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

Alain de Janvry, Manaswini Rao, Elisabeth Sadoulet*

April 5, 2025

Exploiting a two-stage randomized introduction of flood resistant seeds at village and individual-levels, we find that the extent of agricultural technology diffusion in the long run has a significant correlation with the local social structure (e.g., the jati-caste system) in India. We leverage pre-determined village-level social group compositions, where some villages are relatively more homogeneous than the others, to examine subsequent diffusion of agricultural technology following the initial, randomized seeding over the next five years. There are two main take-away. First, modest overall difference in adoption between treated and control villages is largely explained by the degree of heterogeneity in village-level social composition. Second, we observe immediate diffusion among non-recipient farmers in the same social group as the initial, treated recipients and limited diffusion among groups with lower social ranks. These findings highlight the potential efficiency and equity limitations of randomized seeding of new technology in a context with market frictions and limited trade across social groups. (*JEL* O33, Q12)

* Corresponding author email: manaswini.rao@gmail.com. Author affiliations: de Janvy and Sadoulet: UC Berkeley, Department of Agricultural and Resource Economics; Rao: University of Delaware, Department of Economics; We thank Kyle Emerick and Manzoor Dar for their contribution to the project design and implementation, and Girija Prasad Swain, Silu Saha, and the staff of Balasore Social Service Society for data collection. We are grateful to Siwan Anderson, Rema Hanna, Carly Trachtman, Abhilasha Sahay, Ana Paulo Melo, and Carolina Lopez for detailed comments, and seminar participants at UC San Diego Applied Micro Seminar, and NEUDC 2022 for suggestions and feedback. This study was funded through generous grants from the Agricultural Technology Adoption Initiative, J-PAL. This study was preregistered with the AEA RCT Registry under ID Number AEARCTR-0002157.

1 Introduction

A well-recognized puzzle in development economics is that many technologies proven to be useful in enhancing agricultural productivity have low rates of adoption over long periods of time. Recent literature (Magruder 2018; Gollin et al. 2021; Hansen and Wingender 2023) documents substantial costs from 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 (high-yielding varieties of cereal crops). A key challenge in the context of poorly developed markets, as is the case in much of the developing world, is that farmers tend to rely on social networks and informal arrangements to access inputs (Foster and Rosenzweig 2010; Jack 2013; de Janvry et al. 2017). This paper highlights the role of village-level social structures as an important conditioning factor in the long-run diffusion of technology through informal exchanges when markets for inputs are underdeveloped. This addresses an important gap in the literature by connecting the determinants of individual adoption decisions (Duflo et al. 2011; Suri 2011) with the role of social structures (Alesina and Ferrara 2005; Anderson 2011; Banerjee et al. 2013; Aker et al. 2014; Beaman and Dillon 2018; Emerick 2018) in creating potential access barriers in the long run.

In this paper, we study the adoption and diffusion of a new flood-tolerant paddy variety (Swarna Sub-1 or SS1 that improved the flood resistance capacity of the hitherto cultivated variety Swarna) over the long run, covering the entire population of paddy farmers in 126 villages from two rural districts in Odisha, India. We leverage the two-stage experimental variation generated by Emerick et al. (2016), where half of the 126 villages were randomly assigned, stratified by the corresponding administrative sub-district (block), to receiving the new seed variety. Further, about 5 paddy farmers were randomly selected in each of these treated villages to receive a 5-kilogram seed minikit of the new variety for cultivation in 2011. Emerick et al. (2016) document the impact of the seed variety on these treated farmers, showing that it improved agricultural productivity. This was driven by crowding-in complementary investment in inputs as a consequence of reducing the downside risk of crop loss during floods. On the other hand, the technology did not increase the costs of production or affect the sale price of output when compared to the existing variety, Swarna.

The experimental design of the earlier study provides a unique opportunity to examine subsequent diffusion of the seed technology in the long run. We conducted a census of all paddy farmers in the same villages 4 years following the initial introduction, documenting adoption of the new variety among the universe of non-recipients over 5 main agricultural seasons. Specifically, we asked each farmer if they had heard of the new variety and whether they cultivated the variety in each of the years in the period 2011-2015. We also asked about cultivation of other paddy varieties, including both traditional and modern ones, along with stated reasons behind their choice. Additionally, we gathered detailed demographic information about the farmer, including their education levels, whether classified as poor by the government, number of household members, as well as religion, caste, and jati (a key social group in India) membership.

This detailed census data on paddy farmers along with the experimental variation induced by Emerick et al. (2016) enable us to document important facts about agricultural technology diffusion. Importantly for this paper, there were no further interventions either by researchers or by the government in any of the study villages in this duration. After the initial experiment in 2011, the seeds were theoretically available for purchase through existing input markets and government seed centers (seed sale points) accessible to farmers across treated and control villages. In practice, however, these markets are underdeveloped - most are at a great distance from the sample villages and the seed availability at government centers is limited relative to demand.[1]

We present four key results pertaining to the subsequent adoption of the new variety among non-recipient farmers over the long run. First, exogenous introduction of the technology to a few, randomly selected farmers generates a modest diffusion effect in treatment

[1]Demand for the technology in the same context was demonstrated through a door-to-door sales intervention as documented in Emerick (2018). While government seed centers are an important source of seeds, many farmers report that the seeds are never available to them and that some farmers buy more seeds to subsequently share within their own networks.

villages relative to control. We estimate a 23% difference in diffusion rates over the long-run, which is not statistically significant. Economically, this is a modest result indicating a 2 percentage points higher adoption rates relative to control, which catches up through natural diffusion processes. The difference in diffusion rates among flood-exposed farmers is also not spectacularly large between treated and control villages. In terms of timing, the control villages lag treated villages only by 1-2 years in reaching the same level of adoption of the new seed variety. This is plausibly because many farmers report other farmers outside their own village and seed sale points as the source of seed, suggesting that farmers in control villages also hear about and acquire the new technology over time. Lastly, the total village area under cultivation with the new variety expands more rapidly in treated villages relative to control (is nearly two times higher), suggesting better adoption on the intensive margin.

Given the benefits of the technology, why did it not diffuse more rapidly within treated villages first before the control villages caught up? When we asked the farmers about the source of the new seed variety, over a third mentioned themselves (including their families) as the source, another third mentioned block-level seed center, 16% mentioned outside farmer and, only 8% mentioned other farmer within their own village as the source. Since control villages catch-up relatively quickly to fade the head-start of the treated villages, this motivated us to examine the diffusion patterns by village-level social structures among the group of paddy farmers, focusing on jati as social groups.[2]

Jati networks are an important social structure in the context of India, which are predominantly endogamous and based on ancestral occupation hierarchy. Jatis are made up of extended families connected either by blood or marriage. A lot of social and economic transactions happen within jatis, including participating in social events, lending/borrowing, and other peer-to-peer relationships. Jatis have implicit hierarchy where higher status groups occupy more powerful positions such as landed employers whereas lower status jatis provide services to these powerful groups (Deshpande 2011).

[2]The sampling frame for this study is the universe of paddy farmers within the study villages and thus the social grouping and jati affiliations pertain to this population.

In our second result, we find substantial differences in diffusion based on the number of distinct jati groups at the village level. Specifically, we note that treated villages with a large number of jatis experience lower immediate diffusion among the non-recipients relative to treated villages with fewer jatis. The magnitude of these differences is substantial: villages with fewer distinct jatis experience 8-9 percentage points higher initial adoption across all non-recipient farmers relative to similar control villages. This gap in adoption persists over time. This result is robust to potential confounders such as village size and other characteristics, particularly given the fact that the village-level jati composition is predetermined and villages were randomly assigned to receiving the technology in 2011.

Third, farmers are more likely to adopt early if at least one farmer from their own jati received a minikit in 2011. This is consistent with the village-level jati heterogeneity result above, documenting that adoption by non-recipients occurs largely within the same jati groups as the initial, randomly selected recipients. While there was no stratification by jati when randomly selecting minikit recipients, the results are robust to controlling for the probability that a particular jati is given at least one minikit - we still find a significant correlation between non-recipient outcomes and their jati-level connection with the initial recipients. Specifically, we note that this result is not mechanically being driven by villages with few jatis where the probability of initial recipient from own jati group would consequently be high. Interestingly, the effects on adoption are noted in the early period, when the technology was novel and less likely to be available through traditional seed sale points (markets or government seed centers). Such connected farmers are also more likely to report obtaining the seeds from within-village sources and less likely to report outside village sources including farmers in other villages or markets. Further, the increase in total cultivated area under SS1 within the village is driven by an increase in area cultivated by these connected adopters in the long run. Taken together, these results suggest an initial farmer-to-farmer technology exchange between the initial recipients and non-recipient farmers within their own jati. This is not hard to rationalize and is akin to someone sharing new technology within their extended family.

Finally, we note that adoption increases over time among all non-recipient farmers including those belonging to low status jatis if the majority of initial recipients belonged to intermediate social status jati groups such as Khandayats or Gola/Gopal. In contrast, adoption levels are lower if the majority of initial recipients were from low social status jati groups (Dalits, Adivasis, and other non-elite jatis). These differences by jati status are stark even though initial recipients were randomly chosen and jati groups across the social hierarchy were equally likely to receive minikits in 2011. This suggests that random initial introduction of technology could have distributional implications, at least in the initial years, especially if randomization is not stratified by social groups. While the gap may reduce or converge over time, any delays in adoption could have substantial welfare consequences as documented in Gollin et al. (2021).

These results have important implications both for allocative efficiency if such diffusion process does not deliver the technology to those that benefit from it the most, and for equity if marginalized farmers are unable to access such technology. Since the technology reduces downside risk when exposed to flooding conditions, it is likely to generate higher marginal returns to those cultivating land with higher flood risk. This is true in our context where farmers belonging to certain jati groups face higher flood risk relative to others. Particularly, we note that farmers belonging to lower social status jati groups, such as Dalit, Adivasis, and other non-elite jatis (officially classified as backward castes), experience greater probability of flooding as their homes and farm plots are typically located in low-lying areas within the village (as also documented by Dar et al. 2013). The overall study region is low-lying, close to the Bay of Bengal, with elevation in the range of -4 to 25 meters from sea-level.

However, we refrain from making a policy prescription around optimal targeting during the initial introduction of any new technology. This is because it is not obvious that targeting lower status jati groups also improves diffusion within other jatis with similar status as we note in this paper, given the multiplicity of jatis within each social strata (Hoff and Pandey

2006; Deshpande 2011; Neggers 2018; Lowe 2021; Joshi et al. 2022). Instead, it may perhaps be more cost-effective to support market development and reducing market access barriers through other interventions such as supporting local input dealers as documented in Dar et al. (2024).

This paper contributes to many strands of the literature. First, we document limited long-run diffusion of a climate risk-mitigating seed technology even though the technology has been shown to be productive agronomically (Dar et al. 2013) as well as economically (Emerick et al. 2016) in field trials. Adoption rates are not substantially higher even among those more likely to experience flooding conditions since the technology is known to protect yield from flooding. Importantly, we show how long-run patterns in the adoption and diffusion of agricultural technology emerge over time following experimental variation, which has not been extensively documented in the literature. We contribute to a rich literature on agricultural technology adoption that has examined behavioral constraints such as time inconsistency (Duflo et al. 2011), attention (Hanna et al. 2014), or individual-level heterogeneity in profitability and costs (Suri 2011), or information constraints (Aker and Jack 2023) by bringing attention to limited farmer-to-farmer seed exchanges even when there is a stated desire to cultivate the new variety. These barriers are important to consider in thinking about policy scale-up.

Second, we show that social structures 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; Munshi and Rosenzweig 2005; Miguel and Gugerty 2005; Anderson 2011; Lowes et al. 2015; Fisman et al. 2017; Emerick 2018; Oh 2023) with the literature on social networks and technology adoption (Beaman and Magruder 2012; Banerjee et al. 2013; Burlig and Stevens 2024). We provide causal evidence that technology diffusion is limited by the extent of fractionalization of village societies into distinct jati groups where farmer to farmer exchanges are restricted to within-jati-groups of the initial recipients. Additionally, control villages catch up over time as farmers report receiving the technology from other, jati-affiliated farmers outside their village. We specifically contribute to the literature by showing this catch-up by control villages as many studies hitherto have focused on within-village networks.

Third, this paper contributes to the literature on targeting using specific characteristics of social networks (Alatas et al. 2012; Beaman and Dillon 2018; Breza and Chandrasekhar 2019; Beaman et al. 2021; Banerjee et al. 2021). The existing literature has focused on network-based characteristics for targeting to improve the overall diffusion rates. Our paper adds to this by highlighting that the relative social status of different groups within a network and how they interact with each other may matter for subsequent person-to-person transmission of technology. The jati-caste system in India could very well be correlated with the characteristics of the underlying social network structure. While measuring network characteristics is hard and data intensive (Breza et al. 2020), an individual's jati and their relative social status are easier to observe from the perspective of policy. Perhaps just collecting information on social groups (such as jati in the case of India) provides a good measure of important characteristics to determine diffusion.

Lastly, we caution that targeting based on jati affiliation may not necessarily yield the desired outcome, given the multiplicity of identity groups and their complicated interactions even within small geographies such as the context of our study (Munshi and Rosenzweig 2005; Hoff and Pandey 2006; Beaman and Dillon 2018; Neggers 2018; Lowes 2021; Lowe 2021; Joshi et al. 2022; Oh 2023). Instead, targeting based on expected gains using modern technology and individual-level data could result in better outcomes cost-effectively although we need additional research to support this.

The rest of the paper is as follows. Section 2 discusses the context and data. Section 3 elaborates on the data sources and the research design. Section 4 reports on overall diffusion of the technology. Sections 5 presents the results based on village-level jati fractionalization and farmer-level differences in jati affiliation. Section 6 discusses the results using alternate economic frameworks. Section 7 concludes.

2 Context and Data

This study is a follow-up to the original research (Emerick et al. 2016) that examined the impact on adopting farmers (initial recipients) of flood-tolerant Swarna Sub-1 (SS1) paddy variety using a two-stage cluster randomized trial in the flood-prone districts of Balasore and Bhadrak districts in Odisha. A random sample of five farmers from 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 among the treated farmers compared with control farmers who did not receive the seeds. The study showed that the increase in yields was due to both avoided losses during years of flooding and due to farmers' production choices when faced with lower down-side risk guaranteed by the technology, which resulted in higher yields during normal years. Given that the technology induces behavioral response in the treated farmers, the next question to examine is how the technology diffuses ("spills-over") among non-recipient paddy farmers over time. The context provides a good opportunity to understand the role of local social structures in the diffusion process in absence of widespread availability of the seed variety in local agricultural input markets.[3]

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.[4] We first obtained a list of all paddy-growing households from the local ward members (elected representatives), who are knowledgeable about village residents and their occupations. Following the listing exercise, we approached farmers door-to-door and administered a short survey noting their use of dif-

[3]Although the government seed centers at the block-level (already at a large distance from a village) claimed to stock the variety around a 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. Further, there were complaints that some farmers bought large quantities of seeds from the government centers to then distribute it among those within their networks, reducing the availability of seeds to those without such connections.

[4]2 villages were unreachable due to excessive flooding.

ferent 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 with past seasons in decreasing order. We used specific events as props to enable recollection pertaining to particular seasons.[5] 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.

In this paper, we focus on the use of different paddy varieties, including adoption of SS1, among the universe of non-recipient paddy farmers in these villages. On average, there are 66 such 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. Table 1 shows the summary statistics using the census data. Importantly, the population consists mainly of paddy farmers (96% cultivate paddy), with close to 75% cultivating the Swarna variety. SS1 is a modified variety of Swarna, with the additional feature of flood tolerance obtained without any loss in yield in normal years. 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). 13% non-recipient farmers cultivated SS1 but the average area cultivated with the variety is comparatively small relative to total cultivated area. As the source of SS1, over a third of the cultivating farmers mention themselves (including their family) and another third mention seed sale points, which form the two main sources. Farmers also list other farmers (24%), both within (8%) and outside (16%) their village, as the source of seeds.

Finally and importantly, there are many endogamous kinship or jati (also known as sub-castes) groups among these paddy farmers, corresponding to different varnas (social

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

classification of Hindu society as per Manusmriti, a prominent Hindu religious text), within each of 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. Note that this percentage varies a lot, with standard deviation around 30%, indicating that some villages have more Dalit/Adivasi farmer groups relative to others. 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, Dalit and Adivasi 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 Dalits/Adivasis. Two jati groups are particularly important in this context, both in terms of their population share as well as their social mobility in Odisha. They are the 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). The rest, constituting the remaining quarter of the population, are non-elite "backward caste" jatis and occupy low-intermediate status within the social hierarchy.[6]

3 Data and Research Design

For this study, we hand collected data on basic cultivation practices and adoption of SS1 through primary, in-person surveys of the universe of paddy farmers in 126 villages from

[6]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. All the analysis done in this paper is at the jati-level and not at the level of broader groups. There are 87 distinct jati groups in our context, a large fraction of which belong to lower social status.

Emerick et al. (2016). We exploit the fact that about half of these villages as well as the initial set of farmers who received minikits of SS1 in 2011 were randomly assigned to the experimental groups. We use this initial assignment of villages and farmers within the villages to treatment as the main identifying variation to examine adoption among non-recipient farmers over the period 2011-2015. We worked closely with the organization that was involved in the initial experiment and learnt that no further experimental or policy interventions had taken place in these villages, which preserve the sanctity of the experimental variation for this paper.

To estimate the average treatment effects, 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 to examine intensive margin changes on area under the specific variety, and (c) source of SS1 seed, including exchanges with another farmer within the village or outside 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 two distinct periods: early years (2011-12) and later years (2013-15). We also measure treatment effects by each calendar year within our study period in order to trace the diffusion curves. Our main specification is as follows:

$$\begin{aligned} y_{ivt} &= \beta_1 \text{Treat}_v \text{Year 2011-12}_t + \beta_2 \text{Treat}_v \text{Year 2013-15}_t \\ &+ \delta_2 \text{Year 2013-15}_t + \delta_1 + \phi_b + \epsilon_{ivt} \end{aligned} \tag{1}$$

We use $2011 - 12$ as the base year group in the regression specification, so that δ_1 is the constant, capturing the mean outcome in control group in this period. β_1, β_2 are the main causal parameters of interest - the average treatment effect relative to control group for early and later years, respectively. We include randomization strata (administrative block) fixed effects, denoted by ϕ_b. There are 8 administrative blocks within our study. To maintain readability of tables, we do not report the coefficients on block-level dummies, which are absorbed in a high level regression model implemented in the statistical software Stata. For inference, we cluster the standard errors by village, which is the unit of treatment assignment. 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. [7]

Measuring Flood Exposure We categorize farmers as those with 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. Due to budget constraints, we could not collect the GPS coordinates of all the farm-plots since our sample constituted over 8000 paddy farmers and multiples of 8000 in farm-plots.[8]

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. A 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

[7] An alternate specification to our main econometric model is a fully specified model, where we estimate the regression coefficient for each year starting from 2012 (2011 is the excluded group, captured as the constant) as well as year dummy interacted with the treatment indicator to trace out the treatment effect over time. This fully specified model does not impose any linearity restrictions as in Equation 1 but trades-off statistical power.

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

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

[8] We also test for distance cut-offs at 2 km to test for sensitivity to any measurement error in the calculation of flood exposure. 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.

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 (as documented in Dar et al. 2013), and (b) keeping the distance threshold small (but large enough to minimize measurement error) since the entire study region is already low-lying. Since we only have the coordinates of the household and not the plots, measuring flooding based on distance from household location measures farmers' ability to store and carry forward seeds for cultivation in subsequent seasons.[9] Further, we note that many of those with low-lying households also have low-lying plots.

We estimate the following heterogeneous treatment effect specification with interaction terms based on the classification of a farmer as high flood-exposed (flood $<$ 1 km) or low, over early (2011-12) and later years (2013-15) of the study:

$$
\begin{aligned}
y_{ivt} &= \gamma_1^f HiFlood_{iv}\text{Treat}_v\text{Year 2011-12}_t + \gamma_2^f HiFlood_{iv}\text{Treat}_v\text{Year 2013-15}_t \\
&+ \beta_1^f\text{Treat}_v\text{Year 2011-12}_t + \beta_2^f\text{Treat}_v\text{Year 2013-15}_t + \alpha_1^f\text{HiFlood}_{iv}\text{Year 2011-12}_t \\
&+ \alpha_2^f\text{HiFlood}_{iv}\text{Year 2013-15}_t + \delta_2\text{Year 2013-15}_t + \delta_1 + \phi_b + \epsilon_{ivt} \qquad (2)
\end{aligned}
$$

The subscripts denote units as described previously. Year 2011-12 is the base year/leave-out group in the regression, so that δ_1 is the constant, capturing the mean outcome in the control group in that period. $HiFlood_{iv}$ is a dummy variable that takes the value 1 if a farmer's household GPS location is within 1 km from the closest flood layer, for at least 2 days, during 2011-2015 (we run different sensitivity tests around the distance cut-off). The main coefficients of interest are γ_1^f, γ_2^f, which are the mean outcomes among high flood exposure farmers in treated villages relative to low exposure farmers in treated villages in the different time periods. γ_1^f, γ_2^f can also be interpreted as the differential outcome between similarly high-exposure farmers in the control group. β_1^f, β_2^f are the treatment effects among

[9] 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.4.

low flood exposure farmers. Lastly, α_1^f, α_2^f are the mean outcomes among high flood exposure farmers in control villages. We test the null hypotheses $\gamma_1^f + \beta_1^f = \alpha_1^f$ and $\gamma_2^f + \beta_2^f = \alpha_2^f$ to examine whether there are any statistically significant differences in outcomes by flood exposure due to treatment.

4 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 - grouped by early and later periods - among non-recipient farmers across treated and control villages, 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 diffusion by the degree of flood exposure.

Table 2 reports the results on overall diffusion by estimating Equation 1. The dependent variable in Column 1 is whether the farmer adopts the variety in a given year. We notice only a modest and statistically insignificant increase in adoption of the new variety in treated villages relative to control in the later time period $\beta_2 = 0.02$, with a p-value $p = 0.2$, with no meaningful difference in the early years $\beta_1 < 0.01$, $p = 0.46$. We see this in the diffusion graphs as well, where there is a limited divergence in the curves over time (see Figure 1). This lack of a take-off of the technology in treated villages could also be due to the relatively fast catch up by the control villages - 1.5% and 7.5% of farmers in control villages had cultivated SS1 in early and later time periods, respectively, which is surprising particularly considering that no one in these villages received minikits in 2011. In treated villages, the adoption rate among non-recipients is a little more than 10% at the end of the study period. This difference corresponds to a modest but statistically insignificant gap of 23% or 2 percentage points. Moreover, the adoption rate appears to plateau in both treated and control villages over time.

Column 2 reports the difference in village-level total area under SS1 cultivation. While both treated and control villages start with almost no land under SS1, the difference in area under the crop diverges substantially in the later years, with treated villages cultivating 19% more area than control in the later years ($p < 0.1$). Since we regress village-level area under cultivation on treatment and time period dummies, we weight the regressions by the underlying village size. We also find qualitatively similar significant differences if we used fraction of village area cultivated using SS1 as an outcome instead of total area. Measuring effects in terms of area is a useful policy parameter since many of the official crop statistics are reported in terms of area cultivated.

Columns 3-5 examine the ITT effects on the source of seeds reported by the farmers. In the initial years (2011-12), we find limited seed acquisitions by any seed source - within village, outside farmer, or seed sale points - in both treated and control villages. This changes in the later period (2013-15). Buying seeds from seed sale points (market or block seed center) is the dominant mode of acquisition in control villages - 2.3 % of all non-recipients mention sale points as their source whereas only 1.5% and under 1% report farmers within their village or outside village farmer as their source, respectively. In contrast, within village seed source is the dominant mode of technology acquisition in treated villages - close to 3% of all non-recipients acquired their seeds from other farmers within their village, making it the dominant mode of seed acquisition in treated villages. This difference in citing own village seed source is both statistically (p<0.01) and economically meaningful (100% more than in control).

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 other outcomes if we take this variation in treatment intensity into account (see Table A.1). We note that villages with higher intensity of intervention experience higher farmer to farmer seed exchanges within the early period (2011-12) itself.

Flood-Exposure Heterogeneity Examining farmer-level heterogeneity by flood-exposure, we find increased adoption among those with higher flood exposure in treated villages only during the later period (2013-15). While this is reassuring - because the technology mainly reduces the downside risk of flood-exposure on yields - it suggests that allocative efficiency is not immediate and that there could be market frictions limiting adoption. Figure A.3 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.

Table A.2 presents the estimation of Equation 2 in a tabular format. On technology adoption, we find higher adoption among high flood exposed farmers in later years in treated villages relative to those less exposed to floods ($p < 0.05$ for the null hypothesis test $\gamma_2^f = 0$ and $p < 0.1$ for $\gamma_2^f + \beta_2^f = \alpha_2^f$). In control villages, adoption among farmers with higher flood exposure is lower than those with lower flood exposure. In contrast, high flood exposed farmers adopt significantly more than low flood exposed farmers in treated villages as well as more than high flood exposed farmers in control villages. The results on village-level area under the variety (Columns 2 Table A.2) is noisier but the point estimates suggest a similar direction of effects in terms of increasing area by high flood-exposed farmers relative to those less exposed. Lastly, the source of seeds among farmers in control villages is same as before - most acquire through seed sale points (Columns 3-5 Table A.2). We find higher within-village seed transfers among farmers in treated villages, with no additional difference based on flood exposure. However, high flood exposed farmers in treated villages are slightly more likely to have acquired seeds from farmers within their village compared to similarly high flood exposed farmers in control villages ($p = 0.1$).

These results, particularly the modest overall treatment effects, pose a question whether random initial introduction of the technology to a select few reaches those more likely to benefit from the technology compared to status quo and when. 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, many farmers reported non-availability or lack of information about seed availability as among the main reasons (see Figure A.4). This suggested that there could be significant farmer-to-farmer trade and information barriers that could exacerbate market imperfections. Given the pervasive presence of jati-caste divisions in social and economic spheres of a village society in India (Srinivas 1980; Munshi and Rosenzweig 2005; Deshpande 2011; Ban et al. 2012; Joshi et al. 2022), we examine whether such jati-caste networks could be plausible barriers to information exchanges and trade between farmers.

5 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. Panel A Figure 2 shows the distribution of the number of distinct jatis and the associated ethnolinguistic fractionalization index of the sample villages.

Why might jati networks affect economic transactions? First, in the presence of scarcity, people may want to limit the technology among themselves or their extended family (Neggers 2018 documents own-group favoritism). Second, people care about their social status and may want to preserve social hierarchy (Hoff and Pandey 2006; Oh 2023 document changes in subject behavior when their social identity is experimentally revealed). New technology may change this status quo if it enables social mobility through improved productivity and income. Third, people just may not have opportunity to interact or exchange information and technology given the manifestation of social distance into physical distance - lower status jati groups typically live in a different part of the village or may organize into separate villages themselves. This is seen in many parts of India (documented in Munshi and Rosenzweig 2005; Banerjee and Somanathan 2007; Deshpande 2011 and more recently in the context of urban areas in Asher et al. 2023) and also in the context of this paper in Odisha (Dar et al. 2013).

We examine both heterogeneous treatment effects by village-level jati compositions as well as the effect of farmer-level jati affiliation arising out of the exogenous variation in both village-level jati composition as well as the jati identities of initial recipients from the original randomized introduction of the technology. The goal of these analyses is two-fold: a) identify whether there is significant heterogeneity by the structure of local, village-level jati composition, and b) whether individual-level affiliations to specific jati groups explain some of the differences in technology adoption.

5A Village-Level Jati Compositions

To address a), we measure village-level jati composition based on the number of distinct jatis in a village. We acknowledge that there are many different ways to measure the extent of homophily or (to the contrary) fractionalization. Our approach is to examine heterogeneity based on the number of distinct jati groups within a village that captures the essence of homophily/fractionalization as well as leverage variation in the social status of different jati groups. We estimate the following heterogeneous treatment effect specification with the interaction terms based on the extent of varying jati compositions. We also conduct sensitivity tests using many commonly used definitions of fractionalization to verify our results.

$$\begin{aligned}
y_{ivt} &= \gamma_1^J \text{Num Jatis}_v \text{Treat}_v \text{Year 2011-12}_t + \gamma_2^J \text{Num Jatis}_v \text{Treat}_v \text{Year 2013-15}_t \\
&+ \beta_1^J \text{Treat}_v \text{Year 2011-12}_t + \beta_2^J \text{Treat}_v \text{Year 2013-15}_t + \alpha_1^J \text{Num Jatis}_v \text{Year 2011-12}_t \\
&+ \alpha_2^J \text{Num Jatis}_v \text{Year 2013-15}_t + \delta_2 \text{Year 2013-15}_t + \delta_1 \\
&+ X_v \Pi^J + \phi_b + \epsilon_{ivt} \qquad (3)
\end{aligned}$$

The subscript i refers to individual non-recipient farmer in study village v for outcome measured in year t. Num Jatis$_v$ measures the number of distinct jatis in a village v. The rest of the indicators for treatment groups and time periods are as before. The main coefficients of interest are γ_1^J, γ_2^J, which are the differential impact of the treatment in villages with one more jati relative to treated villages with fewer number of jatis. These can also be interpreted as mean differences between treated and control villages with the same number of distinct jatis. β_1^J, β_2^J are the treatment effects in villages with few distinct jatis. α_1^J, α_2^J are the mean outcomes in control villages with one more distinct jati. We test the null hypotheses $\gamma_1^J + \beta_1^J = \alpha_1^J$ and $\gamma_2^J + \beta_2^J = \alpha_2^J$ to examine whether there are any statistically significant differences in outcomes by jati composition due to the treatment. We also examine robustness of the results after controlling for total number of farmers in the village (village size) and the number of farmers interacted by treated status denoted by the vector of controls X_v to account for any mechanical correlation between village size and the number of jati groups.[10]

Results: Figure 3 depicts the diffusion patterns using raw means of the adoption decision, suggesting that any differential patterns in technology diffusion between treated and control villages is plausibly limited by the extent of fractionalization. Only 57 of 126 study villages are relatively homogenous whereas a majority of the villages (69 out of 126) are fractionalized. 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 between fractionalized treated and control villages. These differences in raw means are similar using any of the methods of constructing the fractionalization measure.

Table 3 reports all the coefficients from estimating Equation 3, where γ_1^J, γ_2^J present the heterogeneous treatment effects based on village-level jati fractionalization over time. The coefficients suggest a strong negative effect of one more jati within treated villages, particularly in the early years. We are able to reject the null $\gamma_1^J + \beta_1^J = \alpha_1^J$ showing the advantage of homogeneous social composition of villages ($p \leq 0.05$). We do not find any

[10] Village size and jati composition are balanced by treatment status.

attenuation effect of increasing number of jatis in control villages. Both α_1^J and α_2^J are small and statistically insignificant. Since none of the control villages received any minikits in 2011, it is possible that the information and learning about the technology occurred through multiple ways. First, as seeds became available at seed sale points at the block center and in markets, control farmers naturally encountered the seeds and increased adoption. Second, it is possible that farmers in the treated villages and control villages interacted with each other, either through social connections or through market interactions. We explore the role of jati-based social connection between farmers in treated and control villages later in this paper.

The results on village-level area under the variety (Columns 2 Table 3) is similar but noisier - treated villages with fewer numbers of distinct jatis expand area under the new seed variety, which is attenuated by increasing number of jatis. Examining the source of seeds (Columns 3-5 Table 3), increasing the number of jatis within control villages has a significant negative association with seed acquisition from sale points. Within the treatment group, farmers in few jati treated villages are more likely to acquire seeds from within village farmers. These within village seed exchanges are attenuated with increasing number of jatis in treated villages. We also notice similar attenuation of seed exchanges in control villages with more jatis, albeit with noise.

These findings suggest that connections with initial recipients of the technology could be important, which are more likely to be present in treated villages because of the design of the intervention. We examine this mechanism closely by exploiting farmer-level jati affiliation with the jati identity of the initial recipients within treated villages as well as cross-village jati network between initial recipients in treated and non-recipient farmers in the control villages.

5B *Jati Identity*

We exploit the second stage of the initial randomization, i.e., at the farmer-level, that generates exogenous variation among jati groups that initially received the seed minikits in 2011. There are 87 distinct jatis in our sample and we carry out farmer-level jati heterogeneity analysis at this disaggregated-level.

We begin farmer-level jati analysis by first estimating whether farmers in the same jati groups as the initial recipients within their own villages were more likely to adopt. We implement the following specification, examining the differences in outcomes based on whether at least one from a farmer's own within-village-jati network received a seed minikit in 2011.

$$\begin{aligned} y_{ivt} &= \gamma_1^W \mathbb{1}(Kit > 0)_{iv} \text{Year 2011-12}_t + \gamma_2^W \mathbb{1}(Kit > 0)_{iv} \text{Year 2013-15}_t \\ &+ \beta_1^W \text{Treat}_v \text{Year 2011-12}_t + \beta_2^W \text{Treat}_v \text{Year 2013-15}_t \\ &+ \delta_2 \text{Year 2013-15}_t + \delta_1 + \phi_b + \epsilon_{ivt} \end{aligned} \tag{4}$$

$\mathbb{1}(Kit > 0)_{iv}$ is an indicator variable that takes value 1 if at least one from farmer i's own jati network in their village received a seed minikit in 2011. For control villages, this is coded as 0 since no one in control villages received any minikits in 2011. We also estimate a similar specification only among control group where we define $\mathbb{1}(Kit > 0)_{iv}$ if there exists a jati-level connection between farmer i in a control village v with any of the initial recipients among all treated villages.

In Equation 4, $Treat_v$ is the dummy variable for village-level treatment status as before. β_1, β_2 are the treatment effects when no one from the farmer's own jati network initially received the kit in 2011 and γ_1^W, γ_2^W are the additional effects if at least one from their jati group received a kit. We test the null hypotheses $\gamma_1^W = \beta_1^W$ and $\gamma_2^W = \beta_2^W$ to examine whether there are any statistically significant differences in outcomes by jati connections between non-recipient farmers and initial minikit recipients. The rest of the terms and inference methods are as before.

Jati-level Balance: 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. We test whether the probability of any specific jati receiving a minikit is correlated with village treatment status, village size (number of paddy farmers), jati size (number of jatis in a village and number of farmers in a jati), whether one belonged to any of the specific jati groups that are of high or low social status, and flood-propensity. Table 4 presents the determinants of the probability that at least one from the sample non-recipient farmers' jati received a minikit during the initial dissemination in 2011. We note that only the village treatment status and the village size (number of paddy farmers) significantly determine whether a jati initially received seeds in 2011. These significant correlations are expected and are an artifact of the two-stage experimental design - only farmers in treated villages received kits and choosing 5 out of the village-level population of farmers mechanically affects the probability. On the other hand, none of the jati-level composition of the village - total number of jati groups, individual jati size, nor belonging to specific jati groups correlate with the probability of a jati receiving the initial minikit. Likelihood of flood exposure is also not correlated with this probability. We are unable to reject the joint null hypothesis that all these variables together determine the probability that the respondent farmers' jati group received at least one minikit in 2011.

Results: We estimate Equation 4 and report all coefficients in Table 5. We find that adoption increases in 2011-12 if at least one initial seed recipient belonged to one's own jati group (Column 1). The coefficient is of similar size in 2013-15, suggesting a sustained increase in adoption rates but the estimate is not statistically significant. We are able to reject the null $\gamma_1^W = \beta_1^W$ with $p < 0.05$ but are unable to reject $\gamma_2^W = \beta_2^W$ as adoption increases among those in other jati groups in the treated villages in later years. We also observe an increase in area under cultivation (Column 3 Table 5) among those connected to the initial recipients over time. Examining the source of seeds, we find that those connected with initial recipients via jati are more likely to obtain seeds from seed sale points in the initial years, and from other farmers within village and outside their village in the later years. In contrast, farmers not in the same jati groups as initial recipients are similar to farmers in the control group in terms of technology adoption, area, as well as how they acquired seeds (these farmers are marginally more likely to acquire seeds from other farmers within their own village in the later years). Since all the action in technology diffusion is coming from those connected to the initial recipients across all outcomes, this suggests that connection to initial recipients of technology through close, family-based ties could be important in how information and technology itself spreads.

Additional Robustness: Since we did not stratify treatment assignment by jati at the time of farmer-level randomization for receiving minikits, the balance test is necessary but not sufficient to rule out any mechanical correlations. To account for any possible correlation between treatment assignment and village-level jati composition, we control for the probability that someone within the same jati as the non-recipient farmer received a minikit in Equation 4. We report the regression coefficients in Table A.6, which shows qualitatively similar results.

5C Cross-Village Jati Networks

In order to explain the increasing rates of adoption among farmers in control villages, where no one within the village received any minikits during the initial study in 2011, we examine cross-village jati affiliation between initial recipient farmers in the treated villages and farmers in control villages. How did control farmers acquire the new variety when there was no one in their immediate neighborhood who had any experience with the seeds?

We estimate Equation 4 only on the subsample of the control villages by matching the farmer sample in the control villages with the jati identities of the initial recipients in the treated villages. Thus, the variable $\mathbb{1}(Kit > 0)_{iv}$ would now indicate if at least one from farmer i's own jati network in any of the treated villages received a seed minikit in 2011.

Table 6 presents the results from this exercise. We note that having someone from their own jati receiving a minikit is associated with a higher adoption in control villages in both early and later years but the estimate is noisy and not significant at the conventional levels. However, we find support for the idea of seed exchanges among control farmers from the same jati groups as initial recipients with other farmers both within and outside their own village, particularly in the later years when more seeds are in circulation. Even though no one in the control villages initially received seed minikits, it is possible that many acquired them through block or market-level seed sale points after learning about the technology through their social networks (5% of all farmers in these villages report buying the seed from block or market sources). A very small fraction of farmers with no jati-level connections report other farmers as seed source. As time progressed, farmers with jati-level connections with initial recipients are less likely to use block/market sources and more likely to acquire the seeds from other farmers within and outside their village. These results indicate that diffusion could be more prominent within the jati-network of initial recipients both within and across villages.

5D Alternate Explanation: Physical Geographic Distance

Could the results be explained by physical distance between the initial kit recipient and non-recipient households? In order to test this, we calculate distances between recipient and non-recipient household locations using GPS coordinates collected during the census in 2015. Since there were 5 kit recipients per treated village, we consider minimum of the distances between a non-recipient household and each of the recipient household coordinates. We categorize farmers as living in close vicinity of an initial recipient if the minimum distance is less than or equal to 30 meters. This also corresponds to the median distance between recipient and non-recipient household locations and translates approximately to living along the same street as one of the initial recipients.

Our analysis suggests that neither adoption decisions nor seed exchanges vary substantially by physical proximity to initial recipients house locations (Table A.9). This suggests that social distances could matter more than physical distances. It is possible that proximity of agricultural plots may matter more but we do not have data at the plot-level for our sample of non-recipient farmers to rule out this explanation.

We also examine diffusion outcomes in control villages by distance to any of the treated villages. Control villages are on average 3 km away from its closest treated village and the median distance is 2.2 km. We find no significant results on adoption by distance among farmers in control villages, adding further support to our finding that social distances could matter more.

Next, we examine whether this could have distributional implications, with both efficiency and equity concerns, by examining access to the new variety by jati groups across social ranks.

5E Jati Hierarchy

In addition to greater economic and social interactions within rather than between jati groups, there is also a hierarchy in the relative status of these groups based on their varna (Deshpande 2011) as discussed in Section 2. We assign ranks to jatis based on their relative status within the social hierarchy in Odisha. Jatis belonging to Brahmin and Kshatriya jatis (mapping to the corresponding 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 century (Mitra 2021). We observe 11 distinct jatis belonging to Dalit and Adivasi groups, which we assign a rank 5. Lastly, we assign all other remaining 68 jatis, which mainly belong to the "backward caste" category defined officially, a rank 4, i.e., above the Dalits and Adivasis.

Relevant to analyzing the allocative efficiency and equity implications of technology diffusion in our context, the extent of flood exposure is markedly different between the lowest (Dalits and Adivasis) and some of the higher ranked jati groups. Dalit and Adivasi farmers face significantly higher flood exposure, compared to those from higher ranked jatis (see Table A.4 and also Dar et al. 2013). Given the flood-resistance feature of SS1, it could particularly benefit those from vulnerable groups by mitigating flood risk. While we cannot rule out whether other jati groups could face flood risk in the future and thus unable to comment about efficiency in a dynamic sense, the realized flood events so far suggest that there are at least medium-term efficiency gains in trading seeds with lower ranked jatis.

Farmer-level randomization in 2011 allows us to exploit the rich variation in the initial recipients' jatis and their relative social status. Panel A Figure 4 shows the distribution of initial recipients by their jati social status or rank. There is at least one of each social rank among the initial recipients. Having all 5 recipients from the same social rank occurs in around 10% of the treated villages, which are mainly in homogenous villages with 2-3 jati groups. We examine the average SS1 adoption outcomes among farmers based on the social status (rank) of the majority of the initial recipients using the specification below.

$$\begin{aligned}
y_{ivt} &= \gamma_1^M \text{Majority Recip Rank=r}_v \text{Year 2011-12}_t + \gamma_2^M \text{Majority Recip Rank=r}_v \text{Year 2013-15}_t \\
&+ \beta_1^M \text{Treat}_v \text{Year 2011-12}_t + \beta_2^M \text{Treat}_v \text{Year 2013-15}_t \\
&+ \delta_2 \text{Year 2013-15}_t + \delta_1 + X_v \Pi^M + \phi_b + \varepsilon_{ivt} \qquad (5)
\end{aligned}$$

The "Majority Recip Rank=r_v" is a dummy variable that takes value 1 if the social rank of the majority recipients in treated village v is r. For control villages, this is coded as 0. In order to illustrate this better, consider an example when the majority of the initial recipients belonged to Brahmin jatis. Then, we code Majority Recip Rank=1_v as 1 for that village v and 0 when the majority is not from rank 1. Similarly, if the majority of the initial recipients belonged to Khandayat or Gola jatis, then Majority Recip Rank=3_v is 1, and so on. In order to improve the readability of empirical estimations, we combine ranks 1 and 2 as one group - high status kit recipients, rank 3 as another group - intermediate status, and combine ranks 4 and 5 as the third group - low status. Therefore, γ_1^M, γ_2^M should be interpreted as the differential treatment effects if a majority recipients belonged to rank r. Consequently, β_1^M, β_2^M are the treatment effects on the outcomes when the majority recipients are not from jati rank r (including when there is no majority among any jati groups). We control for the jati size (number of farmers in the respondent's jati) as well as the total number of farmers in the village, denoted by a vector of control variables X_v for additional robustness.

Results: Panel B Figure 4 shows average adoption over time when the majority initial recipients belonged to higher status jati groups (left) and when the majority recipients belonged to lower status groups (right). We estimate Equation 5 on the entire sample of non-recipient farmers and on the subsample of low status non-recipients separately. Table 7 presents the estimates from Equation 5, where odd-numbered columns include the full sample and the even-numbered columns include the subsample of low social status non-recipients. The dependent variable in all the specifications is SS1 seed adoption. Columns 1 and 2 present the effects on adoption when the majority of initial recipients belonged to high ranked jati groups - Brahmin and Kshatriya. Columns 3 and 4 present the diffusion outcome when the majority of the initial recipients belonged to intermediate rank jati groups - Khandayat and Gola/Gopal (those with social mobility). The last two columns - 5 and 6 - focus on the diffusion when the majority of the initial recipients are from lower ranked jatis (Dalit/Adivasis and all other non-elite jati groups).

There are 2 major take-aways from this analysis. First, treated villages where the majority initial recipients belong to intermediate status jati groups are more likely to witness a higher level of adoption across all non-recipients in both time periods. These intermediate status jati groups have also experienced higher social mobility (Mitra 2021) in the past few decades. Thus, this could reflect either the role of relative social proximity in rank or aspirational effects from social mobility. However, we cannot rule out one explanation in favor of the other due to data limitations of this study. Second, treated villages where the majority initial recipients are from lower social ranks are less likely to experience increased adoption. We find no significant effects on adoption when the majority recipients are from high ranked jatis. These patterns are similar among the sub-sample of low-status non-recipients but the standard errors are also wider, leading to the estimates not being statistically significant.

We also examine diffusion using the number of initial recipients from specific jati across the social hierarchy to find similar patterns - lower status jati groups (ranked 4) lead to lower overall adoption (Col 4 Table A.10) as well as lower adoption among low status non-recipients (Col 4 Table A.11). More recipients from higher ranked jati groups are more likely to increase adoption among low status non-recipients (Col 1 Table A.11).

These findings raise questions about how should one target the initial recipients. While the experiment that we leverage in this paper is not designed to answer this, we note a clear reduction in adoption by lower social status non-recipient farmers if there are more initial recipients also from lower social status. In contrast, intermediate status recipients and sometimes higher status recipients do better at spurring diffusion overall as well as among lower ranked jati groups.

6 Discussion

This paper documents modest long-run diffusion of a risk-mitigating agricultural technology (SS1 seed variety), which is known to increase productivity through complementary investments by farmers (Emerick et al. 2016). We posit that one of the plausible reasons for the observed low rates of adoption could be village social structures that may limit exchange of the technology in the presence of severe market frictions. One of the dominant reasons for not cultivating the new variety as cited by farmers in our study sample is limited availability of the seeds. Moreover, even those who cultivated the seed at any point but discontinued, say that they lost the seeds or could not save them for future use. Thus, lack of easy access to and/or storage of seeds locally are important reasons for the low rates of adoption (Figure A.4).

Information frictions could play a role but a large fraction - over 60% of the sample - have heard of the technology even in control villages, which increases further based on the size of the jati (number of farmers within the same jati as the non-recipient farmer) and increases based on the number of initial recipients from high ranked jati groups (Col 1 Table 8). 65% of the respondents cite non-availability of the seeds as the primary reason for not cultivating SS1. This is significantly correlated with the number of jatis within a village - availability is a concern in fractionalized villages, further supporting our main findings. Another 44% said they had no information about where seeds were available.[11] Again, this is positively correlated with village fractionalization - farmers are more likely to raise availability or information related to availability as a concern only in villages with many distinct jatis (Col 2-3 Table 8). Only 4% and 2% of the farmers report other reasons for not adopting, such as cost and preference/taste for other variety, respectively. Interestingly, farmers in villages with more number of jatis are less likely to mention cost as a reason (Col 4) and farmers in treatment villages are more likely to mention preference/taste for other variety as among reasons for not adopting (Col 5). However, these are small effects since a small percentage of farmers - 4.5% of non-recipient farmers mention these reasons compared to over 60% who mention non-availability or information regarding availability as key reasons.

Taken together, jati size and rank matters in learning about the technology. Limited availability of the seed variety in large scale continues to be a significant barrier in the widespread adoption of the variety. In such a situation, farmers may rely on farmer-to-farmer exchanges to try out new technology but these exchanges could be limited by social constraints such as norms surrounding interactions and social hierarchy as imposed by the jati-caste system in India. Furthermore, we note that there is no obvious prescription to increase technology

[11] Note that the farmers could select multiple reasons for not cultivating the new variety and so, the averages in the control group could add up to more than a 100%.

adoption through initial outreach programs - high ranked groups are better at spreading information whereas intermediate ranked groups are better at encouraging adoption. Perhaps focusing on improving access through market mechanisms and correcting market frictions may be more efficient than finding an optimal targeting policy although additional research is needed to answer this question.

7 Conclusion

There is a small literature documenting long-term patterns in the adoption of agricultural technology, and its subsequent efficiency and welfare implication. We contribute to this literature by studying adoption of a risk-mitigating agricultural technology among the population of non-recipients for five years following the initial, experimental introduction. The technology is a new paddy seed variety Swarna Sub 1, which is engineered to lower production losses during flooding events common along the coastal regions of Eastern India.

Our analysis provides two key insights. First, the average differences in diffusion between treated and control villages over a 5 year period is at best modest - there is no transformative "take-off" in treated villages. At the same time, control villages catch up through the natural diffusion process. Second, average effects mask substantial heterogeneity based on the underlying jati-caste social structure of the study villages. The jati-caste structures are integral to the way society is organized in India, where some jatis are more elite than others and social interactions are typically confined within-jati. We find that villages that are more homogenous in its jati composition experience a head-start in diffusion, which persists over time. This can be explained by higher initial adoption by non-recipients belonging to the same jatis as initial recipients. This is also explained by cross-village jati networks enabling control villages catch-up over time.

The jati-caste system in India is very hierarchical, which may generate distributional implications from random initial seeding. We find that the relative social rank of the initial recipients' jatis matter - limiting initial introduction to those from lower status groups limits subsequent diffusion whereas we notice higher information and adoption when higher ranked jati groups are initially provided with the technology. The role of hierarchy is plausibly driven by multiple jati groups within lower social ranks and fewer interactions across jati-lines even within the same rank.

Finally, it is unclear whether the observed gaps based on village structures will disappear with time. 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).

These findings suggest that local social structures like that of the jati-caste system and the relative social hierarchy of some groups relative to others can constitute important trade barriers to technology diffusion in the presence of market failures. It is also very hard to identify an optimal policy for disseminating technology since the composition of initial recipients matters for subsequent diffusion in a complicated way. For example, distributing SS1 minikits to lower ranked jati groups (such as Dalits, Adivasis, and other non-elite jati groups) may limit subsequent diffusion even among members from similar social rank if the social organization at the base of the hierarchy includes numerous jati groups limiting inter-jati exchanges (Munshi and Rosenzweig 2005; Joshi et al. 2022). Targeting higher ranked jatis also does not increase adoption dramatically although we observe small increases in our context. What we can conclude is that random seeding may only be effective in socially homogenous villages when there are market access barriers. On the other hand, the diffusion process from random initial seeding could be no different from the natural diffusion processes in highly fractionalized villages due to constraints imposed by social structures as described. In such a context, it is important to design seeding policies that are consistent with the local social structure.

References

Aker, Jenny C. and B. Kelsey Jack, "Harvesting the Rain: The Adoption of Environmental Technologies in the Sahel," *The Review of Economics and Statistics*, 12 2023, pp. 1–52.

_ , **Michael W. Klein, Stephen A. O'Connell, and Muzhe Yang**, "Borders, ethnicity and trade," *Journal of Development Economics*, 2014, *107*, 1–16.

Akerlof, George A. and Rachel E. Kranton, "Economics and Identity*," *The Quarterly Journal of Economics*, August 2000, *115* (3), 715–753.

Alatas, Vivi, Abhijit Banerjee, Rema Hanna, Benjamin A. Olken, and Julia Tobias, "Targeting the Poor: Evidence from a Field Experiment in Indonesia," *American Economic Review*, June 2012, *102* (4), 1206–40.

Alesina, Alberto and Eliana La Ferrara, "Ethnic Diversity and Economic Performance," *Journal of Economic Literature*, September 2005, *43* (3), 762–800.

Anderson, Siwan, "Caste as an Impediment to Trade," *American Economic Journal: Applied Economics*, January 2011, *3* (1), 239–263.

Asher, Sam, Kritarth Jha, Paul Novosad, Anjali Adukia, and Brandon Tan, "Residential Segregation and Unequal Access to Local Public Services in India: Evidence from 1.5m Neighborhoods," 2023.

Ban, Radu, Saumitra Jha, and Vijayendra Rao, "Who has voice in a deliberative democracy? Evidence from transcripts of village parliaments in south India," *Journal of Development Economics*, 2012, *99* (2), 428–438. Publisher: Elsevier.

Banerjee, Abhijit and Kaivan Munshi, "How Efficiently is Capital Allocated? Evidence from the Knitted Garment Industry in Tirupur," *The Review of Economic Studies*, January 2004, *71* (1), 19–42.

__ **and Rohini Somanathan**, "The political economy of public goods: Some evidence from India," *Journal of Development Economics*, March 2007, *82* (2), 287–314.

__ **, Arun G. Chandrasekhar, Esther Duflo, and Matthew O. Jackson**, "The Diffusion of Microfinance," *Science*, 2013, *341* (6144), 1236498.

__ **, __ , Suresh Dalpath, Esther Duflo, John Floretta, Matthew O. Jackson, Harini Kannan, Francine Loza, Anirudh Sankar, Anna Schrimpf, and Maheshwor Shrestha**, "Selecting the Most Effective Nudge: Evidence from a Large-Scale Experiment on Immunization," April 2021.

Beaman, Lori and Andrew Dillon, "Diffusion of agricultural information within social networks: Evidence on gender inequalities from Mali," *Journal of Development Economics*, July 2018, *133*, 147–161.

__ **and Jeremy Magruder**, "Who Gets the Job Referral? Evidence from a Social Networks Experiment," *American Economic Review*, December 2012, *102* (7), 3574–93.

__ **, Ariel BenYishay, Jeremy Magruder, and Ahmed Mushfiq Mobarak**, "Can Network Theory-Based Targeting Increase Technology Adoption?," *American Economic Review*, June 2021, *111* (6), 1918–1943.

Breza, Emily and Arun G. Chandrasekhar, "Social Networks, Reputation, and Commitment: Evidence From a Savings Monitors Experiment," *Econometrica*, 2019, *87* (1), 175–216.

__ **, __ , Tyler H. McCormick, and Mengjie Pan**, "Using Aggregated Relational Data to Feasibly Identify Network Structure without Network Data," *American Economic Review*, August 2020, *110* (8), 2454–84.

Burlig, Fiona and Andrew W. Stevens, "Social networks and technology adoption: Evidence from church mergers in the U.S. Midwest," *American Journal of Agricultural Economics*, 2024, *106* (3), 1141–1166.

Dar, Manzoor H., Alain de Janvry, Kyle Emerick, David Raitzer, and Elisabeth Sadoulet, "Flood-tolerant rice reduces yield variability and raises expected yield, differentially benefitting socially disadvantaged groups," *Scientific Reports*, November 2013, *3* (1), 3315. Publisher: Nature Publishing Group.

_ , _ , _ , Elisabeth Sadoulet, and Eleanor Wiseman, "Private Input Suppliers as Information Agents for Technology Adoption in Agriculture," *American Economic Journal: Applied Economics*, April 2024, *16* (2), 219–48.

de Janvry, A., E. Sadoulet, and T. Suri, "Chapter 5 - Field Experiments in Developing Country Agriculture," in Abhijit Vinayak Banerjee and Esther Duflo, eds., *Handbook of Economic Field Experiments*, Vol. 2 of *Handbook of Economic Field Experiments*, North-Holland, January 2017, pp. 427–466.

Dell, Melissa and Benjamin A Olken, "The Development Effects of the Extractive Colonial Economy: The Dutch Cultivation System in Java," *The Review of Economic Studies*, January 2020, *87* (1), 164–203.

Deshpande, Ashwani, *The Grammar of Caste: Economic Discrimination in Contemporary India*, Oxford University Press, 08 2011.

Duflo, Esther, Michael Kremer, and Jonathan Robinson, "Nudging Farmers to Use Fertilizer: Theory and Experimental Evidence from Kenya," *American Economic Review*, October 2011, *101* (6), 2350–2390.

Emerick, Kyle, "Trading frictions in Indian village economies," *Journal of Development Economics*, 2018, *132* (C), 32–56. Publisher: Elsevier.

__ , **Alain de Janvry, Elisabeth Sadoulet, and Manzoor H. Dar**, "Technological Innovations, Downside Risk, and the Modernization of Agriculture," *American Economic Review*, June 2016, *106* (6), 1537–1561.

Fisman, Raymond, Daniel Paravisini, and Vikrant Vig, "Cultural Proximity and Loan Outcomes," *American Economic Review*, February 2017, *107* (2), 457–492.

Foster, Andrew D. and Mark R. Rosenzweig, "Microeconomics of Technology Adoption," *Annual Review of Economics*, 2010, *2* (1), 395–424. _eprint: https://doi.org/10.1146/annurev.economics.102308.124433.

Gollin, Douglas, Casper Worm Hansen, and Asger Mose Wingender, "Two Blades of Grass: The Impact of the Green Revolution," *Journal of Political Economy*, August 2021, *129* (8), 2344–2384. Publisher: The University of Chicago Press.

Hanna, Rema, Sendhil Mullainathan, and Joshua Schwartzstein, "Learning Through Noticing: Theory and Evidence from a Field Experiment *," *The Quarterly Journal of Economics*, August 2014, *129* (3), 1311–1353.

Hansen, Casper Worm and Asger Mose Wingender, "National and Global Impacts of Genetically Modified Crops," *American Economic Review: Insights*, June 2023, *5* (2), 224–40.

Hoff, Karla and Priyanka Pandey, "Discrimination, Social Identity, and Durable Inequalities," *The American Economic Review*, 2006, *96* (2), 206–211. Publisher: American Economic Association.

Jack, B. Kelsey, "Market inefficiencies and the adoption of agricultural technologies in developing countries," May 2013.

Joshi, Shareen, Nishtha Kochhar, and Vijayendra Rao, "Fractal inequality in rural India: class, caste and jati in Bihar," *Oxford Open Economics*, March 2022, *1*, odab004.

Lowe, Matt, "Types of Contact: A Field Experiment on Collaborative and Adversarial Caste Integration," *American Economic Review*, June 2021, *111* (6), 1807–1844.

Lowes, Sara, "Kinship structure, stress, and the gender gap in competition," *Journal of Economic Behavior & Organization*, December 2021, *192*, 36–57.

_ , Nathan Nunn, James A. Robinson, and Jonathan Weigel, "Understanding Ethnic Identity in Africa: Evidence from the Implicit Association Test (IAT)," *American Economic Review*, May 2015, *105* (5), 340–45.

Magruder, Jeremy R., "An Assessment of Experimental Evidence on Agricultural Technology Adoption in Developing Countries," *Annual Review of Resource Economics*, 2018, *10* (1), 299–316.

Miguel, Edward and Mary Kay Gugerty, "Ethnic diversity, social sanctions, and public goods in Kenya," *Journal of Public Economics*, December 2005, *89* (11), 2325–2368.

Mitra, Subrata K., *Power, Protest and Participation: Local Elites and the Politics of Development in India*, Routledge, September 2021. Google-Books-ID: U1A2EAAAQBAJ.

Munshi, Kaivan and Mark Rosenzweig, "Economic development and the decline of rural and urban community-based networks*," *Economics of Transition*, 2005, *13* (3), 427–443. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1468-0351.2005.00231.x.

Neggers, Yusuf, "Enfranchising Your Own? Experimental Evidence on Bureaucrat Diversity and Election Bias in India," *American Economic Review*, June 2018, *108* (6), 1288–1321.

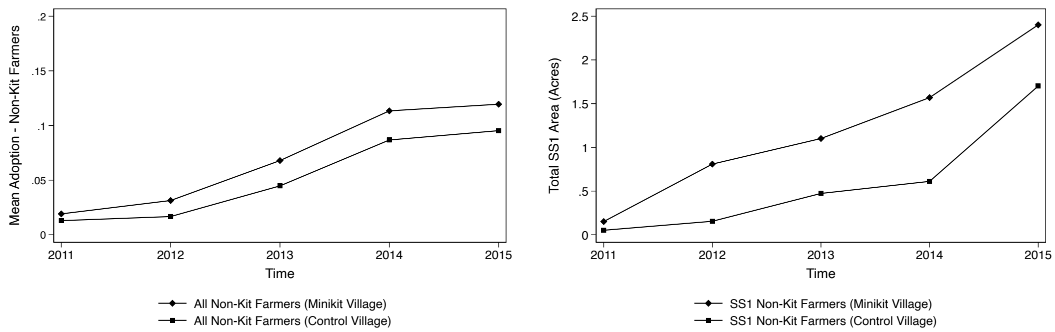
Oh, Suanna, "Does Identity Affect Labor Supply?," *American Economic Review*, August 2023, *113* (8), 2055–83.

Srinivas, M. N., *The Remembered Village* June 1980.

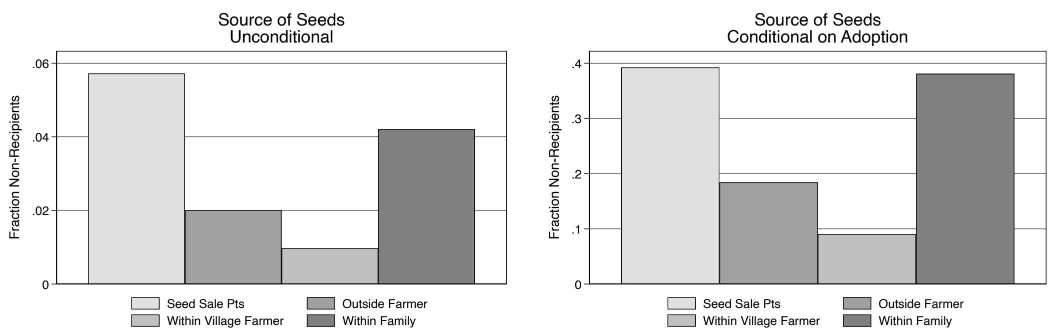
Suri, Tavneet, "Selection and Comparative Advantage in Technology Adoption," *Econometrica*, 2011, *79* (1), 159–209. Publisher: [Wiley, Econometric Society].

8 Figures

Figure 1: Diffusion of Seeds: All Non-Recipient Farmers
Panel A: Farmer-Level Decision to Cultivate SS1 and Village-Level Area under SS1



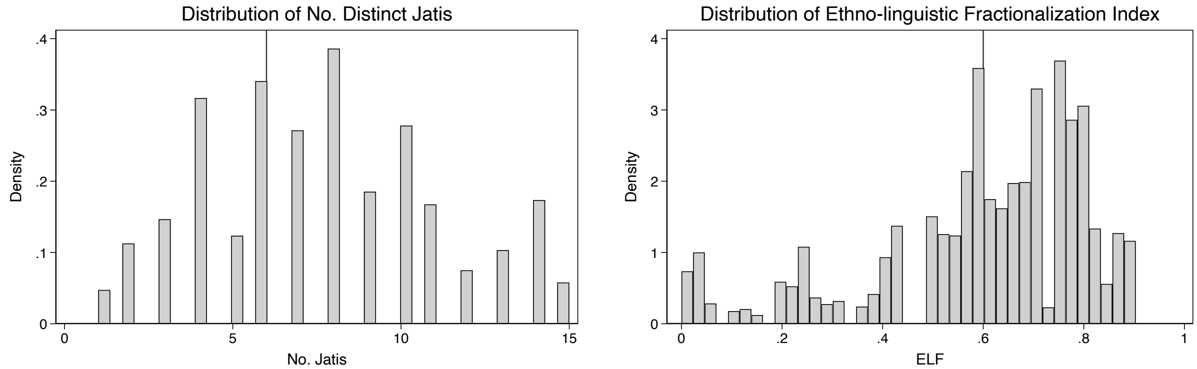
Panel B: Self-Reported Source of SS1 Seeds



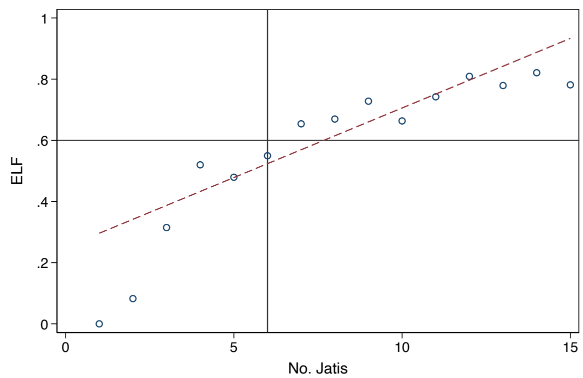
Notes: Panel A left figure shows raw mean levels of adoption in treated and control villages among non-recipients over the years. Figure on the right plots total village-level area under SS1 among non-recipient farmers that grow SS1, broken down by village-level treatment status. Panel B presents raw mean levels of seed source unconditional (left) and conditional on adoption status (right) in 2015. Seed sale points include block-level government seed centers and any market-based institutions such as input vendors, agricultural supply stores, etc. where seeds are purchased at market price.

Figure 2: Jati Fractionalization in Sample Villages

Panel A: Distribution of Villages by Jati Composition

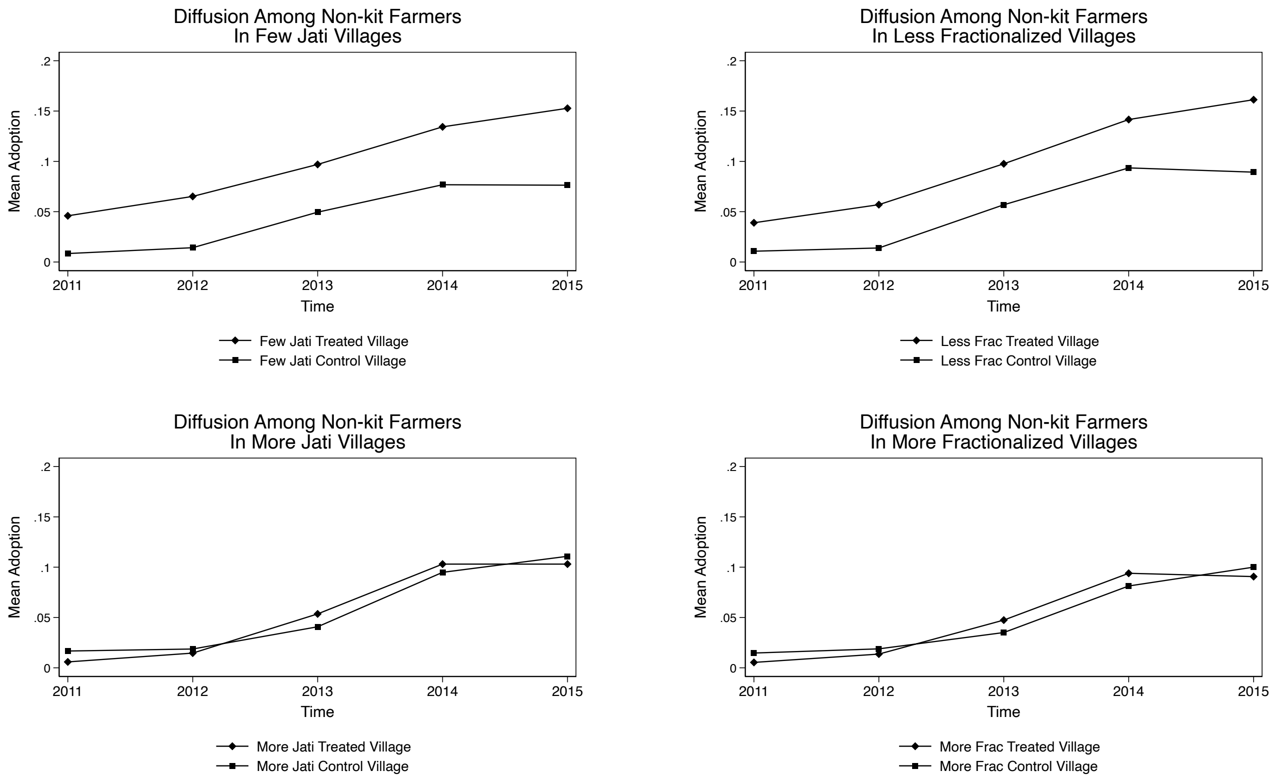


Panel B: Correlation between Distinct Jati Groups and Fractionalization



Notes: Histogram in Panel A (left) depicts the distribution of number of unique jatis per village. The median is 8 unique jatis per village. 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 (Panel A, right). Panel B depicts correlation between the two measures of fractionalization. The vertical and horizontal lines present the cut-offs used for defining fractionalization dummies respectively.

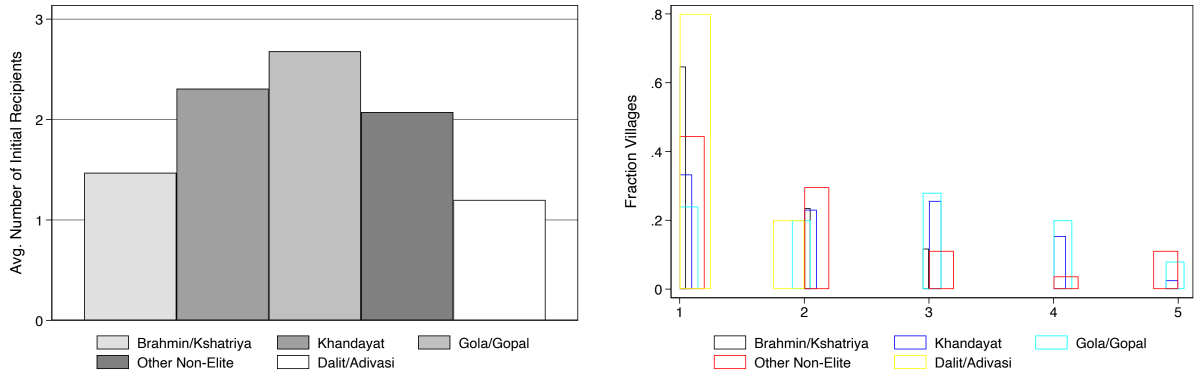
Figure 3: Diffusion of Seeds: By Jati Fractionalization



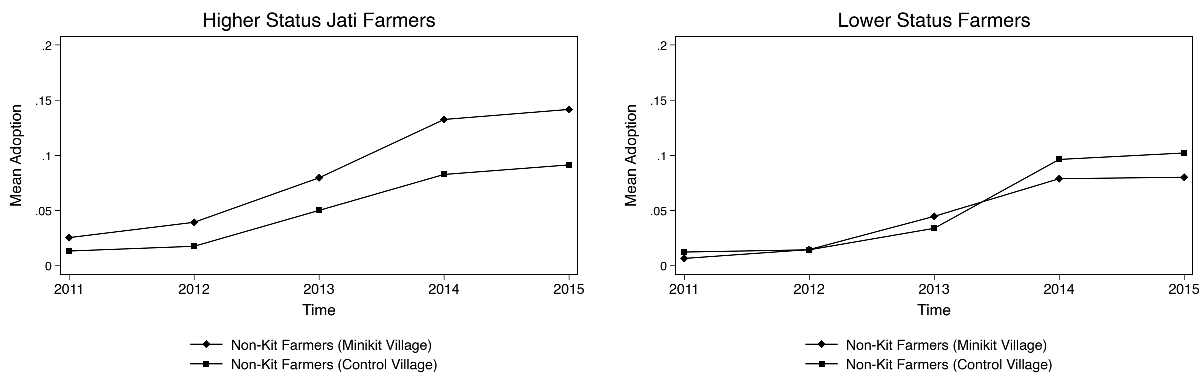
Notes: The chart shows raw mean levels of adoption among non-recipients over the years in homogenous vs. fractional villages. The left panel is based on the number of distinct jati groups in a village (Few Jati Villages are those with 6 or fewer jatis) whereas the right panel is based on the ELF index (a village with ELF above 0.6 is considered fractionalized).

Figure 4: Diffusion of Seeds: Role of Jati Hierarchy

Panel A: Distribution of Initial Recipients by Social Rank



Panel B: Adoption Among Higher Jati Rank vs Lower Rank Non-Recipients



Notes: Panel A shows the distribution of initial kit recipients by their respective jati, including both average number of recipients by each jati (left) as well as their distribution in terms of number of such initial recipients within treated villages (right). Panel B shows raw mean levels of adoption by higher social status jati groups - ranked 1 to 3 that include Brahmin, Kshatriya, Khandayat and Gola - in treated and control villages among non-recipients over the years. Lower status jatis include Dalit, Adivasis and remaining 68 jatis belonging to OBC category (ranks 4 and 5).

9 Tables

Table 1: Summary Statistics

	Observations	Mean	Std Dev	Min	Max
Cultivated Any Paddy (binary)	8498	0.96	0.19	0	1
Cultivated SS1 in 2015	8498	0.13	0.33	0	1
Cultivated Swarna in 2015	8498	0.72	0.45	0	1
Kharif Area Sown (Acres) in 2015	8498	2.58	13.87	0	1200
SS1 Kharif Sown Area (Acres) in 2015	8498	0.03	0.23	0	6
SS1 Source as Block	8498	0.04	0.20	0	1
SS1 Source as Self	8498	0.04	0.20	0	1
SS1 Source as Village Farmer	8498	0.01	0.10	0	1
SS1 Source as Outside Farmer	8498	0.02	0.14	0	1
SS1 Source as Minikit	8498	0.00	0.03	0	1
SS1 Source as Market	8498	0.02	0.13	0	1
SS1 Source as Door Sale	8498	0.00	0.02	0	1
SS1 Source as Other	8498	0.01	0.09	0	1
Dalit & Adivasi	8498	0.11	0.32	0	1
Brahmin	8498	0.05	0.22	0	1
Kshatriya	8498	0.02	0.15	0	1
Khandayat	8498	0.35	0.48	0	1
Gola/Gopal	8498	0.21	0.41	0	1
Other Non-Elite Jatis	8498	0.23	0.42	0	1

Notes: The summary statistics were computed for the most recent year in the survey, i.e., 2015. 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 the 2011 Emerick et al. 2016 study. We exclude the initial kit recipients for our analysis to examine technology diffusion among non-recipient farmers. The source of seed was only asked if the respondent cultivated SS1 in a given year. We code skipped values as 0s since seed sources are a null set for those not cultivating SS1. For our subsequent analysis, we club self (which includes sources among members of respondents' family within their village) and other farmer from within village as within village seed source. We also club block seed center and market to indicate if the farmer acquired the seeds through sale points.

Table 2: Diffusion Over Time Among All Non-Recipients: Dynamic Treatment Effects

	(1) Adopt	(2) Area (Acres)	(3) Seed Src Within Vill Incl Family	(4) Seed Src Outside Vill	(5) Seed Src Block or Market
Years 2013-15	0.0599***	1.887***	0.0149***	0.00972***	0.0234***
	(0.00963)	(0.518)	(0.00264)	(0.00185)	(0.00537)
Treat x Years 2011-12	0.00783	0.633	0.00116	0.000459	-0.000353
	(0.0104)	(0.555)	(0.00205)	(0.00121)	(0.00232)
Treat x Years 2013-15	0.0210	2.248*	0.0149***	0.00413	-0.00271
	(0.0162)	(1.148)	(0.00480)	(0.00311)	(0.00620)
Constant	0.0151**	0.130	0.00110	0.000908	0.000592
	(0.00598)	(0.339)	(0.00139)	(0.000712)	(0.00163)
Observations	41845	252	41845	41845	41845
No.Villages	126	126	126	126	126
Control Mean (2012)	.02	.17	0	0	0
Adj R-Squared	.04	.22	.02	.01	.02
All Treat p-val	.43	.15	.01	.35	.88

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). We report the full set of coefficients from Equation 1 in this table after aggregating years 2011-12 as early period and years 2013-15 as later period for better readability. The estimation includes block (randomization strata) fixed effects, which are "absorbed" in a high dimensional fixed effect regression model. The leave-out group is year 2011-12, whose estimates are captured as the intercept "Constant". The coefficients on "Treatment x Year" dummies should be interpreted as level differences between treatment and control groups in that specific time period. Columns 1 and 3-5 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, from another farmer outside the village, or from a seed sale point like market or block seed center) as outcome variables. Column 2 presents estimates from village-level regressions using total area under the new crop variety, weighted by the number of non-recipient farmers (village size). All specifications are Intent to Treat (ITT). We cluster standard errors by the level of treatment assignment (i.e., village). The last row presents the joint p-value for treatment across both time periods to examine whether the diffusion levels overall are different between treatment and control villages. The coefficient on treatment indicator when using only 2015 data remains stable at 0.02.

Table 3: Adoption Among All Non-Recipients by Village Fractionalization (No. Jatis)

	(1) Adopt	(2) Area (Acres)	(3) Seed Src Within Vill Incl Family	(4) Seed Src Outside Vill	(5) Seed Src Block or Market
Years 2013-15	0.0744***	3.054*	0.0175***	0.0146***	0.0408***
	(0.0214)	(1.683)	(0.00646)	(0.00480)	(0.0134)
No. Jati Village x 2011-12	0.00179	0.129	0.000337	0.000222	-0.000350
	(0.00175)	(0.116)	(0.000387)	(0.000244)	(0.000601)
No. Jati Village x 2013-15	-0.000216	-0.0330	-0.0000253	-0.000451	-0.00275**
	(0.00292)	(0.189)	(0.000847)	(0.000474)	(0.00113)
Treat x Years 2011-12	0.0527**	1.573	0.00906*	0.000796	0.00683
	(0.0263)	(1.215)	(0.00475)	(0.00304)	(0.00592)
Treat x Years 2013-15	0.0506	3.715	0.0281**	0.00226	-0.0212
	(0.0418)	(2.657)	(0.0125)	(0.00777)	(0.0148)
No. Jati Village x Treat x 2011-12	-0.00575**	-0.131	-0.00102*	-0.0000685	-0.000861
	(0.00264)	(0.127)	(0.000536)	(0.000319)	(0.000772)
No. Jati Village x Treat x 2013-15	-0.00365	-0.178	-0.00163	0.000279	0.00256
	(0.00442)	(0.247)	(0.00138)	(0.000766)	(0.00160)
Constant	0.00236	-0.793	-0.00127	-0.000685	0.00320
	(0.0133)	(0.903)	(0.00306)	(0.00205)	(0.00445)
Observations	41845	252	41845	41845	41845
No.Villages	126	126	126	126	126
Adj R-Squared	.05	.22	.02	.01	.02
Num Jati in Treat = Num Jati (Early)	.05	.2	.06	.85	.19
Num Jati in Treat = Num Jati (Later)	.19	.12	.01	.66	.2

Standard errors in parentheses

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

Notes: In this table, we examine village-level heterogeneity by whether a village has few or many distinct jati groups by estimating Equation 3. We measure village social composition as the number of distinct jati groups in a village. The sample includes the universe of non-recipient farmers in the study villages. Columns 1 and 3-5 present ITT effects from farmer-level regressions and those in Column 2 from village-level regressions as before. We report alternate specifications for heterogeneity analysis using other ways to construct a village's jati-level fractionalization in the Online Appendix Table A.5. For example, we examine heterogeneity by village fractionalization index using the share of each jati in the total population. All specifications include randomization strata - block - fixed effects (absorbed) and cluster robust standard errors clustered by village. The last two rows present the p-value of testing the hypotheses $\gamma_1^J + \beta_1^J = \alpha_1^J$ and $\gamma_2^J + \beta_2^J = \alpha_2^J$, to see if time differences in the outcomes are affected by village-level heterogeneity in the number of distinct jati groups.

Table 4: Jati-Level Balance Table: Probability of At Least One Recipient From Own Jati

	(1) Prob. Jati Gets Kit	(2) Prob. Jati Gets Kit	(3) Prob. Jati Gets Kit
Treated Village	0.0534***	0.0539***	0.0533***
	(0.00284)	(0.00292)	(0.00282)
No. Farmers	-0.000404***	-0.000363***	-0.000409***
	(0.0000630)	(0.0000600)	(0.0000624)
No. Jatis	-0.000206	-0.000353	-0.000183
	(0.000596)	(0.000591)	(0.000593)
Jati Size	0.0000702	-0.0000381	0.0000685
	(0.0000689)	(0.0000835)	(0.0000689)
Brahmin		0.00279	
		(0.0105)	
Dalit		0.00363	
		(0.0107)	
Gola		0.0119	
		(0.0108)	
Khandayat		0.0105	
		(0.0105)	
Kshatriya		0.0138	
		(0.0158)	
All Other Jati		0.00339	
		(0.00986)	
Prob. Flood (<1km)			0.0349
			(0.0266)
Prob. Flood (<2km)			-0.0158
			(0.0222)
Prob. Flood (<5km)			-0.00573
			(0.00986)
Observations	41845	41845	41845
No. Villages	126	126	126
Adj R-Squared	.33	.33	.33
Jati Joint P-Value	.41	.72	.43

Standard errors in parentheses

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

Notes: This table shows the determinants of the sample farmers' (non-recipient respondent) jati member getting a minikit during the initial farmer-level randomization in 2011. Columns 2 and 3 add other non-stratified variables to the prediction exercise, including specific jati groups (we classified 87 distinct jatis in this particular region of Odisha into these 6 categories) and flood probability. All specifications include block fixed effect, which was the stratifying variable for village-level random assignment. Standard errors are clustered at the village-level (reported in parentheses). We report joint p-value to test for significance across all jati-level and flood exposure variables in the last row.

Table 5: Within-Village Jati-Level Adoption: At Least One Own Jati Recipient

	(1) Adopt	(2) Area (Acres)	(3) Seed Src Within Vill Incl Family	(4) Seed Src Outside Vill	(5) Seed Src Block or Market
Years 2013-15	0.0599***	0.973***	0.0149***	0.00972***	0.0234***
	(0.00963)	(0.371)	(0.00264)	(0.00185)	(0.00537)
Treat x Years 2011-12	-0.00497	0.0808	-0.000271	0.00120	-0.00278
	(0.00860)	(0.202)	(0.00237)	(0.00129)	(0.00299)
Treat x Years 2013-15	0.00973	-0.496	0.00898*	-0.000543	-0.000941
	(0.0155)	(0.460)	(0.00530)	(0.00275)	(0.00660)
At Least 1 Own Jati w/ Kit x 2011-12	0.0197**	0.158	0.00215	-0.00120	0.00378*
	(0.00807)	(0.259)	(0.00248)	(0.00151)	(0.00222)
At Least 1 Own Jati w/ Kit x 2013-15	0.0174	1.936***	0.00918*	0.00724**	-0.00276
	(0.0141)	(0.650)	(0.00539)	(0.00339)	(0.00441)
Constant	0.0152**	0.122	0.00113	0.000923	0.000592
	(0.00598)	(0.177)	(0.00139)	(0.000695)	(0.00163)
Observations	41845	1702	41845	41845	41845
No. Villages	126	126	126	126	126
Adj R-Squared	.05	.17	.02	.01	.02
Jati Connection 2011-12 = Treat 2011-12	.03	.82	.57	.32	.17
Jati Connection 2013-15 = Treat 2013-15	.74	0	.98	.11	.84

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. "At least 1 Own Jati" variable is defined as a binary variable taking value 1 if any farmer from the respondent's own jati within the treated villages received a minikit in 2011. This variable for control group is 0 for all years since no one in control received minikits in 2011. We report the full set of coefficients from Equation 4 in this table after aggregating years 2011-12 in one group and years 2013-15 in another for better readability. The estimation includes block (randomization strata) fixed effects, which are "absorbed" in a high dimensional fixed effect regression model. Columns 1 and 3-5 present ITT results from farmer-level regressions and those in Column 2 from village-by-jati-affiliation-level regressions weighted by the number of non-recipient farmers (village size). We report standard errors clustered by village in parentheses. The last two rows present the p-value of testing the hypotheses $\gamma_1^W = \beta_1^W$, $\gamma_2^W = \beta_2^W$, to see if over time changes in the outcomes differ by jati-level connections between the non-recipients and the initial recipients in treated villages. 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 6: Cross-Village Jati-Level Adoption (Control Only): At Least One Own Jati Recipient

	(1) Adopt	(2) Area (Acres)	(3) Within Village Source	(4) Outside Village Source	(5) Block Market Source
Years 2013-15	0.0575***	0.707	0.00383*	0.00383*	0.0536**
	(0.0171)	(0.624)	(0.00209)	(0.00218)	(0.0234)
At Least 1 Own Jati w/ Kit x 2011-12	0.0100	0.0102	-0.000314	-0.000584	0.00224
	(0.0107)	(0.195)	(0.00157)	(0.00101)	(0.00464)
At Least 1 Own Jati w/ Kit x 2013-15	0.0127	0.293	0.0115***	0.00569**	-0.0299*
	(0.0151)	(0.582)	(0.00403)	(0.00251)	(0.0178)
Constant	0.00509	0.103	0.00112	0.00137	-0.00163
	(0.00966)	(0.258)	(0.00171)	(0.00105)	(0.00491)
Observations	21180	790	21180	21180	21180
No. Villages	62	62	62	62	62
Adj R-Squared	.03	.08	.01	.01	.03
Joint p-val	.51	.82	.01	.07	.06

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

Notes: The sample includes the universe of non-recipient farmers in control villages only. The definition of "At least 1 Own Jati" variable is updated to take value 1 if any farmer from any treated village from the control group respondent's own jati received a minikit in 2011. Columns 1 and 3-5 present ITT results from farmer-level regressions and those in Columns 2 from village-by-jati-affiliation-level regressions weighted by the number of non-recipient farmers (village size). All specifications include block (randomization strata) fixed effect. We report standard errors clustered by village in parentheses. The last row presents the joint p-value across both time periods by jati affiliation.

Table 7: Optimal Targeting? Adoption by the Social Status of the Majority Recipient Jati

	(1) Rank 1&2 All Non-Kit	(2) Rank 1&2 Low Status Non-Kit	(3) Rank 3 All Non-Kit	(4) Rank 3 Low Status Non-Kit	(5) Rank 4&5 All Non-Kit	(6) Rank 4&5 Low Status Non-Kit
Year 2013-15	0.0599***	0.0648***	0.0599***	0.0648***	0.0599***	0.0648***
	(0.00963)	(0.0134)	(0.00963)	(0.0134)	(0.00963)	(0.0134)
Treat x Year 2011-12	0.00851	0.00681	-0.00515	0.00180	0.0123	0.00790
	(0.0106)	(0.00835)	(0.00831)	(0.0101)	(0.0119)	(0.00912)
Treat x Year 2013-15	0.0208	-0.00777	-0.0104	-0.0101	0.0336*	0.00867
	(0.0163)	(0.0141)	(0.0151)	(0.0159)	(0.0183)	(0.0186)
Majority Kit Rank (Col) x Year 2011-12	-0.0116	-0.00940	0.0241*	0.0102	-0.0170	-0.00699
	(0.0117)	(0.0155)	(0.0137)	(0.0123)	(0.0108)	(0.0120)
Majority Kit Rank (Col) x Year 2013-15	0.00352	0.0524	0.0615***	0.0201	-0.0443**	-0.0278
	(0.0546)	(0.0447)	(0.0201)	(0.0191)	(0.0178)	(0.0179)
Constant	0.0151**	0.00783	0.0156***	0.00834	0.0154***	0.00848
	(0.00598)	(0.00574)	(0.00586)	(0.00589)	(0.00586)	(0.00582)
Observations	41845	14230	41845	14230	41845	14230
Adj R-Squared	.04	.04	.05	.04	.05	.04
Treat=Majority Status (Early)	.28	.41	.08	.67	.15	.41
Treat=Majority Status (Later)	.77	.22	.01	.31	.02	.28

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

Notes: The sample in each of the specification includes all non-recipients (Columns 1, 3, 5) and only those belonging to lower rank jatis like Dalit, Adivasis, and non-elite "backward caste" jatis in Columns 2, 4, 6. The outcome variable in all columns is whether the respondent adopts SS1. The column header indicates whether the majority of the initial recipients belonged to specific rank as indicated. For example, the coefficient of "Majority Kit Rank (Col) x 2011-12" in column 1 should be interpreted as the change in adoption rate in percentage points terms when the majority of initial recipients are from Brahmin or Kshatriya jatis. The coefficient on the treat-year interaction dummies are the adoption rates when these jatis are not in majority during initial seeding. Other specifications to show the role of specific jatis by social status among initial recipients on overall diffusion are presented in Table A.10 and those among low status groups are in Table A.11. All specifications include block fixed effect and the standard errors are clustered at the village-level (reported in parentheses).

Table 8: Information and Other Barriers to Seed Availability

	(1) Heard of SS1	(2) Not Available	(3) No Info on Availability	(4) Expensive	(5) Prefer Other Variety
No. Own Jati Recipients	0.0115	0.00830	-0.00496	-0.000613	-0.00163
	(0.0131)	(0.0108)	(0.0109)	(0.00529)	(0.00210)
No. High Status Recipients	0.0747***	-0.0427**	-0.0462	0.00971	-0.00127
	(0.0239)	(0.0199)	(0.0315)	(0.00968)	(0.00425)
No. Int. Status Recipients	0.0182	-0.00748	-0.0100	0.00645	-0.00549
	(0.0165)	(0.0190)	(0.0204)	(0.00668)	(0.00397)
No. Low Status Recipients	-0.0148	0.0245	0.0328	-0.00793	-0.00603
	(0.0168)	(0.0184)	(0.0227)	(0.00902)	(0.00411)
Treat	0.0112	-0.0804	-0.0440	-0.0129	0.0246*
	(0.0543)	(0.0780)	(0.0947)	(0.0360)	(0.0126)
No. Jatis	-0.00676	0.0129**	0.0206**	-0.0109***	0.000378
	(0.00523)	(0.00537)	(0.00788)	(0.00366)	(0.00129)
Jati Size	0.00144*	0.000736	0.000974	-0.000223	0.000128
	(0.000788)	(0.000586)	(0.000812)	(0.000232)	(0.000157)
Village Size	-0.0000967	0.000883	0.000523	0.000177	-0.000200
	(0.000630)	(0.000624)	(0.000934)	(0.000300)	(0.000213)
Observations	8369	8369	8369	8369	8369
No. Villages	126	126	126	126	126
Adj R-Squared	.09	.11	.19	.14	.05
Control Mean	.6	.65	.44	.04	.02

Standard errors in parentheses

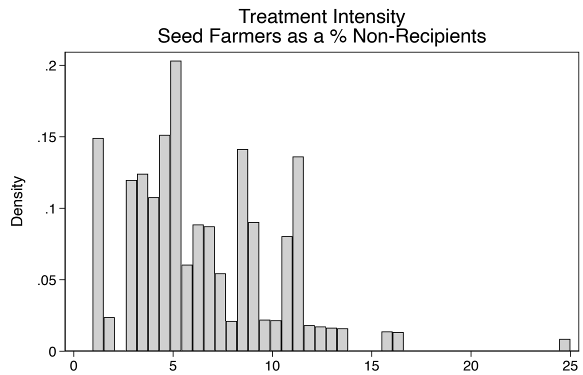
* $p < 0.1$, ** $p < .05$, *** $p < 0.01$

Notes: This table shows correlations between jati affiliation with initial recipients and other plausible channels affecting adoption decisions including informational constraints (whether the respondent has knowledge about the new variety in Column 1) and the stated reasons for non-adoption (Columns 2-5). The outcomes were measured as of the most recent cultivation season, i.e., 2015. All specifications include block fixed effect and the standard errors are clustered at the village-level (reported in parentheses).

Online Appendix

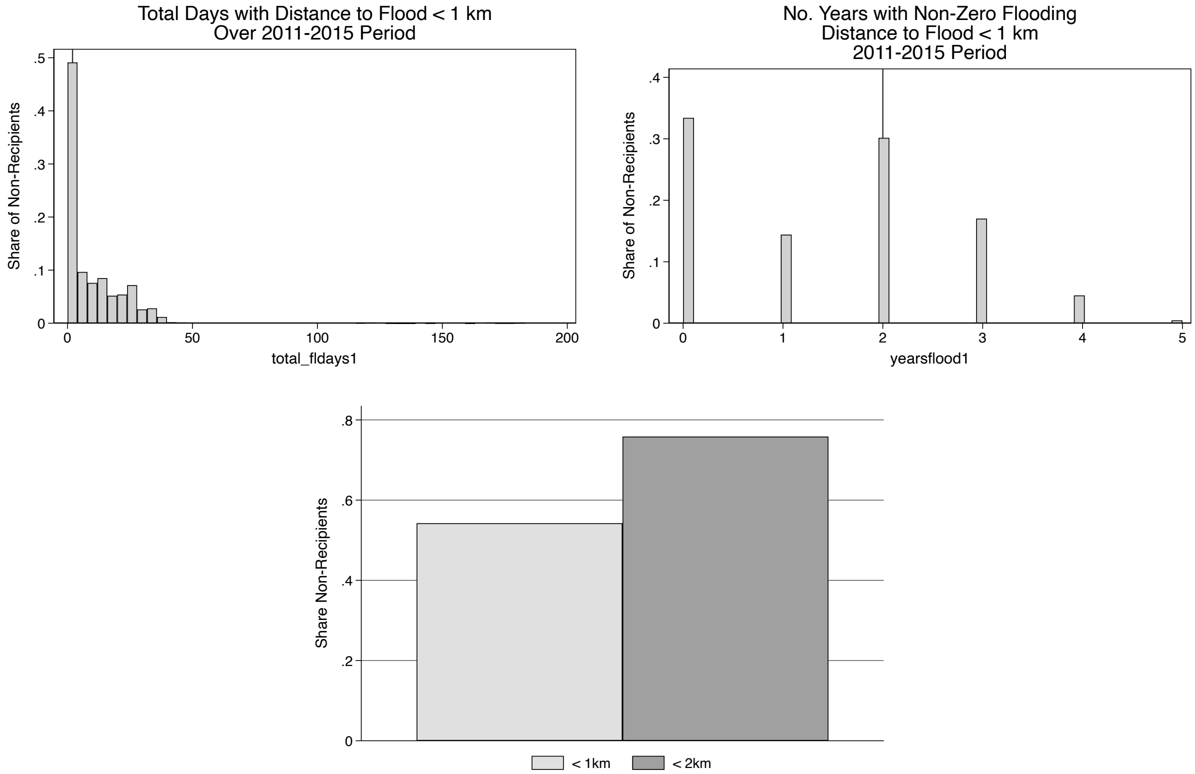
A.1 Figures

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.

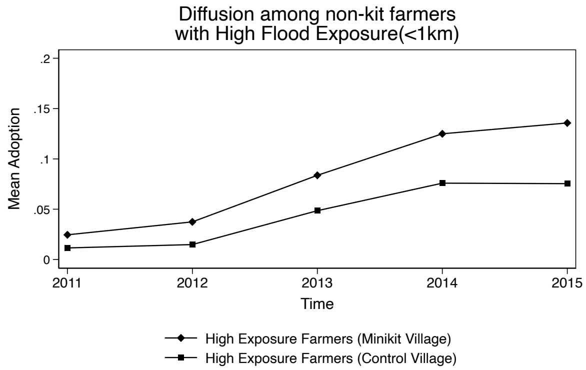
Figure A.2: Distribution of Flood Days



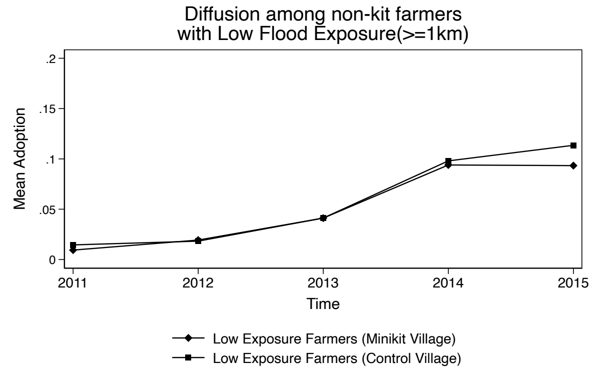
Notes: Data on flood layers is from LANCE-MODIS Flood data product. We select 85 days of satellite data for each year between 2011 and 2015, with 70 days falling during paddy flowering and post-flowering periods and 15 randomly selected days through-out the calendar year. For each satellite day, we computed 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: Long-run adoption among all non-recipients: By Farmers' Flooding Exposure

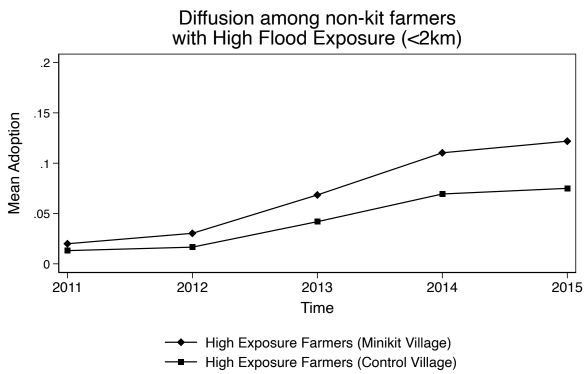
Panel A: High Flood Exposure



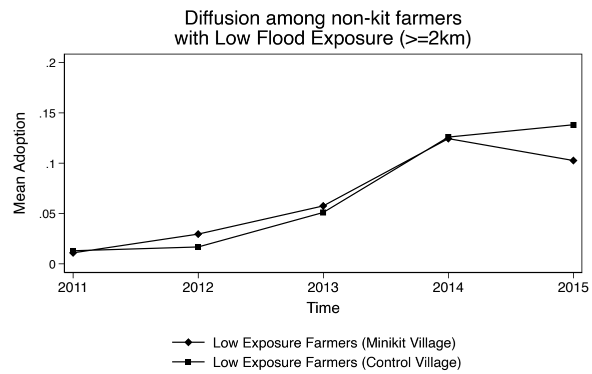
Panel B: Low Flood Exposure



Panel C: High Flood Exposure (2 km)

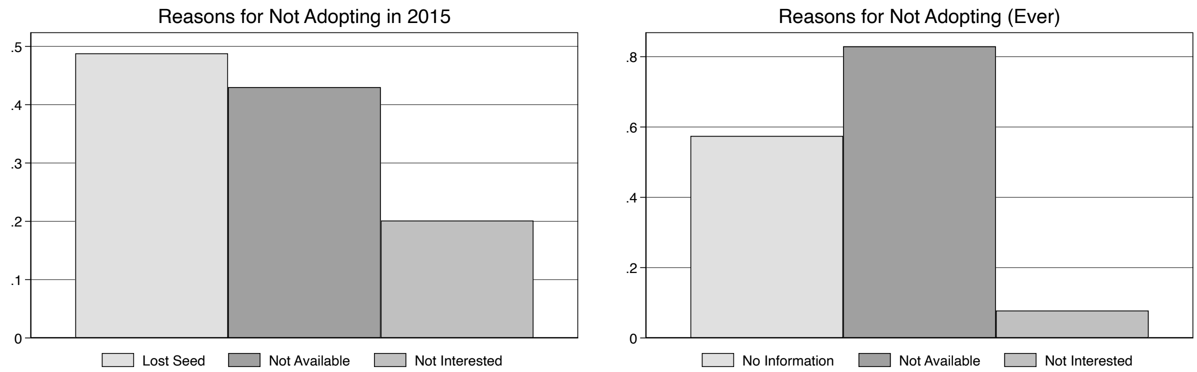


Panel D: Low Flood Exposure (2km)



Notes: The chart shows raw mean levels of adoption among non-recipients over the years by flooding exposure. We code a farmer to be flood exposed if their house location 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.4: 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.

A.2 Tables

Table A.1: Dynamic Effects by Treatment Intensity

	(1) Adopt	(2) Area (Acres)	(3) Seed Src Within Vill Incl Family	(4) Seed Src Outside Vill	(5) Seed Src Block or Market
Years 2013-15	0.0650***	2.023***	0.0179***	0.0106***	0.0247***
	(0.00877)	(0.478)	(0.00279)	(0.00178)	(0.00470)
% Seeded x 2011-12	0.00101	0.0553	0.000420*	0.000149	-0.0000183
	(0.000858)	(0.0532)	(0.000213)	(0.000113)	(0.000254)
% Seeded x 2013-15	0.00146	0.262**	0.00160***	0.000432	-0.000771
	(0.00143)	(0.115)	(0.000491)	(0.000309)	(0.000594)
Constant	0.0158***	0.265	0.000329	0.000659	0.000477
	(0.00552)	(0.293)	(0.00127)	(0.000648)	(0.00148)
Observations	41845	252	41845	41845	41845
No. Villages	126	126	126	126	126
Control Mean (2012)	0.0200	0	0	0	0
Adj R-Squared	0.0400	0.220	0.0200	0.0100	0.0200
Joint p-val	0.430	0.0800	0	0.170	0.430

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. Columns 1 and 3-5 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 sources (binary indicators denoting whether a non-recipient farmer acquired the seed from another farmer within the village, farmer from outside their village, or from sale point) as outcome variables. 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 A.2: Adoption Among Non-Recipients: By Flood Exposure

	(1) Adopt	(2) Area (Acres)	(3) Seed Src Within Vill Incl Family	(4) Seed Src Outside Vill	(5) Seed Src Block or Market
Years 2013-15	0.0669***	2.408***	0.0138***	0.00882***	0.0273***
	(0.0145)	(0.630)	(0.00276)	(0.00246)	(0.00864)
Hi Flood x 2011-12	-0.0189	0.840	-0.00466	0.000904	-0.000298
	(0.0192)	(0.991)	(0.00456)	(0.00263)	(0.00491)
Hi Flood x 2013-15	-0.0332	-0.354	-0.00237	0.00276	-0.00819
	(0.0261)	(1.368)	(0.00669)	(0.00399)	(0.00961)
Treat x Years 2011-12	-0.00523	0.199	0.00226	0.00102	-0.00122
	(0.00945)	(0.530)	(0.00209)	(0.00156)	(0.00355)
Treat x Years 2013-15	-0.0121	1.463	0.0111**	0.00308	-0.00869
	(0.0186)	(1.108)	(0.00536)	(0.00375)	(0.0106)
Hi Flood x Treat x 2011-12	0.0265	0.535	-0.000864	-0.00113	0.00171
	(0.0197)	(1.094)	(0.00399)	(0.00237)	(0.00488)
Hi Flood x Treat x 2013-15	0.0627**	1.147	0.00691	0.00122	0.0117
	(0.0310)	(2.178)	(0.00916)	(0.00598)	(0.0133)
Constant	0.0240*	-0.292	0.00334	0.000475	0.000679
	(0.0124)	(0.571)	(0.00255)	(0.00158)	(0.00302)
Observations	41845	328	41845	41845	41845
No. Villages	126	126	126	126	126
Control Mean(2012)	0.0200	0	0.0500	0.0800	0
Adj R-Squared	0.0500	0.220	0.0200	0.0100	0.0200
High Risk in Treat = High Risk (Early)	0.190	0.950	0.380	0.770	0.910
High Risk in Treat = High Risk (Later)	0.0500	0.300	0.100	0.830	0.460

Standard errors in parentheses

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

Notes: Above table presents the regression coefficients from Equation 2, estimated using heterogeneity by farmer flood exposure, defined as those with distance to flood less than 1 kms for at least 2 days during 2011-2015. Columns 1 and 3-5 are farmer-level specifications. 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). The last two rows present the p-value of testing the hypotheses $\gamma_1^f + \beta_1^f = \alpha_1^f$ and $\gamma_2^f + \beta_2^f = \alpha_2^f$, to see if over time changes in the outcomes differ by treatment status among higher flood exposed farmers.

Table A.3: Adoption Among Non-Recipients: By Flood Exposure (Sensitivity Test)

	(1)	(2)	(3)	(4)	(5)
			Adopters	Adopters	
			Seed Src	Seed Src	Seed Src
	Adopt	Area (Acres)	Within Vill	Outside Vill	Block or Market
Years 2013-15	0.0886***	2.958***	0.0190***	0.0113***	0.0346***
	(0.0185)	(0.881)	(0.00343)	(0.00371)	(0.0116)
Hi Flood (2km) x 2011-12	-0.0176	0.00836	-0.00728**	-0.00377*	0.00681
	(0.0159)	(0.768)	(0.00327)	(0.00200)	(0.00605)
Hi Flood (2km) x 2013-15	-0.0596***	-1.648	-0.0133**	-0.00610	-0.00943
	(0.0222)	(1.179)	(0.00532)	(0.00433)	(0.00868)
Treat x Years 2011-12	-0.00591	-0.222	0.00356	0.00426*	-0.00890
	(0.0104)	(0.482)	(0.00268)	(0.00239)	(0.00671)
Treat x Years 2013-15	-0.0239	3.672*	0.0184*	0.00300	-0.0145
	(0.0255)	(1.975)	(0.00931)	(0.00455)	(0.0195)
Hi Flood (2km) x Treat x 2011-12	0.0201	0.987	-0.00154	-0.00385	0.00910
	(0.0172)	(0.892)	(0.00377)	(0.00276)	(0.00703)
Hi Flood (2km) x Treat x 2013-15	0.0651**	-1.581	-0.00170	0.00247	0.0160
	(0.0322)	(2.426)	(0.0107)	(0.00586)	(0.0205)
Constant	0.0270**	0.116	0.00607***	0.00348**	-0.00410
	(0.0122)	(0.547)	(0.00215)	(0.00138)	(0.00487)
Observations	41845	328	41845	41845	41845
No. Villages	126	126	126	126	126
Control Mean(2012)	0.0200	0	0	0	0
Adj R-Squared	0.0500	0.230	0.0200	0.0100	0.0200
High Risk in Treat = High Risk (Early)	0.230	0.590	0.0600	0.130	0.350
High Risk in Treat = High Risk (Later)	0.0100	0.110	0	0.0700	0.400

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

Notes: Above table presents the regression coefficients from Equation 2, estimated using heterogeneity by farmer flood exposure, defined as those with distance to flood less than 2 kms for at least 2 days during 2011-2015. Columns 1 and 3-5 are farmer-level specifications. 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). The last two rows present the p-value of testing the hypotheses $\gamma_1^f + \beta_1^f = \alpha_1^f$ and $\gamma_2^f + \beta_2^f = \alpha_2^f$, to see if over time changes in the outcomes differ by treatment status among higher flood exposed farmers.

Table A.4: 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/Gopal	0.00679	0.104
	(0.160)	(0.224)
Other Jatis	-0.0975	-0.0114
	(0.161)	(0.198)
Dalit	-0.206	0.474**
	(0.185)	(0.194)
Constant	-1.801***	-0.00583
	(0.145)	(0.185)
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.5: Adoption Among All Non-Recipients by Village Fractionalization (Robustness)

	(1) Less than 6 Jatis	(2) No. Jatis	(3) ELF Less than 0.6	(4) ELF
Years 2013-15	0.0634***	0.0744***	0.0542***	0.104***
	(0.0136)	(0.0214)	(0.0139)	(0.0278)
Frac Village x 2011-12	-0.0419**	0.00620**	-0.00627	0.0303
	(0.0161)	(0.00273)	(0.0138)	(0.0248)
Frac Village x 2013-15	-0.0497**	0.00419	0.00664	-0.0442
	(0.0230)	(0.00359)	(0.0225)	(0.0395)
Treat x Years 2011-12	-0.129**	-0.00992	-0.0855**	0.0171
	(0.0514)	(0.0223)	(0.0418)	(0.0295)
Treat x Years 2013-15	-0.117**	-0.0120	-0.0735	0.00752
	(0.0545)	(0.0339)	(0.0465)	(0.0463)
Frac x Treat x 2011-12	0.0876**	-0.0105**	0.0473*	-0.123*
	(0.0360)	(0.00423)	(0.0265)	(0.0715)
Frac x Treat x 2013-15	0.0903*	-0.00839	0.0513	-0.0834
	(0.0465)	(0.00558)	(0.0374)	(0.0957)
Village Size	-0.000987***	-0.00102***	-0.000639**	-0.000595**
	(0.000290)	(0.000348)	(0.000265)	(0.000252)
Treat x Village Size	0.00134**	0.00127**	0.000962*	0.000851*
	(0.000589)	(0.000613)	(0.000514)	(0.000508)
Constant	0.111***	0.0494***	0.0676***	0.0437**
	(0.0270)	(0.0143)	(0.0214)	(0.0179)
Observations	41845	41845	41845	41845
No.Villages	126	126	126	126
Adj R-Squared	.05	.05	.05	.05
Frac Treat = Frac (Early)	.97	.27	.22	.06
Frac Treat=Frac (Later)	.52	.44	.39	.72

Standard errors in parentheses

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

Notes: Here we examine heterogeneity by other, commonly used definitions of fractionalization including using a cut-off for the number of distinct jati groups that correspond to increasing fractionalization (second moment of population distribution). Additionally, we construct and examine heterogeneity by village fractionalization index based on the inverse Herfindahl-Hirschman Index (called Ethno-Linguistic Fractionalization or ELF), constructed as $1 - \sum_j s_j^2$ where s_j is the population share of jati j within a village and functions of this ELF measure. The sample includes the universe of non-recipient farmers in the study villages. Column headers represent the method used to mesure fractionalization. All estimates are ITT effects from farmer-level regressions using SS1 adoption as the outcome variable. We also control for village size and size interacted with treatment status in this specification in case villages with more jatis are correlated with village size. All specifications include block fixed effects and cluster standard errors by village. The last two rows present the p-value of testing the hypotheses $\gamma_1^J + \beta_1^J = \alpha_1^J$ and $\gamma_2^J + \beta_2^J = \alpha_2^J$, to see if time differences in the outcomes are affected by village-level heterogeneity in fractionalization.

Table A.6: Within-Village Jati-Level Adoption: At Least One Own Jati Recipient (Robustness)

	(1) Adopt	(2) Area (Acres)	(3) Seed Src Within Vill Incl Family	(4) Seed Src Outside Vill	(5) Seed Src Block or Market
Years 2013-15	0.0599***	0.973***	0.0149***	0.00972***	0.0234***
	(0.00963)	(0.371)	(0.00264)	(0.00185)	(0.00537)
Treat x Years 2011-12	-0.00491	0.0823	-0.000298	0.00120	-0.00275
	(0.00862)	(0.202)	(0.00237)	(0.00129)	(0.00300)
Treat x Years 2013-15	0.00979	-0.494	0.00895*	-0.000538	-0.000917
	(0.0155)	(0.461)	(0.00532)	(0.00275)	(0.00660)
At Least 1 Own Jati w/ Kit x 2011-12	0.0267*	0.360	-0.00143	-0.000610	0.00686**
	(0.0158)	(0.375)	(0.00310)	(0.00181)	(0.00313)
At Least 1 Own Jati w/ Kit x 2013-15	0.0244	2.139***	0.00560	0.00783*	0.000319
	(0.0208)	(0.737)	(0.00618)	(0.00422)	(0.00567)
Prob. Jati Gets Kit	-0.0838	-2.426	0.0429	-0.00701	-0.0369
	(0.114)	(2.153)	(0.0276)	(0.0167)	(0.0282)
Constant	0.0151**	0.121	0.00115	0.000919	0.000569
	(0.00597)	(0.177)	(0.00141)	(0.000693)	(0.00163)
Observations	41845	1702	41845	41845	41845
No. Villages	126	126	126	126	126
Adj R-Squared	.05	.17	.02	.01	.02
Jati Connection 2011-12 = Treat 2011-12	.05	.51	.59	.48	.07
Jati Connection 2013-15 = Treat 2013-15	.58	0	.03	.12	.9

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

Notes: The table includes the probability one's own-jati member received a minikit in 2011 as a control variable in all the specifications included in Table 5. The sample includes the universe of non-recipient farmers in the study villages. "At least 1 Own Jati" variable is defined as a binary variable taking value 1 if any farmer from the respondent's own jati within the treated villages received a minikit in 2011. This variable for control group is 0 for all years since no one in control received minikits in 2011. We report the full set of coefficients from Equation 4 in this table after aggregating years 2011-12 in one group and years 2013-15 in another for better readability. The estimation includes block (randomization strata) fixed effects, which are "absorbed" in a high dimensional fixed effect regression model. Columns 1 and 3-5 present ITT results from farmer-level regressions and those in Column 2 from village-by-jati-affiliation-level regressions weighted by the number of non-recipient farmers (village size). We report standard errors clustered by village in parentheses. The last two rows present the p-value of testing the hypotheses $\gamma_1^W = \beta_1^W$, $\gamma_2^W = \beta_2^W$, to see if over time changes in the outcomes differ by jati-level connections between non-recipients and the initial recipients in treated villages.

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

	(1)	(2)	(3)	(4)	(5)
	Adopt	Area (Acres)	Seed Src Within Vill Incl Family	Seed Src Outside Vill	Seed Src Block or Market
Years 2013-15	0.0599***	0.973***	0.0149***	0.00972***	0.0234***
	(0.00963)	(0.371)	(0.00264)	(0.00185)	(0.00537)
Treat x Years 2011-12	-0.00689	0.0658	0.000377	0.000770	-0.00187
	(0.00889)	(0.208)	(0.00221)	(0.00123)	(0.00286)
Treat x Years 2013-15	0.00701	-0.267	0.00902*	0.000321	0.000276
	(0.0158)	(0.472)	(0.00519)	(0.00294)	(0.00727)
No. Own Jati w/ Kit x 2011-12	0.00916*	0.0698	0.000438	-0.000230	0.000982
	(0.00533)	(0.103)	(0.000941)	(0.000599)	(0.000775)
No. Own Jati w/ Kit x 2013-15	0.00870	0.640***	0.00370*	0.00239	-0.00188
	(0.00759)	(0.217)	(0.00198)	(0.00154)	(0.00140)
Constant	0.0153**	0.125	0.00115	0.000933	0.000579
	(0.00597)	(0.177)	(0.00139)	(0.000695)	(0.00162)
Observations	41845	1702	41845	41845	41845
No. Villages	126	126	126	126	126
Adj R-Squared	.05	.18	.02	.01	.02
Jati Connection 2011-12 = Treat 2011-12	.17	.99	.98	.53	.4
Jati Connection 2013-15 = Treat 2013-15	.93	.07	.4	.59	.79

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. Instead of using an indicator variable, we use the number of own-jati recipients as the heterogeneity variable in Equation 4. This variable for control group is 0 for all years since no one in control received minikits in 2011. We report the full set of coefficients in this table after aggregating years 2011-12 in one group and years 2013-15 in another for better readability. The estimation includes block (randomization strata) fixed effects (absorbed and not reported). Columns 1 and 3-5 present ITT results from farmer-level regressions and those in Column 2 from village-by-jati-affiliation-level regressions weighted by the number of non-recipient farmers (village size). We report standard errors clustered by village in parentheses. The last two rows present the p-value of testing the hypotheses $\gamma_1^W = \beta_1^W$, $\gamma_2^W = \beta_2^W$, to see if over time changes in the outcomes differ by jati-level connections between non-recipients and the initial recipients in treated villages.

Table A.8: Jati-Level Adoption By No. Own Jati Recipients (Robustness)

	(1)	(2)	(3)	(4)	(5)
	Adopt	Area (Acres)	Seed Src Within Vill Incl Family	Seed Src Outside Vill	Seed Src Block or Market
Years 2013-15	0.0599***	0.973***	0.0149***	0.00972***	0.0234***
	(0.00963)	(0.371)	(0.00264)	(0.00185)	(0.00537)
Treat x Years 2011-12	-0.00477	0.0949	-0.000271	0.000866	-0.00151
	(0.00899)	(0.214)	(0.00226)	(0.00133)	(0.00288)
Treat x Years 2013-15	0.00913	-0.237	0.00837	0.000417	0.000630
	(0.0158)	(0.487)	(0.00523)	(0.00292)	(0.00725)
No. Own Jati w/ Kit x 2011-12	0.0117	0.105	-0.000354	-0.000113	0.00141
	(0.00822)	(0.126)	(0.00103)	(0.000545)	(0.000888)
No. Own Jati w/ Kit x 2013-15	0.0113	0.676***	0.00290	0.00251	-0.00145
	(0.0103)	(0.229)	(0.00220)	(0.00179)	(0.00148)
Prob. Jati Gets Kit	-0.115	-1.572	0.0351	-0.00518	-0.0191
	(0.145)	(1.605)	(0.0258)	(0.0164)	(0.0188)
Constant	0.0152**	0.124	0.00116	0.000931	0.000569
	(0.00594)	(0.177)	(0.00141)	(0.000694)	(0.00162)
Observations	41845	1702	41845	41845	41845
No. Villages	126	126	126	126	126
Adj R-Squared	.05	.18	.02	.01	.02
Jati Connection 2011-12 = Treat 2011-12	.17	.97	.98	.53	.39
Jati Connection 2013-15 = Treat 2013-15	.91	.07	.39	.58	.8

Standard errors in parentheses

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

Notes: The table includes the probability one's own-jati member received a minikit in 2011 as a control variable in all the specifications included in Table A.7. The sample includes the universe of non-recipient farmers in the study villages. Instead of using an indicator variable, we use the number of own-jati recipients as the heterogeneity variable in Equation 4. This variable for control group is 0 for all years since no one in control received minikits in 2011. We report the full set of coefficients in this table after aggregating years 2011-12 in one group and years 2013-15 in another for better readability. The estimation includes block (randomization strata) fixed effects (absorbed and not reported). Columns 1 and 3-5 present ITT results from farmer-level regressions and those in Column 2 from village-by-jati-affiliation-level regressions weighted by the number of non-recipient farmers (village size). We report standard errors clustered by village in parentheses. The last two rows present the p-value of testing the hypotheses $\gamma_1^W = \beta_1^W$, $\gamma_2^W = \beta_2^W$, to see if over time changes in the outcomes differ by jati-level connections between non-recipients and the initial recipients in treated villages.

Table A.9: Adoption by Distance to Kit Recipients

	(1)	(2)	(3)	(4)	(5)
	Adopt	Area (Acres)	Seed Src Within Vill Incl Family	Seed Src Outside Vill	Seed Src Block or Market
Years 2013-15	0.0599***	1.887***	0.0149***	0.00972***	0.0234***
	(0.00963)	(0.516)	(0.00264)	(0.00185)	(0.00537)
Treat x Years 2011-12	0.0107	0.0893	0.0000638	0.000860	-0.00173
	(0.0131)	(0.349)	(0.00213)	(0.00137)	(0.00240)
Treat x Years 2013-15	0.0275	0.646	0.0143**	0.00359	0.00127
	(0.0199)	(0.799)	(0.00562)	(0.00328)	(0.00761)
Dist (30m) x Treat x Years 2011-12	-0.00686	0.541	0.00259	-0.000933	0.00315
	(0.00998)	(0.422)	(0.00208)	(0.00115)	(0.00211)
Dist (30m) x Treat x Years 2013-15	-0.0155	-0.0559	0.00139	0.00127	-0.00940*
	(0.0155)	(0.923)	(0.00610)	(0.00297)	(0.00526)
Constant	0.0152**	0.135	0.00110	0.000907	0.000608
	(0.00596)	(0.238)	(0.00139)	(0.000713)	(0.00161)
Observations	41845	374	41845	41845	41845
No.Villages	126	126	126	126	126
Control Mean	.02	0	0	0	0
Adj R-Squared	.04	.19	.02	.01	.02
Distance (30m) 2011-12 = Treat 2011-12	.42	.45	.46	.41	.18
Distance (30m) 2013-15 = Treat 2013-15	.19	.6	.21	.65	.38

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

Notes: Above table presents heterogeneous treatment effects by distance between non-recipient household and the recipient households. To identify physically proximate non recipient households, we first calculate distance between all pairs of non-recipient and recipient house-level GPS coordinates. In treated villages, about 50% of all households are within 30 meters of the recipient households. Therefore, we use this distance as a cut-off to classify a non recipient as living in close proximity of one of the initial recipients or not. Specifically, we estimate the following, where $Dist(30)_{iv}$ is an indicator variable is a household is within 30 meters from at least one of the initial recipient house locations. For farmers in control villages, this variable is 0. The specification corresponding to the table above is as follows:

$$\begin{aligned} y_{ivt} &= \gamma_1^D \text{Dist (30m)}_{iv} \text{Treat}_v \text{Year 2011-12}_t + \gamma_2^D \text{Dist (30m)}_{iv} \text{Treat}_v \text{Year 2013-15}_t \\ &+ \beta_1^D Treat_v \text{Year 2011-12}_t + \beta_2^D Treat_v \text{Year 2013-15}_t + \delta_1 \\ &+ \delta_2 \text{Year 2013-15}_t + \phi_b + \epsilon_{ivt} \end{aligned}$$

We include randomization strata fixed effects and cluster standard errors by village. The last two rows present the p-value of testing the hypotheses $\gamma_1^D = \beta_1^D$, $\gamma_2^D = \beta_2^D$, to see if over time changes in the outcomes differ by physical distance between non-recipients and the initial recipients in treated villages.

Table A.10: Optimal Targeting? Adoption Among All Non-Recipients

	(1) Brahmin Kshatriya Recipients	(2) Khandayat Recipients	(3) Gola Gopal Recipients	(4) All Other Non-Elite Jati Recipients	(5) Dalit Adivasi Recipients
Years 2013-15	0.0599***	0.0599***	0.0599***	0.0599***	0.0599***
	(0.00963)	(0.00963)	(0.00963)	(0.00963)	(0.00963)
Treat x Years 2011-12	0.00222	0.0163	-0.000333	0.00959	0.0103
	(0.00890)	(0.0156)	(0.00997)	(0.0128)	(0.0126)
Treat x Years 2013-15	0.0131	0.0224	0.00539	0.0426**	0.0231
	(0.0144)	(0.0225)	(0.0154)	(0.0187)	(0.0190)
No. from Jati (in Col) x 2011-12	0.0147	-0.00684	0.00729	-0.00232	-0.00620
	(0.0108)	(0.00614)	(0.00959)	(0.00399)	(0.00757)
No. from Jati (in Col) x 2013-15	0.0203	-0.00136	0.0152	-0.0227***	-0.00528
	(0.0154)	(0.00804)	(0.0121)	(0.00556)	(0.0128)
Jati Size	0.000601	0.000571	0.000489*	0.000558	0.000571
	(0.000373)	(0.000357)	(0.000283)	(0.000360)	(0.000368)
Village Size	-0.000402***	-0.000446***	-0.000350**	-0.000311**	-0.000421***
	(0.000141)	(0.000139)	(0.000161)	(0.000151)	(0.000139)
Constant	0.0280*	0.0326**	0.0281*	0.0227	0.0306*
	(0.0166)	(0.0133)	(0.0166)	(0.0172)	(0.0159)
Observations	41845	41845	41845	41845	41845
No. Villages	126	126	126	126	126
Adj R-Squared	.05	.05	.05	.05	.05
None From Jati= No. From Jati (Early)	.33	.27	.65	.46	.38
None From Jati= No. From Jati (Later)	.72	.42	.67	.01	.33

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

Notes: The sample in each of the specification includes all non recipients in villages with the number initial recipients belonging to jati mentioned in the column header as the exogenous variation in the jati-level exposure to the new technology. The outcome variable in all columns is whether the respondent adopts SS1. The column header indicates the jati of the recipients whose number in the treated villages varies due to random selection of the initial recipients. For example, the coefficient of "No. From Jati in Col x 2011-12" in column 1 should be interpreted as the change in adoption rate in percentage points terms when the number of initial recipients from Brahmin jati increases by 1. We club Brahmin and Kshatriya jati groups given their similar social stature in the context. The specifications control for the size of the respondent's jati as well as the total number of farmers in the village. All specifications include block fixed effect, which was the stratifying variable for village-level random assignment, and the standard errors are clustered at the village-level (reported in parentheses).

Table A.11: Optimal Targeting? Adoption Among Dalit and Other Non-Elite Jati Non-Recipients

	(1) Brahmin Kshatriya Recipients	(2) Khandayat Recipients	(3) Gola Gopal Recipients	(4) All Other Non-Elite Jati Recipients	(5) Dalit Adivasi Recipients
Years 2013-15	0.0648***	0.0648***	0.0648***	0.0648***	0.0648***
	(0.0134)	(0.0134)	(0.0134)	(0.0134)	(0.0134)
Treat x Years 2011-12	0.00430	0.00502	0.00480	-0.000358	0.00692
	(0.00893)	(0.0106)	(0.0105)	(0.0102)	(0.0104)
Treat x Years 2013-15	-0.0129	-0.0152	-0.00246	0.0200	-0.00145
	(0.0142)	(0.0148)	(0.0157)	(0.0184)	(0.0170)
No. from Jati (in Col) x 2011-12	0.00394	-0.000632	0.000103	0.00260	-0.00510
	(0.00838)	(0.00439)	(0.00597)	(0.00359)	(0.00889)
No. from Jati (in Col) x 2013-15	0.0250**	0.0112	-0.00270	-0.0144***	-0.00607
	(0.0123)	(0.00715)	(0.00698)	(0.00517)	(0.0119)
Jati Size	-0.000199	-0.000220	-0.000278	-0.000119	-0.000310
	(0.000274)	(0.000273)	(0.000274)	(0.000295)	(0.000288)
Village Size	-0.0000796	-0.0000705	-0.000112	-0.0000563	-0.000116
	(0.000155)	(0.000159)	(0.000151)	(0.000166)	(0.000152)
Constant	0.0179	0.0184	0.0226*	0.0155	0.0236*
	(0.0128)	(0.0131)	(0.0121)	(0.0144)	(0.0124)
Observations	14230	14230	14230	14230	14230
No. Villages	113	113	113	113	113
Adj R-Squared	.04	.04	.04	.04	.04
None From Jati= No. From Jati (Early)	.98	.68	.75	.82	.48
None From Jati= No. From Jati (Later)	.08	.15	.99	.13	.86

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

Notes: The sample in each of the specification only includes those belonging to dalit and those in lower social hierarchy (i.e., other than brahmin, kshatriya, khandayat and gola/gopal). The outcome variable in all columns is whether the respondent adopts SS1. The column header indicates the jati of the recipients whose number in the treated villages varies due to random selection of the initial recipients. For example, the coefficient of "No. From Jati in Col x 2011-12" in column 1 should be interpreted as the change in adoption rate in percentage points terms when the number of initial recipients from Brahmin jati increases by 1. We club Brahmin and Kshatriya jati groups given their similar social stature in the context. The specifications control for the size of the respondent's jati as well as the total number of farmers in the village. All specifications include block fixed effect, which was the stratifying variable for village-level random assignment, and the standard errors are clustered at the village-level (reported in parentheses).