffusion within similar or higher ranked jatis as initial recipients but not among jatis lower in social status.

We note similar patterns with area under cultivation (Column 2 Table 4). The increase in village area under SS1 is mainly driven by cultivating farmers in similar ranked jati groups as the initial recipients. Consistent with very little diffusion, farmers from lower ranked groups do not report any area under SS1 cultivation. On the other hand, farmers from higher ranked groups cultivate similar area as similarly ranked farmers.

The adoption and area results are consistent with an increase in reported seed sharing within similarly ranked jati groups. Surprisingly, farmers from lower ranked jati report receiving seeds from other village farmers whereas those from higher ranked jatis report fewer seed exchanges relatively. While this may seem inconsistent with the effects on adoption or area under cultivation, it is likely that higher status farmers are less likely to report that they received seeds from other lower-status farmers.

We also examine variations in the above research design on social hierarchy by examining heterogeneity by whether the majority of the initial kit recipients were from higher jati status groups (brahmin and kshatriya) in Table A.9 or if the majority belonged to intermediate ranked jati groups in Table A.10.[12]

Taken together, these results suggest that the way a technology is introduced can lead to different diffusion processes based on the underlying social network structures and can have distributional implications. These aspects need to be considered when designing policies that either adopt random initial seeding or leverage local social networks to increase adoption.

5 Conclusion

This paper documents the long-term adoption of new agricultural technology among the population of non-recipients, five years from the initial introduction of new flood resilient paddy seeds in this part of Odisha. The two main findings are: (a) there is on average positive but imprecise differential diffusion between experimental and control villages, and (b) this is mainly due substantial heterogeneity in the underlying social network structure of the study villages.

These findings suggest that the structure of jati networks and their relative social hierarchy can constitute important trade barriers to the diffusion of technology. We note that the extent of technology adoption and cultivation outcomes are higher in less fractionalized

[12] These variations use village-level classification by the jati status of the initial group of kit recipients.

villages and that fractionalization attenuates the initial advantage brought in by random chance. From a welfare and distributional perspective, this could be good or bad. Random seeding could be better in socially homogenous villages in the presence of market access barriers. On the other hand, the diffusion process from random initial seeding could be no different from natural diffusion processes in highly fractionalized villages. In such contexts, targeting members of various jati groups, particularly those with lower social status, may spur diffusion.

Finally, it is unclear whether the observed gaps will disappear with time. However, a lack of convergence over a 5-year horizon suggests that such gaps could persist over even longer time horizons. This could imply long-run development impact, as documented by current literature - whether for agricultural technology specifically (Gollin et al. 2021) or for other productivity altering interventions that change the development path of economies (Dell and Olken 2020). However, due to the time scale of our study, we are unable to answer this question using micro-evidence from individual farmer-level data and leave this as an open question for future research.

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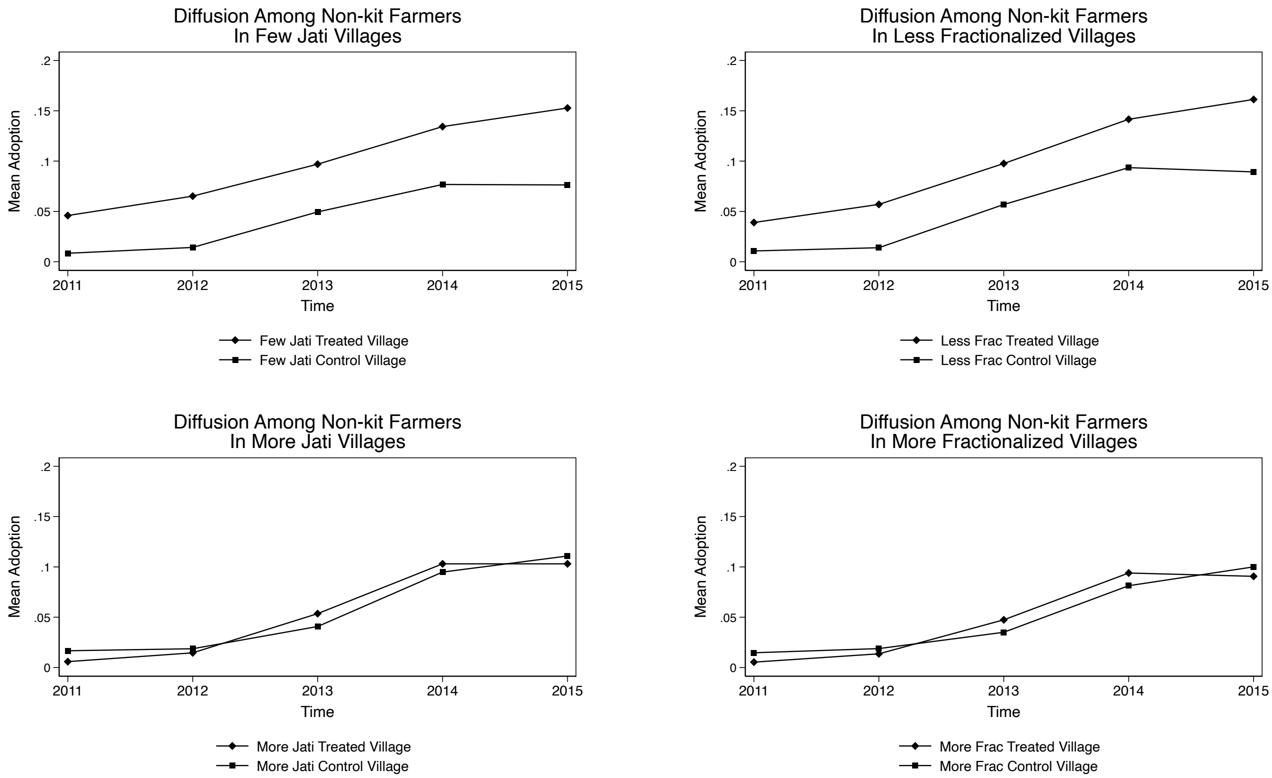
6 Figures

Figure 1: Diffusion of Seeds: By Jati Fractionalization



Notes: The chart shows raw mean levels of adoption among non-recipients over the years in homogenous vs. fractional villages. The left panel is based on the number of distinct jati groups in a village whereas the right panel is based on the ELF index.

7 Tables

Table 1: Diffusion Over Time Among Non-Recipients: Dynamic Treatment Effects

	(1) Adopt	(2) Area (Acres)	(3) Seed Source Within Village
2011	0.0136	0.0363	-0.0642
	(0.00631)	(0.122)	(0.0548)
2012	0.00358	0.0556	0.0915
	(0.00122)	(0.0304)	(0.0609)
2013	0.0317	0.282	0.134
	(0.00735)	(0.149)	(0.0655)
2014	0.0742	0.409	0.150
	(0.0130)	(0.159)	(0.0717)
2015	0.0819	1.224	0.109
	(0.0151)	(0.286)	(0.0672)
Treat x 2011	0.00439	0.00829	0.0522
	(0.0104)	(0.173)	(0.0582)
Treat x 2012	0.0125	0.633	0.229
	(0.0113)	(0.430)	(0.0898)
Treat x 2013	0.0209	0.591	0.00950
	(0.0150)	(0.364)	(0.0449)
Treat x 2014	0.0242	0.876	0.00956
	(0.0193)	(0.401)	(0.0401)
Treat x 2015	0.0227	0.788	0.0816
	(0.0216)	(0.489)	(0.0328)
Control Mean (2012)	0.017	0.12	0.05
Observations	40845	630	1374
No. Villages	126	126	109
Adj R-Squared	.05	.2	.07

Standard errors in parentheses
* $p < 0.1$, ** $p < .05$, *** $p < 0.01$

Notes: The sample includes the universe of non-recipient farmers in the study villages from Emerick et al. (2016). Columns 1 and 3 present results from farmer-level regressions using adoption (a binary indicator denoting whether a non-recipient farmer cultivated SS1 in a given year) and seed source (a binary indicator denoting whether a non-recipient farmer acquired the seed from another farmer within the village) as outcome variables. Regression reported in Column 3 is conditional on adoption. Column 2 presents estimates from village-level regressions, weighted by the number of non-recipient farmers (village size). All specifications include randomization strata fixed effect and cluster standard errors by the level of treatment assignment (i.e., village).

Table 2: Adoption Among Non-Recipients by Village Fractionalization

	(1) Adopt	(2) Area (Acres)	(3) Seed Source Within Village
Treat x 2011	-0.133	-0.610	0.0294
	(0.0527)	(0.852)	(0.0759)
Treat x 2012	-0.126	0.118	-0.0398
	(0.0526)	(0.887)	(0.228)
Treat x 2013	-0.109	0.204	0.0220
	(0.0541)	(0.842)	(0.0907)
Treat x 2014	-0.114	0.345	-0.0325
	(0.0569)	(0.868)	(0.101)
Treat x 2015	-0.129	0.265	0.0648
	(0.0591)	(0.872)	(0.0993)
Few Jati x Treat x 2011	0.0852	0.303	.
	(0.0351)	(0.475)	.
Few Jati x Treat x 2012	0.0916	0.00652	0.388
	(0.0386)	(0.705)	(0.228)
Few Jati x Treat x 2013	0.0700	-0.219	0.0329
	(0.0466)	(0.705)	(0.0925)
Few Jati x Treat x 2014	0.0842	0.180	0.139
	(0.0511)	(0.744)	(0.0849)
Few Jati x Treat x 2015	0.119	0.177	0.0555
	(0.0538)	(0.938)	(0.0893)
More Jati Mean in Control (2012)	0.019	0.05	0.25
Observations	40845	630	1374
No. Villages	126	126	109
Adj R-Squared	.06	.2	.08

Standard errors in parentheses
* $p < 0.1$, ** $p < .05$, *** $p < 0.01$

Notes: The sample includes the universe of non-recipient farmers in the study villages from Emerick et al. (2016). Columns 1 and 3 present results from farmer-level regressions and those in Column 2 from village-level regressions. Importantly, we control for village size and size interacted with treatment status in this specification in case villages with more jatis are correlated with village size. Our preferred measure of fractionalization is whether a village has 6 or more distinct jatis. We only report ϕ_t and γ_t in this table for better readability. All specifications include block fixed effects and cluster standard errors by village.

Table 3: Jati-Level Adoption: At Least One Own Jati Recipient

	(1) Adopt	(2) Area (Acres)	(3) Seed Source Within Village
Treat x 2011	-0.00519	0.0341	-0.0117
	(0.00903)	(0.0733)	(0.0715)
	[0.006]	[0.05]	[0.046]
Treat x 2012	-0.00309	0.00117	0.401
	(0.00904)	(0.0771)	(0.165)
	[0.0065]	[0.042]	[0.153]
Treat x 2013	0.00735	-0.0839	0.0203
	(0.0123)	(0.143)	(0.0473)
	[0.012]	[0.097]	[0.045]
Treat x 2014	0.0205	-0.0409	0.0663
	(0.0210)	(0.155)	(0.0633)
	[0.0163]	[0.053]	[0.065]
Treat x 2015	0.0142	-0.342	0.0516
	(0.0234)	(0.223)	(0.0300)
	[0.0185]	[0.144]	[0.021]
At Least 1 Own Jati w/ Kit x 2011	0.0145	-0.0936	0.0698
	(0.00757)	(0.0878)	(0.0466)
	[0.006]	[0.092]	[0.033]
At Least 1 Own Jati w/ Kit x 2012	0.0238	0.329	-0.215
	(0.00937)	(0.244)	(0.187)
	[0.0098]	[0.047]	[0.158]
At Least 1 Own Jati w/ Kit x 2013	0.0205	0.369	-0.0144
	(0.0132)	(0.198)	(0.0461)
	[0.014]	[0.084]	[0.05]
At Least 1 Own Jati w/ Kit x 2014	0.00548	0.598	-0.0708
	(0.0184)	(0.235)	(0.0634)
	[0.017]	[0.105]	[0.054]
At Least 1 Own Jati w/ Kit x 2015	0.0128	0.935	0.0440
	(0.0181)	(0.265)	(0.0238)
	[0.0176]	[0.071]	[0.048]
Control Mean (2012)	0.017	0.12	0.05
Observations	40845	4059	1374
No. Villages	126	126	109
Adj R-Squared	.05	.16	.08

Standard errors in parentheses
* $p < 0.1$, ** $p < .05$, *** $p < 0.01$

Notes: The sample includes the universe of non-recipient farmers in the study villages from Emerick et al. (2016). Columns 1 and 3 present results from farmer-level regressions and those in Column 2 from village-level regressions weighted by the number of non-recipient farmers (village size) (Equation 4). All specifications include block fixed effect. We report standard errors clustered by village in parentheses and by jati-level in square brackets. We estimate another variation of the specification above using the number of initial kit recipients from own jati network instead of the indicator variable in Table A.7.

Table 4: Adoption Among Non-Recipients in Treated Villages by Jati Rank Difference

	(1) Adopt	(2) Area (Acres)	(3) Seed Source Within Village
Rank Diff==0 x 2011	0.0193	-0.0230	0.0175
	(0.0119)	(0.213)	(0.0485)
Rank Diff==0 x 2012	0.0142	0.924	0.125
	(0.00547)	(0.762)	(0.125)
Rank Diff==0 x 2013	0.0506	0.799	0.0349
	(0.0152)	(0.557)	(0.0682)
Rank Diff==0 x 2014	0.0888	1.203	0.0697
	(0.0149)	(0.645)	(0.0619)
Rank Diff==0 x 2015	0.101	1.472	0.148
	(0.0156)	(0.581)	(0.0697)
Recip. Higher Jati x 2011	-0.0187	0.0349	.
	(0.0122)	(0.206)	.
Recip. Higher Jati x 2012	-0.0247	-0.882	0.541
	(0.0126)	(0.729)	(0.253)
Recip. Higher Jati x 2013	-0.0138	-0.670	0.00152
	(0.0169)	(0.528)	(0.0810)
Recip. Higher Jati x 2014	0.00571	-1.079	-0.0143
	(0.0374)	(0.598)	(0.0868)
Recip. Higher Jati x 2015	-0.00428	-1.340	-0.0365
	(0.0391)	(0.531)	(0.0359)
Recip. Lower Jati x 2011	0.00358	0.108	-0.0937
	(0.0116)	(0.271)	(0.0807)
Recip. Lower Jati x 2012	-0.000674	-0.607	0.119
	(0.0117)	(0.554)	(0.137)
Recip. Lower Jati x 2013	-0.00372	-0.140	0.0525
	(0.0149)	(0.368)	(0.0696)
Recip. Lower Jati x 2014	0.00887	-0.231	0.0149
	(0.0193)	(0.444)	(0.0538)
Recip. Lower Jati x 2015	-0.00201	0.449	-0.0915
	(0.0193)	(0.546)	(0.0449)
Observations	20074	710	782
No. Villages	64	64	56
Adj R-Squared	.09	.2	.1

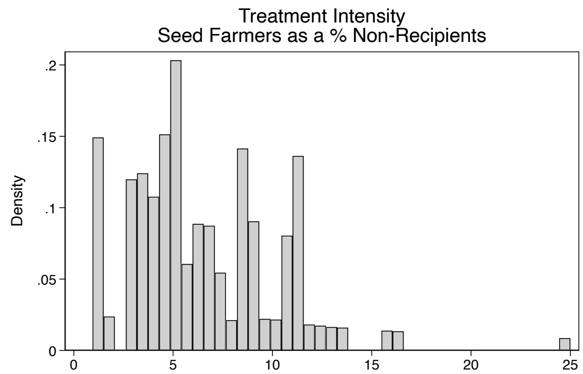
Standard errors in parentheses
* $p < 0.1$, ** $p < .05$, *** $p < 0.01$

Notes: The sample includes the universe of non-recipient farmers in the treated villages only since we examine the effect of relative social status of farmer jati with respect to that of initial recipients (control villages had 0 initial recipients). Columns 1 and 3 present results from farmer-level regressions and those in Column 2 from village-level regressions weighted by the number of non-recipient farmers (village size). All specifications include block fixed effect. We report standard errors clustered by village in parentheses Clustering by jati-level leads to similar, if not stronger, inference.

Appendix

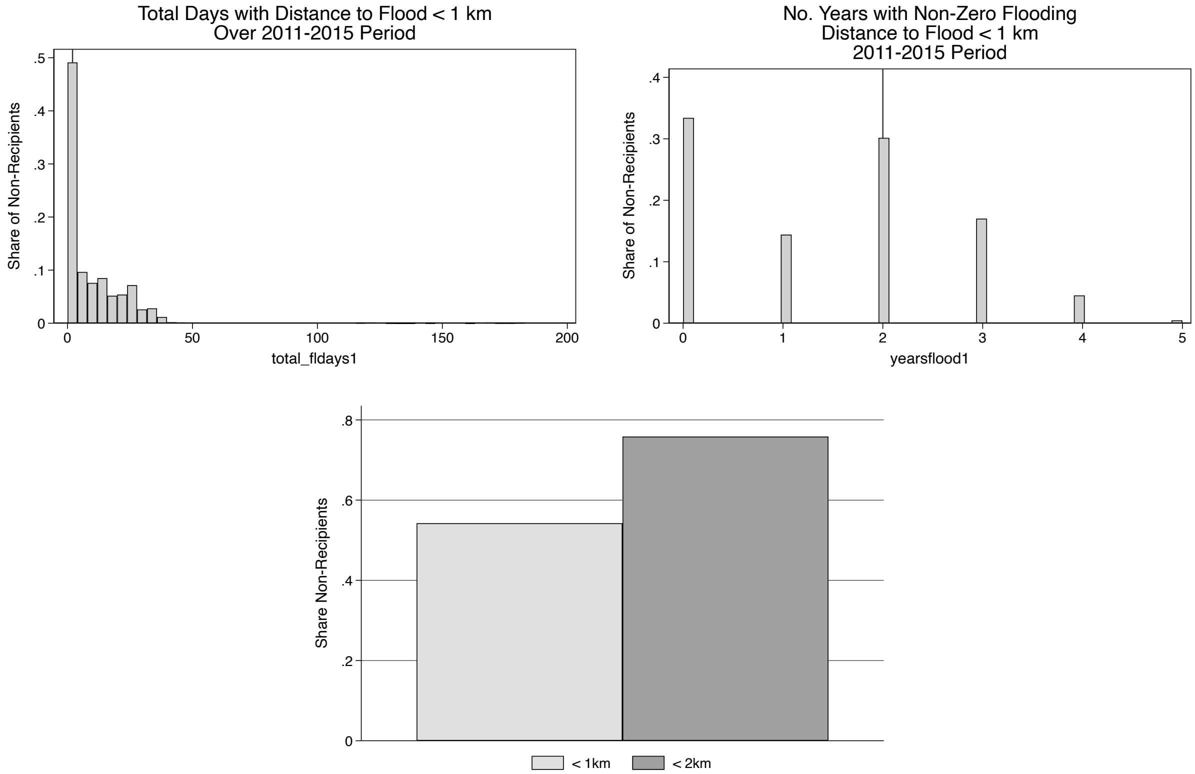
A.1 Figures

Figure A.1: Treatment Intensity



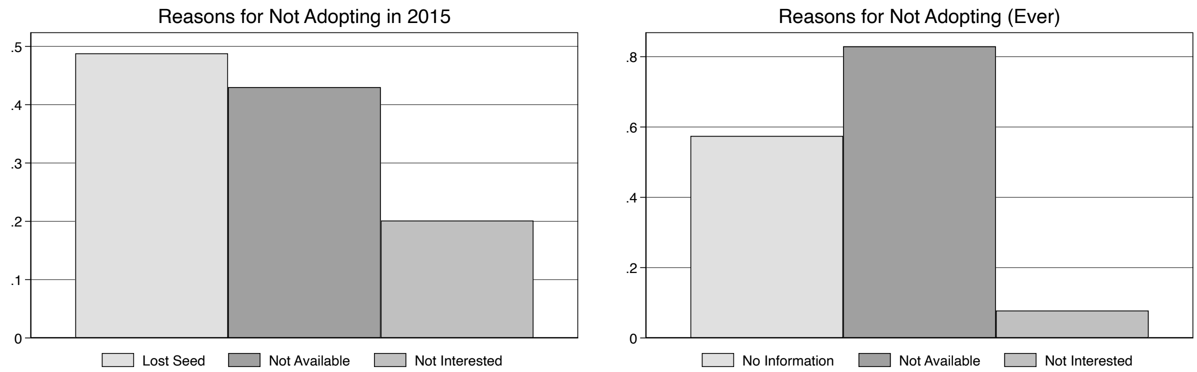
Notes: In each treated village, 5 farmers were randomly selected from a list of all paddy farmers in the village. We define treatment intensity as the fraction of all paddy farmers within the village that were initially selected to receive seed minikits.

Figure A.2: Distribution of Flood Days



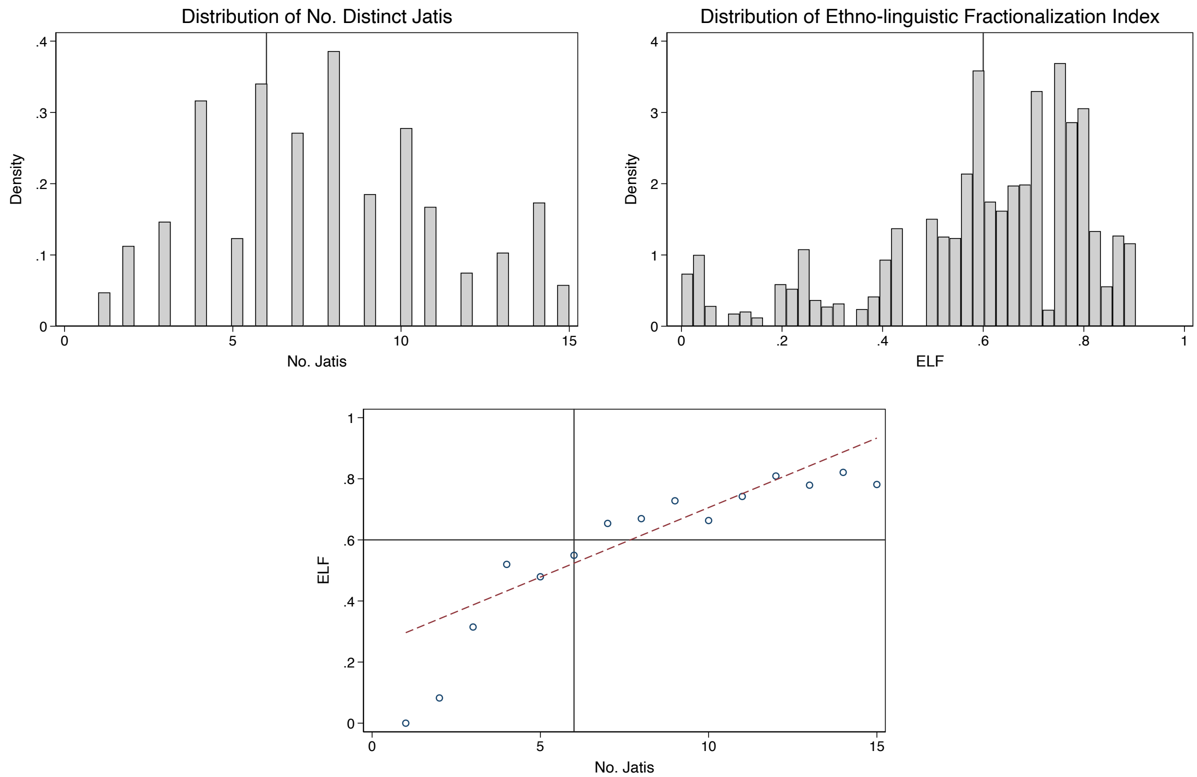
Notes: Data on flood layers is from LANCE-MODIS Flood data product. We select 85 days of satellite data for each year between 2011 and 2015, with 70 days falling during paddy flowering and post-flowering periods and 15 randomly selected days through-out the calendar year. For each satellite day, we computed the minimum distance between farmer household coordinates and the flood layers. We use this distance measure to calculate the number of days where the distance to flood layer is less than 1 k.m. Finally, we classify a farmer as high risk farmer if total number of days of flood exposure is greater than 2 days for the entire 2011-2015 period. Left panel shows the distribution of total number of flood days over the study period. Right panel shows the number of cultivation seasons when a farmer was exposed to floods over the study period. Bottom panel shows the share of non-recipient farmers classified as high flood exposure as per the two distance cut-offs.

Figure A.3: Reasons for Not Adopting



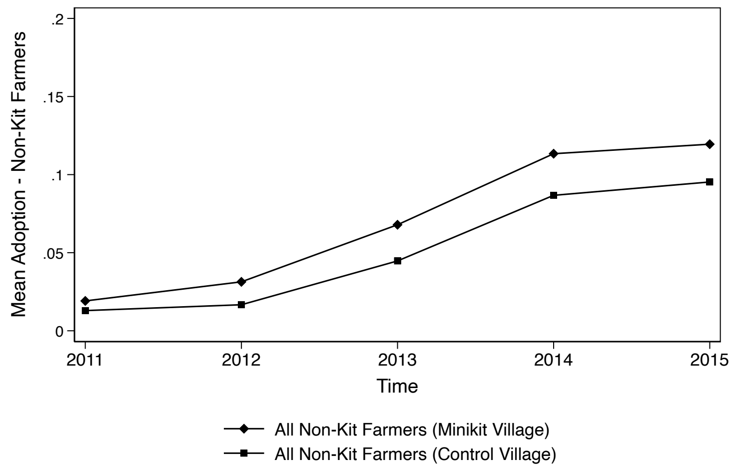
Notes: Figure on the left documents reasons for not adopting SS1 seeds in 2015 among non recipient famers that ever used the seeds in the past. Figure on the right documents reasons for not adopting SS1 ever. Respondents could list more than one reason for not adopting SS1.

Figure A.4: Jati Fractionalization in Sample Villages

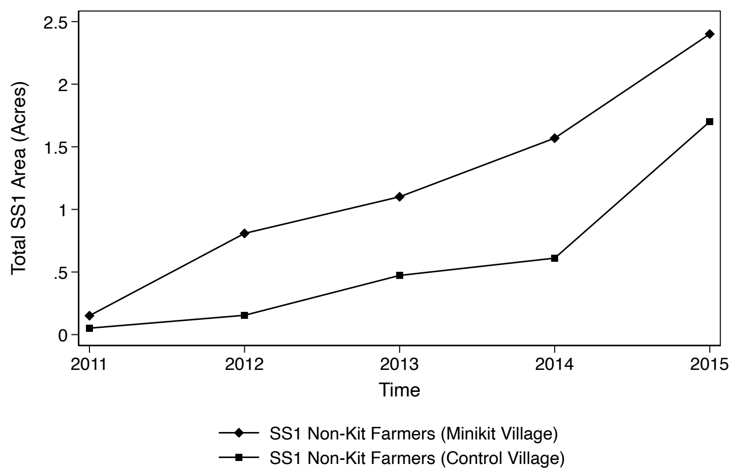


Notes: Histogram on the left depicts the distribution of number of unique jatis per village. A median village has 8 unique jatis. ELF is calculated as $1 - \sum_i s_i^2$, where s_i is the share in the population of a specific jati i. Higher value of the index indicates greater fractionalization. We generate a dummy for homogeneous caste villages below 0.6, as is used in classifying a market structure as a monopoly. The bottom panel depicts correlation between the two measures of fractionalization. The vertical and horizontal lines present the cut-offs used for defining fractionalization dummies respectively.

Figure A.5: Long-run adoption: All Non-Recipient Farmers
Panel A: Decision to Cultivate SS1



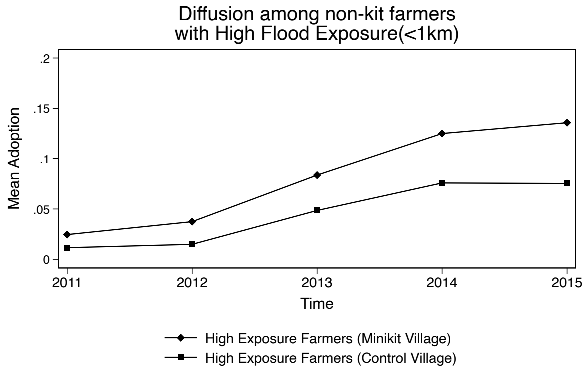
Panel B: Area Under SS1



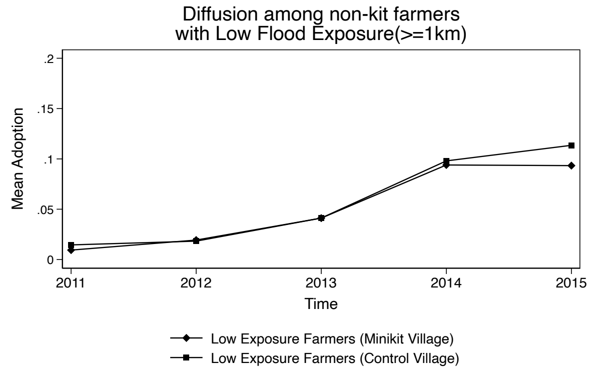
Notes: Top chart shows raw mean levels of adoption in treated and control villages among non-recipients over the years. Bottom chart plots total village-level area under SS1 among non-recipient farmers that grow SS1, broken down by village-level treatment status.

Figure A.6: Long-run adoption among all non-recipients: By Farmers' Flooding Exposure

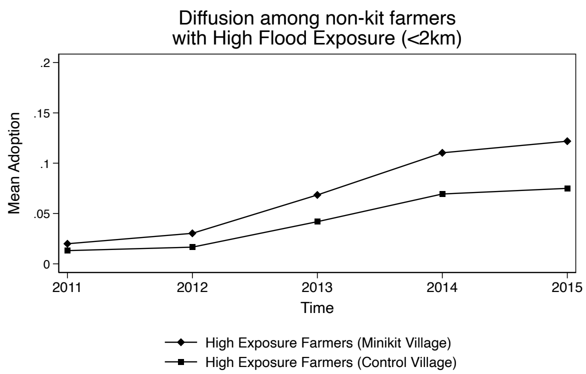
Panel A: High Flood Exposure



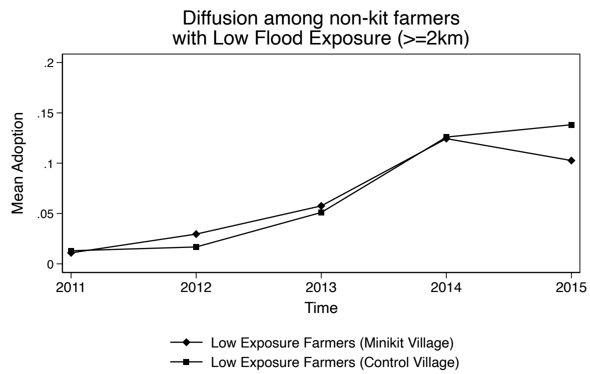
Panel B: High Flood Exposure



Panel C: High Flood Exposure (2 km)

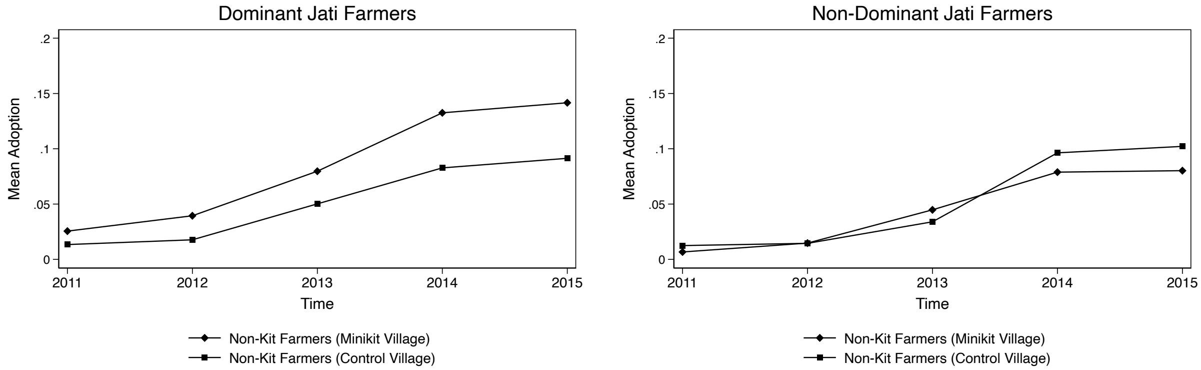


Panel D: High Flood Exposure (2km)



Notes: The chart shows raw mean levels of adoption among non-recipients over the years by flooding exposure. I measure flooding if a farmer experiences more than 2 days of flooding within the study period. Flooding is detected if the distance between the farmer household location and satellite generated flood layers is less than 1km (or 2km).

Figure A.7: Long-run adoption among all non-recipients: By Jati Dominance



Notes: The chart shows raw mean levels of adoption by dominant jati status in treated and control villages among non-recipients over the years.

A.2 Tables

Table A.1: Summary Statistics

	(1)				
	Observations	Mean	Std Dev	Min	Max
Cultivated Any Paddy (binary)	41490	.98	.15	0	1
Cultivated SS1 (Modified Swarna)	41476	.07	.25	0	1
Cultivated Swarna	41798	.47	.5	0	1
Kharif Area Sown (Acres)	15743	2.63	10.66	.01	1200
Rabi Area Sown (Acres)	2435	1.66	2.97	0	70
SS1 Kharif Sown Area (Acres)	476	1.61	5.43	.013	80
SS1 Source as Block	3099	.13	.34	0	1
SS1 Source as Self	3099	.17	.37	0	1
SS1 Source as Village Farmer	3099	.04	.20	0	1
SS1 Source as Outside Farmer	3099	.11	.31	0	1
SS1 Source as Minikit	3099	.01	.096	0	1
SS1 Source as Market	3099	.06	.24	0	1
SS1 Source as Door Sale	3099	.005	.07	0	1
SS1 Source as Other	3099	.03	.18	0	1
SC/ST	42490	.11	.32	0	1
Brahmin (Dom Jati)	42490	.05	.22	0	1
Kshatriya (Dom Jati)	42490	.02	.15	0	1
Khandayat (Dom Jati)	42490	.35	.48	0	1
Gola/Gopal (Dom Jati)	42490	.21	.41	0	1
OBC	42490	.23	.42	0	1

Notes: Summary was computed after organizing data in long format. The summary measures for each variable above is pooled over the period 2011-2015, therefore, each observation is a farmer-year. There are 8796 paddy cultivating farmers (universe) across 126 sample villages (64 treatment and 62 control). Of these 8796 farmers, 298 farmers received minikits in our 2011 study whereas 882 were control farmers. We exclude the initial kit recipients for our analysis to examine technology diffusion among non-recipient farmers.

Table A.2: Jati-Specific Differences in Initial Kit Receipt and Flood Risk

	(1)	(2)
	Pr (Minikit)	Pr (Flood Risk)
Brahmin	-0.0292	0.334
	(0.170)	(0.241)
Kshatriya	0.256	-0.840
	(0.226)	(0.330)
Khandayat	-0.0808	0.116
	(0.154)	(0.168)
Gola	0.00679	0.104
	(0.160)	(0.224)
OBC	-0.0975	-0.0114
	(0.161)	(0.198)
SCST	-0.206	0.474
	(0.185)	(0.194)
Observations	43185	41845

Standard errors in parentheses

* $p < 0.1$, ** $p < .05$, *** $p < 0.01$

Notes: Above table presents results from Probit specifications, regressing minikit receipt and flood risk dummies on jati dummies. Standard errors are clustered by village. The predicted probabilities for receiving kits are not correlated with farmer's jati affiliation. The jati correlations with flooding are significant only for kshatriya (a higher status group) and SCST (lowest status), with former facing lower probability whereas the latter faces higher probability.

Table A.3: Dynamic Effects by Treatment Intensity

	(1) Adopt	(2) Area (Acres)	(3) Seed Src Within Vill
2011	0.0140	0.0431	-0.0554
	(0.00568)	(0.105)	(0.0593)
2012	0.00445	0.173	0.0847
	(0.00143)	(0.102)	(0.0756)
2013	0.0352	0.326	0.106
	(0.00669)	(0.146)	(0.0604)
2014	0.0827	0.557	0.125
	(0.0119)	(0.166)	(0.0735)
2015	0.0869	1.275	0.122
	(0.0135)	(0.266)	(0.0768)
% Seeded x 2011	0.000567	-0.000855	0.00504
	(0.000908)	(0.0162)	(0.00772)
% Seeded x 2012	0.00154	0.0588	0.0299
	(0.000909)	(0.0399)	(0.0121)
% Seeded x 2013	0.00201	0.0751	0.00550
	(0.00125)	(0.0355)	(0.00601)
% Seeded x 2014	0.000945	0.0864	0.00569
	(0.00175)	(0.0397)	(0.00550)
% Seeded x 2015	0.00183	0.103	0.00682
	(0.00200)	(0.0506)	(0.00425)
Observations	40845	630	1374
Control Mean (2012)	0.0200	0.120	0.0500
Adj R-Squared	0.0500	0.200	0.0700

Standard errors in parentheses
* $p < 0.1$, ** $p < .05$, *** $p < 0.01$

Notes: The sample includes the universe of non-recipient farmers in the study villages from Emerick et al. (2016). Columns 1 and 3 present results from farmer-level regressions using adoption (a binary indicator denoting whether a non-recipient farmer cultivated SS1 in a given year) and seed source (a binary indicator denoting whether a non-recipient farmer acquired the seed from another farmer within the village) as outcome variables. Regression reported in Column 3 is conditional on adoption. Column 2 presents estimates from village-level regressions, weighted by the number of non-recipient farmers (village size). The coefficients on years 2012-2015 are relative to 2011. All specifications include randomization strata fixed effect and cluster standard errors by the level of treatment assignment (i.e., village).

Table A.4: Adoption Among Non-Recipients: By Flood Exposure

	(1)	(2)	(3)
	Adopt	Area (Acres)	Seed Src Within Vill
Treat x 2011	-0.00823	-0.0159	.
	(0.00983)	(0.187)	.
Treat x 2012	-0.00201	0.286	0.133
	(0.00998)	(0.209)	(0.163)
Treat x 2013	-0.00315	0.391	0.0686
	(0.0121)	(0.311)	(0.0702)
Treat x 2014	-0.00718	0.454	0.0527
	(0.0255)	(0.333)	(0.0442)
Treat x 2015	-0.0233	0.589	0.114
	(0.0290)	(0.698)	(0.0499)
Hi Flood x Treat x 2011	0.0260	-0.0141	0.0364
	(0.0199)	(0.342)	(0.0564)
Hi Flood x Treat x 2012	0.0291	0.479	0.119
	(0.0213)	(0.765)	(0.188)
Hi Flood x Treat x 2013	0.0429	0.279	-0.0797
	(0.0274)	(0.692)	(0.0843)
Hi Flood x Treat x 2014	0.0607	0.644	-0.0973
	(0.0379)	(0.742)	(0.0826)
Hi Flood x Treat x 2015	0.0881	0.297	-0.0690
	(0.0417)	(0.981)	(0.0666)
Low Flood Mean in Control (2012)	0.018	0.056	0.17
Observations	40845	820	1374
No. Villages	126	126	109
Adj R-Squared	.05	.2	.08

Standard errors in parentheses
* $p < 0.1$, ** $p < .05$, *** $p < 0.01$

Notes: Above table presents the regression coefficients from Equation 2, estimated using definition of farmers with high flood exposure as those with distance to flood less than 1 kms for at least 2 days during 2011-2015. We only report ϕ_t and γ_t in this table for better readability. Columns 1 and 3 are farmer-level specifications, with Column 3 conditional on adoption. Column 2 is village-level regression weighted by the number of non-recipient farmers (village size). All specifications include block (randomization strata) fixed effect and cluster standard errors by the level of treatment assignment (i.e., village).

Table A.5: Adoption Among Non-Recipients: By Flood Exposure

	(1) Adopt	(2) Area (Acres)	(3) Seed Src Within Vill
Treat x 2011	-0.0136	-0.248	.
	(0.00993)	(0.139)	.
Treat x 2012	0.00127	0.325	-0.0143
	(0.0125)	(0.259)	(0.268)
Treat x 2013	-0.00497	0.820	0.0571
	(0.0174)	(0.602)	(0.0886)
Treat x 2014	-0.0131	0.997	0.0734
	(0.0411)	(0.558)	(0.0572)
Treat x 2015	-0.0471	1.867	0.0132
	(0.0392)	(1.276)	(0.0547)
Hi Flood (2km) x Treat x 2011	0.00740	0.307	0.152
	(0.0165)	(0.247)	(0.0761)
Hi Flood (2km) x Treat x 2012	-0.000586	0.326	0.375
	(0.0179)	(0.616)	(0.288)
Hi Flood (2km) x Treat x 2013	0.0185	-0.257	0.0481
	(0.0228)	(0.758)	(0.113)
Hi Flood (2km) x Treat x 2014	0.0409	-0.0983	-0.0252
	(0.0449)	(0.752)	(0.0884)
Hi Flood (2km) x Treat x 2015	0.0808	-1.196	0.159
	(0.0447)	(1.381)	(0.0809)
Low Flood Mean in Control (2012)	0.017	0.015	0.33
Observations	40845	820	1374
No. Villages	126	126	109
Adj R-Squared	.06	.21	.09

Standard errors in parentheses
* $p < 0.1$, ** $p < .05$, *** $p < 0.01$

Notes: Above table presents the regression coefficients from Equation 2, estimated using definition of high flood exposure farmers as those with distance to flood less than 2 kms for at least 2 days during 2011-2015. We only report ϕ_t and γ_t in this table for better readability. All specifications include block fixed effect and cluster standard errors by village.

Table A.6: Adoption Among Non-Recipients by Village Fractionalization (ELF)

	(1) Adopt	(2) Area (Acres)	(3) Seed Src Within Vill
Treat x 2011	-0.00656	0.131	0.0518
	(0.0105)	(0.224)	(0.0530)
Treat x 2012	-0.00281	0.969	0.254
	(0.00971)	(0.776)	(0.120)
Treat x 2013	0.0150	0.796	0.0376
	(0.0129)	(0.585)	(0.0526)
Treat x 2014	0.0154	0.945	-0.0179
	(0.0237)	(0.658)	(0.0653)
Treat x 2015	-0.00559	1.002	0.0400
	(0.0270)	(0.716)	(0.0345)
Homog. x Treat x 2011	0.0253	-0.293	.
	(0.0194)	(0.364)	.
Homog. x Treat x 2012	0.0359	-0.809	-0.0708
	(0.0221)	(0.910)	(0.181)
Homog. x Treat x 2013	0.0150	-0.479	-0.0241
	(0.0307)	(0.832)	(0.0814)
Homog. x Treat x 2014	0.0213	-0.155	0.0561
	(0.0381)	(0.898)	(0.0826)
Homog. x Treat x 2015	0.0670	-0.478	0.0816
	(0.0423)	(1.062)	(0.0707)
Frac Mean in Control (2012)	0.019	0.05	0
Observations	40845	630	1374
No. Villages	126	126	109
Adj R-Squared	.06	.2	.07

Standard errors in parentheses
* $p < 0.1$, ** $p < .05$, *** $p < 0.01$

Notes: The specifications use ethno-linguistic fractionalization index > 0.6 as a measure of fractionalization. Note that more number of villages are classified as fractionalized using this measure relative to our preferred measure of number of distinct jati groups. All specifications include block fixed effects and cluster standard errors by village.

Table A.7: Jati-Level Adoption By No. Own Jati Recipients

	(1) Adopt	(2) Area (Acres)	(3) Within Village Source
Treat x 2011	-0.00839	0.0137	0.00709
	(0.00894)	(0.0757)	(0.0550)
Treat x 2012	-0.00437	0.0263	0.371
	(0.00991)	(0.0909)	(0.138)
Treat x 2013	0.00550	-0.0250	0.0183
	(0.0131)	(0.152)	(0.0430)
Treat x 2014	0.0159	0.0281	-0.0149
	(0.0208)	(0.159)	(0.0562)
Treat x 2015	0.00976	-0.237	0.0208
	(0.0232)	(0.222)	(0.0268)
No. Own Jati w/ Kit x 2011	0.00776	-0.0268	0.0147
	(0.00486)	(0.0346)	(0.0129)
No. Own Jati w/ Kit x 2012	0.0103	0.116	-0.0756
	(0.00608)	(0.0828)	(0.0597)
No. Own Jati w/ Kit x 2013	0.00937	0.112	-0.00267
	(0.00736)	(0.0731)	(0.0150)
No. Own Jati w/ Kit x 2014	0.00495	0.198	0.0146
	(0.00843)	(0.0735)	(0.0252)
No. Own Jati w/ Kit x 2015	0.00785	0.313	0.0354
	(0.00832)	(0.0903)	(0.0129)
Control Mean (2012)	0.017	0.12	0.05
Observations	40845	4059	1374
No. Villages	126	126	109
Adj R-Squared	.05	.17	.09

Standard errors in parentheses
* $p < 0.1$, ** $p < .05$, *** $p < 0.01$

Notes: Above table presents heterogeneous treatment effects on seed adoption by the number of initial kit recipients belonging to a farmer's jati group. We estimate the following:

$$y_{ivt} = \beta_t^1 \text{No. Kit}_{iv} + \beta_t^0 Treat_v + \delta_t + \delta_b + \epsilon_{ivt}$$

We drop the interaction terms because initial kit recipients are only in treated villages. Therefore, β_t^1 can be interpreted as the marginal rate of adoption if an additional recipient belonged to farmer's own jati.

Table A.8: Adoption Among Non-Recipients by Jati Dominance

	(1) Adopt	(2) Area (Acres)	(3) Seed Src Within Vill
Treat x 2011	0.00246	0.161	0.0610
	(0.00922)	(0.129)	(0.0559)
Treat x 2012	0.00834	0.227	0.522
	(0.00896)	(0.127)	(0.134)
Treat x 2013	0.0191	0.262	0.0620
	(0.0105)	(0.120)	(0.0870)
Treat x 2014	-0.00926	0.299	0.0236
	(0.0215)	(0.121)	(0.0537)
Treat x 2015	-0.0138	-0.0154	0.0477
	(0.0253)	(0.207)	(0.0437)
Dom. Jati x Treat x 2011	0.00300	-0.267	.
	(0.0109)	(0.184)	.
Dom. Jati x Treat x 2012	0.00667	0.404	-0.389
	(0.0125)	(0.505)	(0.178)
Dom. Jati x Treat x 2013	0.00369	0.276	-0.0753
	(0.0187)	(0.435)	(0.0972)
Dom. Jati x Treat x 2014	0.0522	0.646	-0.0255
	(0.0233)	(0.477)	(0.0684)
Dom. Jati x Treat x 2015	0.0572	1.012	0.0459
	(0.0260)	(0.532)	(0.0492)
Control Mean (2012) (Non-Dom Jati)	0.014	0.017	0
Observations	40845	1205	1374
No. Villages	126	126	109
Adj R-Squared	.05	.19	.08

Standard errors in parentheses
* $p < 0.1$, ** $p < .05$, *** $p < 0.01$

Notes: Above table presents the regression coefficients estimating farmer-level heterogeneity by dominance of their jati groups. Jatis belonging to brahmin, kshatriya, khandayat, gopal are classified as dominant groups and those not belonging to these as not dominant. Columns 1 and 3 are farmer-level specifications, with Column 3 conditional on adoption. Column 2 is village-level regression weighted by the number of non-recipient farmers (village size). All specifications include block fixed effect and cluster standard errors by village.

Table A.9: Adoption Among Non-Recipients: Majority Recipient Higher Status Jati

	(1)	(2)	(3)
	Adopt	Area (Acres)	Within Village Source
Treat x 2011	0.00474	-0.00722	0.0514
	(0.0107)	(0.180)	(0.0579)
Treat x 2012	0.0136	0.662	0.229
	(0.0116)	(0.448)	(0.0896)
Treat x 2013	0.0233	0.632	0.0100
	(0.0153)	(0.375)	(0.0450)
Treat x 2014	0.0235	0.944	0.0110
	(0.0193)	(0.413)	(0.0402)
Treat x 2015	0.0206	0.904	0.0858
	(0.0213)	(0.501)	(0.0342)
Maj. Higher Jati x 2011	-0.00603	0.163	.
	(0.0121)	(0.371)	.
Maj. Higher Jati x 2012	-0.0185	-0.562	.
	(0.0125)	(0.433)	.
Maj. Higher Jati x 2013	-0.0401	-0.758	-0.000222
	(0.0118)	(0.373)	(0.0386)
Maj. Higher Jati x 2014	0.0103	-1.198	.
	(0.0695)	(0.396)	.
Maj. Higher Jati x 2015	0.0338	-1.972	-0.0562
	(0.0901)	(0.439)	(0.0259)
Control Mean (2012)	0.017	0.12	0.05
Observations	40845	630	1374
No. Villages	126	126	109
Adj R-Squared	.05	.21	.07

Standard errors in parentheses
* $p < 0.1$, ** $p < .05$, *** $p < 0.01$

Notes: Above table presents the regression coefficients estimating village-level heterogeneity by whether the majority initial seeded belong to higher status jatis (brahmin and kshatriya). Columns 1 and 3 are farmer-level specifications, with Column 3 conditional on adoption. Column 2 is village-level regression weighted by the number of non-recipient farmers (village size). All specifications include block fixed effect and cluster standard errors by village.

Table A.10: Adoption Among Non-Recipients: Majority Recipient Intermediate Status Jati

	(1) Adopt	(2) Area (Acres)	(3) Within Village Source
Treat x 2011	-0.00600	0.114	0.0383
	(0.00883)	(0.164)	(0.0726)
Treat x 2012	-0.00368	0.265	0.299
	(0.00852)	(0.159)	(0.122)
Treat x 2013	-0.0102	0.0915	0.0904
	(0.0103)	(0.201)	(0.0661)
Treat x 2014	-0.00404	0.284	0.0324
	(0.0211)	(0.216)	(0.0533)
Treat x 2015	-0.0147	0.245	0.0645
	(0.0233)	(0.513)	(0.0362)
Maj. Int. Jati x 2011	0.0189	-0.247	0.0234
	(0.0134)	(0.321)	(0.0687)
Maj. Int. Jati x 2012	0.0306	0.710	-0.104
	(0.0155)	(0.678)	(0.138)
Maj. Int. Jati x 2013	0.0607	0.979	-0.119
	(0.0199)	(0.475)	(0.0693)
Maj. Int. Jati x 2014	0.0550	1.166	-0.0341
	(0.0246)	(0.562)	(0.0544)
Maj. Int. Jati x 2015	0.0735	1.066	0.0240
	(0.0258)	(0.668)	(0.0502)
Control Mean (2012)	0.017	0.12	0.05
Observations	40845	630	1374
No. Villages	126	126	109
Adj R-Squared	.06	.22	.07

Standard errors in parentheses
* $p < 0.1$, ** $p < .05$, *** $p < 0.01$

Notes: Above table presents the regression coefficients estimating village-level heterogeneity by whether the majority initial seeded belong to intermediate status jatis (khandayat and gopal). Columns 1 and 3 are farmer-level specifications, with Column 3 conditional on adoption. Column 2 is village-level regression weighted by the number of non-recipient farmers (village size). All specifications include block fixed effect and cluster standard errors by village.