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Published online: 28 Oct 2020.

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Changing agricultural stubble burning practices in the Indo-Gangetic plains: is the Happy Seeder a profitable alternative?

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ABSTRACT

Every year after the rice harvest, some 2.5 million farmers in northwest India burn the remaining stubble to prepare their fields for the subsequent wheat crop. Crop residue burning causes massive air pollution affecting millions of people across the Indo-Gangetic Plains. We examine different tillage practices to provide urgently needed empirical evidence on how profitable it is for farmers to adopt no-burn technologies, especially the 'Happy Seeder' (HS) which is capable of sowing wheat directly into large amounts of crop residue. Apart from analysing the cost of rice residue management and wheat sowing under conventional-tillage and zero-tillage, we identify factors influencing the adoption of the HS and quantify its impact on wheat yields and –production costs. While we do not find any evidence of a yield penalty, our analysis reveals significant savings in wheat production costs, amounting to 136 USD ha^{-1}. In addition, our analysis shows that the HS saves water and facilitates timely wheat sowing. We conclude that the private benefits of HS use combined with its societal benefits of reducing air pollution and enhancing agricultural sustainability justify particular policy support for its large-scale diffusion, to be supplemented by a stricter enforcement of the ban on residue burning.

1. Introduction

In the prevailing rice-wheat cropping system in northwestern India, a large share of the 2.5 million farmers burn an estimated 23 million metric tons of rice stubble in October and November to prepare their fields for the subsequent wheat crop (NAAS, 2017). Alongside significant loss of soil fertility due to residue burning (Prasad et al., 1999), the resulting air pollution impacts not only the farmers and their families, but the seasonal meteorological conditions facilitate smoke to blanket a wide area affecting millions of lives in cities and villages downwind (Mishra &

Shibata, 2012; Vijayakumar et al., 2016). In 2016, pollution resulted in the closure of all schools in Delhi (Safi, 2016) and all manner of transport slowed down, with associated economic losses. Of particular importance are health related costs, since air pollution is the second leading contributor to the burden of disease in India (Dandona et al., 2017). Studies indicated that the decrease in air quality due to rice stubble burning has a significant adverse effect on human pulmonary functions (Agarwal et al., 2012; Awasthi et al., 2010). Every year, about 66,000 deaths attributable to particulate matter with an aerodynamic diameter of less than

2.5 micrometers ($PM_{2.5}$) are associated with agricultural burning (HEI, 2018).

Agricultural fires are on the increase in India because of changes in mechanized harvesting, cropping patterns and water stress (Liu et al., 2019). While recent interest has focused on the impacts on air pollution (Liu et al., 2019; Cusworth et al., 2018), evidence also points to their contribution to short-lived climate pollutants, such as methane and black carbon, across central and southern India (Sarkar et al., 2018). The reduction of short-lived climate pollutants, the second largest contributor to climate change (Bond et al., 2013), offer an opportunity to mitigate climate change over a shorter time period.

The Indo-Gangetic plains, covering some 10.5 million hectares, represent India's bread basket (NAAS, 2017). The green revolution, with its new seed technologies and mechanized farming practices, transformed agriculture in India, making it more food secure. The thriving north-western state of Punjab, for instance, covers less than two percent of the country's land area, but grows nearly one-third of India's rice and wheat (Mann, 2017). Recent years, however, have seen a decline in agricultural productivity, at least partly because of changes in climate and water (Kumar et al., 2015). One of the consequences of these changes is a shift in the cropping calendar to match the arrival of monsoonal rains, leaving farmers with a short window of 10–15 days to move from harvesting rice to sowing wheat. Since the physical removal of residues within a short period is not economically viable (Ahmed et al., 2015), most farmers clear their lands by burning their rice stubble.

The central and state governments in north-western India, as well as universities and think-tanks, have put forth several strategies to curtail agricultural fires. Solutions to reduce burning include conservation tillage technologies such as the 'Happy Seeder' (HS), a tractor-mounted machine that mulches rice residues and sows wheat in one single operation (NAAS, 2017; Sidhu et al., 2015); subsidies for agricultural no-burn technologies, currently in place through a new national budget allocation (MoA, 2018); various state directives and fines that penalize farmers for burning (Bhuvaaneshwari et al., 2019); actions by extension agencies to communicate and demonstrate alternate options to farmers (Gupta, 2019); and straw removal for use as inputs in power generation (Watts, 2018). Arguably, these efforts are bearing fruit with some decline in fires in 2018 as compared to preceding years (Singh, 2018).

Given the large number of affected farmers, an agriculture-based solution appears to be the most viable for reducing fires at scale in the short run. Most farmers in north-western India currently practice a form of conventional tillage that makes it convenient for them to burn their rice stubble. However, there is a steady increase in alternate no-till solutions that also offer long-term co-benefits in terms of soil health (Bhan & Behera, 2014; Schmidt et al., 2018; Sidhu et al., 2015). Based on a descriptive comparison of ten different rice residue management and wheat sowing methods with respect to farmer net profits, Shyamsundar et al. (2019) provide recent evidence that the use of the Happy Seeder, in particular, constitutes a practice that avoids stubble burning *and* increases farmer profits. However, the meta-analysis character of the study did not allow for the construction of statistical confidence intervals around net profits, nor did it correct for potential selection bias between farmers applying conventional versus no-till farming practices. With respect to assessing profitability it has to be recognized that individual ownership is not a promising scaling pathway for a highly specialized machine, such as the HS. Rather, most farmers access the HS via custom-hiring services offered by other farmers or specialized service providers.

To help policy makers and development practitioners make informed decisions in addressing the pressing issue of residue burning, the current paper seeks to reduce remaining uncertainties around the viability of no-burn technologies by undertaking a more in-depth and methodologically rigorous analysis of farmer technology choices. Its objectives are to: (1) assess farmers' awareness and perceptions of the HS; (2) analyse conventional-tillage (CT) and zero-tillage (ZT) wheat production regimes in terms of yields, input levels, and implications for rice residue burning practices; under ZT, we differentiate between the use of the simple ZT drill and the use of the Happy Seeder; (3) quantify cost- and time implications of the three considered technologies with respect to rice residue management and wheat sowing; (4) identify determinants of HS adoption, accounting for potential non-exposure bias; and (5) quantify potential yield and cost impacts of using the HS as compared to CT using an econometrically rigorous approach.

The paper is organized as follows: Section 2 provides a brief description of the HS technology; Section 3 describes the research area, data collected, and sampling procedure employed; Section 4.1 lays

out the econometric approach followed to address objectives (4) and (5), while Section 4.2 describes the model specification in more detail; Section 5 presents the results of the descriptive and econometric analyses, which are discussed in Section 6; Section 7 concludes and derives recommendations for policy and development programming.

2. Background on zero-tillage and the Happy Seeder

CT practices in wheat typically involve multiple passes of the tractor to accomplish plowing, harrowing, planking and seeding operations (Erenstein & Laxmi, 2008). In contrast, ZT uses a zero-till drill to sow wheat directly into unplowed fields with a single pass. The typical ZT drill opens 6–13 narrow slits using inverted-T openers to place both seed and fertilizers at a depth of 7.5–10 cm (Mehla et al., 2000). ZT for wheat seeding has been tested extensively and found effective in terms of economics and timeliness of wheat sowing in comparison with CT in the rice-wheat system (Aryal et al., 2016; Erenstein & Laxmi, 2008; Jat et al., 2020; Keil et al., 2017; Krishna & Veettil, 2014). However, significant advances in mechanized (combine) harvesting of rice over the years has resulted in large amounts of loose residues in the field. These conditions create problems for direct drilling of wheat seed into combine-harvested rice fields using the normal ZT seed drill due to: (1) straw accumulation in the furrow openers; (2) poor traction of the seed metering drive wheel due to the presence of loose straw; and (3) the need for frequent lifting of the implement under heavy residue conditions, resulting in uneven seed depth and poor crop establishment (Sidhu et al., 2015). An improved substitute drill is the Happy Seeder, a specialized no-till seeder, which has been developed, validated and refined by agricultural researchers over the last 15 years (Sidhu et al., 2015).

The Happy Seeder is a tractor mounted implement that combines a ZT seeder with a straw management unit. The latter comprises of serrated rotating flails attached to a roller that shreds and clean the residues in front of the tyne openers and then deposits the residue around the seeded row as mulch. This is done in one simple operation of direct-drilling in the presence of standing as well as loose surface residues. The residue left on the surface as mulch helps reduce evaporation losses, suppresses weed growth, buffers soil moisture and temperature, and facilitates a more efficient uptake of water and nutrients by plant roots (Sidhu et al., 2015; Singh et al., 2015). The use of the HS also reduces labour requirements for crop establishment by as much as 80%, irrigation needs by 20–25%, and herbicide use by as much as 50% (Saunders et al., 2012). It further reduces fuel use and improves productivity, particularly under climatic stress conditions (Aryal et al., 2016; Saunders et al., 2012; Sidhu et al., 2015). The HS works best in combination with a simple straw spreading mechanism, called the 'Super Straw Management System' (Super SMS) that can be attached to the combine harvester, which enables uniform spreading residue across the harvesting width. The development of the Super SMS enhances the efficiency of the HS and improves crop establishment and yields (Lohan et al., 2018; NAAS, 2017). Approximately 11,000 HS are already in use in north-west India, of which over 80% operate in Punjab (personal communication with machine manufacturers). Eighteen manufacturers currently produce the HS.

3. Research area, sampling procedure, and data collection

To understand farmer decisions related to the use of different no-burn technologies we undertook a survey in four districts in India's north-western state of Punjab. Out of a gross cropped area of 7.79 million ha in Punjab, some 2.92 million ha (38%) are used to cultivate paddy (DoA, 2015). Farmers mainly grow two categories of rice – coarse (non-basmati) and basmati rice, with coarse rice more likely to be combine-harvested (Gupta, 2012), leaving large amounts of straw on the field. Thus, the area under basmati rice subtracted from the area under paddy cultivation can be used as a proxy for the area prone to residue burning (Lohan et al., 2018).

To select our survey districts, we first identified those districts which had more than 70% of net sown area under coarse (non-basmati) rice varieties during the *kharif* season (July to October) of 2017. Based on the burned area reported by recent studies, these districts were further classified into 'high residue burning' and 'low residue burning': for each district, an index was created by dividing the area under crop residue burning by the total area under coarse grain paddy. Depending on whether the index was below or above the median value we classified the district as low or high burning. The area under coarse rice was computed using data

from APEDA basmati survey report (APEDA, 2017). The area under residue burning was taken from Kaur and Rani (2016). Then, two districts were purposively chosen in each category such that they were geographically located close to each other: Ludhiana and Sangrur districts in the high residue burning group, and Patiala and Fatehgarh Sahib in the low residue burning category; all four districts are located in the South-East Region of the state. We chose neighbouring districts in order to minimize variation in agro-climatic factors across the chosen districts. While, in the *kharif* season, at least 80% of the paddy land is used to grow coarse rice varieties in each of the four districts, wheat is the dominant crop in the *rabi* season (November–April). Other major crops are maize, sugarcane, vegetables, pulses, mustard, and cotton (DoA, 2019).

For selecting study villages, we first identified all villages where at least one person had purchased a HS. To compile a complete list, we combined information from leading HS manufacturers on the machines sold in our target districts, lists of farmers who received HS services from Primary Agriculture Cooperative Societies (PACS),[1] and lists of subsidy recipients for HS purchases provided by the State Department of Agriculture. From the final list, 16 villages were then randomly selected in each survey district using a probability proportionate to village size approach. Since zero-tillage wheat is not very common in the area, as a first stage of data collection a census survey was administered in the 64 (16 × 4) selected villages to stratify the sample by wheat establishment method, differentiating between CT, ZT drill and HS. Based on the data in the census survey, 13 villages were selected from each district, excluding villages that had no HS users. Farm households in the selected 52 (13 × 4) villages were stratified into CT, ZT drill and HS users based on data from the census survey.

To identify farm households for the sample survey, due to their relative scarcity, all no-till households were included in the sample. Out of the stratum of CT users, village-wise random samples were drawn using the following selection rule: if the number of no-till households was less than 15, the number of randomly selected CT households equalled 15 minus the number of no-till households; in cases where the number of no-till households was 15 or more, the number of selected tillage-households was approximately 25% of the number of no-till households in that village. This approach led to a total sample size

of 1021 farm households, encompassing 561 CT users, 226 ZT drill users, and 234 HS users in 52 villages. Some households used more than one wheat establishment method; anyone who used the HS (apart from CT and/or ZT drill) was considered a HS user, and anyone using a ZT drill (apart from CT) was considered a ZT drill user.

The data collected encompassed information on general household characteristics, asset endowment and farming practices, and included particularly detailed questions on rice residue management and wheat sowing. Furthermore, survey respondents were asked to provide basic information on three farmers with whom they interacted most frequently about agricultural issues in order to be able to capture potential individual social network effects on HS adoption. All data were collected from household heads by a team of professional enumerators through structured interviews using CAPI software.

4. Methodological approach

4.1. Model estimation strategy

4.1.1. Accounting for non-exposure to the HS technology

In instances where a technology is relatively new to an area, as is the case with the HS in the research area, a model that identifies adoption determinants needs to account for potentially lacking awareness of the technology among farmers in order to avoid estimates to be affected by non-exposure bias. The bias results from the fact that farmers who are not aware of a new technology have no chance to adopt it, although they may have adopted if they had known about it (Diagne & Demont, 2007). Non-exposure bias can arise due to (1) farmers differing in their ambitions to search for information about new technologies and their ability and willingness to process such information; and (2) farmers differing in their access to information about new technologies; in particular, so-called 'progressive' farmers and communities may be targeted by agricultural development projects or have a higher level of connectivity to state extension or private sector input suppliers (Diagne & Demont, 2007). Based on the approach of van de Ven and van Praag (1981) and building on Keil et al. (2017), we apply a two-stage estimation framework using a probit model with sample selection to correct for potential non-exposure bias. The first-stage probit model identifies determinants of 'knowledge

exposure' (Kabunga et al., 2012); in the second stage, a probit model identifies determinants of technology adoption among the aware sub-sample. Since the sample selection process is non-random, non-exposure bias needs to be controlled for. This is achieved by estimating a 'heckprobit' model which includes the Inverse Mills Ratio (IMR) in the second-stage probit model, analogous to the method proposed by Heckman (1979) for the case of a second-stage regression with a continuous dependent variable.

4.1.2. Accounting for social network effects in the adoption process

Since the seminal review by Feder et al. (1985) on the adoption of agricultural innovations, which focused on individual-specific farm and farmer characteristics as potential adoption determinants, the role of social learning has been increasingly accounted for in later studies (Feder & Savastano, 2006; Foster & Rosenzweig, 1995; Granovetter, 2005). As pointed out by Manski (2000), farmers may not only be influenced by the adoption behaviour of their individual social networks (endogenous network effect), but also by their network members' socio-economic characteristics (exogenous network effect). Drawing on the work of Matuschke and Qaim (2009), we account for endogenous and exogenous individual network effects as in the following equation:

$$y_i = \beta X_i + \delta y_{n(i)} + \varepsilon X_{n(i)} + u_i \qquad (1)$$

where $y_i = 1$ if the household used the HS for wheat sowing in the *rabi* season 2017/18, and $y_i = 0$ if conventional tillage was used. As emphasized by Feder et al. (1985), a binary (yes/no) measure of technology adoption has severe shortcomings if there is great variation in the adoption *intensity* in terms of share of land allocated to the innovation. However, in our case we find that, once the decision is made to use the HS, the practice is used on the entire wheat area by 89% of adopters, justifying the use of a binary dependent variable. Further, X_i is a vector of exogenous regressors, $y_{n(i)}$ denotes the adoption behaviour of household i's individual social network, and $X_{n(i)}$ is a vector of exogenous network member characteristics; β, δ, and ε are (vectors of) parameters to be estimated, and u_i is a random error term. However, adopting the approach of Keil et al. (2017), we extend the methodology of Matuschke and Qaim (2009) by accounting for potential non-exposure bias as elaborated above. Hence, we estimate the model:

$$y_i = \dot{\beta}\dot{X}_i + \beta_\lambda \dot{\lambda}_i + u_{1i} \qquad (2)$$

where $\dot{X}_i$ encompasses all regressors included in Equation (1) and $\dot{\lambda}_i$ is the IMR derived from an exposure equation of the form

$$a_i = \dot{\gamma}\dot{Z}_i + u_{2i} \qquad (3)$$

where $\dot{Z}_i$ in addition to other regressors, contains endogenous and exogenous individual social network characteristics as specified in Equation (1). We use the Stata 15 software package (www.stata.com) to estimate the 'heckprobit' model, specifying heteroskedasticity-consistent standard errors that account for clustering of the sample at the village level. The model produces a Wald test on the null hypothesis that the correlation between error terms u_{1i} and u_{2i} $\rho = 0$, in which case non-exposure bias does not exist, and Equation (2) simplifies to Equation (1).

4.1.3. Estimating the on farm impacts of Happy Seeder adoption

Unless the technology dissemination takes place in a randomized experiment setup, farmers decide themselves whether to adopt or not, making adoption a non-random process. Direct comparison of outcomes between adopting and non-adopting households can be misleading as these groups may differ systematically, both with respect to observed and unobserved attributes. The measure of association between treatment (in our case, Happy Seeder adoption) and outcome (here, yield or PUC of wheat production) could be distorted due to a sample selection that does not accurately reflect the target population. The conventional statistical procedure to address this bias is the use of instrumental variable regression which allows to quantify the impact of technology adoption on outcome variables of interest, whilst eliminating the effect of reverse causation or simultaneity (Angrist & Pischke, 2008). However, when the technology impact is not homogeneous across sample households, interaction terms between the endogenous adoption variable and other covariates (e.g. education) need to be included in the model. The number of instrumental variables required to just identify the model increases with the number of interaction terms. In general, it is difficult to even find a single suitable instrumental variable for model identification, and many a time the choice of the

instruments is debatable for not meeting the exclusion restriction. The magnitude of this challenge increases when one attempts to estimate the heterogenous impacts of an endogenous variable.

A more elegant and convenient way to address self-selection bias is to employ an endogenous treatment effects (ETE) approach, where adoption is treated as a regime shifter, and a single instrumental variable (selection instrument) suffices to capture the heterogenous effects of the technology. The inherent assumption of the ETE framework is that the error terms are independent and identically distributed, meaning that the outcome and treatment status of each respondent are unrelated to the outcome and treatment status of all the other individuals in the population. Thus, although these models are less suitable for modelling correlated data arising from hierarchical or longitudinal study designs, they are ideal for estimating impacts from cross-sectional datasets, as in our study. The main advantages of an endogenous switching model are that they allow to model both the allocation of households to various treatments and the effects of treatment on other outcomes, while estimating the degree to which common, unmeasured variables affect both the outcome and the explanatory variables. This approach considers the potential selection bias and simulates how non-adopters would fare had they entered the adopter group (Winship & Mare, 1992).

Estimation of the ETE model involves two stages. The first stage is a selection equation, based on a binary choice function, where technology adoption (A_i) by household i is hypothesized to be determined by a number of farm-household attributes.

$$A_i^* = \mathbf{z}_i\alpha + \eta_i \quad \text{where} \quad A_i = \begin{cases} 1 & \text{if} \quad A_i^* > 0 \\ 0 & \text{otherwise} \end{cases} \quad (4)$$

The observed realization A_i of the dichotomous latent variable A_i^* captures the expected benefits from technology adoption; $\mathbf{z}_i$ are the observed farm-household characteristics affecting the adoption variable, α is the parameter vector to be estimated, and η_i is the unobserved heterogeneity. In the second stage of the ETE estimation, the outcome of interest is modelled based on the observed adoption realization A_i. The details of the ETE estimation are provided by (Greene, 2008). Two regime equations are specified explaining the outcome of interest, based on the selection function:

$$\text{Regime 1:} \quad Y_{1i} = \mathbf{x}_{1i}\psi_1 + \varepsilon_{1i} \text{ if } A_i = 1 \quad (5a)$$

$$\text{Regime 2:} \quad Y_{2i} = \mathbf{x}_{2i}\psi_2 + \varepsilon_{2i} \text{ if } A_i = 0 \quad (5b)$$

where $\mathbf{x}_i$ are farm-household characteristics affecting the outcome variable (Y_i), ψ_1 and ψ_2 are parameter vectors to be estimated, and ε_1 and ε_2 are the error terms for regimes 1 and 2, respectively. For a robust identification of the model the selection equation should contain at least one variable (i.e. selection instrument) that is correlated with adoption but uncorrelated directly with the outcome (exclusion restrictions; Deb & Trivedi, 2006). We use variables related to social network characteristics (*NM HS use* and *NM age*) as the selection instruments. Similar to the two-stage least squares or control function approach, selection instruments are required in the ETE framework for the model to be identified. Di Falco et al. (2011) suggested a simple falsification test to examine admissibility of these instruments. A valid selection instrument will affect adoption, but not the outcome among non-adopters.

Several studies have modelled the heterogeneous impacts of interventions in agriculture employing the ETE framework (e.g. Krishna et al., 2019; Manda et al., 2016; Yahaya et al., 2018). Here, we use the ETE model to compare the expected outcomes in terms of yield and PUC of Happy Seeder adopters and non-adopters, and to investigate the expected outcomes in the counterfactual hypothetical cases that adopter households had not adopted the technology. We can estimate the average effect of adoption on a population of farm households as $E(Y_1|A_i = 1 - Y_2|A_i = 0)$, where E is the mathematical expectation operator. This is denoted the average treatment effects (ATE) parameter, which in the impact evaluation literature is equivalent to the 'intention-to-treat' effect or the 'supply-of-the-technology' effect (Nguezet et al., 2011), in our case the impact of supplying the Happy Seeder technology to farmers. The impact parameter that identifies the causal effect of adoption in the presence of non-compliance is the average treatment effect on the treated (ATT), which restricts the computation of the average treatment effect to the subpopulation of adopters, that is $E(Y_1 - Y_2)|A_i = 1$.

4.2. Model specification

4.2.1. Determinants of Happy Seeder adoption

The dataset used to identify HS adoption determinants comprises 234 HS users and 561 users of conventional tillage (CT) in wheat. 49 CT users (8.7%) had never heard about the HS technology at the time of the survey. Hence, we account for potential non-exposure bias in our analysis, as elaborated above.

Based on the review of technology adoption determinants by Feder et al. (1985) and drawing on the concept of livelihood resources as depicted in the sustainable livelihoods framework (Chambers & Conway, 1992; Scoones, 1998), we hypothesize the households' asset base and risk preferences to influence the decision to adopt the HS. The asset base includes (1) natural capital, (2) human capital, (3) financial capital, and (4) social capital and information access. Variables measuring access to input and output markets were tested and found to not influence HS adoption; for reasons of statistical efficiency they were omitted from the final models. Definitions and summary statistics of the dependent and explanatory variables used are presented in Table 1. The table further shows that the first-stage equation contains two dummy explanatory variables, TV and internet use to access agricultural information, which are omitted from the second-stage; as pointed out by Rogers (2003), mass media are of particular importance for raising awareness, while interpersonal communication channels have greater relevance regarding the adoption decision. Including at least one variable in the vector of selection equation regressors (Z_i) which is not contained in the regressors of the second stage (X_i) is not only conceptually consistent, but also highly desirable for econometric reasons. If Z_i and X_i are identical, the IMR can be highly correlated with the elements of X_i, resulting in inflated standard errors (Wooldridge, 2006, p. 620).

To adequately reflect the concept of information *access*, the variable *Extension access* indicates the extent to which information from the extension service was generally available, assessed on a Likert scale; frequently used alternative specifications, such as extension visits received or field days attended, constitute combined measures of extension access and the farmer's decision whether or not to make use of it (Doss, 2006). For similar reasons, we chose to measure *Credit access* in terms of potential credit availability on a Likert scale, rather than eliciting the

amount actually borrowed, which potentially confounds access to credit with demand for credit. While most models of technology adoption treat risk preferences as an unobservable factor, we include a proxy of the household head's risk preferences as an explanatory variable, which is based on a self-assessment question and has been previously applied by Gloede et al. (2011).

As elaborated above, a salient feature of our model is the inclusion of the respondents' individual agricultural information network characteristics as explanatory variables. These variables are based on information provided by the survey respondents regarding those three farmers with whom they interacted most frequently about agricultural issues, referred to as network members (NMs) in the following. To capture endogenous network effects, we collected data on the NMs' HS adoption status, including information on the timing of adoption. The latter is crucial to address the so-called reflection problem (Manski, 1993): while the behaviour of NMs potentially influences the survey respondent, the reverse is also the case. As suggested by Manski (2000), we therefore assume that the respondent's adoption decision is influenced by the level of success that his NMs had with the technology, which is consistent with empirical findings (e.g. Foster & Rosenzweig, 1995). Therefore, only those NMs who used the HS earlier than the respondent enter our model as HS-adopting NMs. To capture potential exogenous network effects, i.e. those attributable to who the NMs are, rather than how they behave, we elicited information about their age, education, and caste (not all of which are included in the final model). Individual social networks tend to be characterized by a high degree of homophily, i.e. they are usually formed among farmers of a similar social status (Keil et al., 2017; Rogers, 2003). Econometrically speaking this means that peer group membership itself is likely to be endogenous (Matuschke & Qaim, 2009; Songsermsawas et al., 2016), which the inclusion of NM characteristics as control variables may mitigate to some extent. Potential endogeneity could be better controlled by using instrumental variables: Songsermsawas et al. (2016) used the characteristics of friends of the respondents' NMs (who were unknown to the respondents themselves) as instruments for the NMs' characteristics, but such costly-to-collect information was not available in our case. Table 1 lists the definitions and summary statistics of the

Table 1. Definitions and summary statistics of dependent and explanatory variables in regression models explaining awareness and adoption of the Happy Seeder (HS) for wheat sowing in Punjab, India.

Variable description				Awareness stage (N = 795)		Adoption conditional on awareness (N = 746)	
				Mean	Std. Dev.	Mean	Std. Dev.
Dependent variables							
HS awareness	=		Dummy, =1 if HH[a] head has at least heard about HS, 0 otherwise	0.938	0.241	–	–
HS adoption	=		Dummy, =1 if HH used HS in wheat in the 2017/18 *rabi* season, 0 otherwise	–	–	0.314	0.464
Natural capital							
Cultivable area	=		Total area available for cultivation (ha)	5.241	4.421	5.323	4.480
Human capital							
Dependency ratio	=		Dependency ratio (no. HH members aged <14 and >65 / all HH members)	0.189	0.172	0.190	0.172
Age	=		Age of HH head (years)	51.016	10.923	51.090	11.024
High education	=		Dummy, =1 if educational achievement of HH head is > 12th grade, 0 otherwise	0.196	0.397	0.202	0.402
General caste	=		Dummy, =1 if HH belongs to one of the 'general' (non-marginalized) castes, 0 otherwise	0.936	0.245	0.936	0.246
Risk preference	=		HH head's general risk preference, self-assessed on a scale from 0 (= fully avoiding risk) to 10 (= fully prepared to take risk)	6.031	1.301	6.044	1.297
Financial capital							
Credit access	=		Perceived credit access on a scale from 0 (= no access) to 5 (= very good access)	3.246	0.752	3.266	0.746
Non-farm share	=		Share of non-farm income in total HH income in 2017 (%)	4.110	12.447	3.746	11.532
Information access							
Farmer association	=		Dummy, =1 if HH head is member of the local farmer association, 0 otherwise	0.316	0.465	0.322	0.467
Extension access	=		Perceived access to agricultural extension on a scale from 0 (= no access) to 5 (= very good access)	3.181	0.790	3.186	0.800
TV use	=		=Dummy, =1 if TV is used as source of agricultural information, 0 otherwise	0.160	0.367	–	
Internet use	=		=Dummy, =1 if the internet is used as source of agricultural information, 0 otherwise	0.006	0.079	–	
Social network characteristics							
NM HS use[a]	=		No. network members (NMs) of the respondent who used HS before him/her	0.570	0.994	0.601	1.016
NM age	=		Average age of NMs (years)	45.404	6.991	45.483	6.957
District dummies (Ludhiana is base district)							
Fatehgarh	=		Dummy, =1 if HH is located in Fatehgarh Sahib district, 0 otherwise	0.218	0.413	0.218	0.414
Ludhiana	=		Dummy, =1 if HH is located in Ludhiana district, 0 otherwise	0.216	0.412	0.190	0.393
Patiala	=		Dummy, =1 if HH is located in Patiala district, 0 otherwise	0.191	0.393	0.197	0.398
Sangrur	=		Dummy, =1 if HH is located in Sangrur district, 0 otherwise	0.375	0.484	0.394	0.489

Notes: HH = Household; HS = Happy Seeder; NM = Network member.
[a]Out of three primary agricultural network members.

dependent and explanatory variables used in the awareness and adoption stages of the 'heckprobit' model. The same variables are used in the selection equation of the ETE model.

4.2.2. Impact of the Happy Seeder on wheat yields and production costs

We estimate separate models for two outcome variables of interest: Model 1 explores the impact of HS relative to CT wheat on land productivity, i.e. grain yield measured in kg ha^{-1}; Model 2 assesses the impact on the profitability of wheat production, measured as per-unit production cost (PUC). More specifically, PUC measures the variable cost per quintal (=100 kg) of wheat grain produced. We do not account for fixed costs in our analysis as these are highly idiosyncratic and largely independent of the two technologies under consideration. Land resources can be owned and/or rented in, as is the case with agricultural machinery. Furthermore, machine depreciation depends on use intensity, which in turn depends on the landholding size and

the cropping system practiced. Moreover, the multitude of implements used vary widely in their respective investment cost and useful life, compromising any attempt to capture the associated fixed costs in a meaningful way. Most importantly, as indicated in the introduction, most farmers access specialized machinery, such as the HS, via custom-hiring services offered by other farmers or specialized service providers, so that only variable costs are incurred. PUC does include the imputed cost of family labour input, valued at the median wage rate paid to hired labour in the research area, which amounted to 39 Indian Rupees (INR) per hour (1 USD = 64.8 INR as of Nov 01, 2017).

Both models use the same set of explanatory variables, encompassing agricultural input variables, agronomic control variables, and management related control variables (Table 2). Same as yield, agricultural inputs are measured on a per-hectare basis, which is why land is omitted as an input factor. The variable *Capital input* encompasses all non-labour related variable costs; the cost of hired labour is captured by *Labour expenses*, and total labour input (both family and hired labour) is measured by *Labour hours*. The dependent variables and agricultural input factors enter the model in their logged form as this achieves more compact distributions and a superior fit compared to the unlogged specification. Agronomic control variables are related to the sowing time (which can have important yield implications in the research area, as elaborated in Section 2), wheat varieties used, and soil characteristics. Management related control variables encompass the same set of variables as in the first stage (selection equation) of the ETE model, apart from the following exceptions: *Credit access* is omitted since capital input is directly accounted for. The variables related to social network characteristics, *NM HS use* and *NM age*, are used as selection instruments (see Section 4.1.3) and are therefore omitted from the outcome equations. Variables measuring farmer-to-farmer extension have been used as selection instruments in other studies (Ayuya et al., 2015; Di Falco et al., 2011). As suggested by Di Falco et al. (2011), we perform a simple test to verify the validity of these instruments: while both variables affect the decision to adopt the HS (see Table 8), they should not affect wheat yields and PUC among the non-adopting households. In the case of PUC, both variables are jointly insignificant (*F*-stat. = 0.48, *P* = 0.62), hence clearly passing the validation test. In the yield model, *NM age* is insignificant

($P = 0.42$), but *NM HS use* is significant at the 5% level. While this is a limitation of Model 1, we argue that the inclusion of at least one valid instrument in the selection equation does ensure the identification of the model. Two variables controlling for machine ownership versus use of custom-hiring services, *No. implements owned* and *No. services hired*, are included in the outcome equations only. They are endogenous to HS adoption since the technology reduces the number of implements used for rice residue management and wheat sowing to strictly one. Apart from listing summary statistics, Table 2 indicates whether the means of the explanatory variables differ significantly between CT and HS wheat regimes.

5. Results

5.1. Awareness and farmer perceptions of the Happy Seeder

Our measure of 'awareness' indicates whether or not the respondent household head had at least heard about ZT and the HS at the time of the survey. Table 3 shows that farmers' awareness of ZT/HS was generally high (Column 4). It further compares awareness and use of ZT and the HS across landholding terciles (Columns 1–3), revealing some scale bias with respect to the HS; i.e. the proportion of farmers in the smallest tercile being aware of and using the HS was lower than the respective shares in the largest tercile, whereby the middle tercile took an intermediate position. The adoption rate of the HS is of particular interest, which amounted to 8% of the aware farmers in the smallest tercile, 15% in the largest tercile, and 12% overall. The percentages shown in Table 3 are based on weighted observations to correct for the over-sampling of ZT drill and HS users in the sample (see Section 3) and can thus be considered representative of the situation in villages *with at least some HS presence* in the survey districts. The table further illustrates that, on average, adopting households applied ZT technologies to more than 90% of their total wheat area in the 2017/18 *rabi* season, with use intensities being particularly high among adopters in the smallest and middle landholding terciles.

Table 4 explores the perceptions that 'aware' farmers have about the HS. We presented a number of statements to our survey respondents and elicited their degree of agreement on an ordinal scale ranging from 'strongly disagree' via 'disagree', 'neutral', 'agree'

Table 2. Definitions and summary statistics of dependent and explanatory variables in regression models explaining wheat yield and per-unit production costs in conventional-tillage (CT) and Happy Seeder (HS) wheat growing regimes in Punjab, India.

Variable description			Conventional-tillage wheat (N = 561)		Zero-tillage wheat using HS (N = 234)		Sig. of diff.[e]
			Mean	Std. Dev.	Mean	Std. Dev.	
Dependent variables[a]							
Wheat yield	=	Logged wheat grain yield (kg ha^{-1})	5422.75	327.71	5492.03	268.42	****
Per-unit cost	=	Logged total variable per-unit production cost (INR MT^{-1})[b]	2120.94	2024.37	1469.62	1174.32	****
Agricultural input variables[a]							
Capital input	=	Logged total non-labour capital input (INR ha^{-1})	18,984.90	2254.26	17,741.97	1887.04	****
Labour input	=	Logged hired and family labour input (person-hours ha^{-1})	58.845	21.611	51.984	10.473	****
Labour expenses	=	Logged expenses for hiring labour (INR ha^{-1})[c]	819.82	644.47	693.56	458.41	***
Agronomic control variables							
Late sown	=	Dummy, =1 if wheat was sown later than Nov 13, 0 otherwise	0.045	0.207	0.004	0.065	***
HD2967	=	Dummy, =1 if HD2967 variety was used, 0 otherwise	0.549	0.498	0.615	0.488	*
HD3086	=	Dummy, =1 if HD3086 variety was used, 0 otherwise	0.349	0.477	0.303	0.461	n.s.
PBW725	=	Dummy, =1 if PBW725 variety was used, 0 otherwise	0.077	0.266	0.064	0.245	n.s.
Sandy soil	=	Dummy, =1 if soil is sandy, 0 otherwise	0.800	0.400	0.880	0.325	***
Clay soil	=	Dummy, =1 if soil is clayey, 0 otherwise	0.012	0.111	0.013	0.113	n.s.
Management related control variables							
Dependency ratio	=	Dependency ratio (no. HH members aged <14 and >65 / all HH members)	0.185	0.168	0.200	0.179	n.s.
Age	=	Age of HH head (years)	51.504	10.709	49.846	11.356	**
High education	=	Dummy, =1 if educational achievement of HH head is > 12th grade, 0 otherwise	0.189	0.392	0.214	0.411	n.s.
General caste	=	Dummy, =1 if HH belongs to one of the 'general' (non-marginalized) castes, 0 otherwise	0.920	0.272	0.974	0.158	***
Risk preference	=	HH head's general risk preference, self-assessed on a scale from 0 (= fully avoiding risk) to 10 (= fully prepared to take risk)	6.035	1.287	6.021	1.335	n.s.
Non-farm share	=	Share of non-farm income in total HH income in 2017 (%)	4.678	13.484	2.748	9.400	n.s.
Farmer association	=	Dummy, =1 if HH head is member of the local farmer association, 0 otherwise	0.312	0.464	0.325	0.469	n.s.
Extension access	=	Perceived access to agricultural extension on a scale from 0 (= no access) to 5 (= very good access)	3.247	0.717	3.022	0.925	***
TV use	=	=Dummy, =1 if TV is used as source of agricultural information, 0 otherwise	0.171	0.377	0.132	0.340	n.s.
Internet use	=	=Dummy, =1 if the internet is used as source of agricultural information, 0 otherwise	0.007	0.084	0.004	0.065	n.s.
No. implements owned	=	Number of implements owned which the farmer uses for rice residue management and wheat sowing[d]	2.160	1.453	0.265	0.442	****
No. services hired	=	Number of custom-hiring services used for rice residue management and wheat sowing	0.342	0.809	0.372	0.484	****
District dummies (Ludhiana is base district)							
Fatehgarh	=	Dummy, =1 if HH is located in Fatehgarh Sahib district, 0 otherwise	0.253	0.435	0.132	0.340	****

(Continued)

Table 2. Continued.

Variable description			Conventional-tillage wheat (N = 561)		Zero-tillage wheat using HS (N = 234)		Sig. of diff.[e]
			Mean	Std. Dev.	Mean	Std. Dev.	
Ludhiana	=	Dummy, =1 if HH is located in Ludhiana district, 0 otherwise	0.283	0.451	0.056	0.230	****
Patiala	=	Dummy, =1 if HH is located in Patiala district, 0 otherwise	0.248	0.432	0.056	0.230	****
Sangrur	=	Dummy, =1 if HH is located in Sangrur district, 0 otherwise	0.216	0.412	0.756	0.430	****

Notes: HH = Household; HS = Happy Seeder.
[a]For ease of interpretation, summary statistics are provided for the unlogged variables.
[b]INR = Indian Rupees; 1 USD = 64.8 INR (Nov 01, 2017); MT = metric ton.
[c]Fees paid for mechanization services encompassing a labour- and a machine rental component are included in *Capital input*.
[d]Maximum of 5 implements owned and 4 services hired in CT wheat. In HS wheat maximum is strictly 1 for both implements owned and services hired; a value of 0 for both variables indicates that the machine was rented and farmer-operated.
[e]*(**)[***]{****} Means of CT and HS wheat regimes statistically significantly different at the 10%(5%)[1%]{0.1%} level of alpha error probability. Comparisons based on Mann-Whitney tests in case of interval-scaled variables and chi-square tests in case of dummy variables.

to 'strongly agree'. A 'Don't know' category accommodated cases where respondents were not able to judge a particular statement. For greater clarity, Table 4 aggregates the 'strongly (dis)agree' and '(dis)-agree' categories and omits the 'neutral' category. The percentages shown are based on cases where farmers were able to provide their judgement, i.e. cases of 'Don't know' are excluded. To differentiate between perceptions that are based on hear-say opposed to those that are based on the respondents' own experience, the table compares the perceptions of farmers using CT in wheat to those who practice ZT using a simple ZT drill and those who are actually using the HS.

The results illustrate that aware farmers have mostly positive perceptions about the HS (Column 4), whereby the assessment by farmers who are currently using the technology (Column 3) is generally more favourable than that of aware non-users (Columns 1–2). Approximately two-thirds and half of the aware farmers indicate a short-term and long-term yield benefit from using the HS, respectively. This is confirmed by similar shares of farmers *disagreeing* that the HS *reduces* yields in the short and long run, respectively (Column 4). HS users have a more positive perception about yield benefits than non-users, with 91% perceiving a short-term and 69% a long-term yield increase (Column 3). Three-quarters

Table 3. Awareness and use of the simple zero-tillage drill ('ZT drill') and the Happy Seeder (HS) in the 2017/18 *rabi* season in the survey villages in Punjab, India, differentiated by landholding terciles.

	(1) Smallest tercile (N = 309)	(2) Middle tercile (N = 361)	(3) Largest tercile (N = 351)	(4) All households (N = 1021)	Sig. level of difference
Aware of ZT (% yes)	94.1	95.4	96.9	95.4	n.s.[1]
Using ZT drill (% yes)	5.4	7.5	8.3	7.0	n.s.[1]
Using ZT drill (% yes among aware sub-population)	5.7	7.8	8.5	7.4	n.s.[1]
Mean use intensity (% wheat area among ZT users)	100.0[a]	95.4[b]	87.6[c]	93.4	*[2]
Aware of HS (% yes)	91.0	94.8	94.9	93.5	**[1]
Using HS (% yes)	7.3	12.5	14.1	11.3	***[1]
Using HS (% yes among aware sub-population)	8.0	13.2	14.9	12.0	***[1]
Mean use intensity (% wheat area among HS users)	98.7[a]	93.5[a]	84.5[b]	90.9	*[2]

*(**)[***] Statistically significantly different at the 10%(5%)[1%] level of alpha error probability.
[1]Based on chi-square test, indicating whether distributions across terciles deviate from each other.
[2]Based on multiple Mann-Whitney tests accounting for family-wise error; diverging superscript letters indicate statistical significance *at least* at the indicated level.

Table 4. Perceptions about the Happy Seeder (HS) for wheat sowing among aware[a] farmers in the survey villages in Punjab, India, differentiating conventional-tillage (CT) users, simple zero-till (ZT) drill users, and Happy Seeder (HS) users (values across 'agree' and 'disagree' categories do not sum up to 100%; deviation commensurate to 'neutral' category; values >10% in bold).

Statement	(1) CT users		(2) Simple ZT drill users		(3) HS users		(4) Whole sample		
	(Strongly) agree (%)	(Strongly) disagree (%)	(Strongly) agree (%)	(Strongly) disagree (%)	(Strongly) agree (%)	(Strongly) disagree (%)	(Strongly) agree (%)	(Strongly) disagree (%)	Sig. level of difference[b]
HS increases yields in the short run (N = 461/216/234/911)	**51.6**	4.3	**74.5**	2.3	**90.6**	3.9	**67.1**	3.7	****
HS increases yields in the long run (N = 451/216/232/899)	**41.7**	4.9	**47.7**	6.5	**69.0**	4.3	**50.2**	5.1	****
HS reduces yields in the short run (N = 461/216/234/911)	3.5	**52.3**	1.9	**75.0**	2.6	**91.9**	2.9	**67.8**	****
HS reduces yields in the long run (N = 451/216/232/899)	3.8	**42.8**	3.2	**50.4**	2.6	**70.7**	3.3	**51.8**	****
HS leads to severe weed problems (N = 339/185/229/753)	4.7	**66.7**	1.6	**82.2**	3.9	**83.0**	3.7	**75.4**	****
HS leads to severe rodent problems (N = 317/164/214/695)	7.6	**63.4**	8.5	**67.1**	**15.0**	**68.7**	**10.1**	**65.9**	***
HS saves substantial amounts of water (N = 502/221/234/957)	**91.0**	4.4	**97.3**	1.4	**91.5**	2.1	**92.6**	3.1	**
HS saves substantial amounts of labour (N = 507/221/234/962)	**96.3**	2.4	**97.7**	0.9	**99.6**	0.0	**97.4**	1.5	*
HS saves substantial amounts of fuel (N = 506/221/234/961)	**97.4**	1.6	**99.1**	0.5	**99.6**	0.4	**98.3**	1.0	n.s.
HS helps to reduce air pollution (N = 495/220/233/948)	**87.5**	2.2	**87.7**	4.1	**89.7**	1.7	**88.1**	2.5	n.s.

[a]Excluding cases of 'Don't know', leading to varying numbers of observations per statement, as indicated in brackets; values of N are for CT users/Simple ZT drill users/HS users/Whole sample, respectively.
[b]Based on chi-square test; *(**)[***]{****} indicate that distributions across groups deviate from each other at 10%(5%)[1%]{0.1%} level of alpha error probability.

of farmers disagree that the HS leads to severe weed problems; the share of HS users disagreeing is significantly higher (83%) than that of farmers who use conventional tillage (67%), whereas the perception of simple ZT drill users is in line with that of the HS users. Around two-thirds of farmers in all three groups disagree that the HS leads to severe problems with rodents, but the share of farmers agreeing to this statement is higher among HS users (15%) than among non-users of the technology (around 8%). A large majority of more than 90% of farmers in all three groups agree that the HS saves fuel, labour and water. Finally, close to 90% of farmers in all three groups agree that the HS helps reduce air pollution, highlighting the relevance of this issue to farmers in the research area.

5.2. Comparative analysis of conventional-tillage and zero-tillage wheat production systems

In this section we first compare basic characteristics of CT and ZT wheat production systems related to yield, time of crop establishment, input use and gross margins obtained (Table 5); ZT is again subdivided into two crop establishment methods, applying either the simple ZT drill or the HS. We then compare the three wheat establishment methods with respect to the management of the previous (rice) crop's residues, especially burning practices (Table 6). Lastly, we focus on the field operations carried out for (rice) residue management and wheat sowing under the three production systems, eliciting cost and time implications in more detail (Table 7).

Table 5 shows that, on average, farmers achieved very similar yields of around 5450 kg ha^{-1} using the three wheat establishment methods (Column 1). Nevertheless, the data indicate a slightly, but statistically significantly higher yield obtained in the two ZT systems. Both ZT technologies save time, resulting in earlier wheat establishment (by 2.7 days as compared to CT wheat, Column 2) and a shorter turnaround time between rice harvest and wheat sowing (by approx. 4 days, Column 3). The use of ZT also saves water by making pre-sowing irrigation dispensable through better retention of soil moisture, resulting in an average of 4.9 irrigations applied to ZT wheat as compared to 5.7 irrigations in the CT regime (Column 8).

Table 5. Wheat yields, input use and gross margins in Punjab, India, differentiated by establishment method.

	(1) Grain yield (kg/ha)	(2) Sowing date (days after Oct 31)	(3) Sowing date (days after paddy harvest)	(4) Seed (kg/ha)	(5) Urea (kg/ha)	(6) DAP (kg/ha)	(7) Herbicide expenses (INR/ha)[1]	(8) No. of irrigations (incl. pre-sowing)	(9) Gross margin (INR/ha)	(10) Returns to labour (INR/hour)[3]	(11) Returns to capital (INR/INR)
Conventional-tillage wheat (N = 585)	5429[a]	8.2[a]	18.5[a]	109.5	334.1[a]	135.2	1016[a]	5.7[a]	74,321[a]	1308[a]	3.80[a]
Zero-till wheat (simple ZT drill; N = 237)	5473[b]	5.5[b]	14.6[b]	109.7	334.3[a]	135.4	773[b]	4.9[b]	76,724[b]	1440[b]	4.26[b]
Zero-till wheat (Happy Seeder; N = 234)	5492[b]	5.5[b]	14.1[b]	109.0	326.2[b]	134.4	761[b]	4.9[b]	76,854[b]	1508[c]	4.23[b]
Sig. level of difference	**	***	***	n.s.	***	n.s.	***	***	***	***	***
All cases (N = 1056[2])	5454	7.1	16.6	109.2	332.6	134.9	907	5.3	75,422	1382	4.00

*(**)[***] Means statistically significantly different at the 10%[5%][1%] level of alpha error probability. Comparisons based on multiple Mann-Whitney tests accounting for family-wise error; diverging superscript letters indicate statistical significance *at least* at the indicated level.
[1]INR = Indian Rupees. 1 USD = 64.8 INR (Nov 01, 2017).
[2]Some farmers used more than one wheat establishment practice for which data are available.
[3]Including imputed cost of family labour input, valued at the median wage rate of 39 INR/hour.

Table 6. Primary practice of managing rice residues in Punjab, India, by wheat establishment method (values are percentages).

	Incorporated residues into the soil	Burned all residues	Burned loose residues	Left residues in the field
Conventional-tillage wheat (N = 561)	33.5	45.6	20.9	0.0
Zero-till wheat (simple ZT drill; N = 226)	0.4	7.5	89.4	2.7
Zero-till wheat (Happy Seeder; N = 234)	5.6	0.9	3.0	90.6
Overall (N = 1021)	19.8	26.9	31.9	21.4

Note: Chi-square test significant at the 0.1% level of alpha error probability.

Furthermore, the descriptive analysis indicates a small but statistically significant reduction of herbicide expenses in ZT wheat as compared to CT wheat (Column 7). In the case of HS wheat, also the application of urea was slightly reduced (Column 5); i.e. compared to CT wheat, a (slightly) higher yield was achieved with slightly lower urea input, reduced herbicide expenses and reduced irrigation. The gross margins, i.e. returns to land, achieved with ZT wheat exceed those of CT wheat by approximately 2600 INR ha^{-1}, on average. There is no difference in gross margins between HS and simple ZT technologies (Column 9). Under conditions of increasing rural labour scarcity, as is the case in Punjab (Reddy et al., 2014), returns to labour are of particular relevance. As Column 10 shows, returns to labour differ significantly across all three wheat establishment methods, with returns under the HS exceeding those under conventional tillage by 200 INR hour^{-1} and those under the simple ZT technology by 68 INR hour^{-1}, on the average. Similar to the gross margin, returns to capital are significantly higher under ZT wheat as compared to CT wheat (exceeding the latter by approximately 12%), while there is no significant difference between ZT technologies (Column 11).

Table 6 compares the primary rice residue management practices across the three wheat production regimes; the percentages shown are directly comparable as all survey respondents used a combine harvester for their rice, leaving relatively large amounts of residue behind. The table shows that approximately two-thirds of the farmers who used CT wheat burned either all residues left after the rice harvest or they burned loose residues only. For the remaining one-third of CT users, incorporation of residues into the soil was the primary practice cited. Moving on

Table 7. Costs of rice residue management and wheat sowing in Punjab, India, by establishment method and machinery ownership.

	All cases (N$_{LSW}$ = 545, N$_{ZTW}$ = 226, N$_{HSW}$ = 234)			Machine rental and custom hiring services only (N$_{LSW}$ = 113, N$_{ZTW}$ = 128, N$_{HSW}$ = 172)			Custom hiring services only (N$_{LSW}$ = 51, N$_{ZTW}$ = 37, N$_{HSW}$ = 87)		
	No. of implements used	Total time required (Min./ha)	Total cost[1] (INR[3]/ha)	No. of implements used	Total time required (Min./ha)	Total cost[2] (INR[3]/ha)	No. of implements used	Total time required (Min./ha)	Total cost (INR[3]/ha)
Line-sown wheat with tillage (LSW)	3.3[a]	430.0[a]	3917[a]	2.9[a]	395.1[a]	5908[a]	2.6[a]	377.1[a]	6702[a]
Zero-till wheat, simple ZT drill (ZTW)	1.1[b]	182.4[b]	1868[b]	1.1[b]	173.7[b]	2286[b]	1.1[b]	178.7[b]	3072[b]
Zero-till wheat, Happy Seeder (HSW)	1.0[c]	168.3[c]	2123[c]	1.0[c]	167.5[c]	2540[c]	1.0[c]	167.8[b]	3047[c]
Sig. level of diff.	***	*	***	***	**	***	***	***	***
Overall	2.3	313.3	3039	1.5	231.5	3383	1.5	231.0	4117

*(**)[***] Means statistically significantly different at the 10%(5%)[1%] level of alpha error probability. Comparisons based on multiple Mann-Whitney tests accounting for family-wise error; diverging superscript letters indicate statistical significance *at least* at the indicated level.
[1]Not accounting for depreciation of owned tractors and implements.
[2]Not accounting for depreciation of owned tractors.
[3]Indian Rupees. 1 USD = 64.8 INR (Nov 01, 2017). Only variable costs are considered.

to the simple ZT drill users, the table demonstrates that this does *not* lead to a reduction of rice residue burning as compared to CT. On the contrary, since, by definition, residues are not incorporated into the soil under ZT, and the simple ZT drill is not capable of directly sowing wheat into the large amounts of residue left after combine-harvesting of rice, the burning of loose residues is the dominant practice cited by 89.4% of simple ZT drill users. It is *only* the HS that leads to a dramatic reduction of rice residue burning, with 90.6% of HS users reporting that they retained all residues in the field to decompose. The fact that some HS users reported incorporation or burning of residues indicates that the HS may not always be used as intended.

Table 7 explores the costs and time requirements of the rice residue management and wheat sowing practices across the three technologies. To ensure comparability, 16 cases of broadcast-sown wheat after tillage were excluded from the analysis, so that wheat establishment with tillage refers to line-sown wheat (LSW) only in the following analysis. Furthermore, costs incurred account for variable costs only, i.e. machine depreciation is not taken into account, as elaborated in Section 4.2.2. Therefore, the magnitude of cost savings depends on whether or not machines are owned and can be most clearly quantified for cases where all machines are accessed via custom-hiring services. Hence, Table 7 differentiates between 'all cases' (irrespective of machine ownership), cases where machines are either rented and self-operated or full services are hired, and cases where custom-hiring services are used for all operations.[2] In all scenarios, there are statistically significant differences between all three wheat establishment methods considered, both with respect to number of implements used, time required to complete operation(s), and costs incurred. Both ZT practices entail obvious time- and cost savings as compared to LSW. In the most straight-forward comparison based on custom-hired operations only, the time saving amounts to around 200 min and the cost saving to approx. 3650 INR ha^{-1}. The use of the HS saves an additional 10 min per hectare as compared to the use of the simple ZT drill, but costs incurred are very similar due to slightly higher service fees charged for the HS.

5.3. Determinants of Happy Seeder adoption

We concentrate our following econometric analyses on only two wheat establishment practices, the use of the HS versus the use of CT. As highlighted in Table 6, only the HS has the potential to eradicate rice residue burning, which is the focus of this study. Moreover, Tables 5 and 7 showed that the use of the simple ZT drill does not entail any obvious economic advantages over the use of the HS, at least if we consider accessing the two technologies via machine rental or custom-hiring services rather than individual ownership.

Table 8 displays the estimates from two regression models that explore influencing factors of HS adoption, a simple probit model (Model 1) and the 'heck-probit' model which accounts for potential non-exposure bias as elaborated in Section 4.1.1 (Model 2). Variance inflation factors (VIFs) show that there is no cause for concern about multicollinearity among the explanatory variables in the two models, with the average VIF amounting to 1.29 and the maximum to 2.13 (variable *Sangrur*) in Model 1 and the awareness stage of Model 2, and to 1.34 and 2.30 in the adoption stage of Model 2, respectively. As a rule of thumb, a value of 10 should not be exceeded by individual VIFs (Myers, 1990).

Model 1 shows that cultivable area and belonging to the 'General' caste increase the propensity of HS adoption, whereas the share of income derived from non-farm sources has a negative effect. On average, the cultivable area of HS users amounts to 6.3 ha compared to 4.8 ha among CT users (Mann–Whitney test statistically significant at $P < 0.001$), illustrating some degree of scale bias of current HS adoption. Use of the HS by primary social network members has a large and statistically highly significant effect on the respondent's adoption decision (endogenous network effect). The estimated marginal effect indicates that the respondent farmer's propensity to adopt the HS increases by 13 percentage points if one additional member of his primary network is using the technology. The age of the NMs has an adverse effect on the respondent's propensity to adopt the HS (exogenous network effect), which may indicate that novel technologies are discussed more intensely among relatively younger farmers. The effect is very small in magnitude, however. It is further important to note that the geographical spread of the HS was very heterogeneous at the time of the survey: as indicated by the district dummies, the likelihood of HS adoption increased by 27.7 percentage points if a farmer resided in Sangrur district, relative to the base district of Ludhiana.

The second stage of Model 2 produces very similar estimates as the simpler Model 1. However, the first stage of Model 2 indicates that the factors affecting farmers' awareness of the HS differ from those that affect the adoption decision: landholding size does not significantly affect awareness, but age, education and credit access enhance awareness. The share of income derived from non-farm sources has a highly significant negative effect on awareness. This is plausible as households that depend less on agricultural income may be less active in acquiring information about (and then testing) novel farming practices. The use of the internet for agricultural information acquisition has a surprisingly large and highly significant positive effect, increasing the likelihood of being aware of the HS by more than 50 percentage points. In contrast, the use of TV yields a much smaller coefficient which is significant at $P < 0.15$ only. Our data do not support a significant role of farmer groups or agricultural extension in diffusing information about the HS. We find that HS adoption among respondents' NMs also affected awareness, but, as indicated by the magnitude of coefficients, social networks seem to play a more important role when it comes to the adoption decision.

A Wald test of independent equations indicates that the error terms of the first- and second-stage equations are uncorrelated, which means that the use of the simpler Model 1 is justified (see Equation (1)). This is corroborated by the fact that Model 2 does not lead to an improvement in explanatory power. As indicated at the bottom of Table 8, Model 1 predicts 61.5% of cases of HS adoption and 93.4% of cases of non-adoption correctly, which is slightly superior to Model 2.

5.4. Quantifying the impact of the Happy Seeder on wheat yields and production costs

Table 9 displays the regression results of the second stage of the ETE model, identifying determinants of wheat yields and per-unit production costs under HS and CT production regimes, based on the *rabi* season 2017/18. The first stage (selection equation) of the ETE model is a simple probit model whose use is justified in the case of HS adoption as elaborated in the previous section. The estimates of the first stage are equivalent to Model 1 shown in Table 8 above. Also the second-stage equation of the ETE regression was checked for potential multicollinearity among explanatory variables. The only VIFs exceeding

a value of 10 are related to dummy variables controlling for the widely used wheat varieties HD 2967 (VIF = 21.76) and HD 3086 (20.11), followed by PBW 725 (6.26), in the HS regime. However, the fact that all three variables produce significant coefficients in Model 1 indicates no problem of collinearity. The maximum VIF among the remaining variables is 4.75 (variable *Sangrur*), and the average amounts to 1.73, indicating no cause for concern (Myers, 1990).

Model 1 in Table 9 shows that the level of capital input positively affects wheat yields under both the CT and HS production regimes, whereby the magnitude of the estimated effects is very small. Since both the dependent variable and *Capital input* are logged, the estimated coefficients are elasticities, indicating a 0.08% and 0.04% increase in wheat yield for a 1% increase in capital input under the CT and HS regimes, respectively. No significant effect of labour input (neither total labour hours nor expenses for hired labour) could be identified using our dataset. It is important to note that the variance in both wheat yields and input levels is surprisingly low in our data. A stochastic frontier production function based on our dataset yields an average technical efficiency of 0.97 in wheat production, which illustrates the low level of variability. Indeed, farmers in Punjab have largely optimized and, therefore, equalized their wheat growing practices (Aryal et al., 2015). Aside from capital and labour input, Table 9 identifies a number of statistically significant yield determinants, and it shows that these factors differ between CT and HS wheat regimes. Within the observed range of wheat sowing dates (Oct 28 to Nov 20), the variable *Late sown* indicates a statistically significant – yet practically negligible – yield gain of 2% if CT wheat is sown later than November 13; the estimated coefficient is of similar magnitude for HS wheat, but not statistically significant. As mentioned above, the dummy variables on the three most common wheat varieties produce significant negative coefficients indicating a yield loss of around 3% under the HS production regime, while this is not the case under CT. Belonging to the 'General' caste, being member of a farmer association, and access to agricultural extension have positive implications on CT wheat yields only. Interestingly, in the CT regime the model produces a negative coefficient on *Internet use* and in the HS regime a weakly significant negative effect of extension access. This may indicate a questionable quality of information derived from these sources. However, in the case of *Internet use* the

Table 8. Maximum Likelihood estimates of a probit model explaining Happy Seeder (HS) adoption and a Heckman probit selection model explaining awareness of the HS (1st stage) and HS adoption conditional on awareness (2nd stage) in wheat production in Punjab; coefficients are marginal effects.

| Variable | Model 1: Probit model | | Model 2: Probit selection model | | | |
| | HS adoption | | HS awareness | | HS adoption cond. on awareness | |
	Coefficient[1]	z-value[2]	Coefficient[1]	z-value[2]	Coefficient[1]	z-value[2]
Cultivable area	0.0131	4.02****	0.0024	0.68	0.0129	3.91****
Dependency ratio	0.0562	0.79	0.0038	0.09	0.0617	0.86
Age	−0.0009	−0.64	0.0019	2.43**	−0.0008	−0.60
High education[d]	0.0146	0.56	0.0654	2.57**	0.0124	0.49
General caste[d]	0.0900	2.05**	0.0034	0.08	0.0905	2.08**
Risk preference	−0.0035	−0.34	−0.0020	−0.28	−0.0025	−0.25
Credit access	−0.0247	−1.28	0.0320	2.17**	−0.0255	−1.34
Non-farm share	−0.0014	−1.84*	−0.0012	−3.41***	−0.0014	−1.80*
Farmer association[d]	−0.0074	−0.29	0.0268	0.92	−0.0066	−0.26
Extension access	0.0020	0.10	0.0133	0.81	0.0021	0.10
TV use	−0.0399	−1.38	0.0419	1.49	-	
Internet use	0.0458	0.74	0.5442	5.09****	-	
NM HS use	0.1302	7.64****	0.0477	2.56**	0.1320	7.98****
NM age	−0.0034	−1.93*	0.0018	1.62	−0.0034	−1.96*
Fatehgarh[d]	0.1054	1.81*	0.0780	1.95*	0.0964	1.73*
Patiala[d]	0.0718	0.99	0.1042	2.03**	0.0682	0.97
Sangrur[d]	0.2765	5.25****	0.1344	2.60***	0.2684	5.30****
N =	795		795		746	
Wald chi-square =	614.37****	539.55****				
Wald test of independent equations: chi-square (1) =	-	0.29 (n.s.)				
Explanatory power:						
Cases of HS adopters correctly predicted (%) =	61.5	59.4				
Cases of HS non-adopters correctly predicted (%) =	93.4	93.2				
Overall cases correctly predicted (%) =	84.0	83.3				

*(**)[***]{****} Significant at the 10%(5%)[1%]{0.1%} level of alpha error probability.
[1]Coefficients are marginal effects evaluated at the means of all explanatory variables; for dummy variables, marginal effects are for a discrete change from 0 to 1.
[2]Based on robust standard errors adjusted for 52 village-level clusters.
[d]Dummy variable.

result hinges on very few observations and in the case of *Extension access* the coefficient is barely statistically significant; hence, we do not want to over-interpret these findings. In both production regimes we identify a positive effect of a more risk-taking nature of the farmer; one could speculate that these farmers are less hesitant to apply the required kind and amount of inputs at the right time than their more risk-averse counterparts. Furthermore, we find that the number of mechanization services used for field operations has a small yet statistically significant yield reducing effect in both regimes, indicating that the quality of these services may fall short of that achieved by owner-operators.

The endogeneity test on correlation of treatment and outcome unobservables rejects the null-hypothesis at $P < 0.11$. Hence, there may be unobserved factors affecting both HS adoption and wheat yields attained; the weakly significant coefficient on the IMR derived from the selection equation indicates that these unobserved factors are negatively correlated with CT wheat yields (see Section 4.1.3). Our analysis does not identify a generalizable HS-induced yield benefit as indicated by the statistically insignificant ATE estimate. However, among the farmers who adopted the HS, the estimated ATET is positive and weakly statistically significant. Calculating the difference between the estimated counterfactual yield among HS users (i.e. the estimated yield they would have attained without using the HS) and the sum of the counterfactual yield plus the estimated ATET (i.e. $\exp[8.554565 + 0.055312] − \exp[8.554565]$; rounded values are shown in Table 9), this translates into a yield gain of 295 kg ha^{-1}. However, when interpreting this result one needs to keep in mind that the 95% confidence interval (CI) around this estimate extends from 1 to 610 kg ha^{-1}.

Using the same set of explanatory variables, Model 2 in Table 9 identifies determinants of the per-unit cost (PUC) of wheat production, measured as total variable cost per quintal, including the imputed cost of family labour input (see Section 4.2.2). Only in the

Table 9. OLS estimates of an Endogenous Treatment Effects (ETE) regression explaining wheat yield (Model 1) and per-unit production cost (Model 2) under conventional-tillage (CT) and Happy Seeder (HS) production regimes (= 2nd stage of ETE model; 1st stage estimates of selection equation are equivalent to Model 1, Table 8).

	Model 1: Yield impact				Model 2: Per-unit cost impact			
	CT wheat (N = 561)		HS wheat (N = 234)		CT wheat (N = 561)		HS wheat (N = 234)	
Variable	Coefficient	z-value[1]	Coefficient	z-value[1]	Coefficient	z-value[1]	Coefficient	z-value[1]
Capital input	0.0798	2.12**	0.0423	2.14**	1.3130	5.84****	0.2407	0.49
Labour hours	0.0125	1.13	−0.0048	−0.29	0.7313	5.29****	0.7450	3.66****
Labour expenses	0.0020	0.80	0.0020	1.26	−0.0984	−3.64****	−0.0817	−4.80****
Late sown[d]	0.0196	2.51**	0.0227	0.80	0.2049	2.75***	0.0347	0.14
HD2967[d]	−0.0094	−0.97	−0.0291	−3.13***	−0.0133	−0.09	0.3355	2.06**
HD3086[d]	0.0053	0.59	−0.0342	−2.61***	−0.0677	−0.45	0.2391	1.64
PBW725[d]	−0.0105	−0.90	−0.0322	−2.06**	−0.0215	−0.13	0.1870	1.11
Sandy soil[d]	0.0032	0.24	−0.0045	−0.29	0.0747	1.37	0.0193	0.10
Clay soil[d]	0.0062	0.32	−0.0096	−0.38	−0.0890	−0.39	−0.0281	−0.07
Dependency ratio	0.0134	0.63	−0.0261	−1.48	0.2080	1.34	−0.0083	−0.03
Age	−0.0002	−0.38	−0.0001	−0.53	−0.0063	−2.13**	−0.0047	−1.19
High education[d]	−0.0046	−0.54	−0.0057	−0.71	−0.2445	−3.60****	−0.1125	−0.94
General caste[d]	0.0206	2.58**	0.0134	0.91	0.1625	2.13**	−0.0319	−0.21
Risk preference	0.0052	2.12**	0.0044	2.03**	−0.1459	−7.19****	−0.0694	−1.91*
Non-farm share	0.0001	0.96	0.0002	0.83	0.0047	3.05***	0.0101	3.20***
Farmer association[d]	0.0131	1.85*	−0.0087	−1.09	−0.1982	−3.27***	−0.0407	−0.58
Extension access	0.0112	2.03**	−0.0046	−1.66*	−0.0737	−1.65*	−0.0504	−1.25
TV use	0.0023	0.35	−0.0009	−0.11	−0.2066	−3.64****	−0.0671	−0.56
Internet use	−0.0304	−3.06***	−0.0083	−0.32	−0.2807	−2.26**	−0.5857	−2.16**
No. implements owned	−0.0009	−0.37	−0.0106	−0.96	−0.1498	−7.78****	−0.3641	−4.27****
No. services hired	−0.0105	−3.12***	−0.0149	−1.76*	0.0427	1.24	0.1526	2.21**
Fatehgarh[d]	0.0122	1.34	0.0063	0.39	0.1259	1.17	0.0819	0.39
Patiala[d]	0.0205	1.92*	−0.0220	−1.08	0.1602	1.80*	−0.0296	−0.14
Sangrur[d]	−0.0144	−1.04	0.0251	1.79*	0.4659	4.12****	0.3691	2.15**
Constant	7.6575	19.21****	8.2172	42.37****	−8.5379	−3.63****	−0.0137	−0.00
IMR[2]	−0.0354	−1.92*	0.0005	0.04	1.1291	4.85****	0.7081	3.31***
Endogeneity[3] test chi-square (2) =		4.46 (n.s.)				42.21****		
Outcome_pot. ATE	8.5840	ATE =	0.0021	0.07	5.3472	ATE =	−1.4533	−7.12****
Outcome_pot. ATET	8.5546	ATET =	0.0553	1.97*	6.0706	ATET =	−1.3112	−3.90****

*(**)[***]{****} Significant at the 10%(5%)[1%]{0.1%} level of alpha error probability.

Notes: ATE = Average Treatment Effect HS vs. CT; ATET = Average Treatment Effect HS vs. CT on the Treated, i.e. among HS adopters (explanations in the text).

[1]Based on robust standard errors adjusted for 52 village-level clusters.
[2]Inverse Mills Ratio derived from the selection equation; its inclusion in the second stage equations corrects for potential selection bias.
[3]H_0: Treatment and outcome unobservables are uncorrelated.
[d]Dummy variable.

CT wheat regime is *Capital input* identified as a major driver of PUC. Regarding labour input, in both production regimes the total number of labour hours increase PUC at similar estimated elasticities of around 0.74. In contrast, the expenses for hired labour produce small but highly significant *negative* elasticities, indicating that the marginal benefit of hired labour use is clearly greater than its marginal cost. In the HS regime, Model 2 shows variety-related effects consistent with Model 1, i.e. the most widely used wheat varieties, HD 2967 and HD 3086 (coefficient significant at $P < 0.11$ only) lead to an increase in PUC, which is clearly not the case under CT. The estimated coefficients are quite large, suggesting that they may reflect part of the associated variation in *Capital input* as well, rendering the latter variable statistically insignificant. A number of management related factors are found to affect PUC, especially in the CT regime: the farmer's age has a cost reducing effect which is likely related to farming experience. *High education* is estimated to reduce PUC by 21.7% (calculated as $100 \times [\exp(−0.2445) − 1]$), which may be related to greater allocative efficiency compared to farmers of lower educational status. Furthermore, being member of a farmer association, having better access to agricultural extension, and using television for agricultural information acquisition have cost-reducing effects in CT wheat, while the data do not support the same in the HS regime. This suggests that these information sources are more geared towards traditional agricultural practices. By contrast, the use of the internet to access

agriculture related information is estimated to have a cost-reducing effect in both production regimes. As mentioned above, since *Internet use* has few positive observations only, this result should be interpreted cautiously.

A few other factors affect PUC in both production regimes: consistent with the yield-enhancing effect of a risk-taking nature of the farmer identified in Model 1, Model 2 indicates a cost-reducing effect of the same trait, which is particularly pronounced in the CT regime. The share of non-farm income increases PUC in both regimes, which may be caused by less experience and/or less care being exerted on agricultural activities. Furthermore, we find that the number of implements owned for rice residue management and wheat sowing has a highly significant cost-reducing effect in both regimes, while the number of services hired to accomplish the same operations increases PUC significantly in the HS regime. This is expected as the analysis does not account for fixed costs related to machine ownership, as elaborated earlier. While in the CT production regime the number of implements owned varies between zero and five and the number of services hired ranges from zero to four, strictly one implement is used in the case of the HS regime; therefore, in the latter, *No. implements owned* and *No. services hired* are dummy variables indicating whether the farmer used his own HS or hired a service provider. Relative to the base category of machine rental for self-operation, the magnitude of the coefficients indicate a reduction of PUC by 30.5% if a farmer uses his own HS and an increase by 16.5% if a full service is used.

Unlike with Model 1, the endogeneity test on Model 2 and highly significant IMRs in both regimes shows that there are clearly unobserved factors affecting both HS adoption and PUC of wheat production, justifying the use of our ETE approach. Model 2 produces a highly significant negative ATE of HS use – i.e. a per-unit production cost saving – translating to 161 INR quintal^{-1}. The 95% CI extends from 137 to 177 INR quintal^{-1}. The model further produces a highly significant negative ATET of 316 INR quintal^{-1} with the 95% CI ranging from 208 to 373 INR quintal^{-1}. It is important to stress that these estimates are very robust. In particular, the removal of the wheat variety dummies (which are relatively highly correlated with each other) and the variable *Internet use* (which is highly skewed) leads to virtually identical estimates of −161 and −318 INR quintal^{-1} and very similar CIs for ATE and ATET, respectively.

6. Discussion

In this study we compare yield and cost impacts from different rice residue management and wheat sowing practices. We find strong empirical evidence that the use of the HS does not only have the potential to avoid residue burning, but that it also leads to significant cost savings in wheat production. In particular, given an average wheat yield of approximately 5450 kg ha^{-1} (see Table 5), the estimated HS-induced cost saving of 161 INR quintal^{-1} is commensurate to an average total saving of 8775 INR ha^{-1}, which is well in line with the recent meta-analysis provided by Shyamsundar et al. (2019). Our analysis further produces a 95% CI of the estimated cost savings, extending from 7467 to 9647 INR ha^{-1}. It is important to note that even the lower limit of the 95% CI is significantly larger than the observed difference in gross margins, which does not account for selection bias between HS users and non-users and amounts to approximately 2600 INR ha^{-1} only (Table 5).

We also find that zero-till practices lead to considerable time-savings of 200 min ha^{-1} or more as compared to traditional wheat establishment methods (Table 7). While this is the net time saving of actual field operations, the overall time saving may be much more substantial, especially in cases where farmers rely on custom-hiring services to accomplish operations. Depending on service availability, each field operation may be associated with a waiting period. Accomplishing rice residue management and wheat sowing in one single pass of the tractor, the time-saving potential of the HS is particularly large. Without implying strict causality, the observed difference in turnaround time between rice harvest and wheat sowing of approximately four days (Table 5) implies that farmers are indeed able to establish their wheat crop earlier under zero-tillage, and by using the HS in particular. Timeliness in planting is critical for three reasons: (1) it captures residual soil moisture, hence allowing to skip pre-sowing irrigation; (2) it gives wheat a head start in germination and growth versus *Phalaris minor*, a major weed in the area (Chhokar et al., 2007); and (3) it helps wheat escape terminal heat, a major abiotic stress in north-western India (Buttar et al., 2013; Jat et al., 2009).

Soil water deficits and high temperatures are chronic limitations to wheat productivity in most parts of South Asia. ZT, in addition to facilitating

timely planting, markedly reduces evaporation by retaining crop residues on the soil surface, and it also increases the amount of water that infiltrates the soil and, hence, provides better soil water interactions to the root system (Singh et al., 2011). However, since wheat varieties are developed for CT based management, their performance under ZT varies with their relative adaptation to altered management and soil environment due to Genotype x Environment x Management (GEM) interactions. Therefore, failure to target wheat varieties appropriately for diverse management situations may result in adverse performance and, hence, has implications for agronomic management targeted breeding.

While our analysis reveals clear benefits of HS use for the individual farmer, it has to be recognized that, due to the relatively high investment cost and high degree of specialization of the machine, individual ownership is not a promising route of scaling the technology. Rather, most farmers will access the HS via custom-hiring services offered by other farmers or specialized service providers. Group ownership is another potential option. To assess the attractiveness of HS service provision as an income earning opportunity, more research is required to elucidate its economics, especially in comparison with alternative, tillage related services.

7. Conclusions and recommendations

Among the three wheat establishment methods analysed – conventional tillage, simple zero-till drill and Happy Seeder (HS) – only the HS has the potential to eradicate the practice of rice residue burning due to its ability to sow wheat directly into large amounts of anchored and loose residues. While our analysis does not indicate a general yield benefit caused by using the HS as compared to conventionally tilled wheat, we do find a weakly significant positive yield impact among those farmers who adopted the HS. More importantly, however, at a high level of statistical confidence we show that the HS leads to significant savings in wheat production costs, amounting to 161 INR quintal^{-1}, or approximately 8800 INR ha^{-1} based on average wheat yields in the research area in south-eastern Punjab.

Neither our descriptive nor our econometric analysis nor farmers' subjective perceptions indicate that the use of the HS entails a yield penalty. On the contrary, our detailed descriptive analysis of rice residue management and wheat sowing operations across

establishment methods demonstrates significant benefits in terms of time and water savings, in addition to the monetary savings quantified. Since the availability of custom-hiring services is the prerequisite for most farmers to access the technology, research is required to elucidate the economics of HS service provision as compared to alternative, tillage related services.

The combination of the illustrated private benefits with the societal benefits of reducing air pollution through 'zero burning' justifies the diffusion of the HS to be supported through appropriate policies, such as purchase price subsidies that go beyond the level of subsidy offered for tillage-related implements, such as the rotavator. It should also be recognized that there are economic incentives inherent to the HS technology that could be harnessed if existing subsidy policies were revised, notably the provision of free electricity for irrigation.

Our analysis also shows that the most widely used sources of information are geared towards conventional agricultural practices. Emphasizing the diffusion of information about the HS and its private and societal benefits through these channels would likely support its widespread adoption. In addition, we find that farmers who use the internet for agricultural information acquisition are far more likely to be aware of the HS. Therefore, awareness raising campaigns should use both conventional and novel channels of information to enhance their effectiveness. Furthermore, as with any innovation that deviates significantly from farmers' habitual practices, a social marketing strategy should encompass frontline demonstrations that allow farmers to directly observe the performance of the technology under real-life conditions.

The ETE model further indicates that there are genotype – management interactions affecting wheat productivity under ZT versus CT production regimes. These are likely to apply to any ecology across South Asia that is characterized by deficient soil water and high temperatures. Such interactions should be taken into account by wheat breeders and agricultural extension to ensure the best possible outcomes as the use of ZT – and the HS in particular – becomes more widespread.

Since residue burning imposes tremendous health- and environmental costs, its reduction and, ideally, elimination should be sped up as far as possible; to this end, investments in social marketing and policies supporting the use of the HS will have to be

supplemented by a stricter enforcement of the existing ban on residue burning.

Notes

1. Grass-roots level cooperative credit institutions, many of which supply local farmers with agricultural inputs and machinery services.
2. Note that the costs are generally the highest in the latter category since (1) the first category ('All cases') includes farmers who used their own machinery for all or part of the required operations (and depreciation of owned machinery does not enter the calculation as it is a fixed cost); and (2) the rental fee for machinery to be self-operated by the farmer (contained in the first and second categories) is lower than the fee for a full service.

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