Agricultural Economics Research Review 2020, 33 (Conference Number), 61-74
DOI: 10.5958/0974-0279.2020.00018.X

Interlink between factor and product markets: opportunity for the future of Indian agriculture

A G Adeeth Cariappa*, and B S Chandel

Division of Dairy Economics, Statistics and Management, ICAR-National Dairy Research Institute, Karnal 132 001, Haryana

*Corresponding author: adeeth07@gmail.com

Abstract Farm households' choice of where to sell the product (marketing channel) is endogenous to the decision of where to buy inputs (selection of an input source). Using the latest National Sample Survey Office (NSSO) Situation Assessment Survey data, and endogenous switching probit regression (ESPR), this study evaluates the impact of input market selection on the choice of (formal) product market. Compared to farm households selling to informal markets, those selling to formal product markets had significantly higher profit per unit of land. Households buying inputs from formal sources like cooperatives and government agencies were 50% more likely to choose formal channels.

Keywords Agricultural markets, endogenous switching probit regression (ESPR), agricultural supply chain, agricultural input markets, impact evaluation

JEL codes C31, Q13, Q12, Q18

Value chains strengthen forward and backward linkages and constitute an important catalyst in enhancing farmers' income (Chengappa 2018). Interactions with value chain actors across all crop types, and the complementary services they provide (inputs, credit, information, extension, etc.), help small farmers to upgrade their farming practices and improve productivity (Liverpool-Tasie et al. 2020). The forward linkages in the value chains have found considerable interest among researchers, and research can be found on the extent of price spread, technology use, poverty alleviation, sustainability, organic value chains, price transmission, and integration in value chains (Devi, Hema, and Jaikumaran 2010; Chengappa, Devika, and Manjunatha 2019; Sundaramoorthy, Mathur, and Jha 2014; Kumar et al. 2011; Kumar et al. 2012; Pandey et al. 2010). But there is little research on backward linkages (Sheldon 2017). Many researchers have documented the interlink between input, credit, and product markets (Singh and Bhogal 2015; Chatterjee and Kapur 2016; Negi et al. 2018) but, to the best of our knowledge, no study quantifies the interlinkages between factor and product markets.

Therefore, this study aims to evaluate the impact of input market selection on choice of product market (market channel). Our work is unique in several ways. First, we use data from a nationally representative survey to estimate the impact of a household's input source choice on the probability of selling to formal markets. Second, to account for the endogeneity in the choice of input and output markets, we use the endogenous switching probit regression (ESPR) model. Third, the ESPR model allows us to quantify the probability of a particular product market choice conditional on the input source, which helps us to quantify the exact relationship between a particular input and product market. Thus, this paper will be of extreme utility for researchers and policymakers who aim at developing policies to improve farmers' profitability and access to markets.

Table 1 Correlation estimates

	Input sources				Market channel		
	Own farm	Local trader	Input dealer	Cooperative/ Government	Local trader	Mandi	Input dealer
(a) Input sources							
Own farm	1.000						
Local trader	–0.282***	1.000					
Input dealer	–0.113***	–0.145***	1.000				
Cooperative/Government	–0.129***	–0.171***	–0.066***	1.000			
(b) Market channel							
Local trader	–0.022***	–0.001	0.013**	0.016***	1.000		
Mandi	–0.002	0.014**	–0.004	–0.012**	–0.665***	1.000	
Input dealer	0.014**	0.002	–0.014**	–0.002	–0.309***	–0.155***	1.000
Cooperative/Government	0.031***	–0.014**	–0.007	–0.017***	–0.286***	–0.143***	–0.067***

Note: ** and *** indicates significance at 0.05 and 0.01 level respectively
Source: Estimation based on data from NSSO (2015).

Theoretical framework

The production function approach, used to arrive at the profit and efficiency estimates of a farm, often neglects the endogeneity in the input choice of farm households (Tsionas, Kumbhakar, and Malikov 2015; Amsler, Prokhorov, and Schmidt 2016; Santín and Sicilia 2017; Petrin, Poi, and Levinsohn 2004). This study builds on the premise that a farm household's choice of value chain depends to a certain extent on its selection of input source;[1] in other words, its choice of where to buy (input) influences its choice of where to sell (product).

Agricultural markets are complex interfaces; these perform various tasks important for social reproduction and development, and these connect producers to consumers, villages to towns, and agrarian sectors to non-agrarian sectors (Jan and Harriss-White 2012). Farm households borrow from local traders, input dealers, or cooperative societies for agricultural and personal purposes, and many households offer the final produce as collateral and repay the loan in kind, i.e., the produce. Farm inputs like fertilizers are also commonly bought on a 'pay later' basis, and the final produce is pledged as payment. Farm households are believed to buy their input needs from a particular input source because it is profitable or they have no other choice, and the same can be said about the product market choice. We build on this premise—there is a significant link between factor and product market choices—and try to provide empirical evidence for this theory of interlink of choices.

The naïve methods of establishing the evidence on interlink using correlation and multivariate regression analysis is presented in Tables 1 and 2. Clearly, input and output markets are significantly associated with each other. Further, we use the endogenous switching probit regression (ESPR) model to evaluate the impact of input source selection on the choice of product markets. First, we categorize the product market into formal and informal value chains. Formal markets comprise regulated markets (mandi), cooperatives/ government agencies, and processors. Informal markets comprise local traders, input dealers, and other product markets. We determine the profitable product market among these two groups and evaluate the impact of input market selection on the choice of this profitable product market.

Endogenous switching probit regression (ESPR)

We use an ESPR model for two reasons. First, we believe that the choices of a product market and input source are endogenous, and that these choices depend on the observed and unobserved characteristics of farm

[1] Here, 'value chain' means the output destination (product market), like local traders or regulated markets, where farm households sell their produce. The terms 'value chain', 'output destination', 'market channel', and 'product market' are used interchangeably in this paper.

Table 2 Multivariate regression estimates of interlinking factor onto product markets

	Coefficient	Standard error
Dependent variable = local trader (1/0)		
Own farm (1/0)	–0.026***	0.008
Local trader (1/0)	–0.003	0.007
Input dealer (1/0)	0.025*	0.013
Cooperative/government (1/0)	0.022**	0.010
Constant term	0.572***	0.004
Regulated market (1/0)		
Own farm (1/0)	0.000	0.007
Local trader (1/0)	0.012*	0.006
Input dealer (1/0)	–0.005	0.011
Cooperative/government	–0.014*	0.008
Constant term	0.248***	0.004
Input dealer (1/0)		
Own farm (1/0)	0.009**	0.004
Local trader (1/0)	0.003	0.004
Input dealer (1/0)	–0.013**	0.007
Cooperative/government (1/0)	0.000	0.005
Constant term	0.066***	0.002
Cooperative/government (1/0)		
Own farm (1/0)	0.016***	0.004
Local trader (1/0)	–0.006*	0.003
Input dealer (1/0)	–0.006	0.006
Cooperative/government (1/0)	–0.012***	0.005
Constant term	0.058***	0.002

Note: *, ** and *** indicates significance at 0.1, 0.05 and 0.01 level respectively

Source: Estimation based on data from NSSO (2015).

households. Second, we have binary dependent variables in both the selection and outcome equations (factor and product market choices are binary).

The problem at hand is estimating the impact of an input source selection on formal product market participation. For illustration we will look at the impact of buying inputs from local traders (selection) on formal product market choice (outcome). The treatment here is buying from an input source (local traders in the illustration) and the outcome is the probability of selling to a formal value chain.

Let L_i^* be the propensity of a household to buy from local traders in a linearized form

$$L_i^* = \delta Z_i + \mu_i \qquad \ldots(1)$$

where i is the HH, δ is the parameter vector, Z_i is a vector of observable household characteristics like household characteristics, socioeconomic characteristics, and access to information, training, and social safety nets; μ_i is the error term.

A household's observed input-buying status from a local trader L_i can be written as

$$L_i = 1\ (L_i^* > 0) = 1\ (\delta Z_i + \mu_i > 0) \qquad \ldots(2)$$

where 1(.) is an indicator function.

Further, a household's latent choice of a formal product market can be expressed as

$$F_{ij} = \beta_j X_i + \varepsilon_{ij}, j = 0, 1 \qquad \ldots(3)$$

where X_i are the household characteristics, socioeconomic characteristics, and access to information, training, and social safety nets. β_j is the regime specific parameter vector and ε_{ij} is the error term; j denotes the two regimes (buy/do not buy from local trader). Now, let PM_{ij} denote the households observed choice of a product market, such that:

$$PM_{ij} = 1\ [F_{ij} \geq 0] = 1\ [\beta_j X_i + \varepsilon_{ij} \geq 0], j = 0, 1 \qquad \ldots(4)$$

In ESPR we assume that the three error terms μ_i, ε_{10} and ε_{01} in equation (2), (3) and (4) are jointly normally distributed with zero mean and correlation matrix

$$\begin{bmatrix} 1 & \rho_{\mu 0} & \rho_{\mu 1} \\ & 1 & \rho_{01} \\ & & 1 \end{bmatrix}$$

Here, $\rho_{\mu 0}$ is the correlation between μ and ε_0; similarly, $\rho_{\mu 1}$ is the correlation between μ and ε_1 and ρ_{01} is the correlation between and . As and cannot be observed together, the joint distribution of $(\varepsilon_0 \varepsilon_1)$ is not identified. Thus, ρ_{01} cannot be estimated.

The log-likelihood function for the system of equations (2–4) was estimated using the maximum likelihood (ML) estimation to account for endogeneity in factor and product market choices. We used the 'switch_probit' Stata routine to estimate the ESPR model (Lokshin and Sajaia 2011). Switching models can also be fitted using other ML estimations or by estimating one branch at a time with Stata routines like 'biprobit' or 'heckprob'. However, using these estimation methods to yield consistent standard errors require cumbersome adjustments, and these methods are inefficient (Lokshin and Sajaia 2011).[2]

The log-likelihood functions can be used to generate counterfactual scenarios for households in different regimes of buying from local traders and formal market participation (Lokshin and Glinskaya 2009; Lokshin and Sajaia 2011). These can then be used to calculate the impact of selecting local traders on formal product market choice using the methodological framework provided by Aakvik, Heckman, and Vytlacil (2000; 2005). The impact of choosing a local trader on a household with observable characteristics if it buys from a local trader can be interpreted as the treatment effect on the treated (TT):

$$TT(x) = \Pr[PM_1 = 1|L = 1, X = x] - \Pr[PM_2 = 1|L = 1, X = x] \quad \text{…(5)}$$

TT is the difference between the predicted probability of formal market participation of a household that had bought inputs from a local trader and the probability of formal market participation had the household not decided to buy from local traders. The average treatment effect on the treated (ATT) is obtained by simply averaging (5) over the total number of households buying from local traders (treated).

The impact of buying inputs from a local trader on the probability of a household's formal product market participation randomly drawn from the population of households with characteristics can be called the treatment effect (TE):

$$TE(x) = \Pr[PM - 1| X = x] - \Pr[PM - 0 \mid X = x] = F[\beta_1 X] - F[\beta_0 X] \quad \text{…(6)}$$

The average treatment effect (ATE) is obtained by simply averaging (6) over the total number of households drawn from the population. The impact of treatment on a household with observable characteristics x if it does not buy from a local trader can be interpreted as the treatment effect on the untreated (TU):

$$TU(x) = \Pr[PM_1 = 1|L = 0, X = x] - \Pr[PM_2 = 1|L = 0, X = x] \quad \text{…(7)}$$

TU is the difference between the predicted probability of formal market participation of a household that had not bought inputs from a local trader and the probability of formal market participation had the household decided to buy from local traders. The ATE on the untreated (ATU) is obtained by averaging (7) over the total number of households not buying from local traders (untreated).

Next, we calculate the marginal treatment effect (MTE), which accounts for the unobserved heterogeneity in the sample (Lokshin and Glinskaya 2009); the MTE is used when the impact is believed to vary within the sample population in correlation with the unobservable characteristics (Brave and Walstrum 2014). The MTE identifies the effect of treatment (input source selection) on those induced to change treatment states (selling to formal/informal product markets) by the intervention (input source) (Aakvik, Heckman, and Vytlacil 2005). Therefore, the MTE is the effect of the input source on inducing changes in the product market decision of households because of the particular input source. The MTE can be written as:

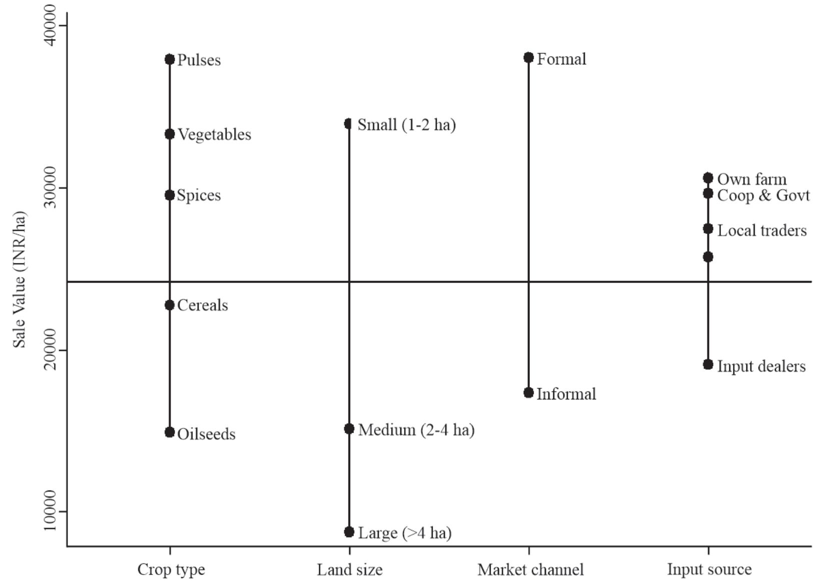
$$MTE(x,\mu) = \Pr[PM_1 \mid X = x, \mu = \bar{\mu}] - \Pr[PM_0 \mid X = x, \mu = \bar{\mu}] \quad \text{…(8)}$$

The ESPR model described in this paper is identified through nonlinearities in the functional form. It is robust in terms of identification and there is no need for exclusion restrictions (in these kinds of recursive multiple equation probit regressions with endogenous binary regressors) if there is sufficient variation in the exogenous variables (Lokshin and Sajaia 2011; Wilde 2000).

Data

The National Sample Survey Organisation (NSSO) conducts the Situation Assessment Survey of Agricultural Households and collects observational data, which is used in this study (NSSO 2015). The data was accessed from the ICSSR Data Service: Social Science Data Repository (http://www.icssrdataservice.in/datarepository/index.php/catalog/104). The survey used stratified multistage random sampling with census villages as first stage units and households as last stage units. The data on the value chain—input source and product disposition—of Visit 1 was used for our work. The NSSO collected this data (Visit 1) using face-to-face interviews, which were conducted from 1 January 2013 to 31 July 2013.

[2] For a discussion of the advantages of the ESPR over instrumental variable and bivariate probit regression see Lokshin and Glinskaya (2009).



Source: Estimation based on data from (NSSO 2015)

Note: Kruskal-Wallis equality-of-populations rank test statistics showed that the sale value of product (per ha) differed significantly among crop type, land size, market channel, and input source categories at 1% level

Figure 1 Commodity sale value across crop grown, landholding, market channel, and input source

Farm income and profits

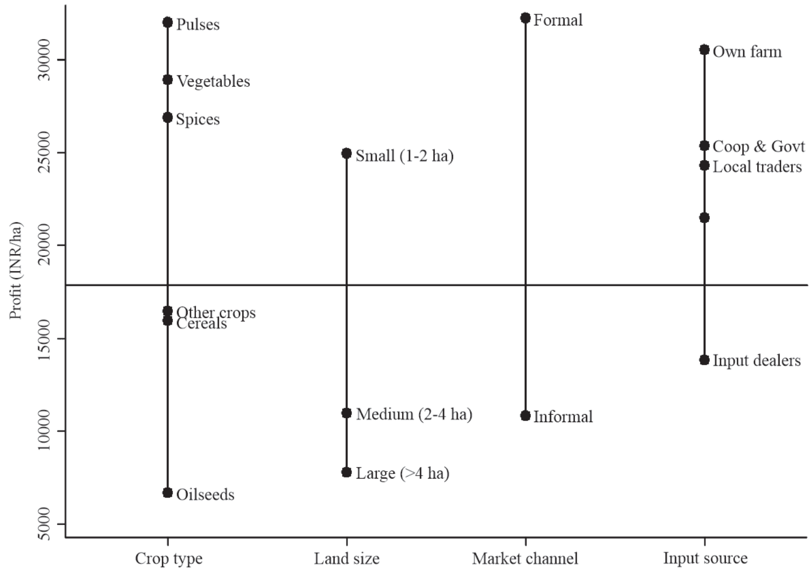
Figure 1 presents the farm income (sale value of product) by crop type, farm size, product destination, and input source. Farm income varied significantly within each group (tested using Kruskal-Wallis equality-of-populations rank test). Farm income was higher among households growing pulses, followed by those growing vegetables, spices, cereals, and other crops and oilseeds. The dispersion from the mean was higher for pulses (16178) than for high-value crops such as vegetables (2555) and spices (4115). 'Other' crops include sugar, fibre, fodder, dye, tobacco, and medicinal, aromatic, and plantation crops. Farm income per hectare was inversely related to farm size; the income was higher for small landholdings than medium and for medium landholdings than large. This finding is in line with other studies (Sen 1962; Bardhan 1973; Deolalikar 1981; Deininger et al. 2015; Sheng, Ding, and Huang 2019).

The income was higher for farmers selling to the formal market channel (regulated markets or mandis, processors, cooperatives and government agencies) than for households selling to informal value chains (local traders, input dealers, and others). Further, farm households that used inputs from their own farm or bought inputs from cooperatives and government sources earned a higher income than households that bought inputs from local traders and input dealers. The pattern of profits was similar to that of farm income across crop type, farm size, product destination, and input source (Figure 2).

Profits were highest among households that used inputs from own farm, followed by households buying from cooperatives, local traders, and input dealers. As the main aim of the study is to know how input market selection affects choice of formal markets, we further test whether the profits differ significantly across formal and informal value chains. The Kolmogorov–Smirnov test revealed that the distribution of formal and informal value chains were significantly different (Figure 3). This justifies the use of formal value chain choice as the dependent variable in the outcome equation of the ESPR.

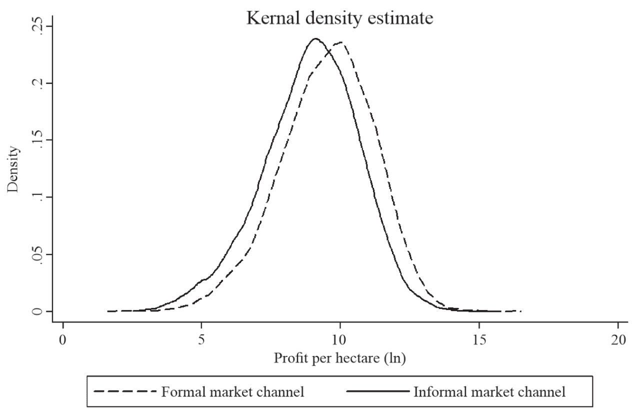
Balance test

The differences between some of the observable characteristics of households selling to informal and formal product markets are calculated to test whether these characteristics in both groups were similar or different (Table 3). The results clearly indicate that the



Source: Estimation based on data from NSSO (2015)
Note: Profit = sale value " input costs
Kruskal-Wallis equality-of-populations rank test statistics showed that the profit per hectare differed significantly among crop type, land size, market channel, and input source categories at 1% level

Figure 2 Farm profit across crop grown, landholding, value chain, and input source



Source: Estimation based on data from NSSO (2015)
Note: Kolmogorov–Smirnov test statistics showed that the distribution for formal and informal market channels differ at 1% level

Figure 3 Cumulative distributions of profits across formal and informal value chain

households selling to informal markets were systematically different from households selling to formal markets. For instance, the proportion of Scheduled Tribes (STs) and Other Backward Classes (OBC) was significantly larger in households selling to informal markets than in households selling to formal markets. Households selling to informal markets were younger, and they had smaller landholdings; they had lower value of product and net return, and less of outstanding loans. Therefore, the results indicated, farm households that had younger members and larger landholdings earned a higher income and profit and enjoyed greater liquidity, and they sold their produce at formal markets.

Results and discussion

The logit estimates of the determinants of the choice of value chain are presented in Table 4. The coefficient of quantity sold was positive and significant. As the quantity sold increases by 1% the chance of selling in formal markets increases by around 5%. Farmers who are able to produce larger quantities are more likely to choose formal marketing channels.

Choice of value chain

Households might find the price paid by informal markets low; they might clear the dues (cash or input credit) at informal markets and sell the rest of the produce at formal markets. Households might also find that the prices at formal markets offset their transaction cost (transporting the produce to the destination). Households growing oilseeds were 14% more likely

Table 3 Mean difference between key indicators of households using informal and formal value chain

Variables	Informal		Formal		Mean difference
	Frequency	Mean	Frequency	Mean	
Schedule Caste (1/0)	20167	0.13	9897	0.14	–0.01***
Scheduled Tribe (1/0)	20167	0.22	9897	0.19	0.04***
Other Backward Caste (1/0)	20167	0.38	9897	0.36	0.02***
General (1/0)	20167	0.27	9897	0.31	–0.04***
MGNREGA (1/0)	20155	0.46	9891	0.45	0.01
PDS (1/0)	20155	0.87	9891	0.88	–0.01***
Land owned (ha)	19842	1.00	9717	1.05	–0.05**
Land leased in (ha)	20167	0.09	9897	0.11	–0.01
Land leased out (ha)	20167	0.03	9897	0.04	–0.01**
Land possessed (ha)	20150	1.10	9886	1.14	–0.04*
Input expenses (INR/ha)	20068	8283	9802	7635.35	647.98
Total value (INR/ha)	19970	45000	9768	54000	–8800***
Net return (INR/ha)	19871	37000	9673	46000	–9300***
Loan outstanding (INR)	20167	72000	9897	90000	–17000***
Family size (number)	20167	5.47	9897	5.56	–0.08**
Age (years)	20167	28.77	9896	28.78	–0.01
Production from irrigated land (ha)	14024	0.59	7019	0.58	0.01
Production from unirrigated land (ha)	6667	0.32	3053	0.36	–0.04

Source: Estimation based on data from (NSSO 2015)
Note: *, ** and *** indicates significance at 0.1, 0.05 and 0.01 level, respectively

to sell at formal markets and those growing fruits were 15% more likely, and households of higher social groups (General) were 4% more likely to sell at formal markets.

Factors such as age group, family size, or education level did not influence farm households' choice of value chain. Households borrowing from professional moneylenders were more likely to sell at formal markets, possibly because they need the higher prices to repay their high-interest loans, or because moneylenders, who are a part of the mandis, have an information advantage and they pass it on to needy farm households.

Finally, households buying inputs from local traders, cooperatives, and government agencies are less likely to sell at formal markets. The opposite is true for households buying inputs from input dealers. They are 9.3% more likely to sell at formal markets relative to households using inputs of their own farm. The logit estimates (Table 4) point to the partial correlation between variables and not the causation.

Impact of input source selection on choice of value chain

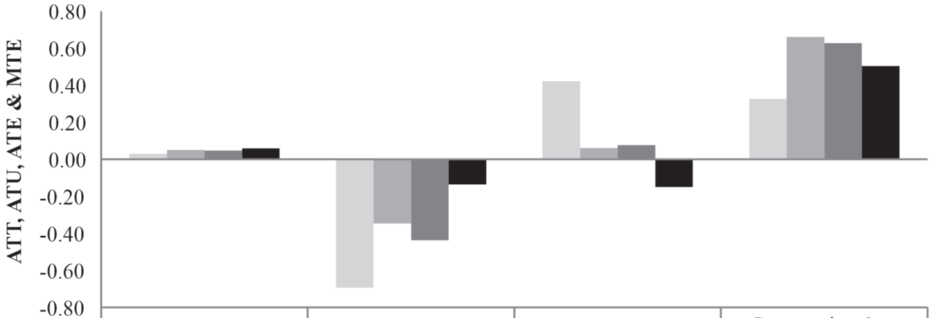
The impact estimates are computed from the ESPR model (Figure 4). Households using inputs from their own farm were 3%–6% more likely to sell through formal value chains relative to had they bought inputs from any other source. The impact estimates of households buying inputs from the local traders ranged from "14% MTE to "69% ATT; these households were 14%–69% less likely to sell through the formal value chains relative to a scenario that they had not bought from the local traders.

Households buying from input dealers had a higher ATT of 42%, implying that they were 42% more likely to sell through formal product markets relative to a scenario that they had not sold to the formal product markets. The MTE, which accounts for the endogeneity in the sample, was negative for households buying from the input dealers; input dealers were less likely to induce changes in the product market choices of households from informal to formal. Considering the

Table 4 Determinants of choice of value chain

	Formal (1/0)	Robust Std. Err.	Marginal effects dy/dx	Std. Err.
Quantity sold (ln)	0.201***	0.019	0.045***	0.004
Type of crops grown				
Cereals (1/0)	-0.040	0.071	-0.009	0.016
Pulses (1/0)	0.114	0.273	0.026	0.063
Vegetables (1/0)	0.012	0.117	0.003	0.026
Oilseeds (1/0)	0.607**	0.285	0.144**	0.071
Fruits (1/0)	0.634***	0.181	0.151***	0.045
Spices (1/0)	-0.160	0.216	-0.034	0.045
MSP awareness (1/0)	-0.004	0.100	-0.001	0.022
Land size (base: Marginal)				
Small (1–2 ha)(1/0)	0.033	0.073	0.007	0.016
Medium (2–4 ha) (1/0)	-0.132*	0.079	-0.029	0.017
Large (>4 ha)(1/0)	0.094	0.116	0.021	0.026
Technical advice (1/0)	0.117	0.107	0.026	0.024
Source of inputs (Base: Own)				
Local trader (1/0)	-0.157**	0.078	-0.034**	0.017
Input dealer (1/0)	0.398***	0.141	0.093***	0.034
Cooperative & Government agency (1/0)	-0.262**	0.105	-0.056***	0.021
Social group/Caste (Base: Scheduled Tribe)				
Scheduled Caste (1/0)	-0.003	0.106	-0.001	0.024
Other Backward Class (1/0)	0.032	0.085	0.007	0.019
General (1/0)	0.183**	0.088	0.041**	0.020
Education level (Base: Illiterate)				
Literate without formal schooling (1/0)	-0.316	0.336	-0.066	0.065
Literate but below primary (1/0)	0.096	0.093	0.022	0.021
Primary (1/0)	0.097	0.123	0.022	0.028
Middle (1/0)	0.085	0.097	0.019	0.022
Secondary (1/0)	0.098	0.152	0.022	0.034
Graduate and above (1/0)	0.024	0.151	0.005	0.034
Source of credit				
Cooperative and government (1/0)	0.035	0.096	0.008	0.021
Bank (1/0)	0.162	0.121	0.036	0.028
Agricultural/ Professional moneylender (1/0)	0.326***	0.100	0.075***	0.024
Shopkeeper/Trader (1/0)	0.107	0.132	0.024	0.030
Friends and relatives (1/0)	-0.020	0.126	-0.004	0.028
Age (years)	0.001	0.002	0.000	0.000
Family size (numbers)	-0.001	0.015	0.000	0.003
Constant	-2.213***	0.194		

Note: *, ** and *** indicates significance at 0.1, 0.05 and 0.01 level respectively



	Own farm	Local trader	Input dealer	Cooperative & Government
ATT	0.03	-0.69	0.42	0.33
ATU	0.05	-0.35	0.06	0.66
ATE	0.05	-0.44	0.08	0.63
MTE	0.06	-0.14	-0.15	0.50

Note: All the estimates were significant at 1% level

Figure 4 ESPR estimates of impact on formal value chain selection

interaction of unobserved characteristics that might drive formal market participation (MTE), the selection of input dealers makes the households 15% less likely to sell through the formal marketing channels.

Households buying inputs from cooperatives and government agencies had positive coefficient values across all impact estimates. Households that buy from cooperatives and government agencies were 33% more probable to choose formal product markets than if they had not bought from cooperatives and government agencies. If those households that do not buy from cooperatives and government agencies had bought inputs from them (ATU), they would have 66% more chance of selling their produce profitably in the formal product markets.

Overall, the ATE of buying from cooperatives and government agencies was 63%, implying again a higher chance of selling the produce profitably. Accounting for the effect of unobservable characteristics, the effect of buying from cooperatives and government agencies was 0.50 (MTE). Therefore, we can conclude that households are more likely to be profitable if they buy inputs from cooperatives and government agencies than other sources.

Dominance of local traders: an opportunity

We further evaluate the effect of choice of input source on formal product market choice by plotting the ATE across different types of crops grown and land holding. The farm households buying inputs from local traders and dealers are more likely to sell at informal product markets (local private traders and input dealers). Oilseeds and pulses growers who buy inputs from local traders are around 50% more (less) likely to sell their produce to informal (formal) product markets (Figure 5). The treatment effect is near homogenous across the landholding sizes (Figure 6). The households that buy inputs from informal sources are more likely to sell at informal markets. Just by the virtue of its scale—around 44% of farm households buy from local private players, 63% sell to them, and around 25% borrow from them (Appendix Figures 1, 2 and 3)—this nexus between

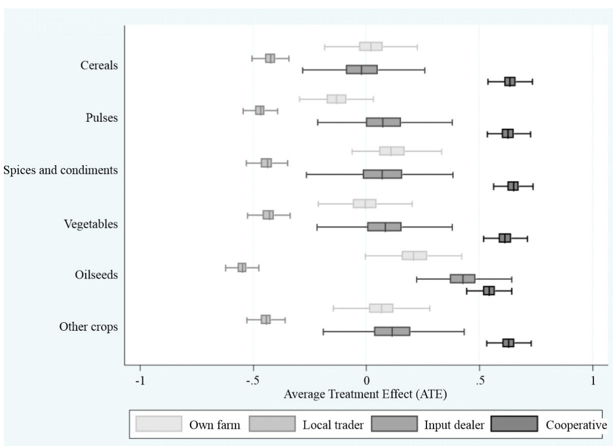


Figure 5 Average treatment effect (ATE) across type of crops grown

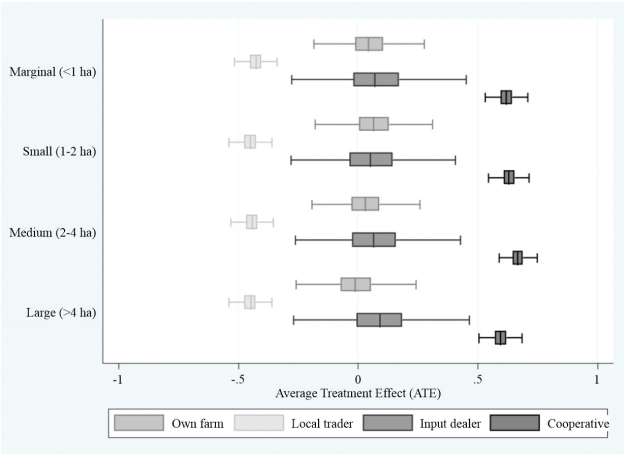


Figure 6 Average treatment effects (ATE) by landholding

informal traders is a huge concern for the agrarian economy.

But this nexus also presents an opportunity: these networks can be used to pass on to farmers new information on inputs, prices, products, technology, and better farm practices and, therefore, benefit farm households. The dominance of informal traders be converted into a new, efficient agricultural marketing system that profits farmers, and this study strongly recommends it. The reliability of these local players can be increased by the interventions of modern value chains like business-to-consumer (B2C) (direct marketing from producer to consumer) and contract farming.

Under contract farming, farmers and private players (large retailers, aggregators, agribusiness firms, etc.) contract to grow crops at a price they mutually agree to; contract farming has improved efficiency, productivity, and farmer income and lowered transaction costs (Kalamkar 2012; Barrett et al. 2012; Birthal, Jha, and Singh 2007; Kumar et al. 2019; Swain 2016; Chengappa 2018). Some challenges—like input pricing, delay in input delivery, and upfront investment— remain, but these are manageable. The Farmers (Empowerment and Protection) Agreement on Price Assurance and Farm Services Act, 2020 (Contract Farming Act) promotes legal contract farming. The Farmers' Produce Trade and Commerce (Promotion and Facilitation) Act, 2020, promotes farmers' freedom of choice in selecting market channels. Together, these Acts could catalyse the process of breaking the dominance of local traders and making them reliable.

A few concerns remain, however, in areas where these interlinkages provide farmers other services, like farm and non-farm credit. Financial institutions should also be a part of this change and supplement the reforms. To accelerate agricultural growth and development, therefore, the need of the hour is a coordinated effort by agribusiness firms, farmer producer companies, corporate investors, entrepreneurs, and financial institutions.

Conclusions

The agricultural market system is undergoing a structural change, and it is important to identify the extent of interconnection between the backward and forward linkages of the value chains and harness the interlinks to the welfare of agricultural households and rural development. Keeping this in mind we aimed at measuring the interlink between agricultural input and output markets.

The study found that households selling their product through formal markets (regulated markets, cooperatives, government agencies, and processors) were realizing significantly higher profits than those selling through informal markets. An attempt was made to estimate the impact of choosing an input source on selling through these profitable formal product markets. It was observed that households buying their inputs from cooperative or government agencies were highly likely to use formal product markets and, conversely, households meeting their farm input needs from local traders were extremely unlikely to sell through formal product markets. A sizeable sample of the households were dependent on these dominant local traders, and the weakness of this informal market is definitely a major concern for the development of agricultural households but, this study strongly holds, this concern can be turned into an opportunity.

The existing links in these massive networks–covering the input, credit, and market requirements of households—can be used to disseminate vital information regarding market intelligence, innovations, best farming practices, crops, inputs, new technologies, weather, and Government schemes. Cooperative and government agencies working in the input markets should be strengthened and encouraged, as these significantly impact the formal market participation of households.

The reliability of these local players can be increased by the interventions of modern value chains like business-to-consumer (B2C) (direct marketing from producer to consumer) and contract farming. The recent Acts and the amendments to the Agricultural Produce Market Committee and Essential Commodities Act by the union government, is a welcome policy response in this direction.

References

Aakvik, A, J J Heckman, and E J Vytlacil. 2000. Treatment effect for discrete outcomes when responses to treatment vary among observationally identical persons: an application to Norwegian vocational rehabilitation programs, Vol 7, Technical working paper series No 262. nber.org/papers/t0262.pdf.

Aakvik, A, J J Heckman, and E J Vytlacil. 2005. Estimating treatment effects for discrete outcomes when responses to treatment vary: an application to Norwegian vocational rehabilitation programs. *Journal of Econometrics* 125: 15–51. doi.org/10.1016/j.jeconom.2004.04.002.

Amsler, C, A Prokhorov, and P Schmidt. 2016. Endogeneity in stochastic frontier models. *Journal of Econometrics* 190 (2): 280–88. doi.org/10.1016/j.jeconom.2015.06.013

Bardhan, P K. 1973. Size, productivity, and returns to scale: an analysis of farm-level data in Indian agriculture. *Journal of Political Economy* 81 (6): 1370–86. jstor.org/stable/1830745

Barrett, C B, M E Bachke, M F Bellemare, H C Michelson, S Narayanan, and T F Walker. 2012. Smallholder participation in contract farming: comparative evidence from five countries. *World Development* 40 (4): 715–30. doi.org/10.1016/j.worlddev.2011.09.006

Birthal, P S, A K Jha, and H Singh. 2007. Linking farmers to markets for high-value agricultural commodities. *Agricultural Economics Research Review* 20: 425–39. dairyknowledge.in/sites/default/files/linking_farmers_to_markets_for_high_value_agricultural_commodities.pdf

Brave, S, and T Walstrum. 2014. Estimating marginal treatment effects using parametric and semiparametric methods. *The Stata Journal: Promoting Communications on Statistics and Stata* 14 (1): 191–217. doi.org/10.1177/1536867x1401400113

Chatterjee, S, and D Kapur. 2016. Understanding price variation in agricultural commodities in India: MSP, government procurement, and agriculture markets. In India policy forum, July 12-13, National Council of Applied Economic Research, New Delhi. ncaer.org/events/ipf-2016/IPF-2016-Paper-Chatterjee-Kapur.pdf

Chengappa, P G. 2018. Development of agriculture value chains as a strategy for enhancing farmers ’ income. *Agricultural Economics Research Review* 31 (1): 1–12. doi.org/10.5958/0974-0279.2018.00001.0

Chengappa, P G, C M Devika, and A V Manjunatha. 2019. Coffee value chains in India: exploring sustainability oriented markets. *Agricultural Economics Research Review* 32 (1): 91–104. doi.org/10.5958/0974-0279.2019.00008.9

Deininger, K, S Jin, Y Liu, and S Singh. 2015. Labor market performance and the farm size-productivity relationship in rural India. In 2015 conference, August 9-14, 2015, Milan, Italy. ideas.repec.org/p/ags/iaae15/212720.html%0Ahttp://files/529/212720.html

Deolalikar, A B. 1981. The inverse relationship between productivity and farm size: a test using regional data from India. *American Journal of Agricultural Economics* 63 (2): 275-79. doi.org/10.2307/1239565

Devi, P I, M Hema, and U Jaikumaran. 2010. Value chain in poverty alleviation - a model for institutional initiatives for organizing and capacity building of farm work force. *Agricultural Economics Research Review* 23: 523–26. search.ebscohost.com/login.aspx?direct=true&db=bth&AN=58657019&site=ehost-live

Jan, M A, and B Harriss-white. 2012. The three roles of agricultural markets: a review of ideas about agricultural commodity markets in India. *Economic and Political Weekly* 47 (52): 39–52. jstor.org/stable/41720550

Kalamkar, S S. 2012. Inputs and services delivery system under contract farming: a case of broiler farming. *Agricultural Economics Research Review* 25: 2012–2515. ageconsearch.umn.edu/bitstream/136383/2/17-SS-Kalamkar.pdf

Kumar, A, D Roy, P K Joshi, G Tripathi, and R P Adhikari. 2019. Impact of contract farming of paddy seed on smallholder farm profits: evidence from Nepal. *Agricultural Economics Research Review* 32 (1): 25. doi.org/10.5958/0974-0279.2019.00003.x

Kumar, A, H Singh, S Kumar, and S Mittal. 2011. Value chains of agricultural commodities and their role in food security and poverty alleviation – a synthesis. *Agricultural Economics Research Review* 24 (June): 169–81. https://ageconsearch.umn.edu/record/109516/files/18-Anjani-Kumar.pdf

Kumar, R, K Alam, V V Krishna, and K Srinivas. 2012. Value chain analysis of maize seed delivery system in public and private sectors in Bihar. *Agricultural Economics Research Review* 25: 387–98. DOI: 10.22004/ag.econ.136392

Liverpool-Tasie, L S O, A Wineman, S Young, J Tambo, C Vargas, T Reardon, G S Adjognon, et al. 2020. A scoping review of market links between value chain actors and small-scale producers in developing regions. *Nature Sustainability* 3 (10): 799–808. doi.org/10.1038/s41893-020-00621-2

Lokshin, M, and E Glinskaya. 2009. The effect of male migration on employment patterns of women in Nepal. *World Bank Economic Review* 23 (3): 481–507. doi.org/10.1093/wber/lhp011

Lokshin, M, and Z Sajaia. 2011. Impact of interventions on discrete outcomes: maximum likelihood estimation of the binary choice models with binary endogenous regressors. *Stata Journal* 11 (3): 368–85. doi.org/10.1177/1536867x1101100303

Negi, D S, P S Birthal, D Roy, and M T Khan. 2018. Farmers' choice of market channels and producer prices in india: role of transportation and communication networks. *Food Policy* 81 (October): 106–21. doi.org/10.1016/j.foodpol.2018.10.008

NSSO. 2015. Situation assessment survey of agricultural households: NSS 70th round, schedule 33, January - December 2013 (visit 1). ICSSR data service: social science data repository, 2015. icssrdataservice.in/datarepository/index.php/catalog/104/data_dictionary

Pandey, T, N Krishna, V Vickers, A Menezes, and M Raghavendra. 2010. Innovative payment solutions in agricultural value chain as a means for greater financial inclusion. *Agricultural Economics Research Review* 23: 527–34. https://www.farm-d.org/app/uploads/2019/05/17-Tushar-Pandey.pdf

Petrin, A, B P Poi, and J Levinsohn. 2004. Production function estimation in stata using inputs to control for unobservables. *The Stata Journal: Promoting Communications on Statistics and Stata* 4 (2): 113–23. doi.org/10.1177/1536867x0400400202

Santín, D, and G Sicilia. 2017. Dealing with endogeneity in data envelopment analysis applications. *Expert Systems with Applications* 68: 173–84. doi.org/10.1016/j.eswa.2016.10.002

Sen, A. 1962. An aspect of Indian agriculture. *Economic Weekly* 14 (4–6): 243–46. epw.in/journal/1962/4-5-6/agricultural-front-commentary/aspect-indian-agriculture.html

Sheldon, I M. 2017. The competitiveness of agricultural product and input markets: a review and synthesis of recent research. *Journal of Agricultural and Applied Economics* 49 (1): 1–44. doi.org/10.1017/aae.2016.29

Sheng, Y, J Ding, and J Huang. 2019. The relationship between farm size and productivity in agriculture: evidence from maize production in northern China. *American Journal of Agricultural Economics* 101 (3): 790–806. doi.org/10.1093/ajae/aay104.

Singh, S, and S Bhogal. 2015. Commission agent system. *Economic and Political Weekly* 50 (45): 56–62. epw.in/journal/2015/45/special-articles/commission-agent-system.html

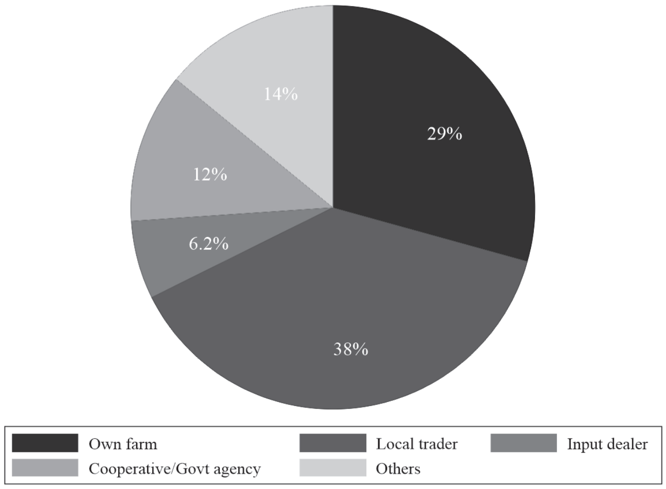
Sundaramoorthy, C, V C Mathur, and G K Jha. 2014. Price transmission along the cotton value chain. *Agricultural Economics Research Review* 27 (2): 177–86. doi.org/10.5958/0974-0279.2014.00022.6

Swain, B B. 2016. Does technological linkage in contract farming increase farm productivity and efficiency? the case of hybrid paddy seed cultivation in undivided Andhra Pradesh. *Agricultural Economics Research Review* 29 (2): 211. doi.org/10.5958/0974-0279.2016.00049.5

Tsionas, E G, S C Kumbhakar, and E Malikov. 2015. Estimation of input distance functions: a system approach. *American Journal of Agricultural Economics* 97 (5): 1478–93. doi.org/10.1093/ajae/aav012

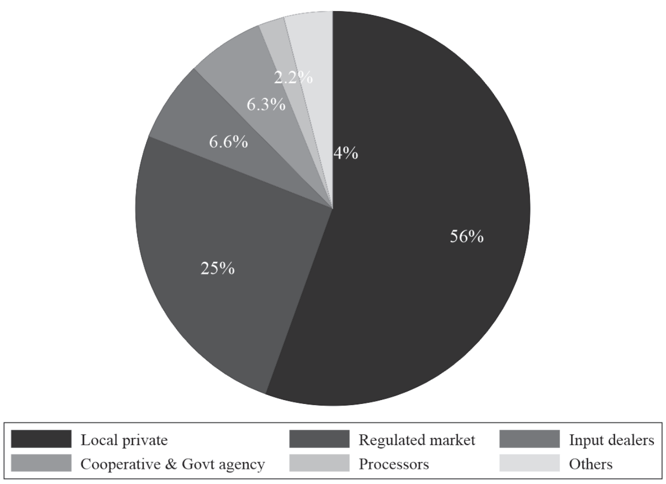
Wilde, J. 2000. Identification of multiple equation probit models with endogenous dummy regressors. *Economics Letters* 69 (3): 309–12. doi.org/10.1016/S0165-1765(00)00320-7.

Appendix



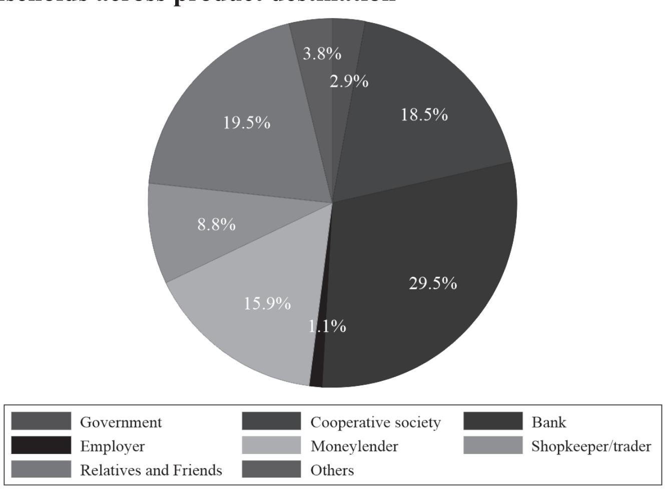
Source: Estimation based on data from NSSO (2015)

Figure 1 Distribution of households across input agencies



Source: Estimation based on data from (NSSO 2015)

Figure 2 Distribution of households across product destination



Source: Estimation based on data from NSSO (2015)

Figure 3 Distribution of households across source of borrowing

Table 1 Distribution matrix of farm households' input and output market choice (%)

Market channel/input source	Own farm	Local trader	Input dealer	Coop & Govt	Others	Total
Distribution of households' input sources within different market channels						
Local private	28.70	40.86	5.45	12.40	12.56	100
Regulated market	28.52	37.22	7.73	10.35	16.33	100
Input dealers	31.74	39.10	6.60	12.83	9.72	100
Cooperative & Govt agency	33.92	30.69	7.90	9.16	18.33	100
Processors	32.57	20.23	9.82	8.52	28.87	100
Others	30.89	31.52	2.53	21.93	13.12	100
Total	29.33	38.43	6.26	11.98	14.11	100
Distribution of households' market channel choice within different input sources						
Local private	53.65	58.29	47.70	56.77	48.80	54.83
Regulated market	25.33	25.23	32.16	22.51	30.14	26.05
Input dealers	7.31	6.87	7.12	7.24	4.65	6.76
Cooperative & Govt agency	7.12	4.92	7.77	4.71	8.00	6.16
Processors	2.60	1.23	3.67	1.67	4.80	2.34
Others	4.09	3.18	1.57	7.10	3.61	3.88
Total	100	100	100	100	100	100

Note: Percentages were calculated based on the weighted frequency distribution across combination of input and output sources
Source: Estimation based on data from (NSSO 2015)