Three Essays on Adoption and Impact of Agricultural Technologies

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Abstract

This dissertation is composed of three essays examining adoption and impact of agricultural technologies. The first two papers estimate adoption and impact of iron-biofortified bean varieties in Rwanda. These varieties are bred to have high iron content and high yields to improve the health and livelihoods of rural households. The third essay estimates the spillover effects of seed producer groups (SPGs) in Nepal on nearby non-SPG member households. These SPGs were established to produce and sell stress tolerant rice varieties (STRVs) and other improved rice varieties and were trained on a number of improved management practices for rice cultivation.

The first essay, titled “Promoting rapid and sustained adoption of biofortified crops: What we learned from iron-biofortified bean delivery approaches in Rwanda” uses duration modeling to estimate how a number of delivery approaches designed to distribute iron-biofortified bean varieties to farmers have increased the speed of adoption, reduced the speed of disadoption, and increased the speed of readoption of iron-biofortified bean varieties. We find that these delivery approaches have been very effective at promoting adoption and reducing disadoption. Policy makers can learn lessons from this research regarding distribution of biofortified crops in Rwanda and elsewhere.

The second essay, titled “The impact of iron-biofortified bean adoption on bean productivity, consumption, purchases and sales” examines the impact of adoption of the most popular iron-biofortified bean variety, RWR2245, on adopting households. We use a control function approach with instrumental variables related to iron-biofortified bean delivery approaches to control for selection bias of adoption. We find that adoption increases yield, household bean consumption from own-production, and bean sales while reducing bean purchases. This implies that iron-biofortified bean adoption has a strong potential to improve nutrition and food security of adopting households, as beans make up a large portion of the average Rwandan diet.

The third and final essay, titled “The spillover effects of seed producer groups on non-member households in local communities in Nepal” examines the spillover benefits of SPGs

onto non-member farmers in villages with an SPG or are adjacent to a village with an SPG. We find that SPGs have increased adoption of STRVs, improved the seed replacement rate, and increased use of some best management practices among non-members within SPG villages, and have increased adoption of the STRVs in at least one past seasons among non-members in adjacent villages.

General Audience Abstract

This dissertation consists of three essays that examine adoption and impact of agricultural technologies that are designed to help rural households in developing countries improve their livelihoods. The first two papers focus on iron-biofortified bean varieties in Rwanda. These bean varieties have high iron content and are also high yielding. They are designed to combat iron-deficiency within the country. The government of Rwanda distributed the bean varieties to households using a number of different delivery approaches. We study the influence of these approaches and find that households who are closer to them adopt the varieties faster and disadopt the varieties more slowly, indicating that they have been successful in promoting adoption. The second paper of this dissertation studies the impact that one of the iron-biofortified bean varieties has had on adopting households. We find that adoption increases household bean yields and bean consumption from own-production, while reducing bean purchases and increasing the likelihood that a household sells beans. This provides evidence that iron-biofortification improves iron consumption for households that adopt the varieties, because they consume greater quantities of their iron-rich bean harvests, and improves household income through reductions in purchases and increased likelihood of sales. Finally, our third paper examines Seed Producer Groups (SPGs) in Nepal in which member farmers produce and sell rice varieties that are tolerant to drought. We find that for non-SPG members, living in or near a village with an SPG increases their likelihood of growing a drought-tolerant variety. Overall, this dissertation contributes to the literature on adoption and impacts of agricultural technologies and provides useful guidelines for policy makers wishing to promote these and other technologies. This can inform future funding allocation and maximize impacts of development projects.

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Chapter 1: Introduction

Millions of households around the globe rely on agriculture for their livelihoods, and are often the ones most likely to suffer from low incomes, poor nutrition, and vulnerability to climate change. Agricultural technologies offer a solution to these problems but often face low levels of adoption. Thus, the study of how agricultural technologies can be promoted and utilized by farmers to maximize their impact on household livelihoods is integral to development work. However, the study of agricultural technologies can be challenging; adoption patterns are often complex, while issues such as selection bias and spillover effects complicate the estimation of causal impacts. This dissertation consists of three papers that examine adoption and impact of agricultural technologies while overcoming these challenges.

The first two papers of this dissertation use a nationally representative dataset of bean growers in Rwanda to study adoption and impact of iron-biofortified bean varieties. These varieties are bred to be high in iron content in order to combat iron deficiency among rural households and are also high-yielding to improve livelihoods and compete with other improved bean varieties. In collaboration with NGOs, the government of Rwanda developed and released ten iron-biofortified varieties between 2010 and 2012, and distributed them to farmers through multiple delivery efforts. The first paper of this dissertation, "Promoting rapid and sustained adoption of biofortified crops: What we learned from iron-biofortified bean delivery approaches in Rwanda," estimates how these delivery approaches have promoted adoption within the country. Adoption dynamics of agricultural technologies including iron-biofortified varieties can be complex; adoption can occur quickly or slowly, and adopting households often disadopt the technologies, sometimes cycling in and out of use. For this reason, we used duration analysis to model adoption and disadoption decision making over time. We found that proximity to the delivery approaches increases the speed of adoption, reduces the speed of disadoption, and increases the speed of readoption. We also found that access to extension speeds up adoption and that female farmers disadopt more slowly than male farmers. We therefore conclude that delivery approaches are an effective strategy to promote adoption, as is increasing access to extension and targeting women when promoting the varieties.

In the second paper of this dissertation, "The impact of iron-biofortified bean adoption on bean productivity, consumption, purchases and sales," we estimate the causal impacts of the most widely adopted iron-biofortified bean variety in Rwanda, RWR2245, on bean yields, bean consumption, bean purchases, and bean sales of adopting households. These impacts have implications for household nutrition and food security, as beans make up a large portion of the average Rwandan diet. The impact pathway of agricultural interventions on nutrition is complex and in the case of biofortified crops, which are bred explicitly to improve nutrition, this pathway has not been widely examined empirically. While randomized control trials have verified that consumption does improve nutrition status (De Moura et al., 2014; Finkelstein et al., 2017; Luna et al., 2015; Murray-Kolb et al., 2017), it is not known how adoption of the crops affects consumption or increases income, both of which could improve nutrition. Our paper contributes to the literature by examining this part of the impact pathway. We use a control function approach (CFA) to deal with potential endogeneity of adoption. CFA utilizes instrumental variables and can be more efficient than two-stage least squares in the case of non-linear endogenous variables (Imbens and Wooldridge, 2007). We use two instruments that are highly correlated with adoption but are otherwise exogenous to our outcomes of interest; the presence of delivery approaches near a household and the previous-season village adoption rate of RWR2245. We find that adoption of RWR2245 increases bean yields but does not affect the amount of land that households devote to bean production, thereby providing farmers with an increase in harvested quantity of beans. We find that this increase in harvest allows farmers to increase consumption of beans from own production while also reducing their purchases of beans, and increasing the likelihood that a household sells beans. Adoption thus has the potential to improve household iron intake and food security, indicating that iron-biofortified beans are a good investment to improve household well-being.

The final paper of this dissertation examines the spillover impacts of seed producer groups (SPGs) on nearby households in Nepal. The SPGs were established by the International Fund for Agricultural Development funded project Consortium for Unfavorable Rice Environments in twelve villages across three districts of Nepal that are prone to drought and also suffer from low access to stress-tolerant rice variety (STRV) seed. The SPG members were trained in best management practices (BMPs) for rice cultivation, and produced and sold STRV and other improved rice varieties locally. Previous research on SPGs and other forms of organized seed production, such as production contracts, has found that farmers benefit from such arrangements (Simmons *et al.*, 2005; Winters *et al.*, 2010; Katungi *et al.*, 2011; Mishra *et al.*, 2016; Tebeka *et al.*, 2017). However, given that the technologies produced by SPGs, both seed and knowledge of BMPs, are highly transferrable to other farmers, it is highly likely that spillover effects from organized seed production will arise within nearby communities. Spillover effects are impacts that arise from a development project on non-targeted households within a local economy (Angelucci and Di Maro, 2015); in the case of SPGs, the targeted households are members of the groups while non-member households within the same or adjacent villages are in the local economy. This paper contributes to the literature by examining the spillover benefits of SPGs, which have not been previously examined. We use two propensity-scored weighted regression methods to control for differences among SPG, SPG-adjacent, and other area villages. We collected in-depth information regarding SPG seed production and training using SPG focus group surveys. This information guided the development of a household survey which asked farmers about the rice varieties they cultivated and management practices they used. We interviewed randomly selected farmers in SPG villages, SPG-adjacent villages, and other randomly selected villages in the surrounding area. We found that SPGs increase adoption of STRVs for non-members within SPG villages and adjacent villages, and increase the seed replacement rate and use of several BMPs for non-members in villages with SPGs. Our study provides evidence that a project that establishes SPGs can have positive and long-lasting impacts not only on the members of the groups, but for nearby non-member farmers as well.

The three papers of this dissertation contribute to the literature on adoption and impact of agricultural technologies. This is accomplished by considering the complexity of both adoption, including adoption dynamics and the existence of spillover effects, and impact pathways that allow agricultural technologies to improve household well-being. Together, the findings indicate that development projects designed to promote adoption of agricultural technologies can be effective in achieving specific development goals, including improving nutrition and reducing vulnerability to climate shocks.

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Chapter 2: Promoting rapid and sustained adoption of biofortified crops: What we learned from iron-biofortified bean delivery approaches in Rwanda

1. Introduction

Over a quarter of the world's population suffers from micronutrient malnutrition, also known as hidden hunger, which can result in poor health, stunted growth, and decreased mental capacity. This can lead to productivity losses and lower lifetime earnings (Alderman et al., 2006; FAO, 2013). The cost of undernutrition and micronutrient deficiency is estimated at up to three percent of global GDP, which corresponds to an economic loss of up to $2.1 trillion per year (FAO, 2013, 2014). In the Copenhagen Consensus 2008, an expert panel ranked three micronutrient interventions in the top-five best investments to foster economic development in low income countries (Copenhagen Consensus Center, 2008). These included providing vitamin and mineral supplements mainly targeted to children and pregnant women, fortification of food with micronutrients during processing, and biofortification, a process by which staple food crops are bred to have higher micronutrient content.

Randomized control trials have proven the efficacy of iron-biofortified crops in improving iron deficiency and functional outcomes. Studies conducted in Mexico and Rwanda found that consumption of iron-biofortified beans for just a few months improved iron status (Haas, 2014; Haas et al., 2016). Finkelstein et al. (2017) conducted a meta-analysis using efficacy trial data from three iron-biofortified crops: beans, rice, and millet, and found iron-biofortification to be effective in improving iron status, particularly for those who are iron-deficient. Moreover, iron-biofortified bean consumption improved memory and ability to pay attention for iron-deficient women (Murray-Kolb et al., 2017), and reduced the time they spent being sedentary (Luna et al., 2015).

Rwanda Agriculture Board collaborated with International Center for Tropical Agriculture and HarvestPlus to release four iron-biofortified bean varieties in 2010 and six in 2012. Rwanda was identified as top-priority for investment in iron-biofortified bean breeding and delivery due to the importance of bean production and consumption in the country and the significant rate of iron deficiency which can be alleviated through iron-biofortification of beans (Asare-Marfo et al., 2013). Over 90% of rural households grow beans (Asare-Marfo et al., 2016a). They are commonly grown during both of Rwanda's agricultural seasons (Seasons A and B[1]) and across its ten agro-ecological zones, which vary by soil type, altitude, terrain, and rainfall. Beans are a staple food in all zones (USAID and FEWS NET, 2011) and contribute 32% of calorie and 65% of protein intake (CIAT, 2004; Mulambu et al., 2017)

Intensive dissemination of iron-biofortified bean varieties began in 2012. Several delivery approaches were used including sales through authorized agrodealers, direct marketing by the HarvestPlus Rwanda country team in local markets, and exchange of local variety grain for iron-biofortified bean seed. Informal dissemination also occurred through social networks. Approximately half a million households grew an iron-biofortified bean variety for at least one growing season between 2010 and 2015 (Asare-Marfo et al., 2016a).

The objective of this study is to determine the effects of formal delivery and informal dissemination on the speed of adoption, disadoption, and readoption of iron-biofortified beans in Rwanda. This research contributes to the literature on adoption of improved crop varieties in three ways. First, it is one of the few studies on adoption of biofortified crops. Improved varieties are bred to increase productivity while biofortified crops, in addition to their yield gains, offer nutritional benefits. Thus, reasons for adopting biofortified crops may differ from those for other

[1] Season A runs from September to February and Season B starts in March and ends in June (NISR, 2015. Seasonal Agricultural Survey (SAS) 2015 Season B. National Institute of Statistics of Rwanda, Kigali, Rwanda.)

improved varieties. As more biofortified crops are released, it is important to identify factors that drive adoption. We also examine the determinants of disadoption and readoption to identify factors that lead to sustained production, since for biofortification to be successful in alleviating hidden hunger, biofortified crops must be produced and consumed in sufficient quantity over long periods of time.

Second, we consider adoption as a dynamic and sequential decision-making process by which households gather new information over time and in each growing season decide whether to begin, continue, stop, or resume the cultivation of an iron-biofortified bean variety. We employ duration models to identify factors that influence the time it takes households to adopt, disadopt, or readopt iron-biofortified beans. These models account for the effects of time-varying variables, control for time dependence in decision making, and avoid bias that occurs from measuring adoption at only one point in time (Keifer, 1988). It is important to understand factors that shorten the time until households adopt a biofortified crop and lengthen the number of seasons they grow it. Nutrient-deficient households require greater intake of micronutrients quickly and consistently, especially those with young children as poor nutrition at an early age can have irreversible consequences leading to fewer earning opportunities throughout life (Alderman et al., 2006). Moreover, rapid adoption also means a higher rate of return on investment in biofortification, improving the cost-effectiveness of the technology and putting policy makers in a better position to justify the investment.

Finally, this study provides evidence on the impact of different delivery approaches for biofortified crops and the role of informal dissemination in improving the speed of adoption. Findings will be incorporated into future delivery of biofortified crops for faster, more cost-effective and sustainable scaling-up of these crops.

The next section of this paper provides background information on iron-biofortified bean delivery in Rwanda. Section three explains our conceptual framework and empirical model of farmer decision making over time and describes our data, explanatory variables, and estimation strategies. Section four provides descriptive and analytical results. The final section concludes with implications for policy and program design for biofortification.

2. Iron-biofortified bean varieties and delivery approaches in Rwanda

In addition to their high iron content, the ten iron-biofortified varieties are also high-yielding[2] and resistant to pests and diseases. The varieties have different agronomic and consumption characteristics to accommodate diverse agro-ecological conditions and consumer preferences and were developed to cater to the traits that female farmers value (Mulambu et al., 2017). Of the ten iron-biofortified bean varieties released, eight are of climbing type and two are bush varieties. Climbing bean varieties are higher yielding than bush bean varieties, grow upright, and require the use of stakes to achieve their high yield potential.

Formal delivery of iron-biofortified bean varieties began in season 2012B and intensified over the following seasons. Contracted seed multipliers produce certified seed from iron-biofortified bean foundation seed. Farmers can purchase the certified seed through authorized agrodealers in packages ranging from 1 to 50 kg, and in local markets in small packets of 200-500 grams; according to the sales records, this direct marketing approach reached a quarter of a million farmers by 2015, the largest number of any delivery approach (Mulambu et al., 2017). To

[2] Yields of the iron-biofortified varieties are similar to those of other improved varieties that were released during the same time period (Rwanda Agriculture Board, 2012. Bean Varieties Information Guide 2012.) Improved bean varieties in Rwanda have been found to yield 80% on average higher than local varieties (Larochelle, C., Alwang, J., Norton, G., Katungi, E., Labarta, R., 2015. Impacts of Improved Bean Varieties on Poverty and Food Security in Uganda and Rwanda, in: Walker, T.S., Alwang, J. (Eds.), Crop Improvement, Adoption and Impact of Improved Varieties in Food Crops in Sub-Saharan Africa. CGIAR Consortium of International Agricultural Research Centers and CAB International, Oxfordshire, UK, pp. 314-337.)

reach more farmers, HarvestPlus and partners initiated a delivery mechanism called payback in season 2013A. Under this mechanism, farmers received iron-biofortified bean seed under the condition that they would give an agreed-upon portion of their harvested grain to the program. In 2015A, payback was replaced by the seed swap scheme, under which farmers traded their local bean grain (which was to be used as planting material) for iron-biofortified bean seed. By 2015, the payback/seed swap mechanism delivered the greatest quantity of seeds of any delivery approach. Like most certified seed in Rwanda, each delivery approach sells or provides seed to farmers at a subsidized price (Mulambu et al., 2017). RWR2245, a bush variety, has been the most widely disseminated, making up between 71% and 86% of total disseminated seed each season since 2013A, followed by MAC44, a climbing variety, which made up 10% to 29% of total disseminated seed each season (Asare-Marfo et al., 2016b).

Figure 2-1 shows the locations of seed multipliers, agrodealers, and direct marketing in season 2012B, the first season of intensive delivery, and 2015A, the last season for which geolocations of direct marketing were available. In 2012B, seed multipliers were only located in the northern part of the Eastern province, where land availability is greatest; by 2015A they were still concentrated in this area, but had also expanded to the remainder of the Eastern province as well as to the Southern and Northern provinces. The area reached by agrodealers also expanded during this period. In 2012B, agrodealers were in all provinces except the Western province, but were sparsely distributed. By 2015A, they had expanded to all provinces, and were more concentrated in the Eastern, Southern, and Kigali provinces than at the start of dissemination. Finally, direct marketing began in the Eastern and Southern provinces in 2012B and by 2015A had spread to all provinces. The number of districts in which payback and seed swap mechanisms operated increased between 2013A and 2015B (Figure 2-2). In 2013A, the first season payback was established, it operated in only two districts. By 2015B, seed swap operated in ten districts.

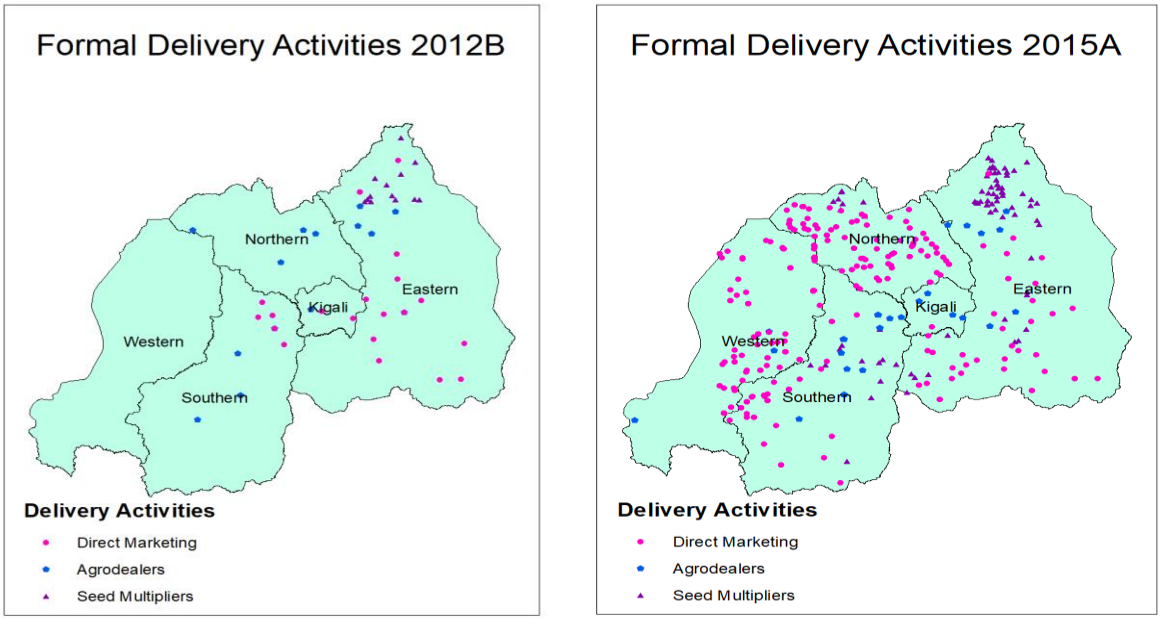


Figure 2- 1: Formal delivery activities in 2012B and 2015A

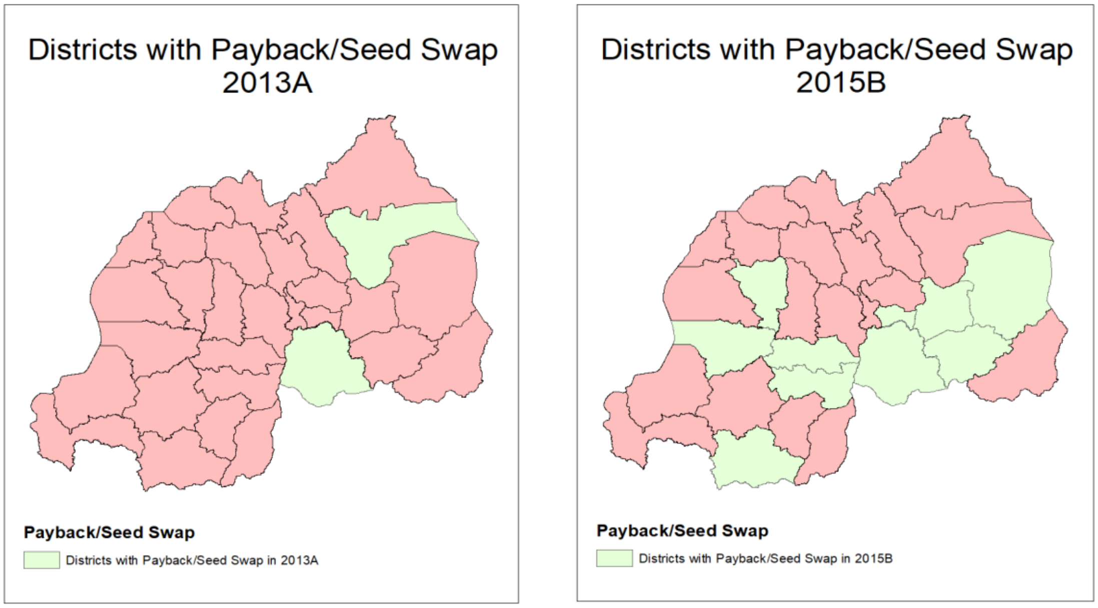


Figure 2- 2: Districts with payback/seed swap in 2013A and 2015B

3. Conceptual and empirical framework of adoption timing and data

3.1. Conceptual framework

We model adoption of an agricultural technology as a sequential process that happens over growing seasons, similar to that of Ma and Shi (2015): households collect information about a technology, make an initial decision to use the technology, and then update their knowledge according to their own experiences. In each subsequent growing season after adoption, households decide whether to continue to use or disadopt the technology; if they disadopt, they then decide in each following season whether to resume using the technology.

The decision of household *i* to grow an iron-biofortified bean variety j, which is part of the set of all available bean varieties J, at the start of each growing season *t* depends on the expected utility of growing the variety in that season $U_{ij}(t)$ compared to the expected utility of growing all alternative varieties $U_{iJ}(t)$, and constraints faced by the household related to income and awareness of the variety. If $\left(U_{ij}(t) - U_{iJ}(t)\right) = v_{ij}(t) > 0$ and constraints are not binding, then household *i* will grow variety *j* in season *t*.

The value of $v_{ij}(t)$ depends on season *t* expected costs and benefits of growing variety *j*. The household accrues monetary and opportunity costs of gathering information about biofortified varieties and obtaining the planting material. Expected benefits include the yield gain and other production advantages of the new variety compared to other varieties, as well as its superior nutritional qualities. The value of $v_{ij}(t)$ and constraints to adoption vary across household and village characteristics (X_{it}) and shift over time as formal iron-biofortified bean delivery approaches (F_{it}) expand and change locations and informal dissemination through social networks (I_{it}) increases.

Formal delivery approaches (F_{it}) and informal dissemination of iron-biofortified bean varieties (I_{it}) through social networks influence adoption decisions in two ways; first, by increasing the likelihood that a household is aware of the variety and second, by reducing the cost of adoption by making planting material more easily accessible. Additional household and village characteristics (X_{it}) that form a household's resources, knowledge and preferences will influence adoption through their effects on income constraints, probability of awareness, and costs and benefits of adoption.

3.2. Duration analysis of adoption, disadoption, and readoption

We use discrete duration analysis to empirically model the sequential adoption process. Duration analysis incorporates the time-dependence of decision making and can also account for the effects of time-varying covariates. The outcome of interest of duration models is the length of a spell, T_{ikj}, where *k* denotes spell order. Thus, we break the sequential adoption process of each iron-biofortified variety into three spells. The first spell (T_{i1j}) begins the season iron-biofortified bean varieties were first disseminated (i.e. 2012B) and ends the first season household *i* adopts variety *j*. The second spell (T_{i2j}) begins the season after household *i* adopts variety *j* and ends the season it disadopts that variety. The third spell (T_{i3j}) begins the season after household *i* disadopts variety *j* and ends the season it readopts that variety. Additional spells exist for households that continue to cycle in and out of growing variety *j*.

We are interested in the lengths of the spells T_{i1j}, T_{i2j}, and T_{i3j}. The cumulative distribution function of T_{ikj} represents the probability that spell T_{ikj} ends prior to season t_{ikj}:

$$F(t_{ikj}) = \int_0^{t_{ikj}} f(t_{ikj})dt = \Pr(T_{ikj} \leq t_{ikj}) \tag{1}$$

The distribution of T_{ikj} can also be represented by the survival function, which is the probability that T_{ikj} ends after t_{ikj}:

$$S(t_{ikj}) = 1 - F(t_{ikj}) = \Pr(T_{ikj} > t_{ikj}) \tag{2}$$

Duration analysis allows the estimation of the hazard rate, $h\left(t_{ikj}\right)=\frac{f\left(t_{ikj}\right)}{S\left(t_{ikj}\right)}$, which is the probability that the spell ends in season t_{ikj}, given that it has not already ended. We model the hazard rate empirically using a proportional hazard model, which allows us to evaluate the effects of covariates on the speed of adoption (h_{i1j}), the speed of disadoption, given adoption, (h_{i2j}), and the speed of readoption, given disadoption, (h_{i3j}). The hazard rate for household *i* and bean variety *j* is:

$$h_{ikj}\left(t_{kj}, F_{it}, I_{it}, X_{kit}, \beta_{kj}\right)=h_{0kj}\left(t_{kj}\right) * \exp(F_{it}+I_{it}+X_{kit})\beta_{kj} \qquad (3)$$

where h_{0kj} is the baseline hazard function, which models the time dependence of adoption, disadoption and readoption decisions, t_{kj} represents the number of growing seasons that have passed since the spell began, F_{it} is a vector of formal delivery variables, I_{it} is a vector of informal dissemination variables, and X_{kit} is a vector of household and village characteristics. Finally, β_{kj} is the vector of parameters to be estimated that captures the effects of covariates on the hazard rate.

Due to low adoption rates of some of the iron-biofortified bean varieties, we pool the varieties together to estimate the following proportional hazard models:

$$h_{ikj}\left(t_{k}, F_{it}, I_{it}, X_{kit}, V_{j}, \beta_{k}\right)=h_{0k}(t_{k}) * \exp\left(F_{it}+I_{it}+X_{kit}+V_{j}\right)\beta_{k} \qquad (4)$$

where V_j is an indicator variable for individual iron-biofortified bean variety. This variety fixed effect allows us to capture differences in the hazard rate associated with each variety, proxying for varietal traits and differences in availability of varietal planting material.

3.3. Data

To estimate the proportional hazard model in equation (4), this study uses nationally representative data of rural bean producers in Rwanda collected in two stages. In the first stage, 120 villages were randomly selected and all households in the selected villages were interviewed as part of a brief listing exercise. The goal of the listing exercise was to collect information about iron-biofortified bean adoption and inform the second stage of the data collection process. To facilitate bean varietal identification, households were shown a seed sample of one iron-biofortified bean variety and asked whether they had heard of the variety, grown it, the season they first adopted, and whether they had grown the variety in each subsequent season. The enumerators repeated this process for the nine remaining varieties. The listing exercise was conducted in May and June 2015 (i.e. season 2015B) and included 19,575 households (Asare-Marfo et al., 2016a).

In the second stage, 12 households per village were re-interviewed in greater depth for the main household survey in September-October 2015, after harvest of the same season. When possible, six households that grew an iron-biofortified bean in 2015B and six non-adopters were selected randomly in each village. In villages with fewer than six iron-biofortified bean adopters, all adopters were selected and non-adopters were randomly selected to obtain a total of 12 households. Enumerators interviewed the household member responsible for bean production decision making during season 2015B about household demographics and composition, bean farming decision making, asset ownership, bean production and consumption, and iron-biofortified bean adoption history from 2012B – 2015B.

A community survey, conducted along with the main household survey, was administered to key informants including the village leader to gather information on village characteristics, services and amenities related to market access, extension, and the presence of formal iron-biofortified bean delivery approaches in the village. One village surveyed during the listing exercise had no bean growers and thus was not considered for the household survey and one household had missing data. Therefore, the final sample includes 1,396 households, located across 119 villages and 29 districts.

We use household geographical coordinates, community survey data, and locations of seed multipliers and delivery approaches to estimate farmer proximity and access to iron-biofortified bean seed for growing seasons 2012B-2015B. We compute the distance between households and agrodealers, and households and seed multipliers for each growing season. To capture proximity to promotion and sales locations of iron-biofortified beans, we count the number of direct marketing approaches in a given sector (an administrative unit smaller than a district) in each season. We cross-reference community survey responses with delivery records to determine whether payback and seed swap operated in each sampled village between 2012B-2015B.

3.4. Variables

The dependent variable is a binary variable that is equal to one if spell *k* ended and zero otherwise for household *i*, variety *j* in season *t.* This allows us to capture the total number of seasons between the beginning and end of a spell. We expect that the probability of adoption will increase as time passes, as households have more time to gain knowledge and awareness of the varieties. After several seasons of growing, households may wish to replace their bean planting material and try new varieties, so we expect that the probability of disadoption will also increase over time. We expect the probability of readoption to decrease over time. Some disadoption that is followed by subsequent readoption may be due to seasonality of bean growing, in which case readoption would occur after just one season of discontinued use. If readoption does not occur after one season, it could indicate that the realized benefits of the variety to the household were lower than expected, making readoption less likely.

The vector of formal delivery approaches, F_{it}, includes the following time-varying variables: number of direct marketing approaches in the household's sector, a dummy variable equal to one if anyone in the village had participated in payback, a dummy variable equal to one if anyone in the village had participated in seed swap, distance from the household to the nearest agro-dealer of iron-biofortified bean seeds, and distance to the nearest seed multiplier (table 2-1). Proximity to formal delivery approaches improves access to and information about iron-biofortified bean varieties, which should reduce the length of time until adoption and readoption, and increase the amount of time until disadoption. While seed multipliers do not disseminate iron-biofortified bean seed to farmers directly, households living near the supply of seeds may face lower opportunity costs of obtaining information about and gaining access to iron-biofortified bean varieties.

Table 2- 1: Variable names and descriptions for covariates of adoption, disadoption, and readoption models

Variable Name	Variable Description	Time Varying
Formal Delivery		
direct markets	Number of direct marketing approaches in the sector	Yes
payback	1 = someone in village has participated in payback	Yes
seed swap	1 = someone in village has participated in seed swap	Yes
agrodealers	Distance to nearest agrodealer selling iron-biofortified bean seeds, in km	Yes
multipliers	Distance to nearest seed multiplier of iron-biofortified bean seeds, in km	Yes
Informal Dissemination		
adoption rate	Previous-season village adoption rate of iron-biofortified beans	Yes
Household and Village Characteristics		
sex	1= respondent is a female	No
education	Education level of respondent: 0 = no schooling; 1 = some primary education; 2 = some secondary education or more	No
experience	Bean farming experience of the respondent, in years	Yes
household size	Number of household members	Yes[a]
share 0-5	Proportion of household members age 0-5 years	Yes[a]
share women	Proportion of household members that are women of child-bearing age (15 to 49 years)	Yes[a]
wealth tercile	Wealth index created using polychoric components analysis (pca) expressed in tercile (measured using 2015B assets)	No[b]
ag. equipment	Count of agricultural equipment[c] owned in 2015B	No[b]
cultivated land	Land cultivated in 2015B for all crops, in $100m^2$	No[b]
city distance	Distance to nearest city of at least 50,000 people, in km	No
extension access	% of households in the village who obtain information from agricultural extension agents	No
social seed source	0 = first planting material came from local markets, RAB, or HarvestPlus (formal channels); 1 = first planting material came from neighbors, relatives or friends (social channels).	No
zone	Agro-ecological zone (1-10)	
Variety		
variety	categorical variable to distinguish between the iron-biofortified bean varieties (RWR2245[d], MAC44, RWV3316, RWV3317, RWV1129, RWR2154[d], CAB2, RWV2887, MAC42, RWV3006); base = RWR2245	No

[a] Values for previous seasons were calculated by subtracting backward from household members' ages in 2015. This requires the assumption that no one died, left the household, or entered the household between 2012 and 2015.

[b] Although these variables are likely to change over time, we only collected data on their 2015 values; therefore, in our estimations, these variables are not time-varying.

[c] Includes plough, wheelbarrow, machete, shovel, pick, and sprayer.

[d] Variety is a bush variety (all other varieties are climbing).

We define informal dissemination, I_{it}, as the process by which households gain access to the new technology through their social networks. We use the village level adoption rate in the previous season, calculated from the listing exercise data, as a proxy for the extent of information about iron-biofortified bean and availability of the technology in one's social network. Learning via social information networks has been found to significantly influence adoption behavior (Beyene and Kassie, 2015; Matuschke and Qaim, 2009; Wollni and Andersson, 2014). Social networks improve access to information, but can also lead to free-riding and strategic delay as households wait for others to gather information about the technology (Bandiera and Rasul, 2006; Beyene and Kassie, 2015; Michelson, 2017).

Few studies have examined the role of social networks on disadoption and findings are mixed (Lambrecht et al., 2014; McNiven and Gilligan, 2012; Michelson, 2017; Moser and Barrett, 2006). Once a farmer has grown an iron-biofortified bean variety, learning from other farmers in the village may become less valuable, though he/she may have better access to planting material when there are several adopters within his/her social network. We therefore expect that the previous season's village-level adoption rate will either have no effect or will lengthen the time to disadoption, and will have either no effect or will shorten the time until readoption.

The vector of household and village characteristics, X_{it}, includes access to extension, household wealth and composition, education, bean farming experience and gender of the respondent, market access, whether the planting material came from a social (informal) or formal source, and agro-ecological zone. Access to agricultural extension (measured at the village level to avoid endogeneity), as an approximation by the village leader of the percentage of households who currently use extension services, is expected to shorten the time until adoption and readoption, and lengthen the time to disadoption, by increasing household ability to access and to some extent process information (Beyene and Kassie, 2015; Feder et al., 1985; Foster and Rosenzweig, 2010; Wollni and Andersson, 2014). In addition, extension agents in Rwanda may teach households the benefit of planting single-variety bean seeds, rather than recycled bean grain or purchased mixed-variety grain, which is commonly practiced (HarvestPlus, 2017). These households may also be more likely to obtain yield gains in line with expectations, making them more likely to continue growing the variety (Lambrecht et al., 2014).

Household wealth, measured using a wealth index, a count of agricultural equipment owned and land area cultivated, is expected to increase the speed of adoption since wealth is associated with greater access to resources and a better ability to bear the risk associated with adopting a new technology (Feder et al., 1985; Foster and Rosenzweig, 2010; Nazli and Smale, 2016). It may also increase the time to disadoption and reduce the time to readoption by reducing income constraints that could prevent households from purchasing new planting material. Household composition includes household size, the proportion of household members made up of women of childbearing age, and the proportion of household members made up of children under five years of age, two of the most vulnerable groups to micronutrient deficiencies. Households with larger shares of women and children may face greater constraints to adopt due to lower labor availability but could also be more likely to adopt quickly and continuously since women and children are the most likely to benefit from the consumption of iron-biofortified beans. This could also make households adopt more continuously (i.e. disadopt later) and be more likely to readopt.

Education and years of bean farming experience of the respondent are expected to speed adoption and readoption while slowing disadoption by improving household access to information and ability to process that information, similar to the expected role of extension. Educated respondents may be more aware of the nutritional needs of their families and the nutritional benefits of biofortified crops, which would make them more likely to adopt quickly and continuously. Both education and farming experience may also increase the household's ability to achieve the yield potential of iron-biofortified beans. Gender has been found to affect production preferences and access to resources (Doss, 2001), although it is difficult to predict the relationship between gender and adoption of iron-biofortified beans. Women may be more resource-constrained but may also value the traits of iron-biofortified beans, particularly since they were developed to incorporate women's preferences (Mulambu et al., 2017).

Market access is measured by distance to the nearest city of 50,000 inhabitants. As of 2012, there were five such cities in Rwanda, with at least one in each province except for the East (Bundervoet et al., 2017). Proximity to cities of this size can facilitate access to information and reduce the cost of input acquisition, promoting rapid adoption.

The models examining disadoption and readoption also include a binary variable indicating the source of planting material in the first season the variety was grown. This variable is equal to one when seeds came from a social, informal source (i.e. a friend, relative or neighbor) and zero if seeds were obtained from a formal source (i.e. local markets, RAB or extension, or a HarvestPlus delivery approach). Certified seed from formal delivery tends to be of greater quality, providing higher yield than second-generation planting material (i.e., grain used for planting). This could make households who first received planting material from social, informal sources more likely to disadopt quickly. Alternatively, when households obtain planting material from neighbors, friends, or relatives, the variety is likely well-suited to their growing conditions, and the households can benefit from this person's experience with the variety. In this case, households whose first source of iron-biofortified beans was a social, informal one may be less likely to disadopt quickly. In addition, households that disadopted may be better able to re-access planting material if their initial planting material was from a social source, making them more likely to readopt quickly.

Variety fixed effects are included as proxy variables for differences in varietal characteristics and availability. They allow us to evaluate whether the hazard rates of adoption, disadoption, and readoption vary by variety after holding other factors constant. Finally, agro-ecological zone fixed effects are included in all models. This is to control for differences in agricultural potential.

3.5. Estimation and data limitations

Discrete duration models are estimated through maximum likelihood techniques. We use the complementary log-log model because its exponentiated model coefficients can be interpreted as hazard rates (Jenkins, 2008). We determine whether unobserved heterogeneity (i.e. unobserved managerial skills of the farmer), or frailty, influences the time to adoption, disadoption and readoption by including household random effects. If frailty is present and not accounted for, estimated coefficients β_k can be biased (Keifer, 1988). We test the null hypothesis of no unobserved heterogeneity using a likelihood ratio test.

The time dependence variable t_k enters each proportional hazard model in equation (4) through the baseline hazard model, h_{0k}, which can take different functional forms. For each model, we estimate the three most common functional forms for discrete duration analysis: log time ($\log(t_k)$), cubic polynomial function of time (t_k, t_k^2, t_k^3), and a piecewise-constant function of time, in which the variable t_k enters equation (4) as a series of dummy variables pertaining to individual growing seasons[3] (Jenkins, 2008). We identify the most appropriate functional form using the Akaike information criterion (AIC).

Standard errors are robust to heteroskedasticity and clustered at the village level. Because the sampling procedure oversampled adopters, we use sampling weights in all descriptive statistics and duration models, meaning that the findings are representative of bean producers in Rwanda.

Households enter spell T_{i2j} the season after spell T_{i1j} ends and they enter spell T_{i3j} the season after T_{i2j} ends. Because season 2015B is the last season for which we observe household adoption behavior, we are not able to estimate h_{i2j} for households who adopted that season. Likewise, we are unable to estimate h_{i3j} for households who disadopted in 2015B[4]. Furthermore, households that adopted prior to 2012B, which make up 3.5% of our sample, cannot be included in the duration analyses because they completed their transition to stage two before the start of the intensive delivery mechanisms analyzed in this study.

Our data has two limitations in estimating coefficients β_k. The first is that the adoption data is dependent on household recall and proper identification of the varieties. While varietal identification was supported with seed samples during the data collection process, households still may not accurately remember when they first began or stopped growing iron-biofortified bean varieties. However, the relatively short time frame between varietal dissemination and data collection, and the fact that most adopters adopted recently reduce the likelihood of recall bias. The second limitation is that several variables, such as asset ownership, which is part of the

[3] Disadoption (readoption) occur sparingly after several seasons of use (discontinued use). We therefore group five seasons of use and more into one category for the disadoption model and four seasons of discontinued use and more into one category for the readoption model.

[4] This could potentially bias the results if 2015B adopters (disadopters) made disadoption (readoption) decisions based on different criteria than previous adopters (disadopters), which we have no reason to believe is the case.

wealth index, and land area cultivated, are only measured in the season we collected data (2015B) while we are attempting to explain adoption behavior that occurred between 2012 and 2015. We must therefore assume that variables for which we do not have time varying information (indicated in table 2-1) did not change during this period. Fortunately, our main variables of interest, formal delivery approaches and informal dissemination, are time-varying.

4. Results

4.1. Descriptive statistics

Prior to 2012B, less than 4% of the population grew an iron-biofortified bean variety (dotted green line in figure 2-3). Adoption increased steadily after 2012B, which corresponds to the beginning of intensive delivery efforts. By 2015B, about 29% of bean producers had cultivated at least one variety in at least one season. The increase in adoption over time is consistent with the pattern of seed delivery; 101,716 kg of seed were delivered in Rwanda in 2012B compared to 540,660 kg in 2015B, with a maximum of 606,696 kg delivered in 2014B (reflected in the large increase in adoption that season).

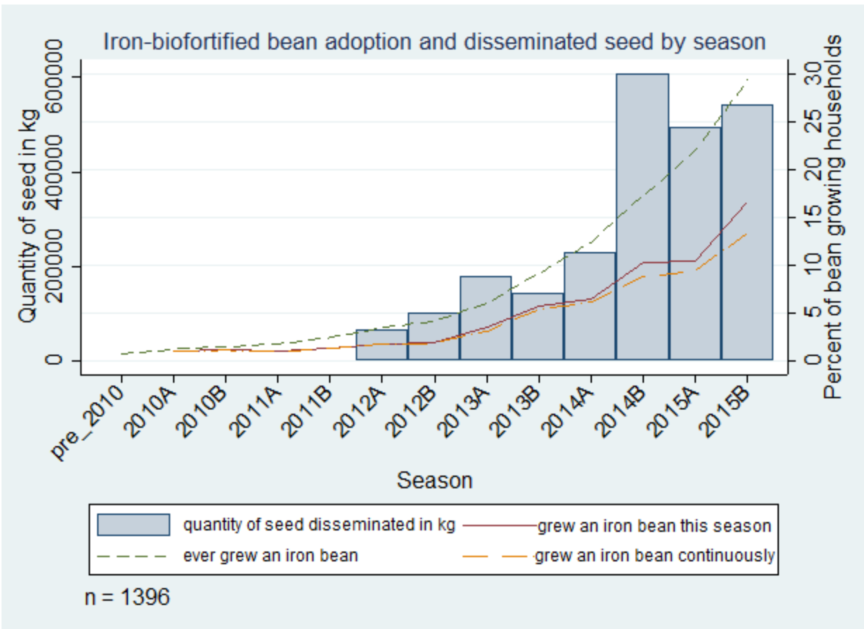


Figure 2- 3: Iron-biofortified bean adoption and disseminated seed by season

Households also disadopted iron-biofortified varieties, as exhibited by the difference between the percentage of households who ever grew a variety (dotted green line in figure 2-3) and those who grew a variety that season (solid red line in figure 2-3). In 2015B, 17% of households grew an iron-biofortified bean variety, indicating that about 12% of households had disadopted. Some households readopted iron-biofortified bean varieties, explaining the difference between current growers (solid red line in figure 2-3) and continuous growers (dashed orange line in figure 2-3). About 13% of households growing an iron-biofortified bean in 2015B had done so every season since adopting, indicating that about 4% of households had readopted.

On average, adopters devote 51% of their land under bean cultivation to iron-biofortified varieties. This value varies with the number of seasons households have grown the variety, ranging from 47% of bean land area the first season to 68% the fourth season an iron-biofortified bean is grown (figure 2-4). This pattern holds when restricting the sample to only varieties grown four or more seasons; intensity of adoption of these varieties increases from 52% of bean area planted in the first season to 68% in the fourth season, after which it fluctuates from 58% to 68%. Households thus ramp up adoption intensity over the first four seasons they grow a variety and then stabilize intensity.

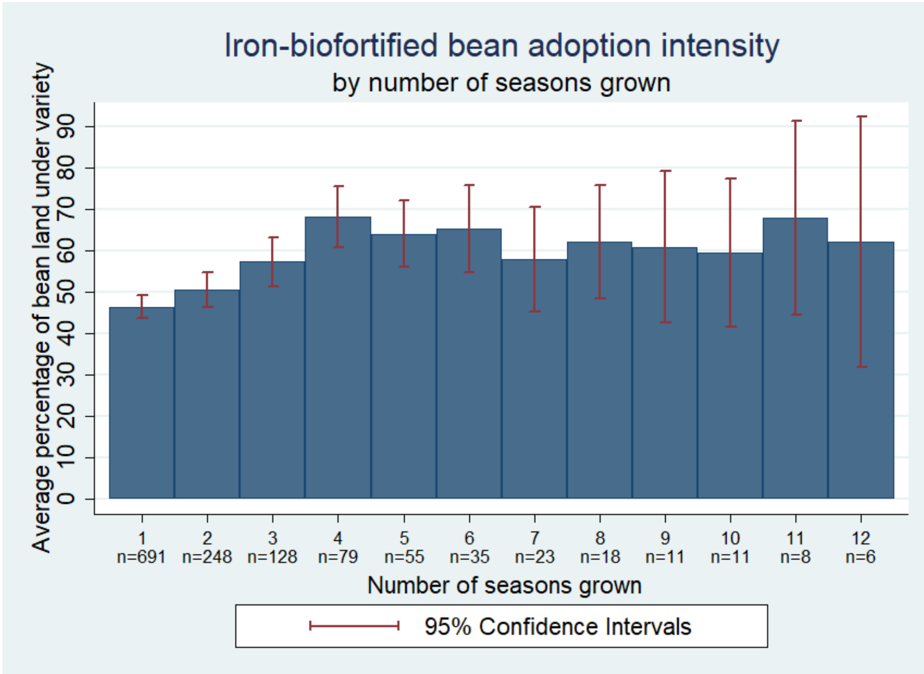
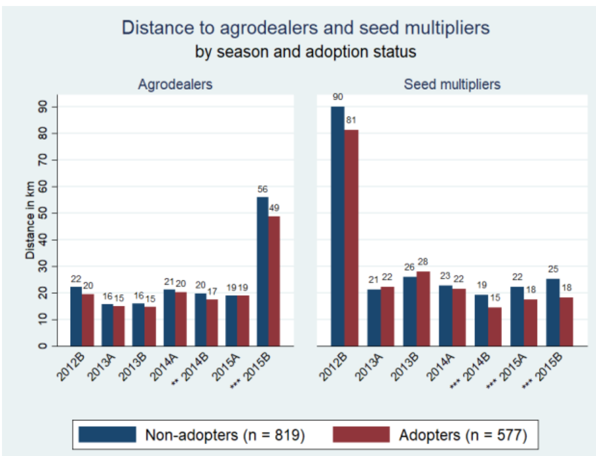


Figure 2- 4: Iron-biofortified bean adoption intensity

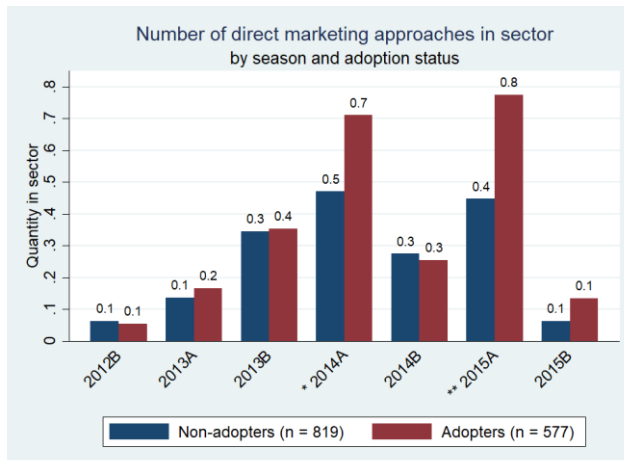
Most adopters have grown only one iron-biofortified bean variety; 14% have grown two and 1% have grown three. Of the households that grew more than one variety, 70% grew these varieties concurrently while 30% grew one, disadopted it, and subsequently grew another.

Summary statistics for delivery approaches, presented by season and adoption status, are presented in figure 5. The average distance between households and agrodealers fluctuated between 15 and 22 km from 2012B to 2015A, and more than doubled in 2015B due to a lower number of authorized agrodealers in that season (panel a). On average, adopters live closer to agrodealers than non-adopters but the difference is significant only in 2014B and 2015B. The average distance between households and seed multipliers fell sharply after 2012B, and fluctuated between 15 and 28 km afterwards (panel a). Adopters resided significantly closer than non-adopters to seed multipliers in 2014B, 2015A, and 2015B.

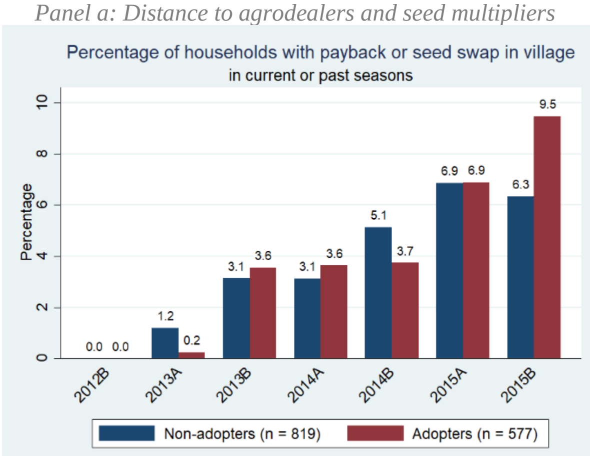
The average number of direct marketing approaches by sector increased steadily from 2012B to 2014A, fluctuated (peaking at 0.78 for adopters in 2015A and 0.47 for non-adopters in 2014A), and then fell in 2015B (panel b) due to a reduction in the efforts to promote and sell iron-biofortified seeds in local markets that season. The intensity of sales in local markets was significantly greater for adopters than non-adopters in 2014A and 2015A.



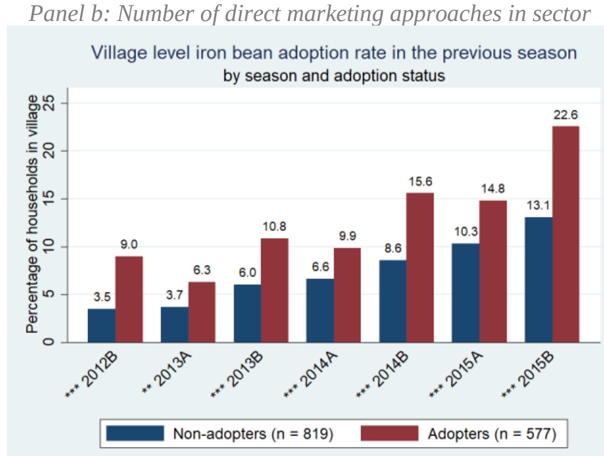
Panel a: Distance to agrodealers and seed multipliers



Panel b: Number of direct marketing approaches in sector



Panel c: Percentage of households with payback or seed swap in village



Panel d: Village level iron bean adoption rate in the previous season

Figure 2- 5: Descriptive statistics for formal and informal delivery approaches

Note: * = significance at 10%; ** = significance at 5%; *** = significance at 1%

The proportion of households living in a village where payback/seed swap took place remained below 10% each season (panel c) and did not vary significantly by adoption status. The previous-season village level adoption rate increased in each season for non-adopters, but fluctuated for adopters from 6% in 2013A to 23% in 2015B (panel d). The previous-season adoption rate in the village was significantly higher for adopters than non-adopters in every season. Summary statistics of remaining covariates are presented in table 2; adopters are defined as households who had ever grown an iron-biofortified bean variety.

Table 2- 2: Descriptive statistics for covariates of adoption, disadoption, and readoption model

Variable Name	Adopters Mean (SD) or %	Non-adopters Mean (SD) or %	Statistical significance of differences in means
gender (1 = female)	0.63 (0.48)	0.63 (0.48)	
education			
no schooling	0.23 (0.42)	0.36 (0.48)	***
some level of primary	0.66 (0.47)	0.58 (0.49)	
some secondary or more	0.10 (0.30)	0.06 (0.23)	**
bean experience (years)	25.71 (15.07)	27.90 (16.86)	*
household size	5.08 (2.07)	4.74 (2.03)	
share 0-5 years old	0.15 (0.16)	0.16 (0.18)	
share women	0.25 (0.15)	0.24 (0.16)	
wealth tercile			
1	0.30 (0.49)	0.40 (0.49)	***
2	0.31 (0.46)	0.33 (0.47)	
3	0.40 (0.49)	0.26 (0.44)	***
ag. equipment (nb)	1.34 (0.79)	1.19 (0.77)	**
cultivated land (100 m^2)	56.81 (83.44)	43.02 (72.95)	**
city distance (km)	37.96 (22.38)	36.59 (19.73)	
extension access (%)	0.68 (0.26)	0.64 (0.28)	*
social seed source (1 = yes)	0.41 (0.49)		
Number of observations	577[a]	819[a]	

Note: * = significance at 10%; ** = significance at 5%; *** = significance at 1%. Values for time-varying variables are given for 2015B.

[a] These values are the unweighted frequencies of adopters and non-adopters in the sample.

The respondent is, on average, significantly more educated among adopting than non-adopting households. Adopters are also significantly wealthier, own more agricultural equipment and cultivate more land, on average, than non-adopters. Households that adopted more than one variety (not shown in the table) have more education, are wealthier, and cultivate more land than those who adopted only one variety. Other household and village characteristics do not vary significantly between adopters and non-adopters.

4.2. Model results and discussion

Results for the adoption, disadoption, and readoption models are presented in table 2-3. Results are expressed as hazard ratios (exponentiated coefficients of the complementary log-log model). A hazard ratio greater (less) than one means that the variable makes the spell end faster (slower). Based on AIC, the piecewise-constant specification is the most appropriate to capture time dependence for the adoption and disadoption models, while the cubic polynomial time function slightly outperforms the piecewise-constant specification for the readoption model[5]. For consistency, and because coefficients change very little over the different specifications, we present the piecewise-constant baseline hazard specification for all three models. The time dummy variables in all three models represent seasons that have passed since the respective spell began; for the adoption model, these refer to the number of seasons since the beginning of intensive delivery approaches in 2012B. For the disadoption (readoption) model, the time dummy variable is the number of seasons since adoption (disadoption) and is household-specific.

We fail to reject the null hypothesis of no unobserved household heterogeneity for the adoption and disadoption models but not for the readoption model[6]. Because we cannot estimate the models with unobserved heterogeneity using sampling weights, which is important given that adopters were over-sampled, we present the results assuming no unobserved heterogeneity. To assess the effect of ignoring unobserved heterogeneity, we re-estimate the models without sampling weights, and compare the estimated coefficients with and without random effects (see tables A2-1 in the appendix).

[5] For the adoption model, AIC = 5,115,295; 5,123,593; and 5,121,468 for time dummies, log time and cubic time respectively. For the disadoption model, AIC = 610,568; 612,310; and 611,518 for dummies, log time and cubic time respectively. For the readoption model, AIC = 123,194; 136,127; and 122,967 for dummies, log time and cubic time, respectively.

[6] $\bar{\chi}^2$ = .00006 & p-value = .490 for the adoption model; $\bar{\chi}^2$ = 1.88 & p-value = .085 for the disadoption model; $\bar{\chi}^2$ = 3.84 & p-vallue = 0.027 for the readoption model. This test had to be conducted without using sampling weights. Model results with and without sampling weights are similar, so we consider the test for unobserved heterogeneity to be valid.

Table 2- 3: Complementary log-log model results for adoption, disadoption, and readoption of iron-biofortified bean varieties[7]

	Adopt		Disadopt		Readopt	
	Hazard Rate	(Robust Std. Err)	Hazard Rate	(Robust Std. Err)	Hazard Rate	(Robust Std. Err)
Time dependence (base = 2012B / one season)						
2013A / two seasons	2.655*	(1.353)	0.566*	(0.183)	0.034***	(0.037)
2013B / three seasons	4.197***	(2.077)	0.300***	(0.118)	0.140*	(0.158)
2014A / four seasons / four seasons or more	4.154***	(1.983)	0.103***	(0.060)	0.714	(0.524)
2014B / five seasons or more	6.505***	(3.414)	0.209**	(0.135)		
2015A	5.361***	(2.393)				
2015B	7.774***	(3.820)				
direct markets (# in sector)	1.208***	(0.047)	0.987	(0.034)	2.078**	(0.664)
payback (1 = in village)	0.889	(0.333)	0.385***	(0.105)	3.312	(3.484)
seed swap[a] (1 = in village)	1.566	(0.535)				
agrodealers (km)	1.003	(0.004)	1.003	(0.004)	1.028***	(0.010)
multipliers (km)	0.998	(0.004)	0.991	(0.008)	0.994	(0.017)
village adoption rate	1.029***	(0.005)	1.007	(0.006)	1.028*	(0.015)
gender (1 = female)	1.103	(0.123)	0.646**	(0.116)	0.448*	(0.188)
education (base = no education)						
some primary	1.450**	(0.226)	0.659**	(0.132)	1.017	(0.576)
some secondary or more	1.442*	(0.301)	0.333***	(0.115)	1.407	(1.551)
experience (years)	0.999	(0.004)	0.977***	(0.005)	1.020	(0.023)
household size	1.048	(0.033)	1.027	(0.041)	1.083	(0.155)
share 0-5	0.642	(0.219)	1.149	(0.510)	0.309	(0.528)
share women	1.150	(0.368)	0.801	(0.427)	3.524	(9.577)
wealth tercile (base = 1)						
2	1.028	(0.134)	1.048	(0.190)	0.800	(0.572)
3	1.277*	(0.175)	0.890	(0.204)	2.080	(1.280)
ag. equipment	1.296***	(0.121)	1.081	(0.127)	1.557*	(0.412)
cultivated land (100 m^2)	1.000	(0.001)	0.998	(0.002)	0.999	(0.003)

[7] Previous versions of these models included variables regarding livestock ownership, household membership in a farmer's association, the percentage of farmers in the village who sell beans in local markets, and a dummy variable indicating whether the household had heard the iron bean promotional song on the radio or seen the accompanying music video on television. These variables were removed due to lack of statistical significance. Removing them did not change the level of significance or magnitude of the coefficients for the delivery approach variables in the adoption or disdoption models, but increased the magnitude of the coefficient for direct marketing and reduced the size of the coefficient for previous season village adoption rate in the readoption model. When these variables were included, direct marketing was not statistically significant in the readoption model, while the adoption rate was significant at 1%. Most of these changes come from removing the variable indicating whether a household member belongs to a farmer's organization.

city distance (km)	0.998	(0.005)	1.003	(0.006)	1.029*	(0.016)
extension	1.008***	(0.002)	1.001	(0.003)	0.991	(0.010)
social source			1.113	(0.162)	0.868	(0.465)
Variety (base = RWR2245[b])						
MAC44	0.319***	(0.072)	1.364	(0.266)	0.243**	(0.166)
RWV3316[c]	0.132***	(0.038)	0.739	(0.193)	0.161	(0.186)
RWV3317	0.072***	(0.019)	0.829	(0.266)		
RWV1129	0.061***	(0.030)	0.324**	(0.171)	1.400	(1.226)
RWR2154[b]	0.031***	(0.012)	0.828	(0.277)	0.614	(0.692)
CAB2	0.045***	(0.016)	0.687	(0.213)	1.559	(1.512)
RWV2887	0.032***	(0.011)	1.322	(0.568)	0.388	(0.448)
MAC42	0.045***	(0.017)	0.666	(0.362)	0.083***	(0.073)
RWV3006	0.057***	(0.018)	1.514	(0.490)	0.008***	(0.008)
N	96197		683		333	

Note: * = significance at 10%; ** = significance at 5%; *** = significance at 1%.

[a] Seed swap had to be dropped from the disadoption and readoption models due to low overlap between villages that had seed swap, villages that were sampled, and adopters in those villages.

[b] Bush variety.

[c] RWV3317 and RWV3006 had to be combined in the readoption model because RWV3317 perfectly predicted non-readoption.

4.2.1. Adoption

The probability of adoption increases steadily over time. Compared with season 2012B, adoption is three times as likely in 2013A, over four times as likely in 2013B and 2014A, six and a half times as likely in 2014B, over five times as likely in 2015A, and nearly eight times as likely in 2015B. These results are consistent with our descriptive statistics, which show adoption increasing rapidly over time. This time-path of adoption holds even after controlling for other factors.

Both formal delivery and informal dissemination significantly increase adoption. An additional direct marketing approach in the household's sector increases the speed of adoption by 21%. An additional percentage point in the village level adoption rate, proxying for dissemination through social networks, increases the speed of adoption by about 3%. The ability to access and process information is positively correlated with adoption speed of iron-biofortified beans. An additional percentage point in the proportion of households that obtain information from extension in the village speeds adoption by about 1%. Households whose respondent has some primary or secondary education adopt about 45% faster than other households. Households in the top wealth tercile adopt 27% faster than the poorest households. Owning an additional piece of agricultural equipment increases the speed of adoption by 30%. Land area cultivated, however, is not correlated with adoption, suggesting that iron-biofortified beans are a scale-neutral technology. Finally, the speed of adoption varies significantly across varieties. All varieties are adopted more slowly than RWR2245. RWR2245 is likely the most popular at least partly because it has been the most heavily disseminated variety through the formal delivery approaches.

Table A2-1 indicates that changes to the results of the adoption model are minimal when including random effects. Therefore, we conclude that any existing unobserved heterogeneity is not significant enough to alter our main findings.

4.2.2. Disadoption

The likelihood of disadopting drops after the first season of growing an iron-biofortified variety. After two seasons of growing, the probability decreases by 57% compared to after one season (significant at 10%), and declines further in subsequent seasons. Thus, the longer households grow an iron-biofortified bean variety, the less likely they are to disadopt in each subsequent season[8].

Payback is the only delivery approach significantly correlated with disadoption of iron-biofortified bean varieties; adopters who live in a village where payback took place disadopt only

[8] Because some households grew more than one iron-biofortified bean variety, we estimated an alternative model specification in which a household that disadopted a variety but was still growing a different variety or immediately began growing a different variety was not considered a disadopter. Results for this specification were very similar to those of the disadoption model presented in table 3.

38% as quickly as households not located in such villages. While direct marketing, which reaches more households, increases the speed of initial adoption, targeting an area more intensively, which payback does, promotes more continuous adoption.

Female respondents disadopt only 65% as quickly as males. This could be due to the inclusion of women's preferences in the development of the iron-biofortified bean varieties, and indicates that such efforts are working. While this difference could also be due to differences in market-orientation and therefore profitability between men and women, our data show that men are no more likely to sell beans in general or iron-biofortified beans in particular compared to women.

Knowledge in the form of education and experience in growing beans is also correlated with a lower speed of disadoption. Households whose respondent has some primary (secondary) education disadopt 66% (33%) as quickly as households whose respondent has no education. An additional year of experience cultivating beans reduces the speed of disadopting by 2%. This supports the hypothesis that more educated and experienced farmers may be more knowledgeable about bean management practices and better able to process and incorporate new knowledge about the variety and thus, more likely to obtain yields in line with expectations and less likely to disadopt.

Disadoption is similar across varieties apart from RWV1129 which is disadopted at a significantly slower rate than RWR2245. There is evidence that disadoption occurs both because varieties do not always meet household expectations and because planting material becomes unavailable. In total, 22% of disadopted iron-biofortified beans were disadopted because planting material was no longer available (table A2-2). This indicates that one in five disadopting households would have continued to grow iron-biofortified beans if planting material were more easily available. The remaining reasons for disadoption mostly pertain to dissatisfaction with variety traits, including yield (39%), other production characteristics (12%), consumption characteristics (2%), and market characteristics (22%). The reasons for disadopting RWV1129, the only variety disadopted more slowly than RWR2245, do not vary significantly from RWR2245.

Results with and without random effects are similar (table A2-1). The most notable change is a reduction in the statistical significance of the time dependence variables, indicating that not controlling for unobservable household heterogeneity may overestimate the effect of time on the disadoption decision. For the other significant covariates, the estimated coefficients are of similar size.

4.2.3. Readoption

The probability of readopting drops dramatically after two seasons of discontinued use; a household is only 3% as likely to readopt after two seasons and 14% as likely after three seasons as it is after just one season of discontinued use. This result could reflect the seasonality of bean cultivation, where some households grow beans every other season (Asare-Marfo et al., 2016a). Households are equally likely to readopt after four or more seasons of discontinued use than they are after one season, likely due to grouping these seasons together.

Having an additional direct marketing approach in the sector more than doubles the speed of readoption, providing strong support that disadoption is partially driven by lack of available planting material. Informal dissemination is also positively correlated with readoption speed; a 1% increase in the previous-season village adoption rate increases the speed of readopting by 3%, although this is only significant at the 10% level.

Living an additional km away from an agrodealer or a city increases readoption speed by 3% (significant at 10%). This is contrary to expectations, but it may be that proximity to agrodealers or market centers makes it easier to switch varieties, reducing the likelihood households will readopt a variety they have stopped growing.

The varieties MAC44, MAC42, and RWV3317/RWV3006 are less likely to be readopted than RWR2245, given disadoption. Reasons for disadopting these varieties do not vary significantly from those cited for disadopting RWR2245.

Unobserved heterogeneity is present in our readoption model. Two differences in results between the models with and without unobserved heterogeneity are worth nothing (table A2-1). First, the impact of variety on readoption is smaller when household random effects are included. Second, we may also be underestimating the effect of agricultural equipment on readoption when not controlling for unobserved heterogeneity.

5. Conclusions and policy implications

The goals of this paper were to determine the most effective formal delivery approaches used so far in Rwanda to deliver iron-biofortified bean varieties and to assess the role of informal dissemination. Direct marketing within a sector speeds initial adoption and readoption while payback within villages (since replaced by seed swap) reduces disadoption. Policy makers should thus focus on these two approaches to improve long-term adoption of biofortified crops.

Our findings that social networks increase adoption indicate that, for biofortified crops, the positive effect of learning and obtaining planting material from neighbors outweighs potential negative effects of free-riding or strategic delay. This result is similar to that of McNiven and Gilligan (2012) who found that having other adopters of vitamin A biofortified orange sweet potato in farming households’ social networks improves their probability of adoption. This is encouraging, as informal dissemination will promote adoption, supplementing formal delivery at no cost. Policy makers should thus reach a broad area with biofortified crop dissemination rather than focus intensively on smaller areas, as informal networks will help to diffuse the crops when available.

Access to extension also plays a large role in initial adoption, indicating that either the general information provided by extension agents or their specific messaging about growing single-variety bean seeds is effective. This indicates that if policy makers continue to invest in the quality and coverage of extension services, adoption of biofortified crops will increase sustainably. Because women farmers play an important role in bean farming, are less likely to disadopt iron-biofortified bean varieties, and are less likely than men to cite agricultural extension officers as an information source (Asare-Marfo et al., 2016b), increasing women's access to extension may be particularly helpful in promoting iron-biofortified bean adoption. In fact, our results indicate that the efforts undertaken so far to make iron-biofortified beans appeal to women have been effective, as women farmers are significantly less likely to disadopt the varieties than men. We also find that, while extension increases initial adoption, it plays no role in disadoption or readoption. Thus, once a household has its own experience with an iron-biofortified bean variety, additional knowledge about the varieties from official sources will likely not alter their adoption behavior.

Results of this paper can be used to inform delivery of biofortified crops in more countries. As biofortified crops continue to be released, policy makers can learn more lessons as to how to get these beneficial varieties to the people who need them most.

Chapter 2 Appendix

A2- 1: Complementary log-log results for adoption, disadoption and readoption models with and without unobserved heterogeneity/frailty

	Adoption		Disadoption		Readoption	
	With unobserved heterogeneity	Without unobserved heterogeneity	With unobserved heterogeneity	Without unobserved heterogeneity	With unobserved heterogeneity	Without unobserved heterogeneity
	Hazard Ratio (Std. Err.)	Hazard Ratio (Std. Err.)	Hazard Ratio (Std. Err.)	Hazard Ratio (Std. Err.)	Hazard Ratio (Std. Err.)	Hazard Ratio (Std. Err.)
Time dependence (base = 2012B / one season)						
2013A / two seasons	2.914***	2.914***	0.547**	0.439***	0.050**	0.049**
	(1.204)	(1.204)	(0.152)	(0.084)	(0.062)	(0.051)
2013B / three seasons	5.136***	5.136***	0.472*	0.353***	0.123*	0.083**
	(1.981)	(1.981)	(0.185)	(0.103)	(0.153)	(0.087)
2014A / four seasons / four	5.741***	5.741***	0.274**	0.198***	2.882	0.800
seasons or more	(2.266)	(2.266)	(0.162)	(0.101)	(3.655)	(0.579)
2014B / five seasons or more	9.252***	9.252***	0.229*	0.153***		
	(3.647)	(3.646)	(0.185)	(0.110)		
2015A	10.176***	10.176***				
	(3.923)	(3.923)				
2015B	20.721***	20.720***				
	(8.258)	(8.258)				
direct markets (# in sector)	1.131***	1.131***	1.064	1.054	2.736	1.588
	(0.037)	(0.037)	(0.062)	(0.049)	(1.702)	(0.449)
payback (1 = in village)	1.194	1.194	0.638	0.677	0.628	0.905
	(0.225)	(0.225)	(0.282)	(0.241)	(1.579)	(1.127)
seed swap (1 = in village)	1.293	1.293				
	(0.450)	(0.450)				
agrodealers (km)	0.995	0.995	1.002	1.001	1.031	1.017
	(0.003)	(0.003)	(0.004)	(0.003)	(0.021)	(0.011)
multipliers (km)	1.001	1.001	0.996	0.996	0.963	0.984
	(0.004)	(0.004)	(0.007)	(0.006)	(0.029)	(0.015)
village adoption rate	1.011**	1.011**	1.009	1.009	1.075*	1.036**
	(0.004)	(0.004)	(0.007)	(0.006)	(0.040)	(0.015)
gender (1 = female)	1.153	1.153	0.632**	0.688**	0.158	0.452**
	(0.101)	(0.101)	(0.125)	(0.101)	(0.177)	(0.168)
education (base = no education)						
some primary	1.311**	1.311**	0.829	0.859	1.781	1.063
	(0.138)	(0.138)	(0.186)	(0.153)	(1.958)	(0.546)
some secondary or more	1.300	1.300	0.432**	0.507**	2.431	1.409
	(0.222)	(0.222)	(0.165)	(0.148)	(4.616)	(1.224)
experience (years)	0.997	0.997	0.985**	0.988**	1.034	1.013
	(0.003)	(0.003)	(0.007)	(0.006)	(0.034)	(0.015)
household size	1.053**	1.053**	1.006	1.017	1.085	1.063
	(0.021)	(0.021)	(0.046)	(0.038)	(0.216)	(0.106)
share 0-5	0.683	0.683	2.222	1.780	1.266	0.696
	(0.187)	(0.187)	(1.297)	(0.784)	(3.448)	(0.924)
share women	0.949	0.949	1.141	1.057	9.04	2.629
	(0.266)	(0.266)	(0.681)	(0.518)	(27.852)	(4.066)
wealth quint (base = 1)						
2	1.089	1.089	0.811	0.844	1.567	1.278
	(0.124)	(0.124)	(0.184)	(0.152)	(1.623)	(0.644)
3	1.397***	1.397***	0.842	0.871	2.284	1.607
	(0.160)	(0.160)	(0.199)	(-0.164)	(2.443)	(0.749)
ag. equipment	1.118**	1.118**	1.119	1.125	4.262**	1.864**
	(0.060)	(0.060)	(0.127)	(0.105)	(3.073)	(0.482)
cultivated land (100 m^2)	1.000	1.000	0.997**	0.996***	1.007	1.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.006)	(0.003)
city distance (km)	1.007**	1.007**	1.005	1.005	1.056	1.022

	(0.003)	(0.003)	(0.007)	(0.005)	(0.035)	(0.014)
ext. percent	1.006***	1.006***	0.996	0.996	0.978	0.996
	(0.002)	(0.002)	(0.004)	(0.003)	(0.020)	(0.009)
social source			0.800	0.835	3.284	1.540
			(0.150)	(0.128)	(3.302)	(0.647)
Variety (base = RWR2245[a])						
MAC44	0.376***	0.376***	1.194	1.177	0.053**	0.293**
	(0.041)	(0.041)	(0.267)	(0.227)	(0.079)	(0.151)
RWV3316	0.186***	0.186***	0.761	0.786	0.043	0.202
	(0.026)	(0.026)	(0.249)	(0.222)	(0.088)	(0.175)
RWV3317	0.085***	0.085***	1.314	1.228		
	(0.017)	(0.017)	(0.472)	(0.357)		
RWV1129	0.099***	0.099***	0.912	0.876	0.514	0.866
	(0.018)	(0.018)	(0.406)	(0.331)	(1.123)	(0.786)
RWR2154[a]	0.042***	0.042***	0.687	0.897	0.285	0.718
	(0.011)	(0.011)	(0.373)	(0.384)	(0.681)	(0.873)
CAB2	0.069***	0.069***	0.828	0.921	0.329	0.398
	(0.015)	(0.015)	(0.360)	(0.338)	(0.603)	(0.474)
RWV2887	0.063***	0.063***	2.079	1.706	0.363	0.714
	(0.014)	(0.014)	(1.107)	(0.681)	(0.608)	(0.594)
MAC42	0.054***	0.054***	0.481	0.542	0.004	0.088
	(0.013)	(0.013)	(0.267)	(0.265)	(0.022)	(0.196)
RWV3006	0.075***	0.075***	1.555	1.487	0.001**	0.048***
	(0.016)	(0.016)	(0.628)	(0.484)	(0.002)	(0.043)
Likelihood ratio test of rho = 0	$\bar{\chi}^2$ = .00006		$\bar{\chi}^2$ = 1.880		$\bar{\chi}^2$ = 3.84	
	p = 0.490		p = 0.085		p = 0.025	
N	96197	96197	683	683	333	333

Note: Models were estimated without using sampling weights. * = significance at 10%; ** = significance at 5%; *** = significance at 1%. RWV3317 and RWV3006 had to be combined in the readoption model because RWV3317 perfectly predicted non-readoption.

[a] Bush variety

A2- 2: Reasons for disadoption by variety

Variety	Low yield	Other production traits[a]	Consumption and storage traits[b]	Market traits[c]	Seed availability[d]	Other[e]	Don't Know	n
RWR2245	38.34%	12.10%	0.41%	7.98%	19.13%	20.50%	1.55%	129
MAC44	41.39%	11.35%	0.00%	7.83%	27.23%	11.18%	1.01%	62
RWV3316	51.18%	20.27%	1.73%	0.00%	19.04%	7.78%	0.00%	25
RWV3317	31.44%	1.23%	14.03%	3.60%	32.93%	16.77%	0.00%	20
RWV1129	39.74%	13.64%	0.00%	0.00%	15.04%	31.57%	0.00%	12
RWR2154	3.53%	42.12%	0.00%	24.74%	14.21%	15.40%	0.00%	8
CAB2	36.96%	16.02%	12.11%	7.87%	4.99%	22.04%	0.00%	15
RWV2887	50.43%	6.73%	0.00%	0.00%	40.46%	2.37%	0.00%	10
MAC42	36.17%	34.62%	0.00%	0.00%	16.16%	13.05%	0.00%	7
RWV3006	28.12%	0.00%	5.23%	0.00%	39.10%	27.55%	0.00%	15
All Varieties	38.47%	12.36%	1.94%	6.62%	22.20%	17.41%	0.99%	303

[a] Maturity period was too long/short; too many inputs required; poor drought resistance; poor flood resistance; poor pest resistance; poor disease resistance; labor intensive

[b] Taste/quality was bad; the variety was difficult to prepare/cook; when prepared, variety tasted than expected; variety had a short/bad storage life

[c] Seed was too expensive; did not fetch a good price at the market

[d] Previous season's harvest was all used; planting material no longer available in the nearby market

[e] Crop management (rotation) practice; this variety is typically not grown in this season; I did not grow beans in this season

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Chapter 3: The impact of iron-biofortified bean adoption on bean productivity, consumption, purchases and sales

1. Introduction

Throughout the world, families subsist on diets high in staple crops and low in diversity due to a lack of income to purchase or produce nutritious foods. Even when calorie intake is sufficient, staple foods are often low in vitamins and minerals, leading to micronutrient malnutrition, also known as "hidden hunger." Hidden hunger can cause numerous health problems, including blindness, anemia, and high risk pregnancy and child birth (World Health Organization, 2018). Over two billion people in the world suffer from hidden hunger, and the consequences go beyond specific health concerns (World Health Organization, 2018). Individuals who lack micronutrients can also suffer from impaired cognitive development, resulting in lower educational outcomes and productivity. Micronutrient deficiency early in life can result in a lifetime of reduced earning opportunities (Alderman et al., 2006), perpetuating poverty.

In the past few decades, crop breeding has greatly increased yields of staple crops. More recently, scientists have turned to crop breeding to develop a new intervention to address the nutritional needs of families whose diets are high in staple crops: biofortification, a process through which staple food crops are bred to be both high yielding and high in micronutrients. Over 290 biofortified varieties across 12 crops have been released or are being tested in over 60 countries (Meyer, 2018). One such biofortified crop is iron-biofortified bean, designed to combat iron deficiency, which can cause anemia, fatigue, poor pregnancy outcomes, and other adverse health effects (World Health Organization, 2018). Randomized control trials have established that consumption of iron-biofortified crops reduces iron deficiency and improves functional outcomes (De Moura et al., 2014; Finkelstein et al., 2017; Luna et al., 2015; Murray-Kolb et al., 2017). Iron-deficient women in Rwanda who consumed iron-biofortified bean varieties instead of non-biofortified varieties for 18 weeks experienced improved memory (Murray-Kolb et al., 2017) and less time spent sedentary (Luna et al., 2015).

Biofortification is most cost-effective at addressing hidden hunger when micronutrient deficiencies of the poor can be addressed by foods they commonly produce and consume (Meenakshi et al., 2007). For this reason, Rwanda was selected as the first country for the release of iron-biofortified beans. Rwanda is a small country that has a high population density and heavy reliance on agriculture and where beans make up 32% of calories and 64% of protein for the average household (Mulambu et al., 2017). Rwanda has two cropping seasons per year; the first (season A) lasts September to January, and the second (season B), lasts February to August. Most farmers produce beans in both seasons (Asare-Marfo et al., 2016a).

In collaboration with the International Center for Tropical Agriculture and HarvestPlus, the Rwanda Agricultural Board released four iron-biofortified bean varieties in 2010 and six more in 2012. These varieties have approximately twice the iron content of non-biofortified varieties, are adapted to local conditions, high-yielding, and resistant to common pests and diseases. They have a wide range of colors, sizes, and agronomic and consumption characteristics to appeal to bean producers and consumers throughout the country. Two of the released varieties are bush bean varieties with potential yields of 2-2.5 t/ha (Katsvairo, 2014). The remaining eight varieties are climbing bean varieties that can yield between 3 and 4.5 t/ha but require additional inputs, including stakes and a higher rate of fertilizer application, to achieve these high yield potentials (Katsvairo, 2014). Climbing varieties tend to be most popular in the North of the country, which is characterized by higher elevations, greater land scarcity, more rainfall, and cooler temperatures.

Since 2012, HarvestPlus and its partners have promoted and distributed iron-biofortified bean planting material to small landholders in Rwanda through several approaches, resulting in fast and sustained adoption of the varieties (Vaiknoras et al., 2017). The approach that has reached the greatest number of farmers is direct marketing, which consists of selling small packets (ranging from 200 to 500 g) of iron-biofortified bean seed to farming households in local markets. By the end of 2015, over a quarter of a million households accessed iron-biofortified seed through this mechanism (Mulambu et al., 2017). Other mechanisms used to distribute iron-biofortified seed include seed swap and payback. Under the seed swap approach, individual farmers and cooperatives receive iron-biofortified seed in exchange for seed of other bean varieties while in the payback system a portion of harvested iron-biofortified grain is given back to HarvestPlus and its collaborators. Agrodealers also sell iron-biofortified seed in shops. Finally, iron-biofortified planting material spreads through informal dissemination via social networks (Vaiknoras et al., 2017).

As a result of both formal delivery and informal dissemination, iron-biofortified bean varieties are widely adopted in Rwanda; approximately 28% of rural households grew a variety for at least one season between 2012 and 2015 (Asare-Marfo et al., 2016b). The most popular iron-biofortified bean variety in Rwanda is RWR2245, a bush variety planted by over half of all adopters. RWR2245 has also been the most widely disseminated variety; in most seasons, over 70% of iron-biofortified bean planting material delivered via formal approaches was RWR2245. The other iron-biofortified bush bean variety, RWR2154, has been planted by about 2% of adopters; the remaining adopters have grown one or more of the eight climbing varieties (Asare-Marfo et al., 2016b).

While the nutritional and health benefits of consuming biofortified crops are well-established (De Moura et al., 2014), the literature on biofortified crops has not yet widely explored the impacts of adoption on earlier links along the impact pathway, such as on yield, consumption, and sales of the targeted crop. Nsengiyumva et al. (2017), using propensity score matching (PSM), find that adoption of RWR2245 in Nyagatare district, Eastern Province of Rwanda, increases household bean yield by 367-810 kg/ha, providing evidence of the benefits of RWR2245 adoption. However, more research is needed that measures the impact of adoption on a wider range of indicators and throughout the entire country, and that takes into account the endogeneity of the adoption decision.

Our paper fills this gap in the literature by using nationally representative rural household data to quantify the impacts of RWR2245 adoption on first- and higher-order outcomes. The specific objectives of this study are to measure the impact on yield, which is the first-order effect of adoption, and to identify the impacts on higher-order outcomes that arise from adoption through higher yield. Higher-order outcomes considered are changes in land area under bean cultivation, bean consumption from own production and purchases, bean sales, and the likelihood of being a net seller of beans. We use a control function approach (CFA) which makes use of instrumental variables (IVs), constructed from rollout data of promotion of iron-biofortified planting material in local markets and informal dissemination to identify the causal effects of adoption. Direct marketing is strongly correlated with adoption but should not be correlated with our outcomes of interest, as the rollout was not related to the bean production, consumption, or marketing characteristics of local communities. Informal dissemination, captured using the previous-season village adoption rate for RWR2245, increases the likelihood of adoption by increasing the quantity of planting material within one's social network, but should otherwise be exogenous to the outcomes of interest.

There are many impact pathways through which agricultural interventions can improve nutrition (Webb, 2013). Two commonly identified pathways are improvements in nutrition through (1) increased consumption of own produced food, particularly if that food is highly nutritious; and (2) increased household incomes via sales of own produced food, which can be spent on healthy foods, such as animal-source proteins, or other health-related goods (Pandey et al., 2016; Webb, 2013). In our impact-pathway framework, adapted from Pandey et al. (2016), adoption of RWR2245 affects households initially through higher bean productivity (figure 3-1). Assuming that households do not change the proportion of land devoted to bean production, which we will test, adoption, as a result of higher yield, should result in greater quantity of beans harvested. Households may choose to consume all or a fraction of this additional harvest, improving nutrition through pathway (1) and/or sell some or all the extra production, contributing to better nutrition via pathway (2).

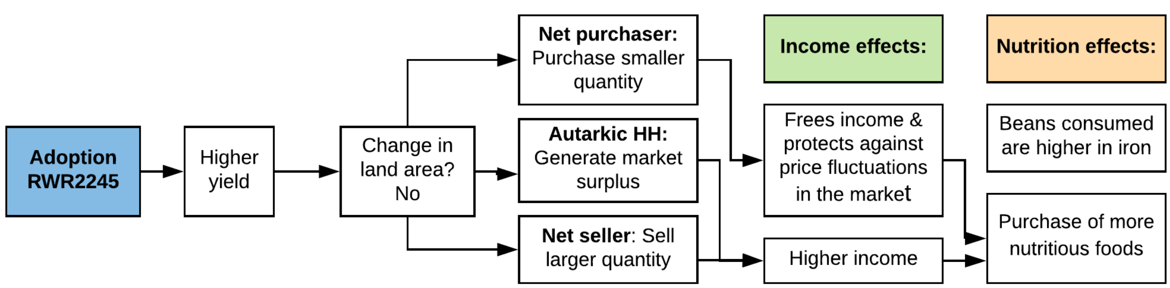

Figure 3- 1: Impact pathway of RWR2245 adoption

Consumption from own production among adopters will improve nutrition all else held equal, as harvested bean grain is higher in iron, meaning that iron intake is higher than it would have been in the absence of adoption. The increased production among net buyers of beans should reduce the quantity of beans purchased to meet household consumption needs, increasing the income available to spend on other goods and improving self-sufficiency in bean production. Food self-sufficiency can protect households against price fluctuations in the market and is often used as a proxy for, or a component of, food security (Noromiarilanto et al., 2016; Rufino et al., 2013; Traore et al., 2017). The more abundant harvest may induce autarkic households, i.e. those that neither purchase nor sell beans, to begin selling beans and become net sellers of beans while the greater harvest can increase the quantity sold among current net sellers. Increased sales have the potential to improve household income, particularly in Rwanda's context of high rates of bean production and consumption.

Findings from this study will inform the development of future programs promoting biofortification, better position decision makers to justify funding for biofortification, and potentially guide the allocation of resources towards programs with the greatest impacts. Rigorously quantifying the yield gain from adoption enhances the identification of the higher-order outcomes that stem from higher productivity. It also informs development practitioners, researchers, and policy makers of the yield achieved under farmer specific conditions. The distributional benefits of biofortified crops depend on their harvest usage. If adopters consume most of their biofortified harvest, we expect that benefits will mainly accrue to adopters themselves, indicating that policy makers should target promotion of the crops to households with high nutritional needs, such as those with young children. By contrast, if adopters sell most of their biofortified harvests, then the nutritional benefits will spread to households who purchase grain from adopters; thus, policy makers should target households with large landholdings and bean production.

The next section describes our data and is followed by an explanation of our identification strategy, including our empirical framework, variables, estimation techniques, and descriptive statistics. We then discuss the results of the econometric analyses and conclude with policy implications that emerge from our findings.

2. Data and Empirical Specification

2.1. Data source

This study uses nationally representative data of bean producers in Rwanda collected in two stages. The first stage was a listing exercise that occurred in May and June 2015, which corresponds to mid-season 2015B. One hundred twenty villages were randomly selected and all households in the selected villages were interviewed, totaling 19,575 households, regarding iron-biofortified bean adoption histories from seasons 2010A to 2015B. To assist respondents in accurately identifying iron-biofortified beans, enumerators showed them a seed sample of the ten varieties, one at the time. They asked respondents if they had ever seen or heard of the variety, if they had ever grown it and if so, which cropping season they had first adopted the variety, and then whether the respondents had grown the variety in each subsequent season. Further questions were asked to verify that the household correctly identified the variety, including the color and bean type (i.e. bush or climbing) of the variety.

Twelve households in each village (six iron-biofortified bean adopters and six non-adopters, when possible) were re-interviewed for the main household survey, which took place in September 2015, after season 2015B harvest. The respondents were the household members who were most knowledgeable about bean cultivation in the household. Enumerators collected the following information for all bean varieties grown during season 2015B: whether it was an iron-biofortified, improved (but not biofortified), or local/traditional variety, the quantity of seed planted, and the quantity of grain harvested. For each bean plot cultivated that season, the respondent reported the size, distance from their home, input usage, and identified the household member responsible for making cropping decisions for the plot. Respondents reported the months, out of the last 12 months, that the household consumed beans from own production, the months that they purchased beans for home consumption, and the average monthly quantities consumed when beans were sourced from the farm and the market. They also reported the total quantity of beans sold in the last 12 months. Finally, the survey elicited information on household demographics, housing characteristics, and asset ownership.

In addition, we use data from a community survey and HarvestPlus delivery records for direct marketing. For the community survey, key informants were interviewed, including the village leader, regarding village characteristics, such as access to extension and the presence of iron-biofortification delivery activities. We use direct marketing delivery records to compute the number of locations where direct marketing occurred in each sector (an administrative unit between village and district) for seasons 2015A and 2015B.

After dropping observations with missing information, outliers, and likely misclassified bean varieties, the sample includes 1,383 households. Because we want to measure the impacts of RWR2245 adoption, which is a bush bean variety, we restrict our sample to households that grew at least one bush bean variety in season 2015B[9]. The characteristics of households that grew only climbing beans are expected to vary significantly from those of bush bean growers as climbing beans are more popular in the North of the country where land scarcity and poverty are more prevalent than in the remaining of the country. Moreover, management practices and yield potential differ between bush and climbing beans. Therefore, the analyses in this paper are based

[9] This is the only season for which we have complete information on all bean varieties the households grew.

on 815 bush bean growing households and 1,112 bush bean varieties, as some households cultivated more than one bush bean variety in season 2015B.

2.2. Empirical Framework

We estimate the impacts of adoption on yield, a first-order effect of adoption, for household *i* and bush bean variety *j* using the following reduced-form equation:

$$M_{ij} = D_0 + \boldsymbol{D_1} T_{ij} + \mathbf{D_2}\boldsymbol{I_{ij}} + \mathbf{D_3}\boldsymbol{H_i} + e_{ij} \qquad (1)$$

The dependent variable in this equation is the multiplication ratio M_{ij}, which we use as a proxy for yield. The multiplication ratio is the quantity of bush bean grain harvested by household *i* for variety *j* divided by the quantity of seeds planted for that variety and household. We use the multiplication ratio instead of yield because we expect the former to provide a more accurate measure of bean productivity. This is because estimates of plot areas are more prone to measurement errors than quantity planted and harvested, especially in Rwanda where plots are often of irregular shape and intercropped. We expect RWR2245 to provide a higher multiplication ratio than local bush varieties, but a similar one to other improved varieties. Thus, the treatment variable T_{ij} is a categorical variable equal to 0 if variety *j* is a local bush variety, 1 if it is an improved bush variety other than RWR2245, and 2 if variety *j* is RWR2245.

We control for agricultural inputs used in the cultivation of variety *j* and plot characteristics on which variety *j* is grown; these covariates enter the vector $\boldsymbol{I_{ij}}$ in equation (1). Household-level variables that could influence productivity and potentially be correlated with adoption of RWR2245 also enter the regression and are represented by the vector $\boldsymbol{H_i}$. Covariates capturing input usage and plot characteristics are whether organic fertilizer was applied, whether chemical fertilizer was applied, the source of planting material (i.e. whether the planting material is from recycled grains, local markets, farmer groups, or HarvestPlus delivery approaches), the slope of the plot (flat, gentle, moderate, or steep), whether the plot was intercropped, and the distance from the plot to the household (in minutes walking). The vector $\boldsymbol{I_i}$ also includes the sex, literacy, and years of experience growing beans of the household member who makes planting decisions for the plot on which variety *j* was grown since the decision maker about bean production activities varies across plots for household *i*. The household-level covariates that do not vary within a household (i.e. those included in vector $\boldsymbol{H_i}$) are dwelling elevation, the number of adults in the household as a proxy for farm labor availability, the number of pieces of agricultural equipment owned, and the percentage of households in the village who obtain advice from agricultural extension agents, which captures access to extension and is measured at the village level to avoid endogeneity. Last, we also include province fixed effects to control for differences in agricultural potential, infrastructure, etc. between provinces.

We estimate the impact of RWR2245 adoption on the higher-order outcomes using the following equation:

$$\boldsymbol{O_i} = f(A_i, \boldsymbol{H_i}, \boldsymbol{D}) + e_i \tag{2}$$

where the dependent variable $\boldsymbol{O_i}$ is the outcome of interest for household *i*, A_i is the treatment variable, and $\boldsymbol{H_i}$ is a vector of exogenous variables. The vector $\boldsymbol{O_i}$ includes eight dependent variables capturing land under bean production, bean consumption from own production, bean consumption from purchases, and bean sales. We use the quantity of seed planted in kg as proxy for land area under bean production since it is less prone to measurement errors than household estimates of land sizes[10]. We measure bean consumption from *own production* using two variables: i) the number of months in the past 12 months prior to data collection that household *i* consumed beans from own production and ii) the average monthly

[10] Planting density is similar between different bush bean varieties.

quantity of beans consumed from own production, measured in kg per adult male equivalent[11], during the months beans were sourced from own production. Adult male equivalents are used to approximate the food requirements of the household based on the proportional energy requirements of household members of different gender and age compared to an adult male, which is the standard reference (Dary and Hainsworth, 2008). Taking into account the food requirements of different household members provides a more accurate indicator of household food consumption adequacy than a simpler per-capita measure. Likewise, bean consumption *from purchases* are captured using: i) the number of months, in the 12 months prior to data collection, that the household purchased beans for consumption and ii) the average quantity purchased per adult equivalent, in kg, during the months beans were consumed from the market. Indicators representing bean sales are: i) whether household *i* sells beans, ii) the quantity of beans sold in the past 12 months, in kg, and iii) whether household *i* is a net seller of beans, which is determined by comparing total bean purchases with total bean sales in the past 12 months. Household *i* is a net seller if total sales exceeded total purchases.

The treatment variable in equation (2) is A_i, a binary treatment variable that measures adoption and varies by dependent variable. When the dependent variable is land devoted to bean production, A_i is equal to one if household *i* grew RWR2245 in season 2015B and zero otherwise. For the remaining outcomes of interest, A_i is equal to one if household *i* grew RWR2245 in season 2015A only, in season 2015B only, or in both seasons 2015A and 2015B and zero otherwise. This approach is used for consistency between the treatment variable and the

[11] Adult male equivalents are calculated based on a scale obtained by USAID Dary, O., Hainsworth, M., 2008. The Food Fortification Formulator: Technical Determination of Fortification Levels and Standards for Mass Fortification. USAID, Washington, DC.

outcomes of interest. The outcomes of interest related to bean consumption and sales cover the 12-month period prior to data collection, which spanned over seasons 2015A and 2015B, so the treatment variable A_i takes into account the adoption decision in both seasons. We have no expectation a priori of the effect of adoption on land devoted to bean cultivation. Households may wish to increase land under bean cultivation to further take advantage of higher yields, or may instead reduce land under bean to devote more land to other crops. We hypothesize that adoption, through higher yield, will increase bean consumption from own production while reducing consumption of purchased beans by increasing (decreasing) the number of months households consume beans from own production (purchases) or/and increasing (decreasing) the average monthly quantity the household consumes from own production (purchases). Last, we expect adoption to increase the probability that a household sells beans, quantity sold, and the probability of being a net seller of beans due to RWR2245's higher yield compared to local varieties.

We control for household-level covariates, which are represented by the vector $\boldsymbol{H_i}$ in equation (2), that could affect the higher-order outcomes of interest $\boldsymbol{O_i}$. These variables include distance to the nearest city of 50,000 people (in km) and population density (in inhabitants/square km) as proxies for proximity to markets, elevation (in meters), the number of household members, the sex, literacy and age of the respondent, land area cultivated in 2015B (in hectares), a wealth index[12] created using polychoric principal components analysis, the number of pieces of agricultural equipment owned, livestock ownership measured in tropical livestock

[12] This included asset ownership (motorcycle/scooter, bicycle, cell phone, radio, and television) and housing characteristics (glass windows, access to electricity, outer wall material) and source of drinking water.

units[13], and access to extension by households in the village. Moreover, we control for whether household *i* grew climbing beans in 2015B as climbing beans have higher yields on average than bush beans and could thus impact bean production, consumption, and sales (Katungi et al, 2018). Finally, we include province fixed effects as in the yield regression.

There may be household or variety-level factors that are correlated with adoption and the outcomes of interest in equations (1) and (2) that are not controlled for, such as unobserved farmer ability or access to resources. As a result, the adoption variables would be correlated with the error terms, e_{ij} and e_i, causing the treatment effect estimates to be biased. To address this problem, we use a CFA.

2.3. Estimation Strategies

We use a CFA to address the endogeneity of adoption as this is more efficient than two-stage least squares (2SLS) when the endogenous variable is non-linear, and is valid for models that are nonlinear in parameters (Imbens and Wooldridge, 2007). A CFA is a two-stage procedure that tests and controls for endogeneity. In the first stage, the treatment variable is regressed on a set of explanatory variables and IVs. The generalized residuals from this regression are collected. In the second stage, the outcome variable is regressed on the treatment variable, other explanatory variables, and the generalized residuals from the first stage regression. A t-test of the coefficient on the generalized residuals tests the null hypothesis that the treatment is exogenous (Wooldridge, 2014). A CFA can thus provide additional evidence beyond the Hausman test as to whether adoption is endogenous to our outcomes of interest and if so, allow us to estimate causal effects of adoption by controlling for its endogeneity. When the adoption variable is categorical (Besamusca et al.), we estimate an ordered Probit model in the

[13] 1 cow = 0.5; 1 sheep = 0.1; 1 goat = 0.1; 1 pig = 0.2; 1 chicken = 0.01; 1 rabbit = 0.02.

first stage. When adoption is measured using a binary indicator (A_i), the first stage regression is estimated using a Probit model.

The second stage estimation methods vary depending on the form of the dependent outcome variable. When the dependent variable is continuous, as it is for the multiplication ratio, quantity of bean seeds planted, and average quantity of beans consumed per month when beans are sourced from own production and purchases, we use ordinary least squares (Kolstad) in the second stage. We assume a log-linear function because the distribution of these outcomes is highly skewed to the right.

For quantity sold, we estimate a double hurdle model, also called Craggit (Burke, 2009), in the second stage because bean sales are censored, with a large number of observations at zero. Since factors that affect the decision to sell beans may differ from those that influence quantity sold, it is appropriate to model these two processes separately. The double hurdle model consists of estimating a probit model in the first stage and a truncated normal regression in the second stage. Combining the first and second stage estimates, we calculate the average partial effect of adoption on quantity of beans sold (Burke, 2009). Unlike the Tobit model, the double hurdle model does not require the explanatory variables to have the same effect on the decision to sell beans and the quantity sold. We test the double hurdle model against the Tobit model to determine which model fits the data best.

When the dependent variable is the number of months beans were consumed from own production, we estimate a Poisson model. For the number of months beans were purchased, we estimate a zero-inflated Poisson model because some households did not purchase beans over the past 12 months. Similar to the double hurdle model, the zero-inflated Poisson model allows the decision to purchase beans to be modeled separately from the number of months beans are purchased. We test whether the zero-inflated Poisson model or the standard Poisson model fit the data better using a Vuong test. Finally, for the decision to sell beans and whether the household is a net seller, we estimate Probit models as these are binary outcomes.

Standard errors are robust to heteroscedasticity and clustered at the household level when the dependent variable is the multiplication ratio since several households cultivate more than one bush bean variety, resulting in more than one observation per household. For the other models, standard errors are also robust to heteroscedasticity but clustered at the village level. Because iron-biofortified bean adopters were oversampled during data collection, we use sampling weights in all descriptive and econometric analyses.

2.4. Instrumental Variables

CFA requires the inclusion of IVs in the first stage regression. A relevant and valid IV is one that is correlated with the treatment variable and uncorrelated with the outcome of interest (Wooldridge, 2010). We use two IVs. The first one is the number of locations where HarvestPlus sold iron-biofortified bean seeds in local markets in a household's sector during seasons 2015A and 2015B. Direct marketing is highly correlated with adoption of biofortified bean varieties (Vaiknoras et al., 2017). The locations of the direct markets selected for the promotion and sale of iron-biofortified seed were chosen independently of bean productivity, consumption, purchases, and sales of local households, which also makes direct marketing exogenous to our outcomes of interest.

Our second IV is the village adoption rate for RWR2245 in the season prior to the one the outcome variables are measured. This is a proxy for the availability of RWR2245 planting material within a household's social network. The previous season village adoption rate strongly correlates with current season adoption (Vaiknoras et al., 2017) and is exogenous to an individual household's yields, consumption, purchases, and sales in the current season as it is based on other farmers' previous adoption decisions. Like the treatment variable, the seasons considered when measuring village adoption rate vary by dependent variable. When the dependent variables are yield and land under bean production, we use the village adoption rate for RWR2245 in season 2015A because in these regressions adoption is defined as growing RWR2245 in 2015B. For the remaining dependent variables, the IV is the village adoption rate for RWR2245 in season 2014B because adoption is defined over 2015A and 2015B. We test the validity of the IVs using a series of diagnostic tests for 2SLS regressions (Baum et al., 2002).

2.5. Robustness checks

To test the validity of our results, we implement several robustness checks. We use PSM to evaluate the treatment effect of adoption on first- and higher-order outcomes. For the multiplication ratio, we first estimate a logit model to evaluate the propensity score, or the probability that variety *j* will be RWR2245, based on observable characteristics in $\boldsymbol{I_{ij}}$ and $\boldsymbol{H_i}$. Then propensity scores are used to match multiplication ratios for RWR2245 and local bush bean varieties that are "similar, i.e. have propensity scores that are close to one another. We compare RWR2245 only to local bush varieties because we are primarily interested in the yield gain of RWR2245 over local varieties rather than other improved varieties. For the higher-order outcomes, we compute the propensity score of a household being an RWR2245 adopter and compare the outcomes of adopting and non-adopting households that have similar propensity scores. The final step is to estimate whether these similar varieties (households) have systematically different outcome values (Austin, 2011).

There are several ways to match control and treatment observations when doing PSM. As a sensitivity check, we use three common algorithms for matching: nearest neighbor matching, radius matching, and kernel matching (Caliendo and Kopeinig, 2005). We set a caliper requirement that matches must have propensity scores that do not differ by more than 0.01. We use the observations in the common support, which is the area where propensity scores between the treatment and comparison groups overlaps, in order to improve matching (Caliendo and Kopeinig, 2005).

PSM only explicitly controls for overt bias, meaning that if hidden bias (based on unobserved characteristics) is present, results will be biased. An advantage of PSM is that it requires fewer functional form assumptions about the relationship between the outcomes of interest and explanatory variables, which is why we use it to assess the robustness of our results. To assess how well PSM controls for overt bias, the balance of matched observations must be examined as this provides evidence of how comparable the treatment and control groups are post-matching. One way to do this is to compute the standardized bias, which quantifies the balance. Harder et al. (2010) consider a covariate to be balanced if its standardized bias is less than 0.25, although they recommend using a stricter cut-off of 0.10 when possible, particularly for covariates that are highly correlated with the outcome variable to ensure that the treatment and control groups are comparable and matching estimates are unbiased[14].

For the multiplication ratio regression, we also estimate a fixed effects (FE) model using a sub-sample of households who grew RWR2245 and at least one other bush bean variety in 2015B. Reducing the sample to partial adopters and using fixed effects eliminates household-level unobserved heterogeneity, which provides a robustness check for the effects of RWR2245 adoption on productivity. The FE estimator only considers within-household variation and, when

[14] We use the user-written Stata commands psmatch2 and pstest to perform PSM and assess post-balance matching, respectively Leuven, E., Sianesi, B., 2003. PSMATCH2: Stata module to perform full Mahalanobis and propensity score matching, common support graphing, and covariate imbalance testing:.

estimating the effect of growing RWR2245 over a local bush variety, only takes into account those households that grew both.

Finally, for a subset of outcome variables, i.e. the number of months beans consumed were from own production and purchased in the market, whether the household sells beans, and whether it is a net seller, we evaluate the sensitivity of the findings to different measures of adoption. The alternative measures for adoption are: i) a variable that takes the value of 0, 1, or 2 to reflect the number of seasons in 2015 that a household grew RWR2245, ii) a dummy variable equal to one if a household adopted RWR2245 in both 2015A and 2015B, iii) a count variable for the total number of seasons a household has grown RWR2245, conditional on having grown RWR2245 in 2015, iv) the average percentage of bean land area under RWR2245 between 2015A and 2015B, v) the sum of RWR2245 seeds planted (in kg) in 2015A and 2015B, and vi) a dummy variable equal to one if a household adopted RWR2245 in any season prior to 2015A but did not cultivate RWR2245 in 2015. For the last estimation, we expect the adoption variable to be either insignificant or have a smaller coefficient than variables measuring adoption in 2015 since adoption in prior seasons should not directly affect bean production in 2015.

2.6. Descriptive Statistics

2.6.1. Adoption measures

About 13% of the 1,112 bush bean varieties planted by bush bean growers in 2015B are RWR2245, 68% are local bush varieties, and 19% are other improved bush varieties, including the other iron-biofortified bush variety, RWR2154, which makes up less than 1% of the observations (figure 3-2). Among the 21% of bush bean growers who cultivated RWR2245 in 2015, 4% cultivated RWR2245 in 2015A only, 11% in 2015B only, and 6% in both seasons (figure 3-3). More than half of the adopters planted RWR2245 for the first time in 2015. Nine percent of households not growing RWR2245 in 2015 had grown the variety in a previous season. Adoption of RWR2245 varies greatly by province; in 2015, 25% of bush bean growing households in the East cultivated RWR2245 compared to 22% in the South, 15% in Kigali, 9% in the West, and 8% in the North.

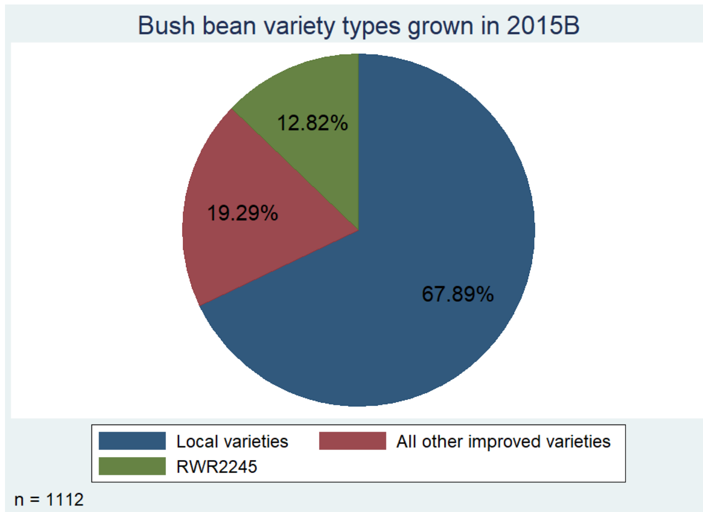

Figure 3- 2: Bean variety types grown in 2015B

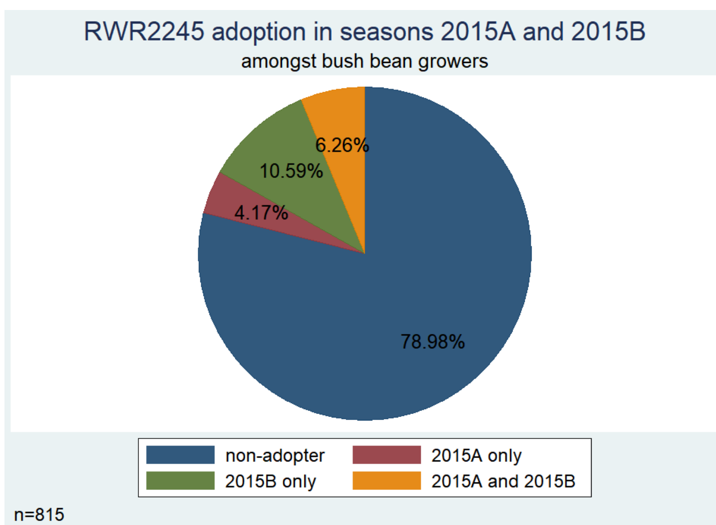

Figure 3- 3: RWR2245 adoption by household in 2015

2.6.2. Outcome variables

The average multiplication ratio is 8.25 for RWR2245, 8.26 for other improved bush bean varieties, and 6.74 for local bush bean varieties (figure 3-4). The average multiplication ratio for

RWR2245 and other improved varieties is significantly higher than that of local varieties. The multiplication ratio for RWR2245 increases with experience growing the variety: the average multiplication ratio for first-time adopters is 7.22 compared to 9.15 for those having grown the variety for more than one season, a difference that is significant at the 10% level. Adopters of RWR2245 planted 16.32 kg of seeds in 2015B while non-adopters planted 14.14 kg (figure 3-5), suggesting that adopters have more land planted to beans.

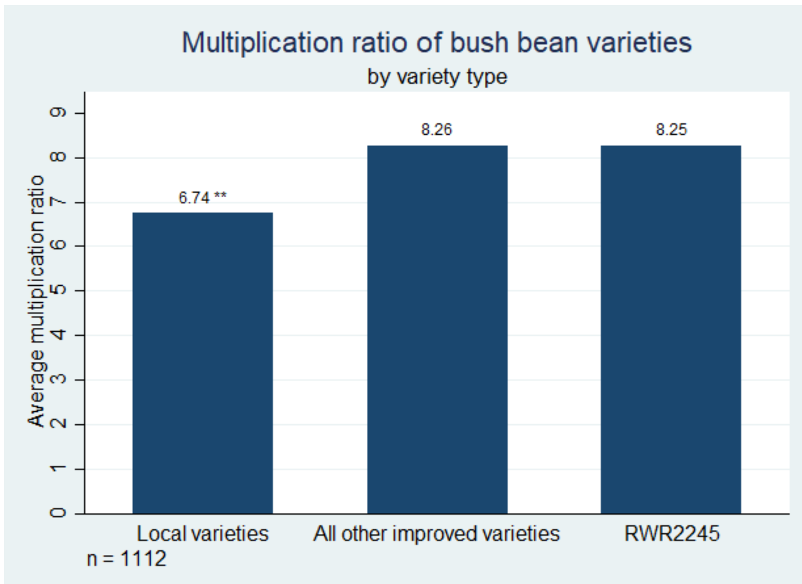

Figure 3- 4: Average multiplication ratio of bush varieties

Note: * = significance at 10%; ** = significance at 5%; *** = significance at 1%

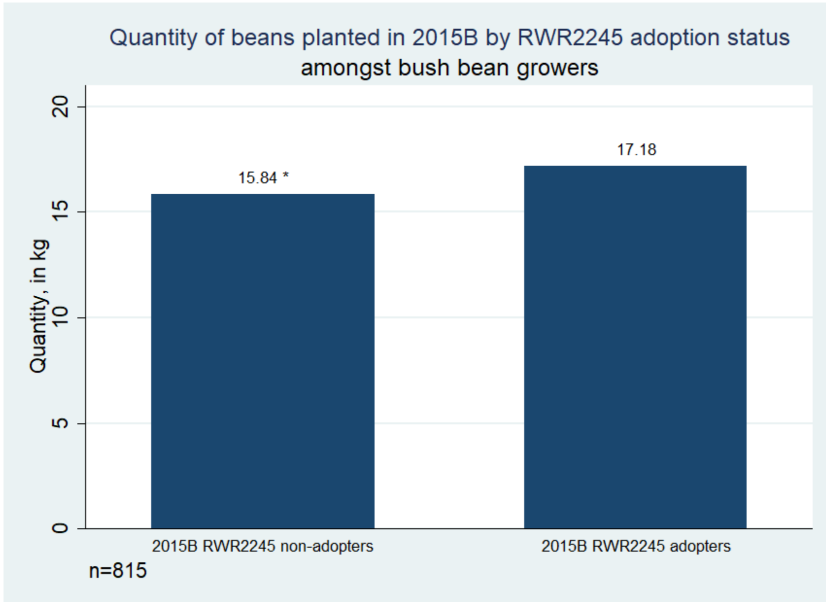

Figure 3- 5: Quantity of beans planted in 2015B

Note: * = significance at 10%; ** = significance at 5%; *** = significance at 1%

Households that grew RWR2245 in at least one season in 2015 consumed beans from own production for 8.59 months on average in the past 12 months, which is 1.3 months (about 40 days) more than non-adopters did (significant at 5%). RWR2245 adopters purchased beans for about 1.3 months fewer than non-adopters (table 3-1). However, the average quantities consumed per month did not vary by adoption status. RWR2245 adopters were more likely to sell beans, sold greater quantities, and were more likely to be net sellers than households that did not grow RWR2245 in 2015.

Figure 3-6 shows bean consumption trends by month and adoption status from September 2014 to August 2015. Consumption from own production is greatest in January and February, following season A, and in June and July, which follows season B (Asare-Marfo et al., 2016b). From March to May and October to November, which are a few months after seasons A and B harvest, respectively, a greater percentage of adopters consume beans from home production compared to non-adopters.

Table 3- 1: Descriptive statistics for outcome variables

Variable	2015 RWR2245 adopters	2015 RWR2245 non-adopters
No. of months bean consumed are from own production **	8.58 (3.31)	7.55 (3.33)
No. of months bean consumed are from purchased ***	2.78 (2.99)	3.80 (3.29)
Average quantity consumed per month when beans are from own production (in kg)	4.07 (2.29)	3.94 (2.25)
Average quantity consumed per month when beans are purchased (in kg)	3.04 (1.81)	3.34 (2.53)
Household sold beans (1 = yes) ***	0.63 (0.48)	0.45 (0.50)
Total quantity sold, last 12 months (in kg) ***	67.91 (112.34)	37.61 (87.02)
Total quantity sold, last 12 months (in kg), conditional on selling beans [a]	108.37 (125.63)	83.55 (114.06)
Net seller (1 = yes) ***	0.55 (0.50)	0.41 (0.49)
N	243	572

Note: * = significance at 10%; ** = significance at 5%; *** = significance at 1% of differences in means.

[a] n = 140 adopters, 244 non-adopters

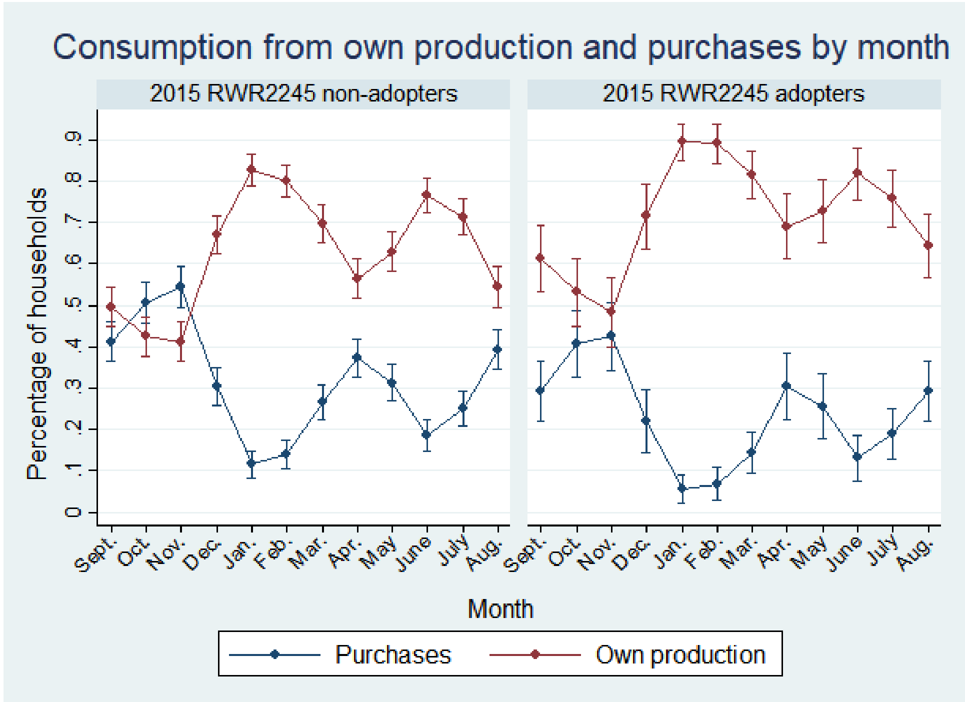

Figure 3- 6: Consumption and purchases of beans by bush bean growers, by month and RWR2245 adoption status

2.6.3. Explanatory and Instrumental Variables

RWR2245 is less likely to be grown from recycled planting material and more likely to be grown using organic and chemical fertilizer than local bush bean varieties (table 3-2). Households who grew RWR2245 in either season of 2015 were less likely to have grown a climbing bean variety in 2015B than those that did not (table 3-3). RWR2245 adopters were also more likely to be literate and live in villages with greater access to extension. The remaining explanatory variables do not statistically differ between plots under RWR2245 and local bush bean varieties, or between adopters and non-adopters, although the average values for the IVs do vary. Households that grew RWR2245 were more likely to live in a sector with a direct marketing approach, although this difference is significant at the 10% level only (table 3-3), and to live in villages with a greater proportion of RWR2245 adopters in 2014B and 2015A.

Table 3- 2: Descriptive statistics of plot-level variables by variety types, season 2015B

	RWR2245	Other improved	Local bush varieties
	Mean (sd)	Mean (sd)	Mean (sd)
Recycled seed (1 = yes) **	0.27 (0.45)	0.44 (0.48)	0.39 (0.49)
Slope			
Flat	0.10 (0.30)	0.12 (0.32)	0.08 (0.27)
Gentle	0.11 (0.32)	0.16 (0.37)	0.14 (0.35)
Moderate	0.39 (0.49)	0.29 (0.46)	0.35 (0.48)
Steep	0.39 (0.49)	0.43 (0.50)	0.43 (0.49)
Intercrop (1 = yes)	0.60 (0.49)	0.51 (0.50)	0.66 (0.48)
Walking time to househ (in minutes)	18.18 (33.07)	22.20 (31.09)	15.58 (23.07)
Organic fertilizer use (1 = yes) **	0.83 (0.37)	0.71 (0.46)	0.71 (0.45)
Chemical fertilizer use (1 = yes) **	0.17 (0.38)	0.12 (0.33)	0.07 (0.27)
Sex of plot decider (1= female)	0.59 (0.49)	0.61 (0.49)	0.61 (0.49)
Literacy of plot decider (1=yes)	0.65 (0.48)	0.59 (0.49)	0.59 (0.49)
Experience of plot worker (in years)	25.92 (14.19)	26.60 (15.40)	27.50 (16.70)
	211	222	679

Note: * = significance at 10%; ** = significance at 5%; *** = significance at 1% of differences in means.

Table 3- 3: Descriptive statistics of household-level variables by RWR2245 adoption status in 2015

	RWR2245 growers	RWR2245 non-growers
Variables	Mean (sd) or % yes	Mean (sd) or % yes
Climbing bean grower (1 = yes) ***	0.18 (0.38)	0.27 (0.45)
Distance to city (km)	36.51 (21.62)	36.09 (23.13)
Population density (people/square km)	484.68 (537.21)	452.54 (453.35)
Elevation (10m)	156.58 (15.69)	159.16 (19.86)
Household size	4.92 (2.06)	4.87 (1.99)
Sex of bean decision maker (1 = female)	0.62 (0.49)	0.64 (0.48)
Literacy of bean decision maker (1 = yes) **	0.69 (0.46)	0.59 (0.49)
Age of bean decision maker (in years)	44.44 (13.74)	43.84 (15.43)
Land size (ha)	0.54 (0.70)	0.50 (0.75)
Wealth		
1	0.18 (0.39)	0.23 (0.40)
2	0.16 (0.37)	0.19 (0.41)
3	0.17 (0.38)	0.20 (0.40)
4	0.20 (0.41)	0.18 (0.40)
5 *	0.28 (0.45)	0.20 (0.39)
Equipment owned (count) *	1.38 (0.75)	1.21 (0.79)
Livestock (TLU)	0.54 (0.88)	0.46 (1.15)
Extension (%) **	65.59 (24.61)	62.06 (25.48)
Direct markets 2015A and 2015B (#) *	0.47 (1.67)	0.26 (1.05)
Village RWR2245 adoption rate 2014B (%) ***	0.11 (0.10)	0.06 (0.08)
Village RWR2245 adoption rate 2015A (%) ***	0.18 (0.15)	0.10 (0.10)
	243	572

Note: * = significance at 10%; ** = significance at 5%; *** = significance at 1% of difference in means.

To provide evidence that HarvestPlus did not deliberately target areas with greater bean productivity, consumption, or marketing for the dissemination and promotion of iron-biofortified beans, we compare households who live in sectors where direct marketing took place in 2015 with those that did not. If the outcomes of interest and explanatory variables do not differ with household proximity to direct marketing, then this provides evidence that direct marketing is a valid IV. The average multiplication ratio does not differ between households who live in sectors with a direct marketing approach in 2015 and those that do not live in such sectors. In addition, none of our higher order household-level outcome variables vary significantly by whether the household has a direct marketing approach in its sector.

The prevalence of direct marketing approaches varies by provinces; in 2015, 22% of bush bean growing households in the Northern province had a direct marketing approach in their sector compared to 23% in the West, 21% in the East, 3% in the South, and none in Kigali. Households in sectors where direct marketing took place live farther from cities (44.11 km vs. 34.80 km) and in villages where a higher percentage of farmers obtain information from extension (77.43% vs. 60.26%) compared to households who did not have direct marketing in their sector. Other household characteristics, including literacy, wealth, and land under cultivation, do not vary by whether the households had direct marketing in their sector. This lends support that data on formal delivery approaches can provide a valid IV for RWR2245 adoption.

3. Results

3.1. Instrument validity, endogeneity tests, and model fit

Diagnostic tests provide evidence that the IVs are valid (table 4). We reject the null hypothesis that the model is underidentified based on a Kleibergen-Paap rk LM statistic test. The null hypothesis of weak IVs is rejected for each outcome using the Cragg-Donald F statistic. In all models, the Hansen J test for overidentification fails to reject the null hypothesis that the IVs are valid, indicating that the IVs are not correlated with the error term and correctly excluded from the outcome regressions. The Hausman test fails to reject the null hypothesis that adoption is exogenous in all models, suggesting that adoption is not endogenous to our outcomes of interest.

In the productivity regression, the coefficient for the generalized residuals is statistically significant (table 3-5), indicating that adoption is endogenous to the multiplication ratio (Wooldridge, 2014). In all remaining regressions, the p-value of the coefficient for the generalized residuals ranges from 0.356-0.892 which is consistent with the Hausman test that adoption is exogenous. In that case, the non-CFA estimation results are equally valid as the CFA results, and likely more efficient (Wooldridge, 2014). Therefore, for these models, we discuss the results for which adoption is considered exogenous.

Table 3- 4: Instrument diagnostic test results for multiplication ratio, consumption, purchases, and sales

	Yield	Log beans planted	Months consumed	Log quantity consumed	Months purchased	Log quantity purchased	Total Sales
Underidentification test							
Kleibergen-Paap rk LM statistic	25.509	31.833	22.415	23.146	22.415	13.023	22.415
Chi-sq (2) P-val	0.000	0.000	0.000	0.000	0.000	0.002	0.000
Weak identification test							
Cragg-Donald Wald F statistic	16.726	31.004	20.236	20.838	20.236	12.337	20.236
Sanderson-Windmeijer test p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Overidentification test							
Hansen J statistic	1.802	0.404	1.263	0.480	1.595	0.036	2.035
Chi-sq (1) P-val	0.179	0.525	0.261	0.489	0.201	0.850	0.154
Endogeneity test							
Hausman test statistic	2.133	0.008	0.066	0.103	0.047	0.001	0.021
Chi-sq (1) P-val	0.144	0.928	0.797	0.749	0.829	0.978	0.886

Based on a likelihood ratio test, the restrictions that the Tobit model holds are rejected (p = 0.000), confirming that the double hurdle model is a better fit than the Tobit model for explaining quantity sold. The Vuong test also confirms that the zero-inflated Poisson fits the data for the number of months beans were purchased better than the standard Poisson (p = 0.000) (Desmarais and Harden, 2013). After performing PSM, the standardized bias for all covariates is less than 25%, and below 10% for most covariates, which is within recommended limits, indicating that our matching procedures do an adequate job at balancing treatment and control groups and thus controlling for overt bias of the adoption decision (Harder et al., 2010). To achieve this balance for the multiplication ratio regression using nearest neighbor matching, we had to use two control matches for each treatment observation; otherwise, the use of chemical fertilizer did not meet the 25% cut-off value (its standardized bias is 27% when one match is used).

3.2. Supply indicator results

Holding other factors constant, the multiplication ratio for RWR2245 is 49% (100*($e^{.398}$ - 1)) higher than that local bush varieties according to CFA estimates, and the coefficient is significant at the 1% level (table 3-5). In the FE model, the treatment effect of adoption indicates a 20% yield increase over local bush bean varieties, statistically significant at the 5% level, for households that grow both RWR2245 and a local variety. Other improved varieties provide a yield gain of about 23% and 37% over local varieties according to the CFA estimates and FE (for households that grow both an improved and a local variety) results, respectively. PSM indicates that the multiplication ratio for RWR2245 is 23-26% higher than for local bush bean varieties (table 3-7). Being grown from recycled grain, the literacy of the plot decision maker, ownership of agricultural equipment, and access to extension have a positive effect on the multiplication ratio. In the reduced sample, growing beans on a flat or gentle slope and applying chemical fertilizer both increase the multiplication ratio.

The average multiplication ratio for local varieties is 6.74, meaning that a 49% yield gain would correspond to a multiplication ratio of 9.44. On average, bush bean growers planted 15.57 kg of bush bean seed in 2015B; if this seed were entirely local bush varieties, the average household would harvest 104.94 kg of beans. Converting all planted bush bean seed from local bush varieties to RWR2245 would provide a harvest of 156.32 kg, which corresponds to an additional 51.38 kg of beans per season compared to no adoption of improved varieties. When excluding RWR2245, 78% of bush bean varieties grown in 2015B were local varieties and 22% were other improved varieties. Taking this into account, and assuming no difference in multiplication ratio between RWR2245 and other improved varieties, the average harvest gain from RWR2245 adoption is 40.08 kg per season, or about 80 kg per year.

Adoption of RWR2245 has no effect on the quantity of bean seed planted (tables 3-6 and 3-7), suggesting that adoption does not lead to changes in the proportion of land devoted to bean cultivation. Adopters therefore obtain higher quantities of harvested grain as a result of adoption. This extra production can lead to higher-order outcomes such as greater quantity consumed and/or sold, and likely an improvement in household nutrition. Households that live farther from cities, have more household members, cultivate more land, own more livestock, and are wealthier have more land under bean cultivation while households at higher elevations have less land devoted to beans.

Table 3- 5: Regression results for multiplication ratio

	Multiplication ratio (quantity harvested/quantity planted)		
	OLS Coefficient (Robust std. err.)	CFA OLS Coefficient (Robust std. err.)	FE Coefficient (Robust std. err.)
Adjusted R2	0.113	0.122	
R2 within			0.145
R2 between			0.002
R2 overall			0.001
Type (base = local)			
Other improved	0.189**	0.207**	0.312**
	(0.081)	(0.080)	(0.137)
RWR2245	0.183**	0.398***	0.182**
	(0.082)	(0.088)	(0.087)
Recycled seed (1 = yes)	0.235***	0.233***	0.191
	(0.062)	(0.061)	(0.121)
Slope (base = steep)			
Moderate	0.138	0.150	0.323
	(0.138)	(0.136)	(0.263)
Gentle	0.044	0.052	0.534**
	(0.130)	(0.129)	(0.266)
Flat	0.145	0.161	0.956***
	(0.128)	(0.127)	(0.226)
Intercrop (1 = yes)	-0.111	-0.096	0.269
	(0.068)	(0.067)	(0.214)
Walk time to house (in minutes)	-0.003*	-0.003*	0.001
	(0.002)	(0.002)	(0.003)
Organic fertilizer use (1 = yes)	-0.097	-0.120	-0.243
	(0.082)	(0.080)	(0.252)
Chemical fertilizer use (1 = yes)	0.087	0.068	0.502**
	(0.113)	(0.113)	(0.236)
Sex (1 = female)	-0.051	-0.059	0.150
	(0.072)	(0.071)	(0.362)
Literate (1 = yes)	0.271***	0.272***	-0.742
	(0.078)	(0.078)	(0.771)
Experience (in years)	0.001	0.001	-0.076
	(0.002)	(0.002)	(0.105)
Elevation (10m)	-0.001	-0.001	
	(0.002)	(0.002)	
Number of adults	0.004	0.003	
	(0.028)	(0.028)	
Equipment owned (count)	0.107**	0.107**	
	(0.045)	(0.045)	
Extension (%)	0.005***	0.005***	
	(0.002)	(0.002)	
Generalized residual		-0.057***	
		(0.007)	
Constant	0.988*	1.029**	3.168
	(0.386)	(0.381)	(2.199)
N	1112	1112	336

Note: * = significance at 10%; ** = significance at 5%; *** = significance at 1%. Standard errors are robust to heteroskedasticity for all models and clustered at the household level for OLS and CFA OLS models. Coefficients for province fixed effects are not shown for brevity.

Table 3- 6: Regression results for log of total kg of beans planted in season 2015B

	Log of total kg beans planted 2015B	
	OLS Coefficient (Robust std. err.)	CFA OLS Coefficient (Robust std. err.)
Adj. R2/Pseudo R2	0.254	0.253
Adopted 2015 (1 = yes)	0.079	0.168
	(0.077)	(0.269)
Climbing bean grower (1 = yes)	0.287***	0.290***
	(0.068)	(0.068)
Distance to city (km)	0.008***	0.008***
	(0.003)	(0.003)
Population density (people/square km)	0.000	0.000
	(0.000)	(0.000)
Elevation (10m)	-0.009***	-0.009***
	(0.002)	(0.002)
Household size	0.022	0.022
	(0.017)	(0.017)
Sex (1 = female)	-0.101	-0.101
	(0.063)	(0.063)
Literate (1 = yes)	0.044	0.039
	(0.073)	(0.073)
Age (in years)	0.003	0.003
	(0.002)	(0.002)
Land size (ha)	0.232***	0.232***
	(0.086)	(0.086)
Wealth (base = 1)	0.000	0.000
2	0.026	0.022
	(0.096)	(0.096)
3	0.103	0.101
	(0.108)	(0.109)
4	0.330***	0.325***
	(0.117)	(0.117)
5	0.261**	0.254**
	(0.109)	(0.116)
Equipment owned (count)	0.022	0.023
	(0.047)	(0.047)
Livestock (TLU)	0.086***	0.086***
	(0.017)	(0.017)
Extension (%)	-0.004***	-0.004***
	(0.001)	(0.001)
Generalized residual		-0.054
		(0.147)
Constant	3.267***	3.261***
	(0.448)	(0.448)
N	815	815

Note: * = significance at 10%; ** = significance at 5%; *** = significance at 1%. Standard errors are robust to heteroskedasticity for all models and clustered at the village level. Coefficients for province fixed effects are not shown for brevity.

Table 3- 7: Matching results for supply indicators

Matching algorithm	Yield	Beans planted
Nearest Neighbor	0.262 (0.094) ***	0.053 (0.123)
Radius	0.232 (0.075) ***	0.074 (0.068)
Kernel	0.228 (0.069) ***	0.083 (0.075)
N	890	815

Note: Standard errors are bootstrapped. Caliper is set to 0.01 for all matching algorithms.

3.3. Consumption indicator results

RWR2245 adoption (season 2015A, B or both) increases bean consumption from home production by 0.64 months (equivalent to 19-20 days) (table 3-8) while reducing the length of time beans have to be purchased by 0.73 months (equivalent to 22-23 days) in a year (table 3-9). However, adoption of RWR2245 has no effect on the average quantity consumed monthly when beans are sourced from own production or the market (table 3-8 and 3-9). This suggests that adoption does not change quantity consumed, but changes the source of beans consumed, moving away from purchases towards own production. As an additional robustness check, we estimated a regression with the log of the sum of bean consumed from own production and purchases as the dependent variable. We find no effect of RWR2245 adoption on the total quantity of beans consumed in the last 12 months.

Adopting RWR2245 increases the probability of selling beans by 12% and increases the quantity of beans sold by 17.28 kg, although the effect on quantity sold is significant at the 10% level only (table 3-10). RWR2245 adopters are also 8% more likely to be net sellers of beans, with the coefficient being significant at the 10% level. The low levels or lack of significance of adoption on quantities consumed, purchased, and sold could be partially due to difficulties for the respondents to recall and correctly estimate these quantities over a 12-month period. However, it should be easier to remember when the household consumed beans from own production and purchase and whether they sold beans. This may also affect the precision and magnitude of our estimate of the impact of adoption on the likelihood of being a net seller of beans.

Climbing bean growers consume beans from own production for more months than those that grow bush beans only, which is not surprising given the yield advantage of climbers over bush beans and is consistent with previous findings (Katungi et al., 2018). Distance from an urban area has a positive effect on the number of month beans are consumed from own production, selling and being a net seller, and a negative effect on the number of months beans are purchased. Population density and elevation have a negative effect on the number of months beans are consumed from own production but a positive effect on the number of months a household purchases beans. Households at higher elevation are also less likely to sell beans or be net sellers of beans. Household size has a positive effect on the number of months beans are purchased, but a negative effect on the average quantity purchased per month, the number of months beans are consumed from own production, and being a net seller of beans. Literacy of the respondent has a negative effect on the number of months beans are purchased but a positive influence on the average monthly quantity consumed from purchases and own production. The age of the respondent increases the number of months beans are consumed from own production while reducing the number of months beans are purchased. Households that cultivate more land consume beans from own production for a greater number of months, purchase beans for fewer months, sell higher quantities of beans, and are more likely to be net sellers of beans. The wealth index and the number of pieces of agricultural equipment owned have a positive effect on the number of months households consume beans from own production and a negative effect on the number of months beans are purchased. The wealth index also has a negative impact on the average monthly quantity consumed from own production while agricultural equipment ownership has a positive effect on the average monthly quantity purchased. Livestock ownership has a positive effect on the average monthly quantity consumed from own production but a negative influence on the number of months a household purchase beans. Finally, access to agricultural extension makes households more likely to sell beans.

Table 3- 8: Regression results for number of months households consume beans from own production and average monthly quantity consumed from own production

	Months consumed from own production		Quantity (kg) consumed each month, per adult equivalent	
	Poisson marginal effects (Delta method Std. Err.)	CFA Poisson marginal effects (Delta method Std. Err.)	OLS coefficient (robust Std. Err.)	CFA OLS coefficient (robust Std. Err.)
Adj. R2			0.107	0.107
Log psuedolikelihood	-2427222.7	-2426875.1		
Adopted 2015 (1 = yes)	0.641**	1.392	0.012	0.079
	(0.287)	(1.234)	(0.057)	(0.235)
Climbing bean grower (1 = yes)	0.752**	0.795***	-0.033	-0.029
	(0.291)	(0.294)	(0.054)	(0.054)
Distance to city (km)	0.026***	0.027***	0.000	0.000
	(0.009)	(0.011)	(0.002)	(0.002)
Population density (people/square km)	-0.001***	-0.001***	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Elevation (10m)	-0.021***	-0.020***	-0.001	-0.001
	(0.007)	(0.007)	(0.001)	(0.001)
Household size	-0.144**	-0.144**	-0.094***	-0.094***
	(0.070)	(0.071)	(0.011)	(0.011)
Sex (1 = female)	-0.368	-0.376	-0.064	-0.065
	(0.272)	(0.268)	(0.049)	(0.048)
Literate (1 = yes)	0.571*	0.518*	0.178***	0.174***
	(0.303)	(0.299)	(0.059)	(0.063)
Age (years)	0.026***	0.032***	0.001	0.001
	(0.007)	(0.010)	(0.001)	(0.001)
Land size (ha)	0.613***	0.616***	0.046	0.046
	(0.125)	(0.124)	(0.032)	(0.032)
Wealth quintile (base = 1)				
2	0.140	0.128	0.062	0.061
	(0.450)	(0.453)	(0.079)	(0.079)
3	0.237	0.236	0.020	0.020
	(0.469)	(0.470)	(0.077)	(0.077)
4	0.947**	0.913**	-0.024	-0.027
	(0.434)	(0.442)	(0.068)	(0.069)
5	1.761***	1.701***	-0.171**	-0.176**
	(0.473)	(0.496)	(0.077)	(0.075)
Equipment owned (count)	0.636***	0.592***	0.027	0.024
	(0.138)	(0.156)	(0.025)	(0.032)
Livestock (TLU)	0.067	0.075	0.069***	0.069***
	(0.077)	(0.078)	(0.012)	(0.013)
Extension (%)	0.005	0.004	-0.001	-0.001
	(0.005)	(0.005)	(0.001)	(0.001)
Generalized residual		-0.458		-0.040
		(0.719)		(0.144)
Constant (coefficient)	2.028***	2.020***	1.736***	1.731***
	(0.182)	(0.183)	(0.227)	(0.233)
N	815	815	804[a]	804

Note: * = significance at 10%; ** = significance at 5%; *** = significance at 1%. Standard errors are robust to heteroskedasticity and clustered at the village level. Coefficients for province fixed effects are not shown for brevity.

[a] Eleven households did not consume beans from own production in any months

Table 3- 9: Regression results for number of months households consume beans from purchases and average monthly quantity purchased

	Months purchased		Quantity (kg) purchased each month, per adult equivalent	
	Zero-inflated Poisson marginal effects (Delta method Std. Err.)	CFA Zero-inflated Poisson marginal effects (Delta method Std. Err.)	OLS coefficient (robust Std. Err.)	CFA OLS coefficient (robust Std. Err.)
Adj. R2/Pseudo R2			0.175	0.174
Log psuedolikelihood	-1995457	-1994473		
Adopted 2015 (1 = yes)	-0.728***	-0.876	-0.102	-0.171
	(0.263)	(1.141)	(0.071)	(0.305)
Climbing bean grower (1 = yes)	-0.270	-0.271	-0.060	-0.063
	(0.275)	(0.280)	(0.067)	(0.069)
Distance to city (km)	-0.019**	-0.019*	0.001	0.001
	(0.009)	(0.010)	(0.002)	(0.002)
Population density (people/square km)	0.001***	0.001***	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Elevation (10m)	0.013**	0.013**	-0.000	-0.000
	(0.006)	(0.006)	(0.002)	(0.002)
Household size	0.187***	0.187***	-0.103***	-0.103***
	(0.055)	(0.055)	(0.015)	(0.015)
Sex (1 = female)	0.142	0.139	-0.010	-0.010
	(0.276)	(0.276)	(0.064)	(0.064)
Literate (1 = yes)	-0.492**	-0.482**	0.177**	0.181**
	(0.229)	(0.238)	(0.075)	(0.074)
Age (years)	-0.031***	-0.031***	0.003	0.003
	(0.008)	(0.008)	(0.002)	(0.002)
Land size (ha)	-0.460***	-0.457***	0.068	0.068
	(0.172)	(0.172)	(0.044)	(0.044)
Wealth quintile (base = 1)				
2	0.189	0.197	0.106	0.107
	(0.365)	(0.365)	(0.086)	(0.085)
3	-0.025	-0.031	0.078	0.078
	(0.398)	(0.397)	(0.098)	(0.098)
4	-0.630*	-0.630*	-0.060	-0.057
	(0.368)	(0.372)	(0.091)	(0.094)
5	-1.359***	-1.374***	-0.006	-0.001
	(0.395)	(0.423)	(0.094)	(0.095)
Equipment owned (count)	-0.517***	-0.511***	0.125***	0.128**
	(0.175)	(0.185)	(0.045)	(0.049)
Livestock (TLU)	-0.893***	-0.889***	-0.075	-0.074
	(0.284)	(0.285)	(0.075)	(0.074)
Extension (%)	0.006	0.006	-0.003*	-0.003*
	(0.005)	(0.005)	(0.002)	(0.002)
Generalized residual		0.085		0.042
		(0.664)		(0.177)
Constant	1.861***	1.795***	1.283***	1.291***
	(0.973)	(0.969)	(0.332)	(0.335)
N	815	815	562	562

Note: * = significance at 10%; ** = significance at 5%; *** = significance at 1%. Standard errors are robust to heteroskedasticity and clustered at the village level. Coefficients for province fixed effects are not shown for brevity.

Table 3- 10: Regression results for sales and net seller

	Sold beans		Quantity sold		Net seller	
	Probit marginal effects (Delta method Std. Err.)	CFA Probit marginal effects (Delta method Std. Err.)	Double hurdle average partial effects (Bootstrapped std. err.)	CFA Double hurdle average partial effects (Bootstrapped std. err.)	Probit marginal effects (Delta method Std. Err.)	CFA Probit marginal effects (Delta method Std. Err.)
Adj. R2/Pseudo R2	0.147	0.147			0.192	0.193
Log psuedolikelihood	-562430.16	-562421.25	-3047935.5	-3047091.6	-852005.65	-526694.95
Adopted 2015 (1 = yes)	0.122***	0.103	17.276*	49.202	0.081*	0.005
	(0.047)	(0.145)	(9.081)	(40.400)	(0.047)	(0.139)
Climbing bean grower	0.024	0.023	-2.991	-1.062	0.068	0.064
(1 = yes)	(0.044)	(0.045)	(9.503)	(10.872)	(0.043)	(0.044)
Distance to city (km)	0.004***	0.004***	1.284***	1.324***	0.005***	0.005***
	(0.001)	(0.001)	(0.339)	(0.334)	(0.001)	(0.001)
Population density	-0.000*	-0.000*	-0.006	-0.004	-0.000**	-0.000**
(people/square km)	(0.000)	(0.000)	(0.011)	(0.011)	(0.000)	(0.000)
Elevation (10m)	-0.005***	-0.005***	-0.732***	-0.672***	-0.003***	-0.003***
	(0.001)	(0.001)	(0.268)	(0.258)	(0.001)	(0.001)
Household size	-0.004	-0.004	0.184	-0.131	-0.031***	-0.031***
	(0.010)	(0.010)	(2.030)	(2.084)	(0.010)	(0.010)
Sex (1 = female)	-0.043	-0.042	-17.436*	-18.132*	-0.017	-0.016
	(0.042)	(0.042)	(9.129)	(10.741)	(0.043)	(0.043)
Literate (1 = yes)	0.022	0.024	20.276*	17.425*	0.005	0.010
	(0.043)	(0.044)	(10.476)	(9.169)	(0.044)	(0.043)
Age (years)	-0.002	-0.002	-0.287	-0.316	0.002*	0.002*
	(0.001)	(0.001)	(0.296)	(0.288)	(0.001)	(0.001)
Land size (ha)	0.043	0.043	14.609**	14.475***	0.070**	0.070*
	(0.033)	(0.033)	(6.215)	(5.313)	(0.036)	(0.036)
Wealth quintile (base = 1)						
2	0.013	0.014	-16.766	-16.698	-0.031	-0.030
	(0.053)	(0.053)	(23.452)	(22.319)	(0.052)	(0.052)
3	-0.006	-0.006	-0.239	-0.550	0.014	0.014
	(0.064)	(0.064)	(13.040)	(13.798)	(0.055)	(0.054)
4	0.099	0.100	10.911	8.829	0.115**	0.118**
	(0.068)	(0.068)	(15.038)	(15.189)	(0.055)	(0.056)
5	0.109	0.110	27.996	25.433	0.254***	0.260***
	(0.072)	(0.072)	(17.186)	(16.682)	(0.064)	(0.067)
Equipment owned	-0.022	-0.021	7.881	5.415	0.062**	0.066**
(count)	(0.027)	(0.029)	(5.437)	(5.943)	(0.030)	(0.030)
Livestock (TLU)	-0.033	-0.033	-0.634	-0.528	0.118***	0.119***
	(0.028)	(0.028)	(5.066)	(6.569)	(0.042)	(0.042)
Extension (%)	0.001**	0.001**	0.076	0.029	0.000	0.000
	(0.000)	(0.000)	(0.161)	(0.169)	(0.000)	(0.001)
Generalized residual		0.012		-19.754		0.046
		(0.086)		(19.017)		(0.077)
Constant (coefficient)	2.120***	2.126***	-1319.285	-1521.003	0.429	0.453
	(0.616)	(0.608)	(1433.048)	(1522.696)	(0.540)	(0.534)
N	815	815	815	815	815	815

Note: * = significance at 10%; ** = significance at 5%; *** = significance at 1%. Standard errors are robust to heteroskedasticity and clustered at the village level. Coefficients for province fixed effects are not shown for brevity.

The results of PSM analysis are consistent with the previous findings, providing evidence of the robustness of our results to econometric methods. According to PSM results, adoption of RWR2245 increases the number of months households consume beans from own production by 0.62-0.64 months, reduces the number of months households purchase beans by 0.66-0.69 months, increases the likelihood of selling beans by 12-14% and the probability of being a net seller of beans by 9-12% and finally, increases bean sales by an additional 18 to 21 kg per year.

Table 3- 11: Matching results for consumption indicators

Matching algorithm	Months consumed from own production	Kg consumed	Months purchased	Kg purchased	Sold beans	Kg sold	Net seller
Nearest Neighbor	0.711 (0.390)*	0.101 (0.077)	-0.924 (0.374)**	0.075 (0.084)	0.142 (0.058)**	15.844 (10.584)	0.124 (0.053)**
Radius	0.621 (0.269)**	0.029 (0.047)	-0.662 (0.243)***	-0.051 (0.068)	0.120 (0.042)***	18.409 (8.834)**	0.093 (0.039)**
Kernel	0.644 (0.249)**	0.032 (0.046)	-0.686 (0.229)***	-0.061 (0.057)	0.129 (0.040)***	20.675 (8.102)**	0.101 (0.037)***
N	815	804	815	562	815	815	815

Note: Standard errors are bootstrapped. Caliper is set to 0.01 for all matching algorithms, and only observations that fall under common support are included.

Alternative specifications of adoption also provide consistent results, providing further indication that our results are highly robust not only to different estimation methods, but also to different measures of adoption (table 3-12). If adoption is defined as a count variable equal to the number of seasons in 2015 that a household grew RWR2245 (0, 1, or 2), results of the Poisson, zero-inflated Poisson, and probit regressions, respectively, indicate that growing RWR2245 for an additional season increases consumption from own production by 0.55 months, reduces the number of months beans are purchased by 0.64 months, and increases the probability of selling beans and being a net seller by 11% and 8%, respectively (each significant at the 5% level or lower). If we consider as adopters only households that grew RWR2245 in both seasons of 2015, adoption increases beans consumption from own production by 1.21 months, reduces bean purchases by 1.39 months, and increases the probability of selling beans and being a net seller by 19% and 21%, respectively, roughly doubling the estimated effects of growing RWR2245 for one season. Increasing the proportion of bean land under RWR2245 by 10% increases (decreases) bean consumption from own production (purchases) by 0.02 months (about half a day) and increases the probability of selling beans and being a net seller of beans by 0.2%. Planting an additional kg of RWR2245 seeds in 2015A or 2015B increases consumption from own production by 0.02 months (0.6 days) and increases the probability of selling beans and being a net seller by 1% each. Conditional on having planted RWR2245 in 2015A or 2015B, growing RWR2245 an additional season prior to 2015 increases bean consumption from own production by 0.18 months, reduces the need to purchase beans by 0.26 months, and increases the probability of being a net seller by 3%, meaning that the benefits of RWR2245 adoption increases as households get more experience growing the variety. Finally, having grown RWR2245 prior to 2015A, but not being an adopter in 2015, does not have a significant impact on the number months beans are consumed from own production and purchases or on the probability of being a net seller of beans, although it does increase the likelihood of selling beans by 12%. Thus, regardless of how adoption is measured, results indicate that adopters replace bean purchases with beans from own production and generate surplus to sell.

When beans are consumed from own production, monthly consumption averages 12.99 kg. Increasing bean consumption from own production by 1.21 months would therefore require an additional 15.98 kg of beans harvested over seasons 2015A and 2015B. This is well within reach given the estimated yield gains of 80 kg over two seasons from converting local bush bean varieties to RWR2245 and adopters would also have a surplus to sell. Adoption should thus improve household nutrition through the consumption of beans high in iron content. It should also increase household income by reducing quantity purchased for net buyers and increasing quantity sold for net sellers of beans, translating into more income to spend on other foods and health-related goods for both types of households.

Table 3- 12: Alternative measures of adoption and its impact on bean consumption from own production, purchases and marketing

	Months of consumption from own production	Months of purchasing	Sell beans	Net seller of beans
	Poisson marginal effects (Delta method Std. Err.)	ZIP Poisson marginal effects (Delta method Std. Err.)	Probit marginal effects (Delta method Std. Err.)	Probit marginal effects (Delta method Std. Err.)
Adoption in both seasons	1.207***	-1.387***	0.182***	0.210***
	(0.425)	(0.499)	(0.063)	(0.057)
Adoption in 0,1, or 2 seasons of 2015	0.552***	-0.642***	0.096***	0.080***
	(0.202)	(0.202)	(0.031)	(0.030)
Number of seasons growing RWR2245 (conditional on growing RWR2245 in 2015A or 2015B)	0.187***	-0.265**	0.018	0.029**
	(0.078)	(0.108)	(0.015)	(0.013)
% Bean area under RWR2245, average between 2015A and 2015B	0.016**	-0.018***	0.002**	0.002**
	(0.006)	(0.007)	(0.001)	(0.001)
Quantity of RWR2245 planted (sum of 2015A and 2015B, in kg)	0.023**	-0.024	0.011**	0.010**
	(0.011)	(0.029)	(0.003)	(0.003)
Household grew RWR2245 in a season prior to 2015A	0.448	-0.326	0.121**	0.090*
	(0.324)	(0.331)	(0.050)	(0.053)

Note: * = significance at 10%; ** = significance at 5%; *** = significance at 1%. Standard errors are robust to heteroskedasticity and clustered at the village level.

4. Conclusions

Biofortified crops are a relatively new and expanding technology developed to address the global challenge of micronutrient deficiency. It is thus important to understand the impact this technology has on households who produce and consume these crops, especially considering the complex pathways through which agricultural interventions can affect household nutrition and well-being. This paper provides highly robust evidence that biofortified crops can improve household nutrition via two main pathways. The first is by increasing nutrient intake via increased consumption of the own produced biofortified crop. The second pathway occurs by increasing household income available for the purchase of other nutritious foods via reductions in purchases and increased sales of the targeted crop. These benefits arise from the enhanced nutritive value of the biofortified crops and their high-yielding properties which boost harvested quantity.

More specifically, we find that adoption of the most popular iron-biofortified bean variety, RWR2245, increases yields by 20-49% over traditional bush bean varieties in Rwanda; this range of estimates from different estimation methods likely provides a lower and upper bound of the yield effect. This productivity advantage is crucial for sustained adoption of RWR2245 and a critical determinant of overall impacts. Having rigorously quantified the productivity gain strengthens the attribution of the higher-order impacts to the adoption of RWR2245. Households who grow RWR2245 in one or two seasons consume beans from own production for an additional 0.62-0.64 months (about 19-20 days) per year compared to those that did not grow RWR2245. RWR2245 adoption also reduces the need to purchase beans by 0.66-0.92 months (about 20-28 days) over a 12-month period. Adoption does not change total quantity consumed, but rather allows households to shift the source of bean consumption away from purchases toward own production. In addition, adoption increases the likelihood that a household sells beans by 12-14%. The results are robust to a variety of estimation methods and specifications for the adoption decision, which provides a high level of confidence in our findings.

Women aged 19-50 need to consume about 18 mg of iron per day (Institute of Medicine, 2018). For an average household, switching all beans consumed from own production from non-biofortified to biofortified would lead to a substantial increase in iron intake. Glahn et al. (2017) estimate that one kg of non-biofortified beans contains 47.5 mg/kg of iron while iron-biofortified beans contain 82.5 mg/kg. Adopting households consume on average 4.07 kg of beans per adult equivalent per month when beans are sourced from own production, which is equivalent to 135 g/day. This consumption level would provide 6.42 mg of iron per adult equivalent per day if beans consumed are non-biofortified compared to 11.15 mg for biofortified beans. This additional 4.7 mg of iron would bring women much closer to their daily requirement of 18 mg per day, lowering their risk of iron deficiency. Iron deficiency can result in reduced cognitive performance and worker productivity, increased maternal mortality, and impaired immune systems, among other consequences, and improving iron status has been found to reverse many of these negative effects (World Health Organization, 2001).

Policy makers and researchers can use these results to inform the promotion and targeting of biofortified crop delivery in Rwanda and elsewhere. By increasing consumption from own production, adoption of iron-biofortified beans directly boosts nutrient intakes among adopting households. This means that targeting households with high nutritional needs during dissemination efforts would further increase the health benefits associated with biofortification. Adoption also increases income available to spend on other foods regardless of whether the household is a net purchaser or net seller of beans and leads to nutritional spillover benefits because of the surplus sold in the marketplace, indicating that biofortified crops can enhance nutrition through several channels.

Our paper provides evidence that biofortification is a promising intervention for improving nutrition and health of rural populations, and supports the need for further research to quantify the impacts of adoption on food consumption patterns and nutrient intake. In countries such as Rwanda where households have both high consumption and production of the targeted crop, biofortification has the potential to provide substantial benefits for both adopting households and their surrounding communities.

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Chapter 4: The spillover effects of seed producer groups on non-member farmers in local communities in Nepal

1. Introduction

Rice is the staple food for billions of people in Asia; however, over half of all rice lands on the continent are in unfavorable environments that are vulnerable to weather shocks such as drought and flood, and suffer from low productivity (Manzanilla et al., 2017). One such unfavorable environment is the mid-hills region of Nepal, where upland farmers lack irrigation, use poor crop management practices, and rely heavily on recycled seed of old varieties, all of which contribute to low yield and can exacerbate vulnerability to climate shocks. Seed that is not replaced frequently can harbor microorganisms including nematodes, fungi, viruses, or bacteria, which cause disease. Some of these diseases are seedborne, and will pass on to the next generation of seed (Gonzales and Huelma, 2013). In addition, poor management practices can reduce yields and old varieties often lack tolerance to adverse climate conditions.

Fortunately, agricultural technologies including stress-tolerant rice varieties (STRVs) and best management practices (BMPs) as well as replacing seed frequently with high-quality seed have the potential to improve livelihoods by increasing yield and reducing vulnerability of rice farmers. High-quality seed can improve yield by 5-20% (IRRI Rice Knowledge Bank, 2012). STRVs are bred to withstand climate stress conditions better than non-STRVs; for instance, yield of drought-tolerant varieties suffer less from reduced rainfall than other varieties.

The Consortium of Unfavorable Rice Environments (CURE), an International Fund for Agricultural Development (IFAD) project developed in 2002 with support from the Asian Development Bank, promotes STRVs, BMPs and seed replacement in several Asian countries, including Nepal, to increase yields and reduce the environmental vulnerability of rice crops. In Nepal, CURE took over after another IFAD program, IFAD Technical Assistance Grant (TAG)

706, which operated from 2005-2008, ended. IFAD TAG 706, in collaboration with the Nepal Agriculture Research Council (NARC) and the Institute of Agriculture and Animal Science (IAAS) located in Lamjung district, Nepal, assisted in the validation of over 30 improved technologies for rice and other crops in the mid-hills region of Nepal. Participatory varietal selection (PVS) was conducted on upland and rainfed rice, which led to high demand of seeds among participating farmers. However, supply of these varieties was not high enough to meet this demand. This was a reflection of the seed system nationally; according to the Nepal Agricultural Research Council, insufficient quality rice seed is multiplied in the country (Gauchan et al., 2014). As a result, the seed replacement rate (SRR) is around 12%, much lower than the recommended rate of 25-30%, and the informal seed sector in which farmers save and trade seeds within their social networks makes up about 90% of planted rice seed. The remaining 10% comes from the formal sector, which consists of public sector agencies, the private sector, and community led seed production (Gauchan et al., 2014).

To facilitate multiplication of these newly validated varieties, IFAD TAG 706, and later the CURE project, along with the Gates Foundation-funded Stress Tolerant Rice for Africa and South Asia (STRASA) project, established 12 seed producer groups (SPGs) between 2007 and 2013 in three neighboring districts in the Western development region of Nepal: Lamjung, Tanahu, and Gorkha. The SPGs were community-based organizations which received extensive training in rice production and sales, and in which members produced and sold improved rice seed, including that of STRVs. These districts were chosen because they are prone to drought and they are in close proximity to IAAS. Three groups were also established in Bajhang district in the Far Western development region, but given this district's distance from the IAAS campus and from consistent sources of seed, these groups received far less support and monitoring than those in Lamjung, Tanahu, and Gorkha and are not included in our study.

The SPGs were established in villages that were accessible to roads, recommended by extension workers, and where rice is cultivated each year. Local farmers volunteered to join the groups. The first SPG was Sundar SPG (later renamed Sundar Cooperative), established in 2007 near IAAS campus in Sundarbazar, Lamjung. The CURE program provided technical support to the SPGs; through the IAAS campus, group members received two trainings per year on rice cultivation practices. IAAS, as well as the District Agricultural Development Office (DADO) and the National Agricultural Research Council (NARC) also provided inspection services such that the SPGs could sell their seed as either truthfully labeled, which required only IAAS inspection, certified, which required inspection by DADO, or foundation seed, which required inspection by NARC. Many SPGs sold their seed to Sundar Cooperative, which operated its own SPG and collected and sold seed from other SPGs. The SPGs can also sell seed independently, to other cooperatives, NGOs, and private seed dealers called agrovets. Although the CURE program ended in 2013, many of the SPGs have remained highly active, while others have ceased operating entirely or have only a few active members remaining.

The goal of this paper is to estimate the spillover effects of the SPGs in Lamjung, Tanahu and Gorkha districts onto non-member farmers in SPG villages and nearby villages on the following outcomes: adoption of STRVs, SRR, and use of BMPs in rice cultivation. Spillover effects are effects of a program on a non-targeted population within the local economy (Angelucci and Di Maro, 2015); here, the targeted population is the SPG member farmers and the local economy is the villages where SPGs were established as well as adjacent villages. We hypothesize that non-member households in SPG villages and adjacent villages will have greater adoption of STRVs and a higher SRR due to their improved access to STRV and other improved rice seed varieties. We also hypothesize that non-member households in SPG villages will have higher rates of BMP use, as their close proximity to SPG members may expose them to greater knowledge of BMPs. This increase in BMP utilization may not extend to neighboring villages however, as they are more likely to spread amongst farmers who either know one another or who observe one another's rice fields. We do not examine the impacts of the SPGs that were established in Bajhang because these had little support from the CURE program.

We are interested in the spillover effects of SPGs because the technologies that they use (BMPs) and produce (STRVs, other improved rice seed) are highly transferrable to other farmers within their communities, which can enhance spillover effects (Winters et al., 2011). In fact, when technologies are highly transferrable, spillover effects can exceed direct program impacts, and ignoring these spillover effects can drastically underestimate the impact of a program (Winters et al., 2011). In addition, while existing literature has documented the benefits of SPGs and other organized forms of seed production such as contracts on producing farmers (Simmons et al., 2005; Winters et al., 2010; Katungi et al., 2011; Mishra et al., 2016; Tebeka et al., 2017), there is no research to our knowledge that examines spillover benefits of seed production, which is surprising given that the main technology produced by SPGs, seed, is designed to be sold/transferred to other households.

Previous studies found that SPGs and other forms of seed production are beneficial for producers. Katungi et al. (2011) found that farmer-based bean seed production in Kenya was profitable for producer farmers, despite the higher costs of producing bean seed over bean grain. Tebeka et al. (2017) examined community-based seed multiplication of common bean in Ethiopia and found that producing and selling seed is more profitable for farmers than producing and selling grain. Contracts to produce hybrid maize seed and broiler chickens have proven beneficial for smallholder farmers in Indonesia, improving returns to farm capital, although contracts to produce rice seed did not increase returns (Simmons et al., 2005). In Nepal, Mishra et al. (2016) found that farmers who entered into contracts with private seed companies for the production of high yielding rice varieties earned higher profits than farmers who produced high yielding varieties independently.

There is a significant literature arguing the importance of estimating spillover effects, due to the fact that indirect effects of interventions, particularly agricultural and health interventions, can arise for many reasons (Winters et al. 2011; Benjamin-Chung et al., 2015). For agricultural programs, positive externalities exist if agricultural practices can be transferred from farmer to farmer, and general equilibrium effects can occur if a project changes input or output prices (Winters et al. 2011). Benjamin-Chung et al. (2015) outline many ways in which spillover effects can arise from health interventions: learning/imitation effects (the untreated population may learn new skills or behaviors from the treated), norm shaping (the treated population may change social norms, which the untreated follow passively), and general equilibrium effects (changes in prices or other aspects of the economy that change economic behaviors of community members). Although these authors focus on health interventions, the same effects could arise from agricultural interventions, including SPGs.

Empirical studies have found evidence of spillover effects of many different types of development programs. Miguel and Kremer (2004) investigated a project in Kenya that provided deworming medicine to some students in randomly selected schools and found high evidence of spillover effects: untreated students in selected and neighboring schools also experienced improved health and school participation due to treatment externalities that likely arose from a reduced number of worms in the environment. Thome et al. (2013) found evidence of spillover effects on the value of local agricultural production arising from general equilibrium impacts of a cash transfer program in Kenya. Wanjala and Muradian (2013) found that spillover effects on production margins and household income arose from the Millennium Village Project in Kenya. Finally, Haile et al. (2017) estimated the impacts on households who participated in a participatory action research program in Malawi. This program selected villages, and households within those villages volunteered to participate, similar to how the CURE program selected villages for SPGs in Nepal. The authors found evidence of positive program impacts, but noted the difficulty of evaluating the effectiveness of the program due to possible spillover effects onto other households within the program villages. Because we hypothesize that spillover effects of the CURE SPGs could be very high for non-members within and near SPG villages, we estimate these effects explicitly.

Haile et al. (2017) note another difficulty in estimating program impacts: the possibility that unobserved village characteristics could bias effect estimates. This is a potential problem in our study, as well, because villages were not chosen randomly for the establishment of SPGs. We control for potential selection bias by using two different propensity-score weighted regression adjustment estimation methods. These methods estimate both the treatment model (generating propensity scores, or the probability that each village was treated), and the outcome model. By weighting the outcome model using the propensity scores, these estimation methods improve the balance between treated and untreated groups, and are considered to be "doubly-robust," as they are valid if either the treatment or outcome model is incorrectly specified (Wooldridge, 2010). They also allow for multi-valued treatment effects, which we need as we are interested in spillover effects onto two separate groups: non-members in SPG villages and non-members in adjacent villages. These methods only reduce bias arising from observed village characteristics. In the case of SPG village selection, some traits that were considered for selection are easily observable: distance to roads and rice being grown each year. However, unobserved bias could arise as if we cannot observe all factors that influenced extension workers' village recommendations. While we include several village-level covariates that could have influenced these recommendations, we also perform statistical tests to examine whether unobserved bias, or endogeneity, is likely to bias our results.

This research has implications for policy makers in Nepal and other Asian countries who wish to increase the supply and adoption of improved agricultural technologies. It will provide evidence as to whether the scaling up of similar IFAD-funded or other projects that focus on community-based seed production is an effective way to protect communities from drought and other climate stressors through the spread of agricultural technologies.

2. Data

We conducted three types of surveys in Lamjung, Tanahu and Gorkha districts of Nepal (shown in Figure 4-1) for the CURE impact evaluation. The first was an SPG leader survey, in which we interviewed executive committee members of the 12 SPGs established by CURE in Lamjung, Gorkha, and Tanahu districts in September-October, 2018. The second was a household survey in which we interviewed randomly selected households in the three districts regarding their 2018 monsoon season rice production, household demographics, credit usage and asset ownership. Finally, we conducted a community survey in which we interviewed village leaders in each selected village about village amenities, access to extension, sources of rice seed, etc. The household and community surveys were administered between November 26, 2018 and

December 20, 2018. The monsoon season runs from July to November each year, so data collection occurred shortly after the end of the season.

Figure 4- 1: Map of Nepal showing CURE districts

The SPG leader survey was a focus group survey in which we interviewed 3-6 executive committee members from each SPG. It was conducted a month prior to the household and community surveys so that it could inform the household survey regarding specific rice varieties and best management practices about which to collect data. The SPG leader survey collected basic information on year that the group was established, membership history, and services available to members. A detailed module on training asked questions on when, where, and by whom SPG members were/are trained. We also asked specific questions regarding how SPG members were trained on planting methods, fertilizer application, weed and pest management, and processing seed after harvest. Finally, we collected the complete list of varieties each SPG has ever grown and which of these varieties are STRVs. The purpose of this was to put together a list of BMPs and STRVs to ask about in the household survey. Information on the quantity of seed produced in 2017 and sold in 2018, the most recent years of production and sales, and quantities sold to different buyers in different locations (for instance, agrovets, extension agencies, and local markets) was collected. We also collected information on rice storage: whether the SPG has a storage facility, its capacity and the year it was built, and the location(s) where the SPG members stored rice in 2018. Finally, the survey asked about current challenges the SPGs face and what resources could help them overcome these challenges.

For the household survey, we interviewed 900 households in 75 villages (12 households per village) across Lamjung, Tanahu and Gorkha districts. These 75 villages included the 12 villages with SPGs. We also randomly selected one adjacent village to each of these (12 in total) in order to capture spillover effects of the SPGs onto neighboring villages. The remaining 51 villages were randomly selected to be representative of rice-growing households in the surrounding Village Development Committees (VDCs)[15]. Our sampling frame included VDCs that contained the SPG villages as well as each VDC that was adjacent to these or that connected them into one continuous area, for a total of 41 VDCs (Figure 4-2). We chose this study area because it covers a range where dissemination of SPG seeds is realistic, while still containing villages that vary by distance to SPGs, access to roads, elevation, and other factors that could affect adoption of STRVs.

We determined the number of villages to randomly sample from each district based upon district total population, leading to 14 randomly selected villages in Gorkha, 22 in Lamjung, and 27 in Tanahu. Because lists of villages and households were not available, staff from a local NGO called CHESS Nepal collected this information. To ease this process, we first randomly selected wards in our study area using proportional to population size sampling (each VDC

[15] VDCs are administrative units in Nepal that are smaller than districts but larger than villages.

contains wards numbered 1-9 and each ward contains about 3-6 villages). Once the names of villages and their approximate number of rice-growing households from each of the selected wards was collected, we randomly sampled one village per ward, again using proportional to population size sampling. These randomly selected villages and the SPG/SPG-adjacent villages are located in 37 of the 41 VDCs in our study area; thus, our sample covers a wide range of the study area.

Once villages were selected, CHESS Nepal collected a list of all rice-growing households within each sampled village. Twelve households were randomly selected from each village in addition to five alternate households in case selected households were not available on the day of survey enumeration. The study area VDCs as well as locations of SPGs and sampled households are shown in Figure 4-2.

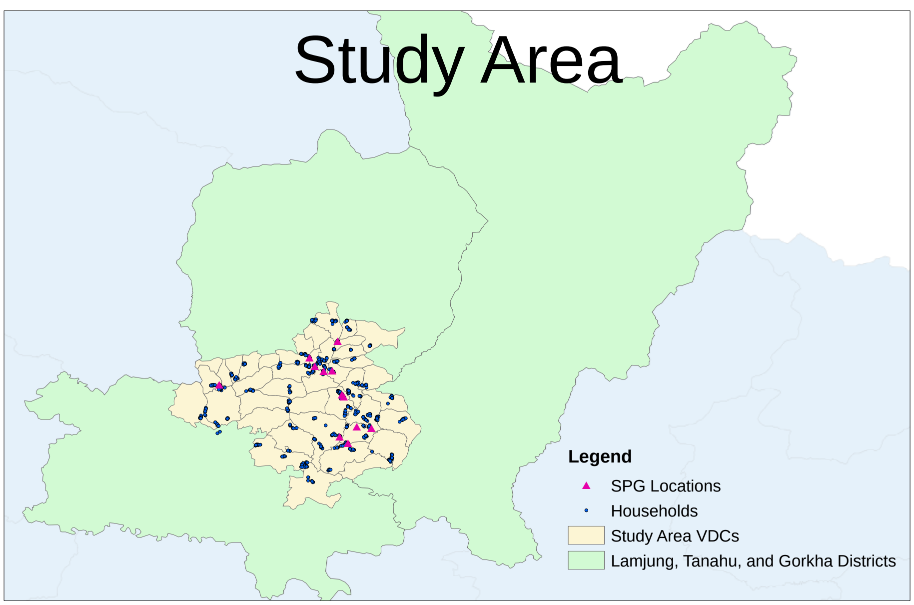

Figure 4- 2: Map of Lamjung, Tanahu and Gorkha districts showing study area:

Note: Some households appear to be outside of study area VDCs; this is likely due to fuzziness of border boundaries on the ground

To administer the household and community surveys, we hired twelve enumerators. Each enumerator had or was pursuing an undergraduate degree related to agriculture. Most of the enumerators had previous survey experience, and many had worked previously with our partner organization, iDE Nepal. The remaining enumerators were selected for interviews based on the recommendations of faculty at IAAS.

The household survey began with a household roster, followed by a module on STRV adoption. Households were asked if they had ever heard of each of the improved drought-tolerant varieties grown by SPGs. If the household reported having heard of the variety, we asked when they first heard of it and from where/whom, if they had ever grown it, in which season they first grew it, and where they obtained their initial planting material.

The bulk of the remaining survey collected detailed information on rice cultivation during the 2018 monsoon season, as well as some information on rice cultivation in the 2017 monsoon season. The plot roster module collected basic information on all plots cultivated by the household in the 2018 monsoon season such as size, land ownership, crops grown, and whether the crops have suffered from insufficient water availability in the past five years. For plots under rice cultivation that season, more detailed questions regarding irrigation, fertilizer and pesticide use, and paid and unpaid labor were asked. Half of the households received an extended version of this module, which included questions regarding the type of fertilizer applied, timing of fertilizer application and weeding, and more detailed questions about labor activities. The next module collected information on each rice variety grown by the household in the 2018 monsoon season, including the source of planting material, the year the household first grew the variety, and whether they identify it as an improved and/or drought-tolerant variety. To assist in varietal identification, we asked a series of questions including when the household first grew the variety and where they obtained the planting material, whether they thought it was improved or local, and drought-tolerant. The survey then collected information at the variety-plot level for both 2018 and 2017, since more than one rice variety can be grown per plot; specifically, plot area cultivated under each variety, quantity of seed planted, method of planting, and quantity harvested.

Remaining household survey modules asked about social capital, access to agricultural extension, and asset ownership. We collected GPS coordinates for all interviewed households, which we combined with Landsat data (National Center for Atmospheric Research Staff, 2018) to calculate the Normalized Difference Vegetation Index (NDVI), a measure of the extent of green vegetation that ranges from -1 (a body of water) to 1 (rain forest), OpenStreetMap (OpenStreetMap contributors, 2018) road data to calculate the distance from each household to the nearest road, and elevation data to calculate the slope of land on which each household resides.

The community survey, administered at the same time as the household survey, collected information from village leaders on amenities and services availability within the villages. This included distance to the nearest asphalt road, agrovet, and DADO, which provides extension services. We also asked about adoption of STRVs at the village level and whether local names were used for any of the STRVs varieties to further assist in correct varietal identification.

The success of our study relies on households accurately identifying the rice varieties they cultivated, particularly the STRVs. Prior to conducting the household survey, we asked local extension agents, agrovets, other individuals knowledgeable about rice production within the study area about farmers' ability to identify varieties. All reported that farmers are well aware of the official names of the varieties they cultivate, particularly the more recently released improved varieties including the STRVs. They stated that the only problem that could arise was that farmers in different villages could have different names for local varieties. To help in proper varietal identification during data collection, we put together a list of variety names from which enumerators could select. This list came from the SPG leader survey and government documents on rice varieties (Crop Development Directorate, 2015). For varieties named but not on our pre-defined list, local experts helped classify whether they were improved, hybrid, or STRV. For the purposes of this study, identification of STRVs is most crucial, and we feel very confident that households were able to correctly identify these varieties.

3. Conceptual Framework

A farmer is more likely to adopt a new agricultural technology (e.g. a new rice variety or management practice) if he/she is aware of the technology and the benefits from doing so outweigh the costs. Probability of awareness can depend on many factors, including access to information within the community (from formal and informal sources) level of education, and gender, as preferences and access to resources can vary by gender (Doss, 2001). The costs and benefits of adoption also vary by community and household and can depend on the actual cost of the technology, ease of accessing the technology, farmer’s land type and size, and the availability of complementary resources such as knowledge or agricultural inputs (Feder et al, 1985; Foster and Rosenzweig, 2010).

SPGs bring resources into their communities including improved rice seed of STRV and other varieties, as well as knowledge of improved management practices members receive as part of their training. SPGs can have spillover effects onto local farmers through the following mechanisms (Benjamin-Chung et al., 2015; Winters et al., 2011):

1. Improved rice seed becoming easier (and thus, less costly) to obtain for farmers near SPGs. Similarly, general equilibrium effects can lower the price of seed within the local economy due to increased production;
2. Learning/imitation effects: local farmers learn about new varieties and BMPs from SPG members, either by talking with them or by observing them;
3. Norm-setting effects: SPG farmers may establish new social norms within the village surrounding cultivation practices;

We hypothesize that non-SPG member farmers in SPG villages and nearby villages will have a higher rate of adoption of STRVs than other farmers in the area, due to their proximity to SPGs which increase farmers' access to (and lower the costs of obtaining) STRV seed. Similarly, they will have an increased SRR due to their improved access to STRV and other seed. Learning/imitation, norm-setting, and general equilibrium effects could also contribute to this.

We also hypothesize that non-member farmers who live in SPG villages will be more likely to adopt BMPs than farmers in all other villages, due to their proximity to SPG members who received CURE training. These impacts arise primarily through learning/imitation and norm-setting effects. This effect could be greater for practices that are more "visible" (e.g. crop rotations) than those that are less visible (e.g. rice cleaning and drying), are easy and/or cheap to implement, and/or are very profitable. The increase in BMP usage may not spread to adjacent villages, as learning and norms may not extend as easily across villages compared to rice seed.

4. Empirical Framework

4.1. Outcomes of Interest and Treatment Variable

Table 4-1 defines our outcomes of interest in evaluating the spillover effects of SPGs. We examine adoption of STRVs in three time periods: any season up to and including the 2018 monsoon season; the 2017 monsoon season; and the 2018 monsoon season. This is to capture trends over time, allowing us to examine whether impacts of SPGs have become stronger or weaker over time. The SRR is calculated as the percentage of seed grown by the household in 2018 that came from certified or truthfully labeled seed. Our list of BMPs comes from interviews with SPG executive committee members about topics on which they were trained, and span practices from the beginning of the rice season (pre-transplanting) to the end (post-harvest processing). More information on these practices is provided in Section V.a of this paper, which describes the results from the SPG leader survey.

Table 4- 1: Dependent variables

Outcome variable	Description
STRV adoption	Household has grown an STRV in the current or any previous season
STRV adoption (2018)	Household grew an STRV in monsoon season of 2018
STRV adoption (2017)	Household grew an STRV in monsoon season of 2017
SRR	Seed Replacement Rate of rice at the household level, measured by the % of seed that was grown from certified or truthfully labeled seed in the 2018 monsoon season
Use of BMPs:	Household practiced the following in 2018:
○ Clean rice seed prior to planting	Rice seed was cleaned prior to planting; either by floating it in water and removing seeds that float to the top and/or picking through it to remove damaged seeds
○ Seeding ratio	Quantity of rice seed planted in kg/hectare of land cultivated under rice
○ Age of seedlings	Age of seedlings in days when they were transplanted into rice fields
○ Organic fertilizer	Quantity of organic fertilizer in kg applied per hectare of rice land
○ Chemical fertilizer	Quantity of chemical fertilizer in kg applied per hectare of rice land
○ Roguing	Number of times the household rogued their rice fields
○ Moisture testing	Moisture of seed was checked prior to storage, either using a moisture control machine or by biting the seed to determine if it snaps in half
○ Legume cultivation	Household grew lentils
○ Vegetable cultivation	Household grew vegetables

We quantify the impact of living in an SPG village or an adjacent village on the outcome variables defined in table 4-1 using multivalued treatment effects models. We specify the treatment variable as the multi-valued categorical treatment variable SPG_m, where *m* refers to individual villages. $SPG_m = 0$ for control villages, i.e. those that were randomly selected. SPG_m is equal to 1 if village *m* is adjacent to an SPG village and 2 if village *m* is an SPG village.

4.2. Doubly-Robust Weighted Regressions

The challenge of estimating the impact of SPG_m on our outcomes of interest is that SPG villages were not chosen randomly by CURE program staff. Therefore, we would expect that SPG villages, and possibly adjacent villages, may vary systematically from randomly selected villages. If some of this variance is correlated with our outcome variables, then our treatment effect estimates will be biased.

To control for this bias, and to ensure that our treatment and control villages are comparable, we use two weighted regression estimators: the augmented inverse-probability weighted (AIPW) estimator and the inverse-probability weighted regression adjustment (IPWRA) estimator. We also estimate unweighted regression adjustment (RA) estimators as is commonly done in the weighted regression estimator literature (Smale et al. 2018; Haile et al. 2017).

Weighted estimators work similarly to RA estimators, but involve an extra step (the weighting). RA estimates the outcome model using a linear, logit, probit, or Poisson model, where the outcome variable Y_i is regressed on covariates X_{mi} which vary by village *m* and household i, and Z_m, which vary by village *m.*

$$Y_i = f(X_{mi}, Z_m, \mathrm{B}) + \epsilon_{mi} + \epsilon_m \qquad (1)$$

The error terms ϵ_{mi} and ϵ_m are the household and village level error terms, which are assumed to be independent and, in our models, robust to heteroskedasticity. Then, RA involves averaging the predicted outcomes for each treatment level (0-2) of SPG_m. The third step of the RA consists of calculating the difference between the two treatment groups (1-2) and the control group, which gives the average treatment effect for each level of treatment.

Weighted estimators add the weighting which involves the following steps. First, the treatment model is estimated using a multinomial logit model for multi-valued treatments, where the treatment is regressed on a set of village characteristics represented by the vector Z_m in equation (2)

$$SPG_m = h(Z_m, \Lambda) + w_m \qquad (2)$$

The error term w_m includes any village heterogeneity in treatment not captured by Z_m, and Λ is a vector of parameters to be estimated. Then, the generalized propensity score is calculated: this is the conditional probability that a village receives each specific level of treatment (SPG_m = 0, 1, 2) given Z_m. The outcome regression models (in IPWRA) for each treatment level or the computed averages for each treatment level (in AIPW) are then weighted by the inverse of the propensity score for the respective treatment level (McCaffrey et al., 2013). The variables in Z_m can overlap with the variables in X_{mi}, but they do not have to. In our models, Z_m only includes variables captured at the village level because treatment is at the village level.

Weighted estimators create a more balanced data set based on observable characteristics than RA or other unweighted regression methods such as OLS or logit outcome models, making treatment and control observations more comparable to each other and further reducing the bias that arises from observables (Austin, 2011). Weighted estimators are called "doubly robust" because they only require that either the outcome model or the treatment model be correctly specified (Wooldridge, 2010). An additional advantage is that they allow for multi-valued treatment effects, which our regressions require (Cattaneo, 2010; Smale et al. 2018). Both IPWRA and AIPW have been used in recent literature evaluating the impacts of agricultural interventions. Smale et al. (2018) use multivalued AIPW and IPWRA estimators to evaluate the effects of hybrid sorghum adoption on household sorghum yields and purchases, and dietary diversity. Esposti (2017) uses multivalued AIPW to estimate the impacts of the Common Agricultural Policy on farm production choices of farmers in Italy. Haile et al. (2017) use the

AIPW estimator to determine the effects of participatory action research in Malawi. Finally, Cavatassi et al. (2011) use inverse propensity score weighted least squares (a different type of weighted estimator) to evaluate the impacts of Plataformas, a program in Ecuador that links smallholder potato producers with agricultural support service providers.

Weighted regression estimators rely on two major assumptions: overlap and unconfoundedness. The overlap assumption requires that the values of the weighting variables Z_m are similar enough between treatment and control villages that these villages can be meaningfully compared. We assess the overlap assumption by examining the distribution of the propensity scores for treatment and control groups. When a group has a high density of propensity scores in the same range as the other groups, there is a high level of overlap (Imbens and Wooldridge, 2007).

The unconfoundedness assumption stipulates that there are no unobserved village characteristics that are both correlated with being selected for an SPG and our outcomes of interest. We control for observed characteristics known to have influenced selection of SPG villages, but if unobserved characteristics exist then selection bias could arise. A common way to assess the validity of the unconfoundedness assumption is to verify that the weighting models properly balance the covariates (Haile et al., 2017; Esposti, 2017). We do this using a balance test derived by Imai and Ratkovic (2014).

Our set of weighting and control variables (Z_m) include village-level variables that likely had an impact on selection of villages for SPGs (table 4-2). Proximity to roads was an explicit criterion for SPG location; we therefore include distance from the village center to asphalt road in minutes travel time using the most common mode of transportation. In addition, all SPG villages were villages in which farmers grew rice every year. While all of our villages (SPG, adjacent, and randomly selected) are villages where rice is grown each monsoon season, we include a few agro-ecological variables to control and weight for suitability of rice production. These include village averages for altitude, NDVI, and slope. We also include distance to IAAS campus in minutes travel time, as CURE program implementers may have been more familiar with, and thus more likely to select, nearby villages. Similarly, we include distance to the nearest DADO, as extension agents may have been more likely to recommend villages near their offices. Finally, we include distance to the nearest agrovet. Villages close to agrovets may be more likely to experiment with different varieties, and thus be assessed as more likely to sustain a successful SPG by CURE.

Our set of variables X_{mi} includes one village characteristic and several household characteristics that could be correlated with both treatment and the outcome variables (table 4-2). The village level variable used as a control is a dummy variable equal to one if the village had a farmer's association 6-10 years ago, around the time of the SPG establishment. We initially wanted to include it as a weighting variable but it impaired overlap significantly. Moving it to the control variable list X_{mi} did not change results substantially, thus we removed the presence of a farmer's association 6-10 years ago from the $Z_m$vector. We believe it is an important to control for this variable as farmer's associations can improve access to information within a village that could influence adoption of STRVs, SRR, and BMPs (Foster and Rosenzweig, 2010; Beyene and Kassie, 2015).

We control for a number of household characteristics. The first is whether any household member has ever been a member of an SPG. Controlling for membership is essential to separate out the direct impact of belonging to a SPG from the spillover effects onto non-members. We also control for the age, sex, and education of the head of household, as these traits could influence access to information and other resources related to our outcomes of interest. Households whose head is more educated may be more likely to replace rice seed according to the recommended rate and adopt improved varieties and BMPs since they likely have greater access to and ability to process information. Education enters the models as a binary variable indicating whether the household head has completed primary education. The number of adults in the household aged 15 and older is included as a measure of household labor availability as labor availability could influence rice cultivation decisions including what varieties and practices to use. We control for household wealth and resources using two variables: a wealth index created using polychoric principal components analysis based on housing characteristics and asset ownership in 2008, and a variable for land owned (in hectares) in 2008. Wealthier households and households owning more land may be more likely to replace rice seed and to adopt new varieties, as they have a greater ability to purchase seeds, and have access to more resources that may promote adoption (Feder et al., 1985). We use information from 2008 to avoid any potential endogeneity problem that could arise if SPGs have increased household wealth or land ownership over time. Finally, distance to the nearest road can influence household rice cultivation by affecting how easy it is for households to access new planting material as well as information.

Table 4- 2: Village and household level covariates

Variable	Description
Weighting variables (Z_m)	
Altitude	Average village altitude
NDVI	Average village NDVI
Slope	Average village slope
IAAS	Average village distance to IAAS in minutes traveling by car
DADO	Distance from the village center to the nearest DADO office in km
Agrovet	Distance from the village center to the nearest agrovet in minutes traveling using the most popular mode of transportation
Asphalt road	Distance from the village center to the nearest asphalt road in minutes traveling by the most popular mode of transportation
Control variables (X_{im})	
SPG Member	Has anyone in the household ever been a member of an SPG?
Sex	Sex of the head of household
Age	Age of the head of household
Education	Did the head of household complete at least a primary education? (1 = yes)
Land owned, 2008	Quantity of land owned, in ha, in 2008
Wealth index quintile, 2008	Wealth index created using polychoric principal components analysis based on asset ownership and housing characteristics in 2008
Distance to road	Distance from household to the nearest road
Farmer's association	Did the village have a farmer's association at least 6 years ago?

4.3. Robustness Checks

We perform several robustness checks to assess the sensitivity of our results to model and treatment variable specification. As first robustness check, we estimate unweighted OLS, logit, Poisson and fractional logit models, depending on the outcome variable, controlling for variables in Z_m and X_{im} and using as treatment variable distance to the nearest SPG measured in km and then in minutes travel time. Having two measures for distance to the nearest SPG serves as a sensitivity check of the results to the treatment variable specification. Moreover, using a continuous variable sheds light on how far spillovers effects can occur. Spillovers could potentially reach beyond adjacent villages, particularly for adoption of STRVs as the transfer of seeds can occur along marketing channels which can extend past neighboring villages.

We also estimate the direct effects of SPG membership on members using RA; our treatment variable is a dummy variable equal to one if a household member has ever been a member of an

SPG and zero otherwise. It is more difficult to deal with the problem of unobserved bias when examining direct effects of membership because members volunteered to join SPGs and are very likely to be the most capable or entrepreneurial farmers within their villages. However, examining the effects of SPG membership can shed light on whether the magnitude of the estimated indirect effects are plausible by serving as upper bounds for spillover effects. For example, if SPG members did not follow recommended BMPs, then it is unlikely that SPGs would have an impact on the adoption of BMPs among non-members based on our conceptual framework of how spillover effects arose.

5. Descriptive Statistics

In this section, we first present key findings from the SPG leader interviews. Then, descriptive statistics from the community surveys disaggregated by SPG villages, adjacent villages, and randomly selected villages are discussed. This section concludes with descriptive statistics from the household survey broken down by SPG members from any village, non-members in SPG villages, non-members in adjacent villages, and non-members in randomly selected villages.

5.1. SPG Leader Survey Statistics

Our SPG survey results yield extensive descriptive information on the SPGs. Each SPG had active membership (figure 4-3), even the groups that did not produce rice in the 2017/2018 season (figure 4-4). Membership numbers ranged from 7 to 75. In some groups, not all members sold rice seed in 2018 (the number of members who sold rice ranged from 7 to 52). Most members live within the same village as their SPG, though some SPGs have members that come from neighboring villages.

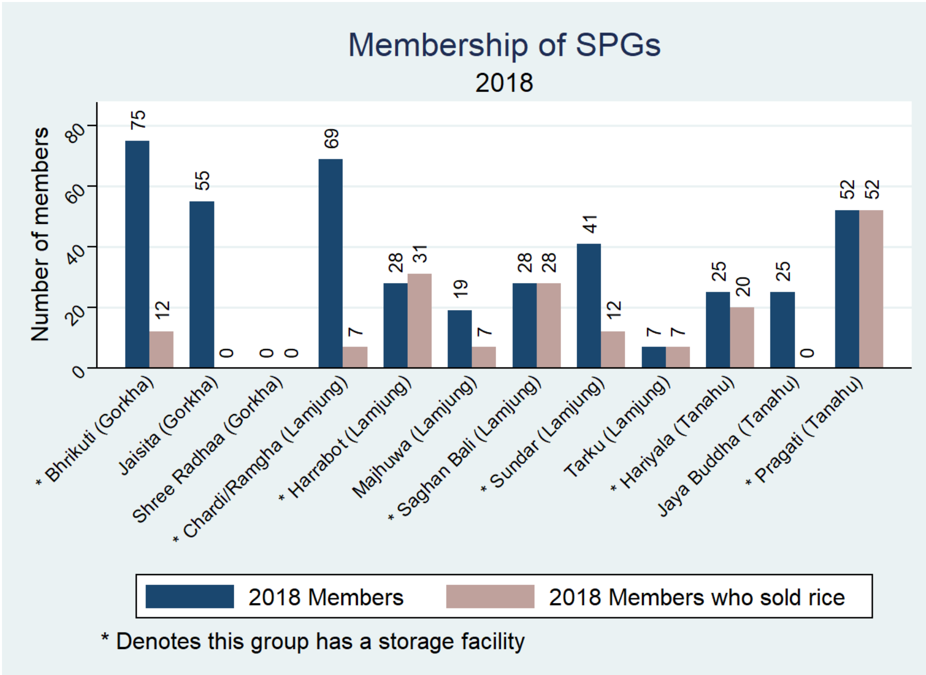

Figure 4- 3: SPG membership, 2018

The SPGs varied in how active they were as of 2018 (figure 4-4). Nine of the groups still actively produce and sell rice seed (one in Gorkha, two in Tanahu, and six in Lamjung). The remaining three groups did not sell any rice seed in 2018 (two in Gorkha and one in Tanahu). The active groups produced between 200 kg and 16 mt of rice seed in 2017 to be sold in 2018. Seven out of the twelve groups had their own (or a shared) storage facility. The three inactive groups did not have dedicated storage facilities.

Not all groups provided information from the year prior (2016 production/2017 sales), but judging by the information we recieved, it appears that production in 2016/2017 was higher than in 2017/2018. Production in many of the groups was significantly higher in 2016/2017 compared to 2017/2018. Bhrikuti produced over 9,000 kg; Saghan Bali produced 21,500 kg; Sundar produced 20,500 kg; Pragati produced 15,000 kg. Even two of the smaller groups from 2017/2018 produced more in 2016/2017: Jaya Buddha produced 1800 kg and Chardi/Ramgha produced 20,000 kg. We do not know why 2016 production tended to be higher than 2017 production.

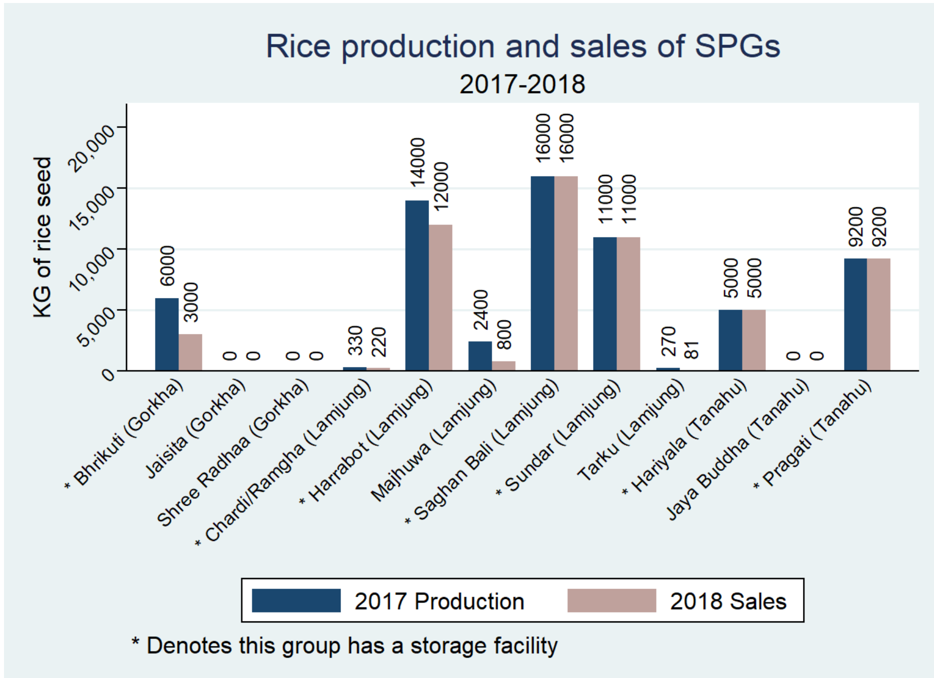

Figure 4- 4: SPG production and sales in 2017/2018

We asked each SPG to list all rice seed varieties its members had ever produced. The groups had cultivated nine drought-tolerant varieties: Sukkha-1, Sukkha-2, Sukkha-3, Sukkha-4, Sukkha-5, Sukkha-6, DRR 44, Hardinath, and Radha-4 and one submergence tolerant variety, Swarna Sub-1. Members also grew Sabitri, Ramdan, and Loktantra, which are varieties suitable for rainfed conditions but not considered drought-tolerant (Adhikari, 2017). Additional varieties produced and sold by SPGs are Makwanpur, Sunaula Sagunda, CR Sub-1, Kirbhan Sub-1, Chait-5, Radha-9, Bindeswore, and Mansuli, which are other improved varieties.

Groups most commonly sold to farmers directly from the SPG storage facilities, to the district agricultural development offices (DADO) located in district capitals, and to Sundar Cooperative in Sundarbajar, Lamjung. Only two groups sold to agrovets in 2018. We spoke to two local agrovets who reported that they used to purchase SPG varieties but have recently stopped because they can buy cheaper seed from producers in the plains, or terai, region of Nepal, particularly from nearby Chitwan district.

SPG leaders also reported what they learned about rice cultivation from their IAAS trainings. They were trained on many topics, including nursery bed preparation, seeding ratio, land preparation, weeding, input use, seed cleaning and storage. Respondents also reported that, prior to training, the members of their SPGs did not follow many of these practices. Information from these surveys, as well as supporting information from Bishnu Bilas Adhikari of IAAS, who was responsible for training the SPGs, allowed us to put together the list of BMP outcome variables (table 1).

Training topics considered for our BMPs ranged from the beginning of the rice season to the end. Prior to planting seed in nursery beds, SPG members were trained to clean their rice seed by floating it in water and removing seeds that float to the top. When planning how much seed to plant and subsequently transplant into their rice fields, SPG members were trained to plant 2-3 kg of seed per one ropani of land (40-60 kg/ha). Prior to training, SPG members reported planting over twice as much, and sometimes three times as much. SPG members were also trained to transplant seedlings when they are 18-22 days old, and prior to June 30. They were trained on fertilizer use for both nurseries and fields, although they were not given precise fertilizer recommendations, as fertilizer needs can vary by soil type and quality. Specifically, they were trained that there are no limits on the quantity of organic fertilizer they could apply, and that if chemical fertilizer was required, the rice plants needed phosphorous and potassium in addition to nitrogen. This was contrary to common practice, which was to apply only urea as a chemical fertilizer, which supplies only nitrogen. After harvest, farmers were trained to ensure that seed is dried prior to storage; they could do this using a moisture testing machine if available, or a “bite-test”: if the seed snaps when bitten, it is dry enough to be stored. Finally, in addition to rice cultivation, SPGs were also trained in cropping patterns; specifically, they were trained on the benefits of growing lentils and vegetables on rice fields after the rice was harvested. The ability to do this was enhanced by cultivating short-duration rice varieties, which includes STRVs.

Finally, SPG leaders were asked about their group’s challenges regarding rice cultivation and sales. The most commonly listed cultivation problems were lack of labor and lack of machinery. These are exacerbated by the high level of migration from rural areas to urban areas in Nepal and to other countries. The biggest problem, however, related to finding consistent buyers for their rice seed. Some groups used to sell to Sundar Cooperative, but said that Sundar could no longer purchase their seed. Some noted communication difficulties with Sundar. It was not entirely clear what the problem was between the groups and Sundar. Sundar noted that a lack of labor made it challenging to manage their cooperative. This problem relates to what the agrovets had mentioned to us; seed production is cheaper in the terai region of the country, and the SPGs face competition from seed producers there. Two of the more remote, inactive groups (Jaisitar and Shree Radha) also noted transportation difficulties for selling seed, but other groups did not mention this as a challenge.

5.2. Community Survey Descriptive Statistics

Villages where SPGs were established differ from other villages in terms of agroecology and access to other resources and seed sources (roads, IAAS, farmer’s associations more than 5 years ago, agrovets), which is not surprising since these villages were not chosen randomly. SPG villages are at lower elevation than randomly selected villages, and have somewhat flatter slopes than randomly selected villages (table 4-3). They also have a slightly lower average NDVI value than adjacent and randomly selected villages, denoting less vegetation. SPG villages and adjacent villages are closer to asphalt roads on average than randomly selected villages. Finally, SPG villages are closer to IAAS than randomly selected villages.

Table 4- 3: Community Survey Descriptive Results

	Randomly selected villages (Group 0)	Adjacent villages (Group 1)	SPG villages (Group 2)	Statistically significant differences
Average household altitude (masl)	629.05 (33.56)	577.56 (41.62)	523.62 (24.89)	5% difference 0 vs 2
Average household slope	10.27 (0.78)	10.42 (1.24)	7.81 (1.19)	1% difference 0 vs 2
Average village NDVI	0.34 (0.01)	0.34 (0.01)	0.32 (0.01)	1% difference 0 and 1 vs. 2
Distance from village to asphalt road, minutes travel time	55.39 (9.11)	25.83 (6.57)	20.00 (10.44)	5% difference 1 and 2 vs 0
Average household distance to IAAS campus, minutes travel time	56.74 (4.03)	41.21 (10.00)	35.69 (8.78)	5% difference 0 vs 2
Village had a farmer's association more than 5 years ago (1 = yes)	0.29 (0.06)	0.33 (0.14)	0.75 (0.13)	1% difference 0 vs 2; 5% difference 1 vs. 2
Distance to agrovet, minutes travel time	87.06 (14.25)	32.08 (8.47)	23.75 (0.11)	1% difference 0 vs 1 and 2
Distance to DADO, km	16.75 (3.96)	11.00 (3.11)	14.47 (1.87)	
n	51	12	12	

5.3. Household Survey Descriptive Results

SPG villages have a higher percentage of SPG members than adjacent and randomly selected villages (figure 4-5). The difference between adjacent and randomly selected villages is not significant. This is not surprising, as SPGs reported that most of their members live within their villages. We present the remaining household descriptive statistics broken into four categories in order to examine differences by both membership and village: SPG members from any village (9.7% of the sample), non-members in SPG villages (10.1%), non-members in adjacent villages (14.7%), and non-members in randomly selected villages (65.56%).

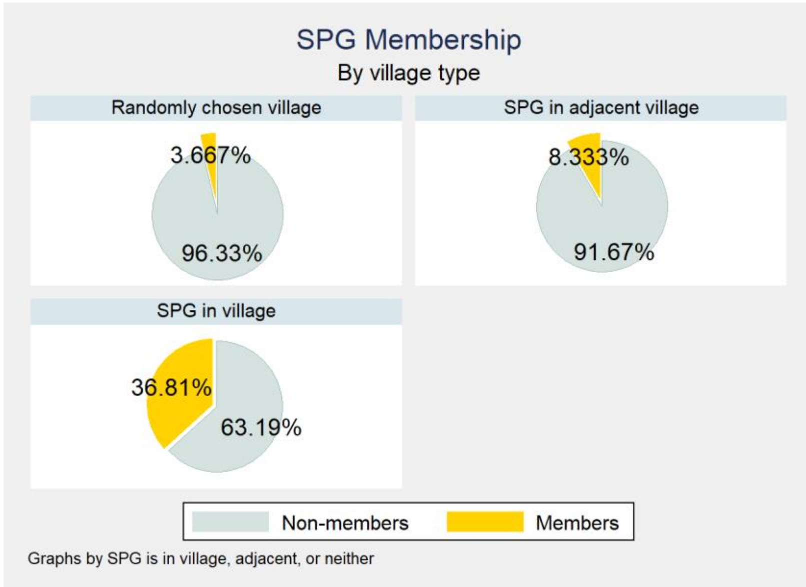

Figure 4- 5: SPG membership by village type

Adoption of STRVs varies greatly by membership and village type (figures 4-6 to 4-8). Overall adoption rates among SPG members (76%) and non-members in SPG villages (59%) do not vary significantly but all other groups have differences that are significant at the 5% level or lower; adoption of STRVs is 50% for non-members in adjacent villages and 40% for non-members in randomly selected villages. Adoption in individual seasons (2017 and 2018) is lower than adoption overall. In 2017, non-members in randomly selected villages, who had the lowest level of adoption at 19%, vary significantly from non-members in adjacent villages (29%) and SPG members (37%) at a 5% level or lower. Other differences are not statistically significant. In 2018, adoption of STRVs among non-members in randomly selected villages (28%) and non-members in adjacent villages (33%) is significantly lower than for SPG members (48%), while the adoption rate of non-members in SPG villages (36%) do not vary significantly from that of other groups.

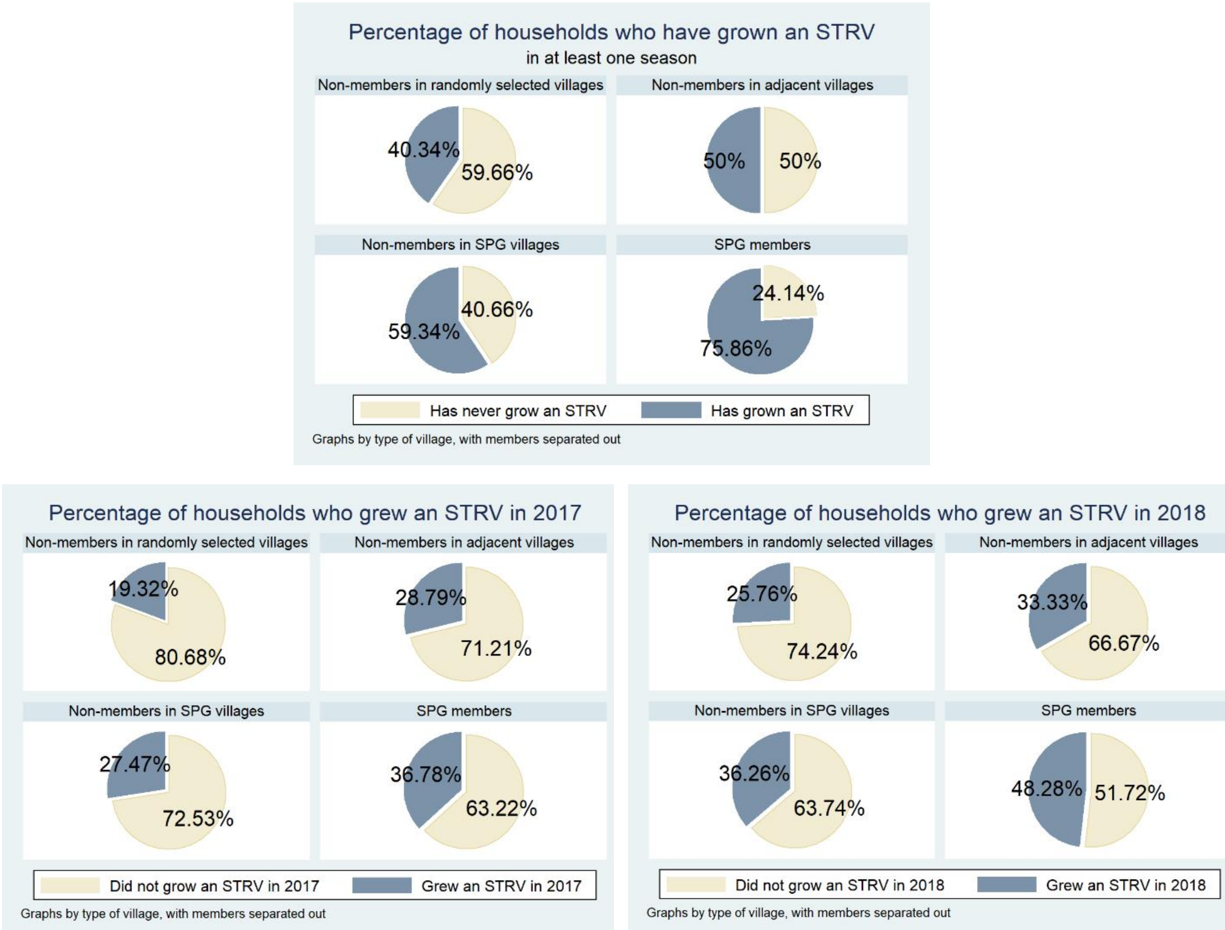

Figure 4- 6: STRV adoption by membership and village type

The SRR is highest for SPG members (79%), followed by non-members in SPG villages (64%) while non-members in adjacent and randomly selected villages have the lowest SRR (about 52% each) (figure 4-7). SPG members plant their seedlings when they are about 1.3 days younger than any other group (this difference is significant at a 5% level against all groups). Non-members in SPG and adjacent villages plant their seedlings when they are about 0.7 days younger than non-members in randomly selected villages (significant at a 5% level). SPG members have the lowest seeding rate (47.9 kg/ha), which differs from the seeding rate of all other groups at a 5% level or lower. Non-members in SPG villages also have a lower seeding rate (80.9 kg/ha) than households in adjacent villages, a difference that is significant at 5%. SPG members rogue their rice fields more times (1.83 compared to 1.46-1.53) in a season than any other group (significant at 1%).

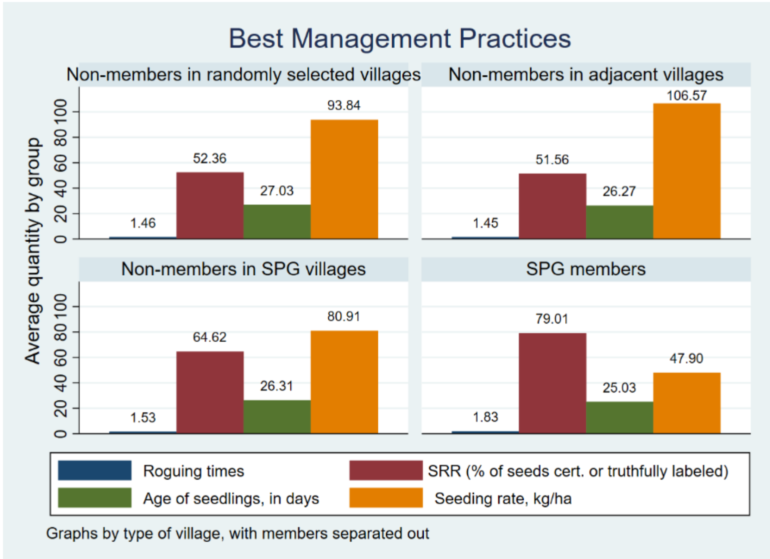

Figure 4- 7: Best management practices and SRR

Households use 135.88 kg of chemical fertilizer and 8,163.51 kg of organic fertilizer per ha of rice land on average. There are no significant differences between groups for chemical fertilizer (figure 4-8). However, SPG members use more organic fertilizer than any other group, although the difference between SPG members and non-members in SPG villages is significant at just the 10% level (figure 4-8).

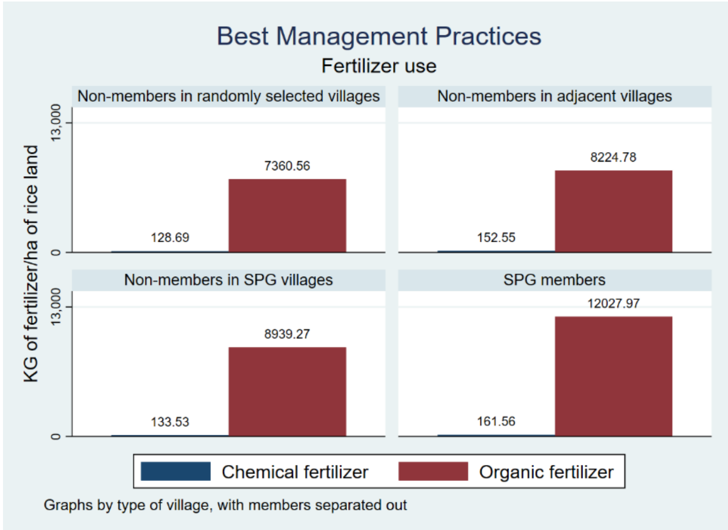

Figure 4- 8: Fertilizer use

About 60-65% of households in our sample cleaned their seeds prior to planting; there are no significant differences between groups (figure 4-9). By contrast, 39% of SPG members test their seed moisture prior to storage which is over twice as likely as any other group; there are no significant differences between the other groups (figure 4-10). SPG members and non-members in SPG villages are equally likely to plant legumes (51 – 60%), and more likely to plant legumes than non-members in adjacent and randomly selected villages, who are equally likely to do so (about 40% in each group). SPG members are more than twice as likely than any other group to plant vegetables (figure 4-11); 22% compared to 10% or less for the other groups (this difference is statistically significant for each group).

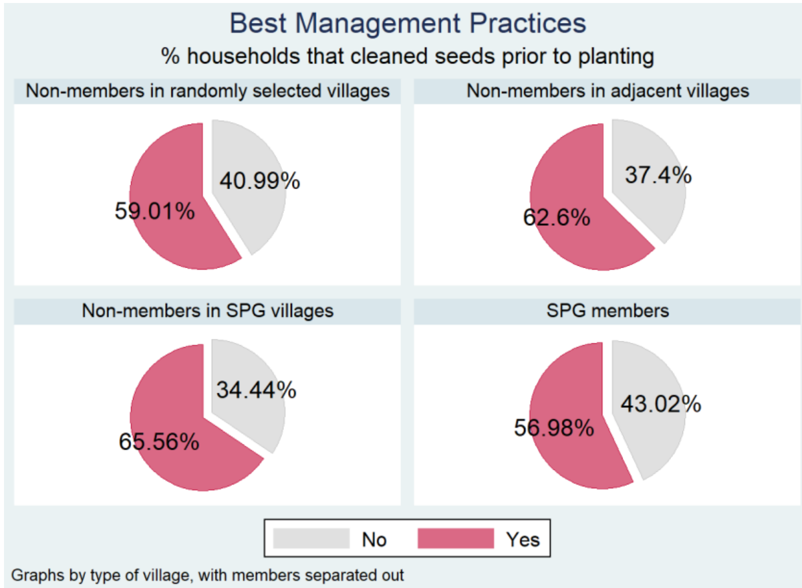

Figure 4- 9: Seed cleaning

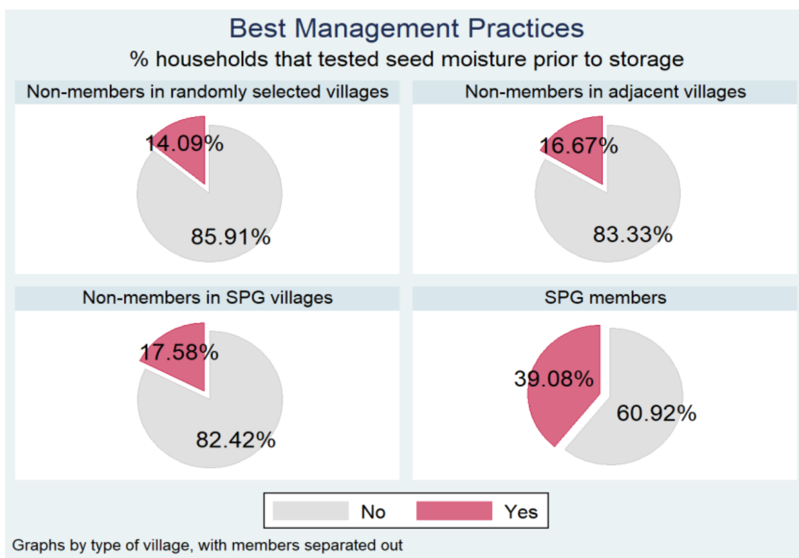

Figure 4- 10: Seed moisture testing

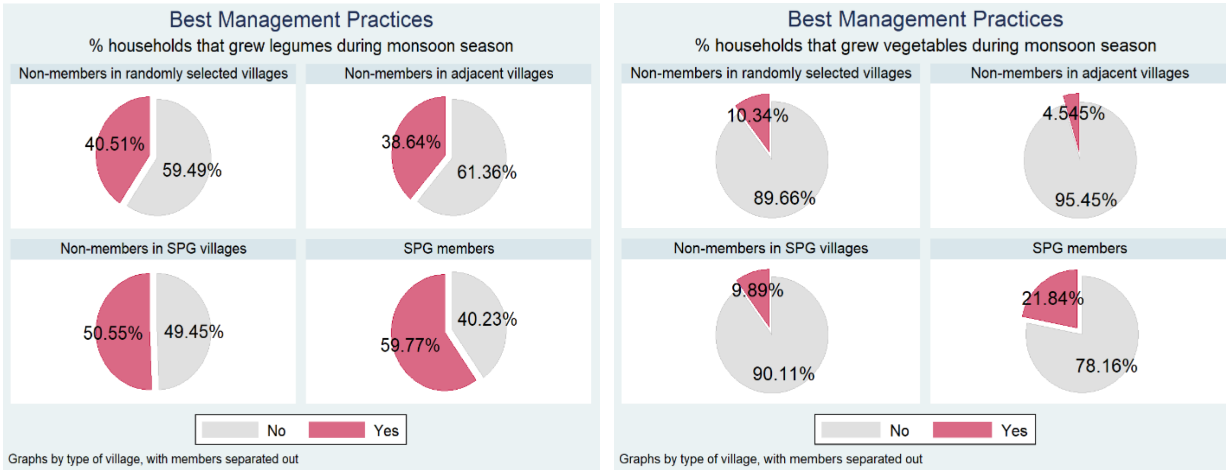

Figure 4- 11: Legume and vegetable cultivation

Half of the respondents, selected at random, were asked more detailed questions about fertilizer use and labor use on rice fields. We present descriptive statistics for these questions disaggregated by membership status and village type, although we do not estimate econometric models for these outcome variables. CURE training taught farmers that plants need more nutrients than just nitrogen, and there is evidence that SPG members and non-members in SPG villages are more likely to use additional inorganic fertilizers compared to non-members in other villages; 83% of members and 89% of non-members in SPG villages used inorganic fertilizer other than urea. This is significantly higher than for non-members in adjacent and randomly selected villages, where 78% and 76% of respondents used non-urea chemical fertilizer, respectively.

We examine labor requirements descriptively to explore whether the differences in management practices lead to an overall increase or decrease in labor usage in rice cultivation for SPG members. We find that labor usage varies somewhat by membership status and village type. SPG members use less unpaid labor (138.5 person hours/ha) than non-members in randomly selected (179.1) and adjacent villages (191.0), but a statistically equivalent quantity as non-members in SPG villages. Non-members in SPG villages use the most paid labor (167.8 person hours/ha); this varies significantly from non-members in adjacent villages (104.7); SPG members and non-members in randomly selected villages fall in between. However, total labor usage (unpaid plus paid) does not vary significantly by group. Therefore, changes in management practices adopted by SPG members do not change total labor requirements; though they use less unpaid labor than some other groups, their use of paid labor falls between that of the other groups.

Table 4- 4: Household Characteristic Descriptive Statistics

	Non-members in randomly selected villages (Group 0)	Non-members in adjacent villages (Group 1)	Non-members in SPG Villages (Group 2)	SPG Members (Group 3)	Statistically significant differences
Sex of HoH (1 = female)	0.21 (0.02)	0.17 (0.03)	0.27 (0.05)	0.29 (0.05)	10% difference 1 vs 2; 5% difference 1 vs 3
Age of HoH	51.99 (0.55)	52.80 (1.13)	51.03 (1.52)	52.21 (1.42)	
HoH has primary education (1 = yes)	0.68 (0.02)	0.71 (0.04)	0.82 (0.04)	0.77 (0.05)	1% difference 0 vs 2; 10% difference 0 vs 3; 10% difference 1 vs 2
Number of adults in household	2.90 (0.05)	3.11 (0.12)	2.82 (0.15)	2.93 (0.14)	
n	576	129	90	87	882
Land owned in 2008, m2	5560.81 (313.81)	5468.69 (455.61)	5268.08 (371.02)	6156.19 (640.33)	
Wealth index in 2008	2.87 (0.06)	2.87 (0.12)	3.57 (0.15)	3.46 (0.14)	1% difference 0 vs 2 and 3; 1% difference 1 vs 2 and 3
n	587	128	90	87	892
Distance to road, meters	46.82 (2.86)	47.53 (5.35)	27.52 (3.05)	40.83 (4.82)	1% difference 0 vs 2, 1% difference 1 vs 2; 5% difference 2 vs 3
n	590	132	91	87	900

Note: Differences in n across characteristics are due to missing observations.

Households in SPG villages tend to be better educated and were wealthier in 2008 than households in other villages (table 4-4). They also lived closer to roads than non-members in adjacent and randomly selected villages, though non-members in SPG villages live closer to roads than SPG members. This result does not change if we look at only SPG members within

SPG villages, who live an average of 39.0 meters from roads. Non-members in adjacent villages have a lower percentage of female-headed households than SPG member households. Non-members in randomly selected villages have the lowest level of education, while non-members in SPG villages have the highest. The differences that exist between these groups highlight the importance of controlling for these factors and weighting our results to improve comparability of villages.

6. Econometrics Results

6.1. Statistical Test Results

Propensity score overlap graphs are presented in the Appendix. For each treatment level (0-2), a high proportion of villages from each group are in the area of common support (i.e. the area where all groups have an above zero density of propensity scores), indicating that the overlap assumption is met and our villages are comparable (Imbens and Wooldridge, 2007).

The Imai and Ratkovik test used to check balance between groups can only be estimated with binary treatment variables. Therefore, to check balance, we specify treatment in three different ways: SPG villages vs. randomly selected villages (we dropped adjacent village observations); adjacent villages vs randomly selected villages (we dropped SPG village observations); SPG and adjacent villages vs. randomly selected villages. For each specification, we fail to reject the null hypothesis that our treatment model balances covariates between treatment groups ($p = 0.178$, $p = 0.390$, and $p = 0.999$, respectively). This provides evidence that covariates are well balanced and that the unconfoundedness assumption holds (Haile et al., 2017; Esposti, 2017).

6.2. STRV Adoption

Living in a village with an SPG raises the probability that a non-member household has adopted an STRV at some point in the past by 17-18% above non-member households in randomly selected villages (table 5), indicating the presence of spillover effects within villages where SPGs were established. But there is no evidence that SPGs have spillover effects on overall STRV adoption in adjacent villages. In 2018, non-members in SPG villages were about 15% more likely to have adopted STRVs than non-members in randomly selected villages (though the IPWRA results were not significant). Compared to 2018, the effect of SPGs in 2017 on adoption of STRVs among non-members in SPG villages was stronger and spilled over onto adjacent villages; SPGs raised adoption levels by 23-24% and 19-22% for non-members in SPG villages and adjacent villages, respectively compared to non-members in randomly selected villages. It is not surprising that spillover effects were greater in 2017 compared to 2018, as rice seed production of SPGs was higher in 2017 than 2018. Our conceptual framework predicts that the spillover effects of increased adoption will extend along market channels as far as SPG seed is commonly sold, likely to adjacent villages. Given our results, there is evidence that spillover effects may extend farther in years of high production.

Table 4- 5: Results for ra, ipwra, aipw models on impacts of SPGs on adoption of STRVs

	Adoption in any season			Adoption in 2018			Adoption in 2017		
	RA ATE	IPWRA ATE	AIPW ATE	RA ATE	IPWRA ATE	AIPW ATE	RA ATE	IPWRA ATE	AIPW ATE
SPG Village	0.17 (0.04) ***	0.18 (0.04) ***	0.18 (0.04) ***	0.15 (0.06) ***	0.13 (0.09)	0.15 (0.06) ***	0.23 (0.06) ***	0.24 (0.06) ***	0.23 (0.06) ***
Adjacent village	0.02 (0.07)	0.06 (0.11)	0.02 (0.07)	0.11 (0.07)	0.17 (0.10) *	0.12 (0.07)	0.19 (0.10) *	0.22 (0.07) ***	0.19 (0.10) **
N	872	872	872	872	872	872	872	872	872

Note: */**/*** denotes statistical significance at 10%/5%/1% respectively. All standard errors are robust to heteroskedasticity. Results provide comparison with SPG villages/adjacent villages to randomly selected villages.

6.3. Seed Replacement Rate

Results from the SRR estimation (table 4-6) indicate that the seed replacement rate is 52-53 percentage points higher for non-members in SPG villages compared to non-members in randomly selected villages. Given our conceptual framework, we expected spillover effects onto adjacent villages as well, but there is no evidence that this occurred. However, these results are in line with the previous findings that SPGs did not stimulate STRV adoption in adjacent villages in 2018; it would be interesting to determine if SPGs had an effect on SRR in 2017 but we only have this data for 2018.

Table 4- 6: Results for ra, ipwra, aipw models on impacts of SPGs on SRR

		SRR	
	RA ATE	IPWRA ATE	AIPW ATE
SPG Village	0.52 (0.20) ***	0.52 (0.21) **	0.53 (0.20) ***
Adjacent village	-0.03 (0.14)	-0.10 (0.13)	-0.03 (0.14)
N	869	869	869

Note: */**/*** denotes statistical significance at 10%/5%/1% respectively. All standard errors are robust to heteroskedasticity. Results provide comparison with SPG villages/adjacent villages to randomly selected villages.

6.4. Best Management Practices

Non-members in SPG villages plant 56-59 fewer kg of seed per ha and rogue their rice seeds almost one complete additional time compared to non-members in randomly selected villages. Given the nature of the roguing outcome variable, which ranges from 0 to 5 times, estimating a Poisson model would be most appropriate. However, given that these models would not converge, a linear model was used to explain the number of time seeds were rogued. If we remove the variable distance to agrovet, the Poisson models converge and results indicate that non-members in SPG villages rogue their rice fields 0.59-0.64 times more than non-members in randomly selected villages, though this difference is significant at the 10% level only. SPGs increase the likelihood that non-members in adjacent villages will test the moisture of their seeds by 13% compared to non-members in randomly selected villages. This effect on non-members in

SPG villages is not statistically significant but of greater magnitude than that in adjacent villages. Finally, SPGs increase the likelihood that non-member households in SPG villages will grow lentils during the monsoon season by 16-17% compared to non-members in randomly selected villages.

Table 4- 7: Results for ra, ipwra, aipw models on impacts of SPGs on seeding ratio, roguing, moisture testing and legume cultivation

	Seeding Ratio			Number of times household rogued rice fields			Tested moisture of seed prior to storage			Grew legumes during monsoon season 2018		
	RA ATE	IPWRA ATE	AIPW ATE	RA ATE	IPWRA ATE	AIPW ATE	RA ATE	IPWRA ATE	AIPW ATE	RA ATE	IPWRA ATE	AIPW ATE
SPG Vill.	-59.60 (28.90) **	-56.40 (26.35) **	-59.37 (23.83) **	1.16 (0.35) ***	1.26 (0.40) ***	1.16 (0.35) ***	0.25 (0.15) *	0.23 (0.14)	0.24 (0.15)	0.17 (0.04) ***	0.16 (0.04) ***	0.16 (0.04) ***
Adj. Vill.	23.84 (24.49)	25.26 (26.35)	23.83 (24.55)	0.03 (0.23)	-0.04 (0.23)	0.04 (0.23)	0.13 (0.03) ***	0.13 (0.04) ***	0.13 (0.03) ***	-0.10 (0.10)	-0.13 (0.08) *	-0.11 (0.10)
N	868	868	868	872	872	872	871	871	871	872	872	872

Note: */**/*** denotes statistical significance at 10%/5%/1% respectively. All standard errors are robust to heteroskedasticity. Results provide comparison with SPG villages/adjacent villages to randomly selected villages.

Table 4- 8: Results for ra, ipwra, aipw models on impacts of SPGs on probability of cleaning seeds, quantity of chemical fertilizer applied to rice fields, and age of seedlings at time of transplantation

	Clean seeds			Chemical Fertilizer			Age of Seedlings		
	RA ATE	IPWRA ATE	AIPW ATE	RA ATE	IPWRA ATE	AIPW ATE	RA ATE	IPWRA ATE	AIPW ATE
SPG Village	0.01 (0.04)	0.01 (0.12)	0.00 (0.04)	95.75 (66.05)	135.87 (75.96)	-303.89 (252.72)	-1.63 (1.55)	-1.16 (1.53)	-1.67 (1.55)
Adj. Village	-0.05 (0.07)	-0.02 (0.12)	-0.04 (0.07)	-308.66 (256.38)	-202.31 (172.0)	95.26 (66.32)	0.26 (0.75)	0.55 (0.75) *	-0.24 (0.75)
N	868	868	868	866	866	866	854	854	854

Note: */**/*** denotes statistical significance at 10%/5%/1% respectively. All standard errors are robust to heteroskedasticity. Results provide comparison with SPG villages/adjacent villages to randomly selected villages. For the Age of Seedlings regression, one randomly selected village had to be dropped because its propensity score was too low for estimation.

There is no evidence of significant SPG spillover effects on non-member households in SPG villages and adjacent villages for the probability that a household cleans seeds prior to planting, the age of seedlings at time of transplantation, and the quantity of chemical fertilizer applied to rice fields. Finally, the models examining whether SPGs impact the quantity of organic fertilizer applied to rice fields and the probability that a household grows vegetables did not converge.

6.5. Robustness Checks

6.5.1. Distance to SPGs

To assess the sensitivity of the results to the treatment variable specification and explore how far SPG spillover effects might travel, we estimated unweighted regressions with distance to the nearest SPG as the treatment variable (controlling for the same variables). For continuous outcome variables, we used OLS, for binary outcome variables, we used logit (marginal effects are presented), and for outcome variables measured as a percentage, we used fractional logit models. Living one km (one minute in travel time) farther from an SPG reduces the probability that a non-member has adopted an STRV by about 2% (0.1-0.2%) at any point in time, in 2018 and in 2017. All effects are significant at the 5% level or lower except for the effect of one-minute travel time in 2018 (table 4-9). This provides additional evidence that living in or nearby an SPG village increases the likelihood of STRV adoption among non-members and indicates that results are robust to treatment variable specification. These results also indicate that we may have underestimated the spillover effects of SPG on STRV adoption if access to these seeds have improved beyond adjacent villages. However, the spillover effect of SPGs on SRR in 2018 is not significant when using distance to the nearest SPG as treatment variable. This is consistent with the weighted results that suggest that SPGs spillover effects on SRR do not extend beyond SPG villages, at least in 2018.

We found no evidence of SPG spillover effects on use of BMPs. The spillover effects of SPGs on adoption of BMPs may be more localized, reaching non-members in the SPG and adjacent villages only. This follows our theory that knowledge about BMPs is most likely to spread through social networks resulting in localized spillover effects only. This finding is also consistent with our RA, IPWRA, and AIPW results, which suggest no spillover effects for BMP adoption among non-members in adjacent villages except for testing moisture.

Table 4- 9: Effect of distance to SPGs in km and minutes travel time on outcome variables

	1 Additional km	1 Additional minute
STRV adoption	-0.021 (0.005) ***	-0.002 (0.001) ***
STRV adoption 2018	-0.019 (0.005) ***	-0.001 (0.001) *
STRV adoption 2017	-0.015 (0.005) ***	-0.001 (0.001) **
SRR	0.007 (0.021)	-0.003 (0.002)
Clean rice seed prior to planting	0.003 (0.005)	0.000 (0.001)
Seeding ratio	-1.476 (0.829) *	-0.097 (0.103)
Age of seedlings	-0.008 (0.04)	-0.007 (0.004) *
Organic fertilizer	5.899 (98.412)	8.41 (12.06)
Chemical fertilizer	0.150 (1.547)	-0.200 (0.170)
Roguing	-0.002 (0.008)	-0.001 (0.001)
Moisture testing	-0.003 (0.004)	-0.000 (0.001)
Legume cultivation	-0.000 (0.003)	-0.000 (0.001)
Vegetable cultivation	-0.004 (0.005)	-0.000 (0.000)

6.5.2. Direct Effects

Our unweighted model results provide evidence of the direct effect of SPG membership on STRV adoption, SRR, and use of BMPs among members. While we do not claim that these effects are unbiased, they indicate whether the significance and magnitude of the estimates of SPG spillover effects are plausible. We find that SPG members are 22-26% more likely to have grown an STRV at any time in the past, in 2018, and in 2017 than non-members (table 4-10). The magnitude of the direct effects are similar to the estimated indirect effect of SPGs on non-members within SPG villages in 2017 (23-24%), but higher than the estimated indirect effects in

2018 (15%) or in any previous season (17-18%). SPG members also have an SRR that is 12 percentage points higher than non-members, but the effect is significant at the 10% level only. This estimate is smaller in magnitude and estimated with less precision than the SPG spillover effect on SRR among non-members in SPG village (52-53 percentage points). Descriptive analysis of the data indicate that 11.5% of SPG members continue to cultivate local varieties compared to 11.0% of non-members in SPG villages, 6.8% of non-members in adjacent villages, and 23.7% of non-members in randomly selected villages. Local varieties are valued for their taste and importance in festivals, so it is not surprising that SPG members would want to maintain their cultivation. This could reduce our estimated direct effects of SPG membership on SRR.

SPG members plant 27 fewer kgs of seed per ha than non-members. This direct effect is smaller in magnitude than the estimated indirect effect on non-members in SPG villages; although the direct and indirect effects do not vary statistically based on 95% confidence intervals. SPG members also rogue their rice fields on average an additional half times over non-members; these results are consistent whether we estimate a linear or Poisson model, or whether we remove the variable for distance to the nearest agrovet as we did for the Poisson model spillover results for roguing. The direct effect of SPGs on roguing is smaller in magnitude but statistically equivalent to the spillover effects (based on 95% confidence intervals) on non-members in SPG villages estimated from the linear model, which indicates that non-members in SPG villages rogue their rice fields one additional time compared to non-member households in randomly selected villages. This direct effect is similar, however, to the Poisson model spillover results, which estimated that non-members in SPG villages rogued their rice fields an additional 0.6 times. SPG members are 13% more likely to test seed moisture prior to storage compared to non-members, which is similar in magnitude to the spillover effect on non-members in adjacent villages. SPG members are 19% more likely to grow lentils and 25% more likely to grow vegetables than non-members. This direct effect for growing lentils is similar to the indirect one for non-members in SPG villages. SPG members also transplant seedlings when they are on average one day younger than non-members and use over 6,000 kg/ha more organic fertilizer on rice plots than non-members. However, the effect of SPG membership on chemical fertilizer is not significant. For age of seedlings, organic and chemical fertilizer use, we found no evidence of spillover effects. Increasing organic fertilizer use could be costly for farmers, and this is why this practice has not spilled over. In the case of seedling age, it could be that SPG members transplant seedlings one day earlier than non-members but there is a lack of spillover effects because this practice is not easily visible to other farmers.

Table 4- 10: RA direct effects of SPGs on SPG members for all outcome variables

	SPG Membership
STRV adoption	0.22 (0.08) **
STRV adoption 2018	0.26 (0.08) ***
STRV adoption 2018	0.23 (0.06) ***
SRR	0.12 (0.06) *
Clean rice seed prior to planting	-0.08 (0.06)
Seeding ratio	-26.87 (7.13) ***
Age of seedlings	-1.00 (0.50) **
Organic fertilizer	6667.05 (2673.16) **
Chemical fertilizer	-37.42 (49.60)
Roguing	0.41 (0.11) ***
Moisture testing	0.13 (0.06) **
Legume cultivation	0.19 (0.05) ***
Vegetable cultivation	0.25 (0.07) ***

7. Conclusions

Although the CURE program officially ended in Nepal in 2013, most SPGs in Lamjung, Tanahu and Gorkha districts (9/12) are still actively producing and selling rice seeds, and members still follow many of the BMPs they learned from their CURE training. SPGs that struggled had trouble finding buyers for their seed. Seed produced in the Terai region is sold in the districts at a lower price; as a result, agrodealers are less willing to purchase SPG seed. Sundar Cooperative, a major buyer of SPG seed, no longer buys from some of the SPGs. The reasons for this are not entirely clear, but may be due to a lack of labor.

Our qualitative analysis of the SPG interviews suggests that helping groups establish and maintain buyers may be crucial for group success. Sundar Cooperative was initially established to both produce seed and serve as a buyer of the other CURE SPGs, but it no longer purchases from some of the groups. Follow-up discussions with Sundar Cooperative could inform on the types of initial and ongoing support that would be most helpful for them to continue purchasing seed from other SPGs. It is clear from our qualitative interviews with SPG executives that it is important to ensure that seed buying networks are well-established by the end of program to increase the likelihood that SPGs will remain active once the program ends.

Our analysis provides evidence that the SPGs had several spillover effects, benefiting local and adjacent communities. This includes greater adoption of STRVs and increased SRR among non-members in SPG villages, and increased STRV adoption for non-members in adjacent villages in 2017 compared to non-members in randomly selected villages We also find that SPGs induced greater use of some, but not all BMPs, including reduced seeding ratios, increased roguing, and increased legume cultivation among non-members in SPG villages compared to non-members in randomly selected villages. Non-members in adjacent villages were also more likely to test seed moisture prior to storage than non-members in randomly selected villages. We hypothesize that legume cultivation and roguing may have spread due to the fact that they are highly visible practices while seeding ratios and seed moisture checking may have spread because they are easy to implement and have no-cost. However, more research is needed to understand how/why some BMPs have spread and catch on locally, while others have not.

Our study provides evidence that a short-term program to establish and support SPGs can have long-lasting impacts on members; in this case study, SPG members have continued to produce and sell seed and use BMPs. Technology transfer also occurred, generating spillover benefits onto non-member households in SPG and adjacent villages. This indicates that if we had considered only direct effects of the CURE project, we would have significantly underestimated its benefits (Winters et al., 2011). SPGs can help improve communities' resilience to climate change if climate-smart technologies are targeted. Members of future established groups could be explicitly encouraged to share their knowledge of BMPs in order to enhance project benefits.

Chapter 4 Appendix

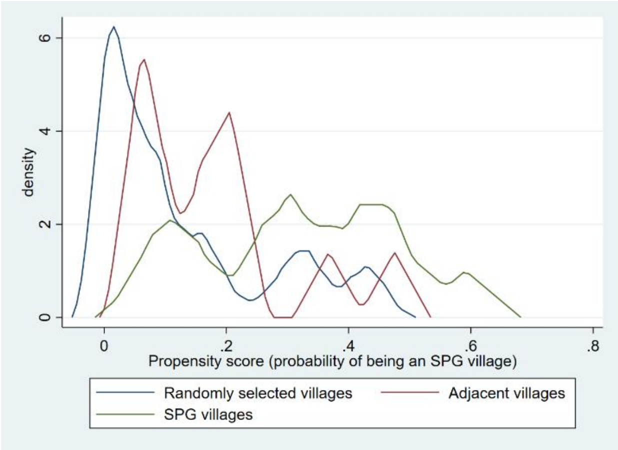

Figure A4- 1: Propensity score overlap graph: SPG village

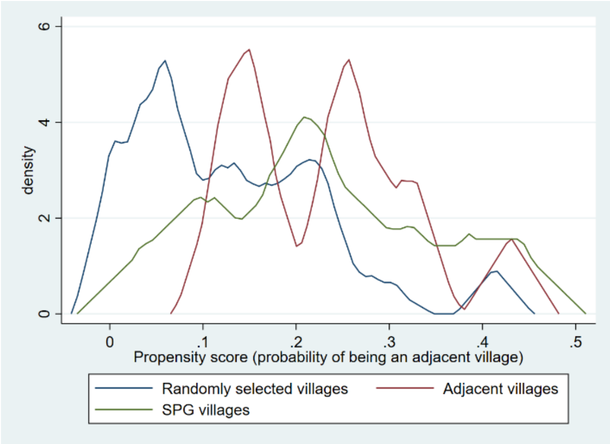

Figure A4- 2: Propensity score overlap graph: SPG-adjacent village

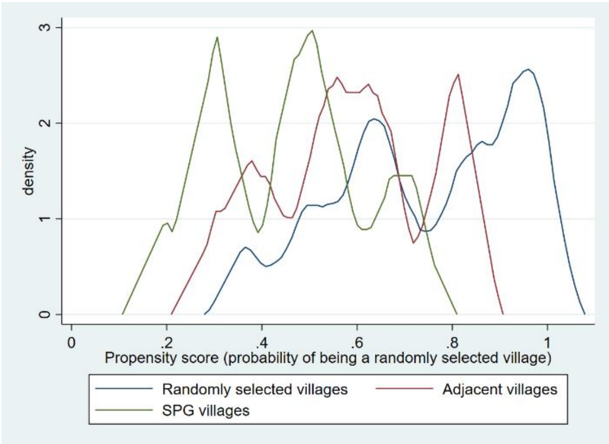

Figure A4- 3: Propensity score overlap graph: Randomly selected village

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Chapter 5: Conclusion

Agricultural technologies can help address many of the world's rural development challenges. The goal of this dissertation is to examine how policy makers can implement effective strategies to encourage adoption of these technologies, and how the technologies themselves impact the well-being of rural households. It evaluates the effectiveness of different distributional strategies for iron-biofortified beans, which are designed to improve nutrition, as well as STRVs and BMPs in rice production, which aim to reduce vulnerability to climate change. It also evaluates how adoption of an iron-biofortified bean variety can improve household nutrition and food security through its impacts on bean yields, bean consumption, and bean sales. Overall, it finds evidence that strategies to distribute agricultural technologies influence adoption decisions of producer households, and that adoption can improve a number of household outcomes.

The first paper provides evidence of the effectiveness of different delivery approaches at speeding up adoption and reducing disadoption speed of iron-biofortified bean varieties in Rwanda. This is important, as fast and sustained consumption of high iron beans is necessary to achieve health improvements of iron-deficient household members. This paper contributes to the literature on technology adoption by using duration models to analyze adoption, disadoption, and readoption speed, allowing us to model adoption as a complex and dynamic process. We find that the direct marketing delivery approach, which delivers small quantities of seed to a large number of farmers, speeds up adoption, while mechanisms that delivery larger quantities of seed to fewer farmers reduce disadoption speed. In addition, informal dissemination also speeds up adoption, supplementing formal delivery approaches. We also find evidence that plant breeding efforts to incorporate traits that female farmers prefer into the iron-biofortified bean varieties have been successful, as female farmers disadopt the varieties more slowly than male farmers.

Policy makers or program implementers who wish to disseminate biofortified or other improved crops can learn from this research and develop similar strategies adapted for their own contexts.

The second paper examines the impacts of the most widely adopted iron-biofortified variety, RWR2245, on bean yield, bean consumption from own production and purchases, and bean sales of adopting households. This is important for policy makers, who need to know if biofortified crops are good investments for health improvements, and contributes to the literature on agriculture-nutrition impact pathways. By using a control function approach with IVs related to iron-biofortified bean delivery, we control for endogeneity in adoption to obtain causal impacts. First, we provide evidence that RWR2245 adoption improves bean yields without reducing land under bean cultivation, thus increasing the overall quantity of bean harvested. We then examine how households use this increased harvest, which influences who will benefit from these high iron bean varieties. We find that adoption increases household consumption of own-produced beans while reducing purchases of beans. Adopters are also more likely to sell beans, increasing farm income for these households while also providing nearby purchasing households with high-iron beans for consumption. These findings provide evidence that adoption of an iron-biofortified bean variety can improve household nutrition and food security through two major impact pathways: first by increasing iron intake through the consumption of own-produced iron-biofortified beans, and second by freeing up or increasing household income that can be used to purchase other healthy foods. Policy makers should thus primarily target households that have high iron needs with distribution of iron-biofortified beans.

Agricultural technologies can reduce farmers vulnerability to climate change. Our final paper demonstrates that the IFAD-funded CURE program in Nepal has been successful in promoting the adoption of these technologies, including STRVs and BMPs, through the establishment of SPGs in a drought-prone area of the country. We contribute to the literature on the impacts of agricultural technologies by estimating the spillover benefits of the SPGs, which produce technologies that are highly transferrable to non-targeted farmers (i.e. non-SPG members) within their local economies (villages that contain SPGs and adjacent villages). We find that the SPGs have increased adoption of STRVs among non-members in SPG villages and adjacent villages, and have also increased the SRR and use of BMPs among non-members in SPG villages. The CURE program officially ended in Nepal in 2013, but most of the SPGs are still active and still generating spillover benefits. This is encouraging and implies that short-term projects can have long-term impacts on reducing vulnerability to climate change.

The three papers of this dissertation explore the link between agricultural technology distribution, technology adoption, and technologies' impact on household well-being. The first paper finds that formal delivery and informal dissemination of iron-biofortified beans have sped adoption while reducing the speed of disadoption. The second paper finds that the most widely adopted of these varieties has the potential to improve household nutrition by increasing household consumption of own-produced beans and increasing household income that can be spent on other healthy foods. Finally, the third paper finds that a short-term IFAD project to establish SPGs in Nepal has had long-lasting spillover effects on local household's adoption of STRVs, SRR, and use of some BMPs in rice production. Altogether, these results are promising for the future of rural development in Africa and Asia. Researchers, policy makers, and program implementers should continue to work together to develop and release agricultural technologies. These efforts can improve adoption of new varieties, management strategies, and other innovations that can not only increase farmer's crop yields, but also contribute to crucial development goals such as improving health and reducing vulnerability to climate change. By having the opportunity to update their farm inputs and practices, farmers in the developing world will improve their livelihoods and contribute to the development of their countries.