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Tests for Separability and Factor Market Participation in Afghanistan

by

Hayatullah Ahmadzai

Abstract
Using nationally representative data from repeated cross section surveys conducted in 2011/12, 2013/14, and 2016/17, we test for separability in the household model and analyse household factor market participation in Afghanistan. Estimates of a household labour demand model and tests for separability reject the null hypothesis that household labour supply and demand decisions are separate. The fact that the magnitude and quantity of labour demanded by the farm household is strongly influenced by the household endowment of labour can be interpreted to mean that there exist potential market failures in multiple markets in Afghanistan. Exploring input market participation, results reveal that ownership of information and communication technologies and transport assets by households has a strong positive influence on the use of inputs. In addition, households living in communities with better access and within a closer radius of markets are more likely to participate in factor markets and spend more on purchased inputs. Standard factors such as household socio-demographic and socio-economic factors were also observed to have an important influence on factor market participation: household size, literacy and education; land endowments and quality; off-farm income; and ownership of farming assets such as tractors, oxen and livestock, are significant determinants of participation and expenditure on inputs. The analysis allows observed transaction costs to be endogenous using instrumental variables and employing a control function approach. The endogeneity of ownership of ICT and transport equipment in fertilizer and chemical, and tractor rental markets is confirmed (we reject endogeneity in the case of hired labour). Correcting for endogeneity bias revealed a negative association between the error terms in the reduced form and structural model, but the main results were maintained.

JEL Classification: O12, Q12, Q13, Q18

Keywords: Transaction Costs, Factor Markets, Separability, Afghanistan

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Outline

The Author
Hayatullah Ahmadzai is a PhD candidate in the School of Economics at the University of Nottingham.
Email: hayatullah.ahmadzai@nottingham.ac.uk & ahmadzaihayat@outlook.com

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I. Introduction

Improving farm productivity, crop yields, and market-oriented production to improve rural incomes entails improved access to input and output markets. However, small-scale subsistence and semi-subsistence farmers often face a number of barriers and constraints that make it difficult for them to become part of the commercial agriculture economy. One of the limiting constraints faced by farmers, especially subsistence farmers, is lack of market access due to higher transaction costs (Ouma et al., 2010). Higher costs associated with market transactions often result in lower input utilization by farm households, and can be associated with market failures (de Janvry et al., 1991). To better understand input markets in Afghanistan, we test whether household production and consumption decisions are consistent with the hypothesis of separability and use the results to investigate the presence of potential market failures or missing markets. Moreover, we extend our analysis to empirically assesses the critical implications of transaction costs on farmers' input utilization decisions in an attempt to address potential market failures.

In the context of Afghanistan, barriers such as poor infrastructure development, poor access to all-season roads, long distance from farming communities to the district and provincial markets, limited or no access to farm assets such as transport equipment, and poor access to market information make it difficult or even impossible for small-scale farmers to purchase and transport inputs from the respective markets. As a result, farmers are often forced to use less or no inputs which lead to the under-utilization of production inputs that in turn significantly decrease crop yields and production efficiency. Therefore, it is essential to assess farmer's behaviour and decisions regarding the extent of input use, especially in the context of high transaction costs and potential missing markets or market failures.

Market failures or missing markets effect household behaviour and decisions that subsequently affect welfare outcomes. Analysing household behaviour under imperfect market conditions helps observe and understand different strategies that households devise to mitigate the welfare costs that market failures impose (Vakis et al., 2004). Household decisions under perfect markets implies separability between production and consumption decisions. This means that households can solve recursively first the production problem and then, based on the profit (income) from the production stage, make consumption choices. Under imperfect markets, production and consumption decisions are non-separable; this implies that household production decisions are affected or jointly determined by consumption preferences, and it becomes analytically difficult to resolve the joint decisions (Benjamin, 1992; Bowlus and Sicular, 2003; Dillon and Barrett, 2017; LaFave and Thomas, 2016). In order to better understand household labour demand, production and consumption decisions, and their investment choices, as well as formulate and evaluate relevant policies, it is essential to model the opportunities and constraints they face (LaFave and Thomas, 2016). Thus, in this study we attempt to provide evidence base on household's behaviour in relation to the market conditions and identify factors underlying separability of the household's production and consumption decisions.

Market participation for both inputs and outputs is a prerequisite and a key step towards commercialization of rural farms. In order to break out of the subsistence poverty trap and improve rural farm incomes, agriculture development policies must aim to identify and address barriers to market participation and potential missing markets (Barrett, 2008). Market imperfections and high transaction costs are generally thought of as limiting factors that hinder the exchange of goods in the local markets. Rural markets are often imperfect and transaction costs can be so high that farmers are unable to participate in markets (de Janvry et al., 1991). The existence of high transaction costs including costs related to search and information, transportation, bargaining, monitoring, and contract enforcement implies that some households will opt for self-sufficiency instead of market participation (Key et al., 2000).

In many developing economies, lower crop yields due to underutilization of inputs and imperfect markets for both inputs and outputs are generally responsible for slow productivity growth and income generation. As in many low-income countries, input use in Afghanistan lags behind the world average. For example, the average consumption of commercial fertilizer is negligible and far below the world average and average of south Asia (Figure 1). Consequently, the question arises as to what factors limit the application of fertilizer and other inputs and are input markets failing? And Can improving household access to markets and reducing transaction costs improve market participation? Analysing the main drivers and constraints of input usage helps to design effective policies and interventions to expand agriculture input use and output marketing opportunities.

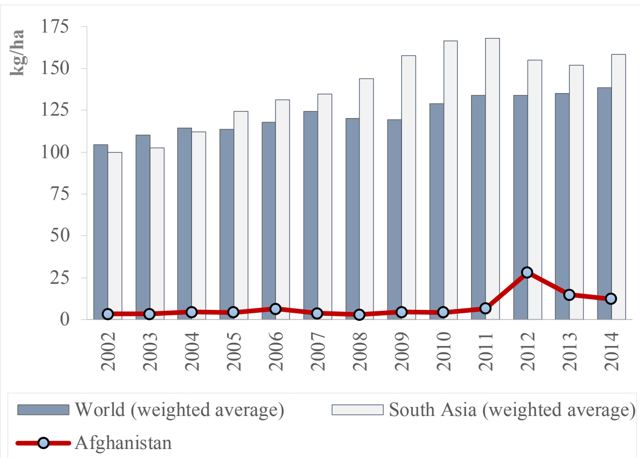


Figure 1: Fertilizer consumption (Kg/ha of arable land) in Afghanistan, South Asian region, and World (weighted average)

Source: World Bank Microdata, Development Indicators

Poor infrastructure development and weaker institutions together cause the costs of transaction to substantially rise, that in turn greatly alter farm household's production and marketing related decisions. In most remote areas, smallholder farm households struggle to overcome the cost of entering the market due to the absence of sufficient means available to them (Barrett, 2008). Furthermore, in many occasions, these resource-poor farm households do not possess the level of asset endowments required to guard them against adverse agro-ecological conditions and other production, market related, and political risks and shocks (Donovan and Poole, 2014). Besides, lack of access to reliable price information as well as information on potential exchange partners and players is yet another constraints making it hard for them to enter markets (Ouma et al., 2010). Analysing farm household's behaviour in the context of imperfect market conditions requires an empirical understanding of both production decision-making at the farm level and market conditions, especially in low-income countries where production is carried out by smallholder farm households that make production and consumption decisions together.

Promoting market-orientation among farm households necessitates improving the ability of farm households to participate in markets, particularly smallholder resource-poor farmers. The essence of participation in output and input markets is based on the premise that crop yields, incomes and, hence, the livelihoods of smallholder farmers are likely to improve if they gain greater access to markets for inputs and outputs produced. Transformation of subsistence agriculture to a market-led practice must be based upon the establishment of efficient and well-functioning markets and marketing systems that reduce transaction costs, mitigate risks, reduce search costs and extend information access to all players, particularly those living in rural areas of marginal productivity with poor public infrastructure (Jagwe, 2011).

Agriculture policy in Afghanistan encourages market-led development to ensure resource-poor peasant farmers are effectively a part of the broader agricultural economy so as to improve their incomes and livelihoods. Despite the recent economic growth in the country, a number of concerns and questions are raised about poorly functioning factor markets. A major concern is that potentially incomplete markets and high transaction costs may hamper the overall commercialization process. Thus, empirical evidence to generate information about these factors affecting smallholder farmers' marketing decisions is required to better understand the decision making environment.

The remainder of this study is organized in five sections: Section II covers the relevant literature overview on the concept of separability and transaction costs. Section III provides information on the theoretical framework for modelling farmers' marketing decisions . Section IV presents Identification strategy and econometric specification for the analysis and the data and variables used in the analysis. We conclude with Section V by presenting our empirical results and findings.

II. Overview of Related Literature

The majority of the rural poor in Afghanistan directly or indirectly depend on small-scale farming for their livelihoods and improving access to local markets remains a challenge for policy makers. Often living in remote areas with poor infrastructure, they face high transaction costs that significantly reduce their incentives for market participation (Barrett, 2008; Fischer and Qaim, 2012). Many barriers such as lack of sound institutional and physical infrastructure necessary to ensure low-cost access to competitive and well-functioning markets on the one hand, and diseconomies of scale on the other, impede smallholder market participation significantly (Lapar et al., 2003). Despite the disadvantages they face, there is evidence that smallholders successfully participate in local markets. Barrett (2008) suggests that interventions aimed at facilitating smallholder organization, at reducing the costs of intermarket commerce, and at improving poorer households access to improved technologies and productive assets are central to stimulating smallholder market participation. Poulton et al., (2010) argue that small family farms may have an advantage because of their greater local knowledge. Narrod et al., (2009) provide a number of examples of small-scale family farms that successfully participate in local markets through collective action and institutional support.

The most significant barriers to smallholder market participation are argued to be transaction costs including search, information, transportation, bargaining, monitoring, and contract enforcement costs (de Janvry et al., 1991; Goetz, 1992; Holloway et al., 2000). A number of empirical studies assess the influence of transaction costs on household decisions to participate in the output market (e.g., Key et al., (2000), Makhura, (2001), Ouma et al., (2010), and Jagwe, (2011), Mather et al., (2013)). A common finding is that transaction costs proxied by distance from the market, access to or ownership of farm assets such as transport equipment, and farm households' access to information and communication technologies have a significant impact on the decision to market their produce.

A few studies explicitly focus on the role of transaction costs in input market participation, e.g. Winter-Nelson and Temu (2005), Alene et al., (2008), Liverpool-Tasie, (2014), and Ricker-Gilbert et al., (2011). Winter-Nelson and Temu (2005) and Alene et al., (2008) argued that market participation is a two-stage decision-making process, where in the first stage households decide to participate in the input market, and in the second stage they decide on the intensity of the inputs used. Fixed transaction costs affect the decision to participate but not the intensity of participation, and non-participation is unobserved due to incidental truncation (the studies use a sample selection model which assumes non-participation is the outcome of prohibitive fixed transactions costs). Variable transaction costs significantly determine both the household decisions to participate in market and the degree of input use.

In assessing household decisions to participate in fertilizer markets, Ricker-Gilbert et al., (2011) and Liverpool-Tasie, (2014) adopted the same conceptual framework underlining that input utilization is the outcome of a two-stage decision (i.e. participation in market and extent of use) where fixed transaction costs affect only the first stage, not the second stage. However, they argued that zero values of the input use (i.e. non-participation) is an optimal choice and therefore used a double hurdle model that is designed to allow the possibility that different factors might affect each stage. Both found that distance to markets and roads, access to farm assets, communication and transport equipment, and other proxies for transaction costs significantly affect market participation decisions and quantity of the inputs used.

Even though past studies have focused on the impact of transaction costs on households factor marketing decisions (Alene et al., 2008; Jagwe, 2011; Mottaleb et al., 2014; Ouma et al., 2010), they have not addressed the possible endogeneity problem in observable transaction costs. In most of these studies transaction costs were proxied for by distance to markets, ownership of transport assets (e.g. bike, motorbike, vehicles) and access to information and communication technologies (i.e. mobile phones, radios and TV, and internet services). However, household unobserved factors could possibility be simultaneously associated with the access to transport and ICT equipment and their marketing decisions. Thus, one major contribution of the current study is to allow for endogeneity in transaction costs and estimate their unbiased casual effects on household marketing decisions.

Imperfect market conditions and potential market failures or missing markets are other severe conditions that prohibits smallholders from market participation, that could be as a result of high transaction costs or non-competitive market prices, or legal barriers (de Janvry et al., 1991; Dillon and Barrett, 2017). Imperfect markets, market failures or missing markets affect household behaviour (i.e. different condition leads to different outcomes such as separablity and non-separability of production and consumption decisions) and consequently affect their welfare outcomes (Le, 2010; Vakis et al., 2004). When markets are incomplete or not competitive, consumption and production decisions are non-separable: production depends on the price of consumer goods and household preferences. On the contrary, under complete market conditions households are price takers, production decisions are made to maximize profits without reference to the consumption preferences, while consumption choices take into account the income from production (Benjamin, 1992; Dillon and Barrett, 2017; LaFave and Thomas, 2016) .

Correct modelling of household production and consumption decisions requires a thorough understanding of behaviours (whether separable or non-separable). The relevant literature offers a number of different tests that aim to assess the separation hypothesis (Le, 2010; Vakis et al., 2004). Jacoby, (1993), Abdulai and Regmi, (2000), and Grimard, (2000) used a structural form approach that involves two steps; in the first step production function is estimated and shadow wage or marginal product for labour is derived and compared with the market price. A number of studies including the seminal work of Benjamin, (1992), Bowlus and Sicular, (2003), LaFave and Thomas, (2016), and more recently Dillon and Barrett, (2017) used a reduced form approach which aims to test whether variables that affect consumption decisions also affect the labour allocation and production decisions. We summarize these studies and their findings in Table (1).

The reduced form approach involves whether the size of the household significantly affects the farm household labour demand. Some of these studies have raised concerns about potential econometric issues due household level unobserved heterogeneity in the size of the household when estimating the household labour demand function to test the hypothesis of separation (i.e. changes in household demographic composition should not be related to the demand). These unobserved changes in the household composition mainly arise from births of new members of the households but could also be as a result of death and aging of household members as well as migration into and out of the household (LaFave and Thomas, 2016). Some of these studies employed econometric techniques such as fixed effect models and instrumental variable approach to correct for this bias. Using a longitudinal data, LaFave and Thomas, (2016) and Bowlus and Sicular, (2003) used fixed effect techniques along with instrumental variables, whereas Grimard, (2000) used instrumental variable techniques to control for possible endogeneity. Using a cross-sectional sample, in a recent study Dillon and Barrett, (2017) defined the household size as the prime aged members of the household (members aged above 15 years) and excluded children from the analysis in an attempt to reduce the bias associated with potential endogeneity in the household composition.

Table 1: Studies that tested the hypothesis of separation

Study	Country of study	Type of test	Findings
Benjamin, (1992)	Java, Indonesia	Reduced form approach	Fail to reject separation
Jacoby, (1993)	Peruvian Sierra	Structural form approach	Reject separation
Grimard, (2000)	Côte d'Ivoire	Structural form approach	Reject separation
Abdulai and Regmi, (2000)	Nepal	Structural form approach	Reject separation
Bowlus and Sicular, (2003)	Zouping County, China	Reduced form approach	Fail to reject separation
LaFave and Thomas, (2016)	Central Java, Indonesia	Reduced form approach	Reject separation
Dillon and Barrett, (2017)	Sub-Saharan Africa	Reduced form approach	Reject separation

Unfortunately our data lack the presence of good contemporaneous instruments, so we follow the recent study by Dillon and Barrett, (2017) and exclude children from our analysis as that should largely mitigate the bias due to unobservables, particularly the unobserved changes in the household composition associated with new births or children.

Other studies have raised a suspicion regarding potential endogeneity in the cultivated land area variable as well, as decisions regarding land and labour use may both be determined by other common factors omitted from the regression (Bowlus and Sicular, 2003). One way to tackle this problem is to include control variables related to land quality and household human capital, as well as for regional variation. Following Bowlus and Sicular, (2003), we include covariates that control for land quality, landscape characteristics, age , literacy and education of the household head along with district fixed effects to try to avoid potential endogeneity.

III. Concept and Theoretical Framework

To ease modelling and the interpretation of results, it is important to understand and clearly define the concepts of transaction costs, market participation and market failures. A number of studies have defined and contextualized transaction costs. Holloway et al., (2000) distinguish transaction costs between tangible (i.e. transportation costs, communication costs, legal costs) and intangible (uncertainty, moral hazard, etc.) costs. Pingali et al., (2005) contextualize transaction costs from the point they occur. Key et al., (2000) broadly categorizes transaction costs into two sub-categories: 1) Fixed Transaction Costs (FTC's), and 2) Proportional or Variable Transaction Costs (VTC's). FTC's are invariant to the quantity of an input purchased such as screening and search or information costs, while VTC's vary with the volume of inputs traded such as the cost of transportation. Because FTC's are one-off costs incurred, thus they may increase entry barriers but are unlikely to affect the quantity of the input used by households once the entry costs are paid for. VTC's on the contrary, increase with the amount of input used by farm households resulting in the raise of the input prices for buyers and lowers the price effectively received by sellers, creating a "price band" within which some households find it unprofitable to either sell or buy.

The variable and volatile nature of transaction costs has challenged researchers attempting to measure and assess their impact on household's marketing decisions. When transaction costs are adequately high to prevent exchanges from occurring, then costs associated with transactions are unobserved (Alene et al., 2008). Information on transaction cost are also hard to collect in a survey particularly if farmers have no access to transportation and information equipment as there would be no paid out costs to observe (Alene et al., 2008; Key et al., 2000). In addition, when farmers transport their produce to the market or inputs from the market using their own transportation means, it would be difficult to measure the actual transport costs (Alene et al., 2008). Thus majority of the literature that studied transaction costs resorted to the observable factors that proxy for transaction costs such as ownership and access to transport and information equipment, distance to roads and markets, etc. (Winter-Nelson and Temu, 2005; Alene et al., 2008; Ouma et al., 2010).

Given the two distinct categories of transaction costs (i.e. FTC's and VTC's), we follow Winter-Nelson and Temu, (2005), Alene et al., (2008), and Ouma et al., (2010) and divide transaction costs into two categories. We use access to or ownership of transport equipment by households (bike, motorbike, or vehicles) and access to information and communication equipment (radio, TV, mobile phones, and internet services) as a proxy measure for FTCs, with farm or households distance to all-season drivable roads and time taken to reach nearest permanent market as a proxy for VTCs. Input markets may be subject to different transaction costs than the output markets which may impose different constraints on the households input utilization and intensity decisions. For instance, farm households may have to travel a longer distance to purchase inputs because input markets are usually located in the province centres, whereas outputs could be marketed at the village or district centres. This longer distance in turn imposes higher travel costs.

Most studies conceptualize that market participation is the outcome of a two-step decision process, namely the rate of participation and intensity of the volume of inputs applied by the farm households (Alene et al., 2008; Liverpool-Tasie, 2014; Ricker-Gilbert et al., 2011; Winter-Nelson and Temu, 2005). The rate of market participation is the percentage of farmers that actually purchase inputs from markets, whereas intensity of input use is the level of a particular input applied by farm households. Thus, participation is defined as the percentage of farm households who actually reported a positive value of purchased inputs, while extent of participation is defined is the quantity of inputs applied conditional on the first stage.

de Janvry et al., (1991) and Dillon and Barrett, (2017) distinguishes between three different cases of market failures. If the exchange of goods is legally prohibited or rendered infeasible by some non-market force, then markets are truly missing. In the second situation, markets are functional, however exchange of goods takes place at non-competitive prices (i.e. prices that do not equate marginal profit and marginal costs), then markets are functional but are failing. The third condition of market failure may occur when markets exist and operate at the competitive and market-clearing prices but welfare outcomes for households are sufficiently low or sub-optimal so require interventions to improve wellbeing. Market failures that mismatch supply and demand can be induced by different factors such as legal restrictions, weak enforcement of contracts, transaction costs, and poor access to infrastructure. The design of interventions to tackle the market failure issue also depends on the type of the situation confronted as explained above. For instance, policy instruments to target completely missing markets may involve removal of legal restrictions or imposing property rights, whereas the later situation may require interventions aiming at increasing investment in public infrastructure to reduce transaction costs (roads, access to telecommunication, etc.), termination of collusion and formation of oligopolistic situation, education and provision of extension services, and possibly government subsidies.

In the context of subsistence or semi-subsistence agriculture systems, production decisions are made in a complex environment where production is carried out by households that both demand and supply labour. Under complete and competitive markets, these households exchange (hire in and hire out) their desired amount of labour freely to maximize profits. In this case, households are profit-maximizers and the amount of labour employed to carry out production would in theory be independent from their consumption decisions and household's endowment and preferences of labour therefore should not affect the production allocation of labour. This separation or independence implies that household decisions are recursive such that households first aim to make optimum production choices, and consumption decisions are made in the second stage taking based on the profits and income from the first stage (Benjamin, 1992; Bowlus and Sicular, 2003; De Janvry and Sadoulet, 2006; Dillon and Barrett, 2017; LaFave and Thomas, 2016; Le, 2010). Alternatively, if the separation hypothesis fails (i.e. production and consumption decisions are non-separable), then markets are dysfunctional or fail.

Following De Janvry and Sadoulet, (2006), we illustrate the concept of non-separability and the role of transaction costs in Figure (2). Consider the following hypothetical situation where we assess the impact of transaction costs on the market for a particular input; take as a second market failure inexistence of a land market. Let the demand for the input of labour be denoted by $D(p, L)$ for households $i = 1,2,3$ with different farm sizes. To make comparison across households feasible, we assume that all households face the same supply denoted by $S(p, L_c)$ which is determined by the level of household labour endowments (L) as a supplier. Let p^m denote market price, p^vdenote effective price of sale defined as market price net of transaction costs (t_p^v), and p^a denote the effective purchase price defined as market price (p^m) plus the transaction costs (t_p^a) for the input incurred in buying.

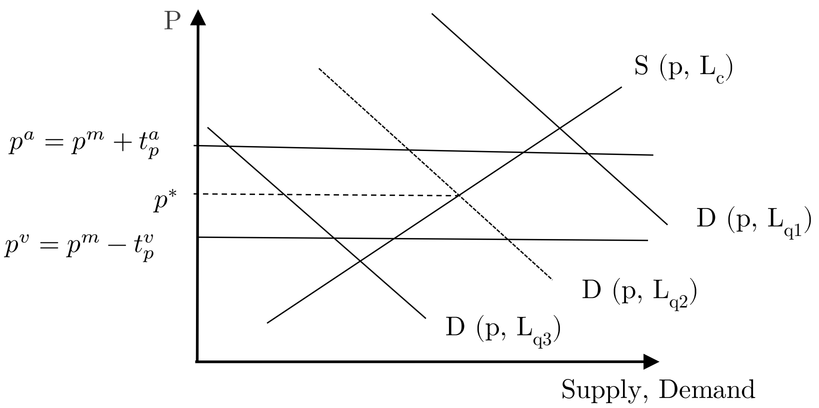


Figure 2: Variable transaction cost and market participation

Source: Adopted from De Janvry and Sadoulet, (2006)

Household decision to purchase inputs from the market depend on the relative positions of households' supply and demand functions which are shaped by the level of household endowments of productive resources (L_c) and demand characteristics (L_q) . Because variable transaction costs add to the market price and as a result there exists a non-zero price interval forcing households represented by the dashed line of L_{q2} not to purchase inputs from the market. For these households their internal equilibrium defines a new shadow price $p^*(L_q, L_c)$ specific to each of them, as a result their behaviour is of a non-separable type where it is optimum for them to adjust production and consumption decisions and remain self-sufficient. Hence, both heterogeneity in household's endowments and differences in transaction costs t_p^v and t_p^a correspond to heterogeneity in the input market participation.

3.1. The hypothesis of separation in the agriculture household model

We define our utility function based on the standard time allocation model so that it simplifies and reflects the theory underlying the hypothesis of separation more clearly. The outline of this model is theoretically grounded in the generic household model (Singh et al., 1986) as articulated by Benjamin, (1992), and later applied by Bowlus and Sicular (2003), Le (2010), LaFave and Thomas (2016), and Dillon and Barrett (2017), to test for the separation hypothesis.

Consider a farm household that aims to maximize its utility represented by a strictly increasing and concave utility function (6). The utility is derived from the preferences over consumption (C) and leisure (L^l) which is conditional on household preference shifters (Z) such as household endowments. The household is endowed with a fixed amount of labour ($\overline{L}$) which is supplied to the farm work (L^f) to produce output that can be consumed by the household or sold to the market at the market price (p), and off-farm work (L^m) to receive market wages (w). Households can also hire labour from the market, here denoted by (L^h) at a market wage (w) and purchase non-labour inputs (X) such as seeds, fertilizer, etc. at the market price of p_x. Household's total land is denoted by A, which consists of household own land ($\bar{A}$) and land rented in (A^r).

$$MAX_{C,A,,L^m,L^h,X}\ U(pF(A,L,X)+wL^m,L^l|Z) \tag{1}$$

Subject to:

$$pC \leq\ pF(A,L,X)+wL^m-p_aA^r-\ wL^h-p_xX \tag{2}$$

$$0 \leq L^m \leq L^M \tag{3}$$

$$L \equiv L^f+L^h \tag{4}$$

$$\overline{L} \geq L^f+L^m+L^l \tag{5}$$

$$A=\ \bar{A}+A^r \tag{1}$$

$$L^l,L^f,L^h,L^m,C,A,X \geq 0 \tag{7}$$

Market imperfections are introduced into the model as the upper and lower constraints on the market labour: $0 \leq L^m \leq L^M$ where L^M is the maximum number of hours a farm household can work in the labour market. The farm household faces imperfections if either the lower constraint or the upper constraint is binding ($L^m=0$ or $L^m=M$). Then the hypothesis of separation holds. However, the farmer faces no imperfection if neither the lower nor the upper constraint is binding ($0 < L^m < L^M$), thus the farm household's behaviour is consistent with the separation (Le, 2010).

Based on the Langrangian function, the FoC for labour (L) can be calculated as in equation (8) and FOC for L^m can be derived as in and (9 and 10) depending on the market conditions and separation:

$$w^*=\ pF_L(A,L,X) \tag{8}$$

$$w^* = w \qquad \text{if} \quad 0 < L^m < L^M \tag{9}$$

$$w^* \neq w \qquad \text{if} \quad L^m = 0 \;\text{ or }\; L^m = L^M \tag{10}$$

Where w^* is:

$$w^* = \frac{U_l \; pF(A, L, X) + wL^m - p_a A^r - \; wL^h - p_x X; Z)}{U_c \; pF(A, L, X) + wL^m - p_a A^r - \; wL^h - p_x X; Z)} \tag{11}$$

Where F_L in (8) is the derivative of output with respect to labour and w^* is called the shadow wage or the opportunity cost of time. If the separation hypothesis holds, then the constraints are not binding as in equation (9) and therefore $w^* = w$. Pluging w for w^* in Equation (8) we get $w = pF_L(A, L, X)$ where Z does not appear implying that the choice of labour does not depend on the preference shifters. In other words, under complete and competitive market conditions, labour allocations in production are not affected by the household endowments of labour. In this case the farm household hires in labour or supplies labour to the market, and exchanges other inputs at exogenous, market-clearing prices, so that it allocates labour to maximize farm profits first, and then makes consumption choices conditional on the profit from production. On the contrary, in the case of non-separation where $w^* \neq w$ and the labour market constraint is binding (i. e. $L^m = 0 \; or \; L^m = L^m$), then L can be derived by substituting equation (8) into (11) such that:

$$w^* \neq w \;\Rightarrow pF_L(A, L, X) = \frac{U_l \; pF(A, L, X) + wL^m - p_a A^r - \; wL^h - p_x X; Z)}{U_c \; pF(A, L, X) + wL^m - p_a A^r - \; wL^h - p_x X; Z)} \tag{12}$$

Where preference shifters (Z) do appear in the equation (12), meaning that labour allocation in the first stage of production is affected by the household endowments, thus the production and consumption decisions are not separate from each other. For further discussion on the theoretical model see Le, (2010).

As discussed earlier, there are two sets of tests available in the literature to analyse the above relationship. The first set of these test implemented by Benjamin, (1992), Bowlus and Sicular, (2003), Le, (2010), and more recently by LaFave and Thomas, (2016) and Dillon and Barrett, (2017) involve a reduced form approach that tests whether variables that affect consumption decisions (household preference shifters denoted by Z) also affect the labour allocation decisions in stage, while the second set of these tests implemented by Jacoby, (1993), Abdulai and Regmi, (2000), and Grimard, (2000) involve a structural form approach testing the relationship between w and w^*. In the later approach, since w^* cannot be observed, it should be estimated using a production function (Le, 2010). The marginal product of labour from production function is equivalent to w^* which then can be compared to the market price w to test the hypothesis of separation (Le, 2010; Vakis et al., 2004).

Because the second approach involves estimation of a production function, questions arise with regard to choosing the correct functional form and due to the fact that endogeneity of variables in the production function may contaminate the results (Le, 2010). We choose the reduced form approach to test the hypothesis of separation without the need to estimate the production function. One point to bear in mind is that using the reduced form approach, rejection of the separation hypothesis may not be directly interpreted as a test for a market failure in a specific input market, as failure in any market will induce non-separable behaviour (Dillon and Barrett, 2017; Vakis et al., 2004). Similarly, rejecting the separation hypothesis can indicate failure of multiple markets simultaneously as relative prices of inputs or outputs (not absolute prices) may generate distortions resulting in market failure (Dillon and Barrett, 2017). Moreover, failing to reject the null hypothesis which implies consistency with the recursive or separation behaviour, may not mean that complete markets actually exist, it may rather be the result of household decision to allocate resources in a manner that make up for missing markets (LaFave and Thomas, 2016).

3.2. Market participation and agriculture household model

For simplicity and to avoid further complications, we redefine our theoretical model and utility function to better accommodate the impact of transaction costs on household's marketing decisions. Following Key et al., (2000), Winter-Nelson and Temu, (2005), and Alene et al., (2008), and Ricker-Gilbert et al., (2011) input use by the farm households can be modelled as a two-step decision process: 1) household decision whether to purchase inputs from the market, and 2) household decision on the extent or level of expenditures on inputs. These household decisions can be analysed using a generic static household model in which utility is a function of net revenue:

$$MAX(U) = U(p_q Q - w_i X_i) \tag{13}$$

Subject to:

$$F(Q, X; Z) = 0 \tag{14}$$

Where equation (13) is the objective utility function and equation (14) represents production technology constraint in which p_q and Q represent output price and volume, w_i and X_i represent unit price and quantity of the i^{th} input used, and the vector of Z collects household characteristics. Production technology is represented by a well-behaved production function such that $\partial Q/\partial X_i > 0$ and $\partial^2 Q/\partial^2 X_i < 0$.

The utility function in (13) can be expanded to accommodate transaction costs explicitly. Let VTC_o and VTC_i denote variable transaction costs for unit of output and input respectively, so that the adjusted output price becomes $p'_q = (p_q - VTC_o)$ which is a downward adjustment in the output price, and the adjusted input price becomes $w'_i = (w_i - VTC_i)$ which reflects an upward adjustment in the input price (i.e. an increase in price due to VTCs).

Households market their surplus produce which is assumed to be equal to total output produced less total output consumed ($Q_i^s = Q_i - Q_i^0$) and purchase required inputs from the market which is assumed to be equal to total input applied to production less own input ($X_i^b = X_i - X_i^0$). This illustrates that for purchased modern inputs (i.e. from the market) such as certified seed, chemical fertilizer, and pesticides, the household relies entirely on the market (i.e. $X_i^b = X_i^0$), whereas in the case of the labour input, total input may equal to the sum of the hired and own labour e.g. $X_i^b = X_i - X_i^0$ (Goetz, 1992). Let FTC_o and m_q be fixed transaction costs incurred at selling and the quantity of the output sold to the market, FTC_i and m_i be the fixed transaction costs for inputs incurred at buying and the volume of input purchased from markets respectively, then the objective function in (13) can be redefined to accommodate transaction costs such that:

$$\begin{aligned} MAX(U) = U(p_q Q^c + (p_q - VTC_o)Q^s - w_i X_i^0 - (w_i + VTC_i)X_i^b \\ -FTC_0(m_q) - FTC_i(m_i) \end{aligned} \tag{15}$$

Where

$$m_q = \begin{cases} 1 & Q^s > 0 \\ 0 & otherwise \end{cases}$$
$$m_i = \begin{cases} 1 & X_i^b > 0 \\ 0 & otherwise \end{cases}$$

Taking the first order condition of the objective function will yield a reduced form of the input demand conditional on the market participation which implies that for households that actually purchase inputs from the market, the quantity is unaffected by the FTC. This means that once entry costs are paid, then fixed transaction costs do not affect the rate or quantity or expenditures on the inputs being purchased by the households.

$$m_i = f(p_q, VTC_o, w_i, VTC_i, FTC_o, FTC_i; Z) \tag{16}$$

$$X_i^b = f(p_q, VTC_o, w_i, VTC_i; Z) \qquad if \;\; X_i^b > 0 \tag{17}$$

Equation (16) and (17) represent input market participation and input demand by the household, where participation is a function of prices, fixed and variable transaction costs, household characteristics, whereas input demand is a function of prices, variable transaction costs, and household characteristics but not fixed transaction costs.

IV. Estimation strategy and econometric specification

The estimation strategy and econometric techniques in this section build on the conceptual model presented in the previous section. To test the hypothesis of separation, we estimate the labour demand equation in (18) using ordinary least square (OLS). As discussed in the previous sections, under the complete and competitive market conditions, the separation hypothesis specifically states that labour demand is invariant to the household endowments of labour (i.e. household size and composition are jointly statistically indistinguishable from zero). Rejecting the null hypothesis (separation) in favour of the alternative (non-separation) implies that markets for multiple inputs such as credit, insurance or land are failing as multiple market failures are required to generate distortions in factor markets because relative prices - not absolute price - are what matters in determining the efficient allocation of resources (Dillon and Barrett, 2017), whereas failing to reject the hypothesis of separation implies the presence of complete and competitive markets. To empirically test the hypothesis of separation, we estimate the following econometric model:

$$lnL_i = \alpha_i + \beta lnA_i + \delta_0 lnN_i + \sum_{s=1}^{S} \delta_s \frac{N_i^s}{N_i} + \sum_{k=1}^{K} \theta_k X_i + \sum_{j=1}^{J} \gamma_j D_j + W_t + \varepsilon_i \tag{18}$$

$$H_0\text{: } \delta_0 = \delta_s = 0$$
$$H_A\text{: } \delta_0 \neq \delta_s \neq 0$$

Where L_i represents the total labour employed (household own labour and hired labour) by the i^{th} household measured in person-days, A is the total amount of land cultivated by the farm households, N_i is the size of the household for i^{th} household, N_i^s are the household composition or structure variable such as age-sex demographic groups, X collects additional control variables such as land quality, D_j represents dummies to control for regional variation, and W_t represent the year dummies for the repeated cross section. Since we do not have data on wages in our survey to include as a variable in (26), we follow Bowlus and Sicular (2003) and Dillon and Barrett (2017) and rely on the district and year fixed effects in (18) to mitigate difficulties arising from complex wage structures. The null hypothesis of separation ($\delta_0 = \delta_s = 0$) states that household structure variables (e.g. age-sex demographic groups) and the estimated coefficient of the household size are jointly indistinguishable from zero. Rejection of the null hypothesis implies non-separability of the household's production and consumption decisions.

The estimation strategy follows the empirical approach seminally outlined by Benjamin (1992) and recently applied by Dillon and Barrett (2017). We define four sex-age demographic groups that are included in (18) along with the household size. Following Dillon and Barrett (2017), prime age comprises of household members aged between 14-64 years and elderly sex-age group comprises of household members aged above 64. Household members (males and females) aged below 14 are excluded from the regression to avoid mixing children and adults and to try and reduce concerns about the productivity differences and more importantly to mitigate concerns of potential endogeneity problem in the household size. However, children's contribution to the agriculture labour demand (total labour days – the dependent variable) is accounted for, assuming that each child day is equivalent to half of an adult work day.

As a large percentage of the households in our sample do not purchase inputs from the market, it is plausible to argue that the Heckman sample selection models may better represent the data. However, this model assumes that the zero values for the input use (i.e. for household who did not actually participate in the market) are incidental truncation where the zero values are unobserved. In the context of Afghanistan, it is safe to argue that use of inputs is very common among farmers and that they are aware of their economic benefits. The zero observations may therefore be an optimal outcome as farmers may not purchase inputs due to market conditions or unfavourable agronomic and climatic conditions. In this context, a corner solution model seems to be more appropriate than the sample selection. As pointed out earlier under the theoretical framework section, the use of inputs can be an outcome of a sequential two-step decision process namely participation in the input market and intensity of expenditures. Therefore, we choose a Lognormal Double Hurdle (LDH) model proposed by Cragg (1971) which is more flexible compared to the standard Tobit model as it is designed to allow that there might be different factors that affect the first stage decision of participation and the second stage decision that determine the probability of participation. The LDH model can also allow us to consider that the same factor can potentially affect participation and expenditures in different ways (unlike the sample selection model that requires a strict exclusion restriction).

We hypothesize that fixed transaction costs are likely to affect the first stage, but not the second stage decision related to the intensity of the expenditures. Once the entry costs are paid, the household decisions on the amount of expenditures on the inputs is unaffected by them. Following Winter-Nelson and Temu (2005), Alene et al., (2008), and Liverpool-Tasie (2014), we use ownership or use of ICT and transport equipment by households as proxies for fixed transaction costs, with time taken to reach nearest permanent market and distance to nearest all-season driveable road as proxies for variable transaction costs. Given the dependent variable (i.e. the decision to participate in input market and extent of expenditures), access to ICT equipment can mitigate the one-off information or search cost, whereas ownership of transport equipment may mitigate transportation costs. However, given, the dependent variable (expenditures on inputs), distance to roads and markets proxy for proportional costs; the longer the distance to markets and roads, the higher are the costs incurred to transport input or outputs.

One potential problem in our analysis is the estimation bias due to endogeneity in the use of ICT and transport equipment ownership by the farm households. To remove the possible endogeneity bias and capture the true casual effect, we allow these variables to be endogenous and use Instrumental Variable (IV) technique to overcome the endogeneity problem. Chowdhury (2006) stated that the use of the telephone is possibly correlated with the household unobservable characteristics that may also be correlated with their market participation decisions. Thus, the estimated coefficient for the use of ICT equipment could possibly suffer from the endogeneity problem due the omitted variable bias. It can be hard to priori anticipate the direction of the bias as these unobserved characteristics may simultaneously increase or decrease the use of both ICT and transport equipment and market participation. However, it is plausible to assume that households that patriciate in markets are more likely to own or use ICT and transport equipment too, thus one would expect the coefficient estimate of the ICT and transport equipment variables to be biased upward. Similarly, ownership of the transport equipment by household is likely to be endogenous. Household unobserved characteristics may be correlated with both the ownership of transport equipment and market participation in a similar passion leading to an upward estimation bias.

We choose two instrumental variables to correct for the potential endogeneity bias in the use of ICT equipment by farm households, namely: 1) whether the farm household has access to electricity, and 2) mean of off-farm income of other farmers at the community level. Access to electricity involves electrification from household own, private, and public electricity sources[1] of power. One could argue that electrification may signal regional investment and that households located closer to local markets may have better access to electricity and input markets, and therefore access to electricity may be correlated to the household input use decisions. However, in reality and given the data on access to electricity, the major sources of power are solar, community generator (hydro) and use of battery which are mostly common throughout the country regardless of whether household are located close to local market places. This means that the primary source of power is not from the public (government) source which is more likely to be more accessible by households that live near the local market centres. Thus, household access to electricity could not be directly correlated with their decisions to participate in the input markets, however it is directly linked to using ICT equipment. We also control for potential regional variations by including district fixed effects in our structural model. Therefore, access to electricity may affect household marketing decisions only through using ICT technologies that play a vital role in reducing search costs. Our second IV is the mean of off-farm income of other farmers in the community which is constructed as:

$$Mean\ off-farm\ income\ of\ other\ farms = \frac{sum\ OFY_s - OFY_i}{N_s - 1} \tag{19}$$

Where $sum\ OFY_s$ is the sum of off-farm income at Shura/community level, $sum\ OFY_i$ is the off-farm income of the i^{th} farmer in the community, and N_s is the number of farm households/observations in the respective community. The Mean of off-farm income of other farms in the household is intended to capture the status of local non-farm employment; higher non-farm employment in the community signifies high prevalence of non-farm employment opportunity at the local level which may in turn translates into greater potential for households to use ICT equipment. While we control for the household own off-farm income, household and farm assets, and other district level fixed effects directly in our structural model, our assumption is that the instrument will affect market participation only through the use of the ICT equipment channel.

[1] Household power sources of electricity are: electric grid (6%), government generator (0.16%), private generator engine (1.2%), private generator hydro (2%), community generator engine (1%), community generator hydro (12%), solar (52.5%), wind (0.5%), and battery (13%).

Similarly, we instrument the ownership of or access to transport equipment using two instruments. Firstly, we use the number of road and bridge construction/rehabilitation projects being implemented in the community within 12 months. Controlling directly for distance between farm and local markets and road density within the community and other district level fixed effects in our analysis, the only remaining pathway for the instrument to influence household decisions to participate in input market is through the farm's accessibility to local input markets via improved roads development. Secondly, we use mean of the off-farm income of other farms within the community as an instrument to remove bias due to unobservable that may affect both household decisions to own/use transport equipment and participate in input markets. In assessing households machinery investment decisions, Ji et al., (2012) used similar instruments (mean off-farm employment time and wage for other household in the district) to account for possible endogeneity in household's decisions to invest in farm machinery.

We use a Control Function (CF) approach to correct for possible endogeneity problem in the use of ICT and transport equipment. The CF approach requires the use of Instrumental Variables (IV) that should be included in the reduced form estimation but not included in the structural model of the factor market participation and demand equations and that they should satisfy the orthogonality condition. The CF technique entails that the endogenous variable is regressed over the instrumental variables in the reduced form estimation and subsequently generalized residuals from the reduced form estimation are estimated and used as an independent variable in the structural model in addition to the actual endogenous variables themselves (Petrin and Train, 2010; Wooldridge, 2015).

Given the LDH model and the binary nature of endogenous variables in the context of corner solution, we choose control function because it is more efficient for binary outcome endogenous variables which other instrumental variable techniques (such as 2SLS, GMM, ivprobit) do not estimate efficiently. In addition, the CF approach is efficient even for weak instruments (Tadesse and Bahiigwa, 2015; Wooldridge, 2007). The CF approach is more efficient due to the prevalence of zeros in our structural equation, giving it the properties of a non-linear corner solution. Similar estimation strategy was applied by Winter-Nelson and Temu (2005), Ricker-Gilbert et al., (2011), Liverpool-Tasie (2014), Tadesse and Bahiigwa (2015), and Ragasa and Mazunda (2018) who analysed household's marketing decisions in the input or output markets.

Using the CF approach, in the first stage we estimate the following reduced form equation using a Probit model where we regress the binary endogenous variables (use or ownership of the ICT and transport equipment) over a number of controls and IVs:

$$\Pr(T_i = 1|M) = \alpha + \gamma Z_i + \varphi M_i + v_i \tag{20}$$

Where T_i represents the endogenous variables of transaction costs for the i^{th} household proxied for by the ownership of transport and ICT equipment, M_i represents the vector of explanatory variables that affect T_i, and Z_i represents instrumental variables that are not included in X_i (or explanatory variables) in the structural model, v_i represents the error term that follows a normal Probit distribution $N(0, \sigma^2)$. Following Wooldridge (2015), the generalized residuals after the reduced form equation (20) estimated by Probit model can be obtained as:

$$\widehat{gr_i} = T_i \ \lambda(Z_i \ \gamma) - (1 - T_i) \ \lambda \ (-Z_i \gamma) \qquad i = 1,2,3, \dots N \tag{21}$$

Where $\widehat{gr_i}$ is the generalized residual obtain from equation (16), and $\lambda = \phi(.)/\Phi(.)$ is the inverse mills ratio.

In the second step of the CF approach, we use the generalized residuals $\widehat{\mathrm{gr}_1}$ obtained from the reduced form equations (20) as additional regressors in the structural models estimated by the LDH models (i.e. the residuals are used as explanatory variable in the first hurdle-Probit regression of the LDH model). Following Wooldridge (2002), the general form of the LDH model can be written as:

$$\text{Hudle 1: } Pr(y_i = 0|x) = 1 - \Phi(x\gamma) \tag{22}$$

$$\text{Hurdle 2: } Log(y) \mid (x, y > 0) \sim Normal(x\beta + \sigma^2 \ ) \tag{23}$$

Where the decision to participate is governed by the Probit model in hurdle1 and the extent of expenditure is estimated by the truncated model. The LDH model in the second hurdle assumes that $log(y)$ follows a normal distribution for $y > 0$. Given the general LDH model in (22) and (23), our empirical model[2] takes the following form:

$$Pr(y_{1i}^* = 1|x_i) = \alpha_i + \ \delta\widehat{gr}_i + \theta T_i + \beta X_{1i} + W_t + D_j + u_{1i} \qquad \text{Participation} \tag{24}$$

$$y_{2i}^* = exp(\alpha_i + \theta T_i + \ \beta X_{2i} + W_t + D_j + u_{2i}) \qquad \text{Extent of expenditures} \tag{25}$$

$$\begin{array}{ll} y_i = 1 & Only \ \ if \quad y_{1i}^* > 0 \quad and \ y_{2i}^* > 0 \\ y_i = 0 & Otherwise \end{array}$$

Where y_{1i}^* is a latent variable denoting the household's decision to participate in the input market (e.g. participation=1, and 0 otherwise) and y_{2i}^* is a latent variable presenting the expenditures on the i^{th} input purchased by the farm household, y_i represents the actual observed dependent variable, which is the expenditure on i^{th} input purchased by the household, $\widehat{gr}_i$ is the residual obtained from the reduced form equation (20), X_i is a vector of controls including household demographic and socioeconomic characteristics, D_j represents district dummies that capture regional variation for

[2] We did not include the subscript of (t) in our equations because each farm household is repeated in the survey only once, however since we use a repeated cross-sectional data that are collected in different years, we added a dummy variable representing individual survey year (indicated by W_t in equation (24) and (25).

j^{th} district, W_t represent the year dummies in our pooled cross-sectional sample, ε_i is the error term. If the coefficient on $(\widehat{gr})$ is significantly different from zero in the structural model (24) then transaction costs (represented by ownership of transport equipment and use of ICT equipment) are endogenous in a farmer's decision to purchase inputs from the market.

The participation and extent of expenditure equations in (24) and (25) are assumed to be independent (Hsu and Liu, 2008; Wooldridge, 2010) of each other, and are estimated using a Maximum Likelihood (ML) estimation procedure. The log-likelihood of function of the LDH model can be written as:

$$\ln(L) = [1 - \Phi(\beta X_{1i})] + \ln[\Phi(\beta X_{1i})] + \{(\phi\ [\ln(y_{2i}) - \beta X_{2i}/\delta]) - \ln(\delta) - \ln(y_{2i})\} \tag{26}$$

where $\phi(.)$ and $\Phi(.)$ are the normal probability density function (pdf) and cumulative distribution function (cdf) respectively. As in most non-linear models, coefficient estimates from the LDH model are directly hard to interpret, we estimate Average Partial Effects (APE) of the explanatory variables on the participation probability and expected expenditures level (in the second stage) given the positive decisions on participation. The APE of participation from the first hurdle Probit model (24) is:

$$Pr(y_{1i} = 1|X_{1i}) = \Phi\left(\frac{-\beta X_{1i}}{\delta}\right) \tag{27}$$

The average partial effects in the input purchase decision in hurdle 1 represent the probability of input market participation for changes in corresponding explanatory variables. The expected value of expenditures in hurdle 2 (estimated using truncated regression) conditional on a positive purchase decision is given by:

$$E(y_{2i}|X,\ y_{2i} > 0) = \exp(\ \alpha + \theta T_i + \ \beta X_{2i} + W_t + D_j + \delta^2/2) \tag{28}$$

For the extent of expenditures model in hurdle 2, the conditional APE's show the conditional expectations for strictly positive expenditures on inputs with respect to the change in independent variables (for dummy variables, change implies switching from zero to one) evaluated at the ML estimates. Because the dependent variable in the second hurdle is in logarithmic form, the conditional APE can be interpreted as elasticities for log-transformed continuous variables when y_{2i} is strictly positive, whereas for discreet variable the APE measure percentage changes in the dependent variable when the variable shifts from zero to one, ceteris paribus. APE and Standard errors of the estimated marginal effects are computed using the margins command and delta method. The maximum likelihood estimation of the log normal hurdle model was obtained in Stata® 15 using *probit* and *truncreg* commands for participation and extent of expenditures, respectively.

4.1. The Data

This study uses repeated cross-section data from the Afghanistan Living Condition Survey (ALCS) conducted by the Central Statistics Organization (CSO) in 2011/12, 2013/14, and 2016/17. The surveys include both quantitative data and in-depth qualitative information on several key indicators including farming and livestock production in Afghanistan. Each survey covered all 34 provinces of the country. In total 35 strata were identified each year, 34 for the provinces and one for the nomadic (Kuchi) population. The sampling frame used for the resident population in the individual year was based on the pre-census household listing conducted by CSO in 2003-05, updated in 2009. Households were selected on the basis of a two-stage cluster design within each stratum. In the first stage Enumeration Areas (EAs) were selected as Primary Sampling Units (PSUs) with probability proportional to Enumeration Area (EA) size. Subsequently, in the second stage ten households were selected as the Ultimate Sampling Unit (USU).

The surveys use largely similar structured questionnaires, so data on similar indicators and variables were collected every year on sectors including agriculture, livestock, labour, household assets, income, and expenditures. One limitation is that it is not possible to disaggregate data at the crop level, restricting our analysis to aggregate farm level data. A strength of the surveys, however, is that they are representative at the national and provincial level, and a distinguishing feature is the continuous data collection over a cycle of 12 months to capture potential variations across the seasons. The surveys also include district and community level questionnaires that aim to collect data on development priorities, projects being implemented within the community, access to education and district level market prices.

Each survey covered about 20,786 households and roughly 157,262 persons across the country. In total, the pooled sample from three years covers about 61,452 households. About 50% of the households reported any engagement in farming (i.e. with positive agriculture production and cultivated land area), reducing the analytical sample to roughly 30,000 households. Moreover, after accounting for missing values on key variables especially labour, our total usable sample became 21,189.

4.2. Summary statistics and description of variables

Before presenting the summary statistics on key variables used in the analysis, we introduce and define each variable and the measure in Table (2). For the first part of the study where we test the hypothesis of separation, the dependent variable is total (owned and hired) labour measured in person-days. The dependent variables in the second part of this study include a set of standard variables that are theoretically expected to influence household's decisions of participation in the factor markets and intensity of expenditures on each input.

Table 2: Description of variables used in the analysis

Variable	Description	Measure
Dependent variables		
Total labour days	Total labour (own & hired) employed in farm	Labour days
Fertilizers & chemicals use	Whether farm HH uses fertilizers & chemicals	1=use, 0 otherwise
Rent tractor	Whether the farm HH hire tractor	1=hire, 0 otherwise
Hire labour	Whether the farm HH hire labour	1=hire, 0 otherwise
Fertilizer & chemical expense	HH spending on fertilizers and pesticide	Afghani
Tractor expenditures	HH expenditures on hiring tractor	Afghani
Labour expenditures	HH expenditures on labour hire	Afghani
Explanatory variables		
ICT equipment	Whether HH owns ICT equipment such as TV, mobile, radio and internet	1=own, 0 otherwise
Transport equipment	Whether HH owns transport equipment such as car, bike, and motorbike	1=own, 0 otherwise
Time taken to reach market	Time taken to reach the nearest permanent market by car	Hours
Distance to road	Nearest all-season drivable road to the community	Km
Total land	Total land cultivated annually	Jeribs
Off-farm income	HH income from non-farm activities	10k Afghani[3]
HH size	Number of members of the household	Count/persons
HH head literacy	Whether HH head can read and write	1=can read & write
HH head education	HH head's highest formal education	Years
HH head age	Age of the household head	Years
HH head age square	Square of the age of the household head	Years
Land type	Whether the cultivated land is all irrigated or combined irrigated and rain-fed	1= all irrigated, 0=irrigated & rainfed
Landscape	Terrain or slope of the cultivated land (i.e. hills, valleys, and open plain)	2=open plan, 1=hills & valleys, 0=hills
Number of livestock	Number of livestock owned by the farm HH (cows, sheep, goat, donkey, and horses)	Count
Number of oxen	Number of oxen owned by the farm HH	Count
Number of tractors	Number of tractors owned by the farm HH	Count
Electricity cost	HH spending on electricity	Afghani
Instrumental variables		
Mean off-farm income of other farms in the community	Mean of the off-farm income of other farmers at the Shura/community level	Afghani 10K
Access to electricity	Whether HH has access to electricity	1=yes, 0 otherwise
Road/bridge project	Whether road/bridge project is completed in the community in the last 12 months	1=yes, 0 otherwise

Household level summary statistics on the key variables used in the analysis are presented in Table (3). Column 1,2, and 3 present means and standard deviations of key variable for each wave (2011/12, 2013/14, and 2016/17) respectively, while column 4 reports descriptive statistics for the pooled sample.

[3] Note: 68 Afghani is equivalent to 1 USD (based on 2018 exchange rate)

Table 3: Summary statistics[4] of variables used in the analysis

	2011/12		2013/14[5]		2016/17		Pooled	
VARIABLES	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Total labour (days)	14.60	13.90	13.15	14.69	13.92	15.78	13.95	14.69
Own labour (days)	11.83	8.950	11.30	11.09	10.68	7.35	11.35	9.323
Hire labour (days)	3.777	11.04	2.704	9.953	4.01	14.49	3.490	11.76
Fertilizer & chemical (1=use)	0.702	0.457	0.731	0.443	0.723	0.448	0.717	0.450
Tractor hire (1=yes)	0.560	0.496	0.579	0.494	0.542	0.498	0.561	0.496
Labour hire (1=yes)	0.323	0.468	0.194	0.396	0.217	0.412	0.253	0.435
Fertilizer & chemical expenditures (AFN)	3,246	5,029	5,324	9,880	5,043	8,661	4,399	7,933
Tractor rental (AFN)	1,974	3,455	2,688	5,354	2,515	4,880	2,350	4,542
Labour expense (AFN)	944	2,759	672.2	2,474	1,027	3,714	877.9	2,966
ICT equipment (1=own)	0.826	0.379	0.813	0.390	0.845	0.362	0.827	0.378
Transport assets (1=own)	0.470	0.499	0.456	0.498	0.544	0.498	0.485	0.500
Distance to road (km)	3.420	6.613	2.527	9.052	1.284	5.559	2.561	7.310
Time to market (>4 hrs)	0.266	0.442	0.095	0.294	0.087	0.281	0.163	0.369
Time to market (1-4 hrs)	0.201	0.401	0.354	0.478	0.000	0.000	0.197	0.398
time to market (<1 hrs)	0.533	0.499	0.550	0.497	0.913	0.281	0.640	0.480
Total land (Jeribs)	7.628	24.53	8.303	23.28	8.098	12.32	7.972	21.50
Off-farm inc. (10K AFN)	3.527	6.744	5.375	11.71	4.822	8.169	4.472	9.028
Livestock owned (N)	15.70	30.73	11.84	23.43	14.40	25.67	14.10	27.25
Oxen (own=1)	0.212	0.409	0.158	0.365	0.191	0.393	0.189	0.391
Tractor/threshers (N)	0.024	0.155	0.054	0.233	0.033	0.181	0.036	0.191
Land type (1=all irrigated)	0.711	0.453	0.767	0.423	0.686	0.464	0.723	0.448
HH size (count)	8.188	3.485	8.348	3.447	8.482	3.424	8.318	3.458
Prime male share	0.474	0.144	0.476	0.149	0.473	0.147	0.474	0.147
Prime female share	0.476	0.134	0.475	0.135	0.464	0.137	0.473	0.135
Elderly female share	0.017	0.063	0.018	0.063	0.025	0.072	0.020	0.066
Elderly male share	0.032	0.084	0.032	0.082	0.038	0.088	0.034	0.084
HH head education (yrs)	1.942	4.030	2.202	4.285	2.224	4.218	2.101	4.166
HH head literacy (1=yes)	0.280	0.449	0.318	0.466	0.309	0.462	0.300	0.458
HH head age (yrs)	42.76	13.54	44.43	13.73	44.72	13.38	43.82	13.59
HH head age square	2,012	1,281	2,162	1,316	2,179	1,282	2,105	1,295
Electricity (1=access)	0.543	0.498	0.824	0.381	0.949	0.220	0.742	0.437
Road/bridge project (1=yes)	0.265	0.441	0.258	0.437	0.175	0.380	0.238	0.426
Off-farm inc. of other farms in community (10K AFN)	4.692	4.394	6.440	5.675	5.908	5.456	5.583	5.184
Electricity cost (AFN)	70.44	233.9	87.97	291.7	61.77	251.5	73.81	258.7
Observations		8,663		6,876		5,650		21,189

Source: Author's calculation of the ALCS Data

The descriptive statistics on the input use by the farm households show that roughly 2/3 of the farmers in the pooled simple purchase fertilizers and pesticides from the market, whereas about 56% hire tractor

[4] A full summary statistics table (including minimum and maximum) by year is reported in appendix (Table 1A).

[5] It should be noted that Afghanistan's economy suffered from a recession in 2013/14 as the majority of international assistance withdrew from the country. This may have affected the estimated averages for certain variables presented in Table (3).

for ploughing or other farming activities. However, a relatively lower percentage (about 25% of the total sample) hire labour from the market. Perhaps household demand for the hired labour is seasonal and therefore they hire labour only during specific seasons such as planting or harvest seasons. Although the geographical coverage of the sample slightly changes from year to year, the average use of these inputs does not seem to fluctuate much over the years (Table 3). The average participation of the household in the input markets is relatively high. Liverpool-Tasie, (2014) reported that about 70 % of households used chemical fertilizers in the Kano state of Nigeria. Dillon and Barrett, (2017) reported that on average 30% of Ethiopian households hire labour from the market, 40% in Malawi, 48.8% in Niger, 30% in Tanzania, and 45% households hire labour from the market in Uganda.

For households that have actually participated in the market, the estimated average expenditures on chemical and fertilizer in the pooled sample is 4,399 Afghani, tractor rental 2,350 Afghani, and average expenditure on labour hire is 878 Afghani (Table 3 and Figure 3). Overall, the averages are higher for the recent survey year, which may indicate a relatively higher application of inputs in the farm and expenditures (this could simply be due to inflation). Note that in our econometric estimation, we include a dummy for the survey year which will allow to control for fluctuations in the inflation rate from year to year.

Table 4: Household's market participation and expenditures by the input use status

Input	Year	Percent of households		Expenditures (AFN)
		Non-users	Users	
Fertilizers & Chemicals	2011/12	29.77	70.23	3,246.06
	2013/14	26.87	73.13	5,324.49
	2016/17	27.71	72.29	5,043.08
	pooled	28.28	71.72	4,399.36
Tractor rental	2011/12	43.97	56.03	1,974.22
	2013/14	42.1	57.9	2,687.50
	2016/17	45.79	54.21	2,514.89
	pooled	43.85	56.15	2,349.74
Hired labour	2011/12	67.65	32.35	944.21
	2013/14	80.58	19.42	672.20
	2016/17	78.29	21.71	1,026.57
	pooled	74.68	25.32	877.95

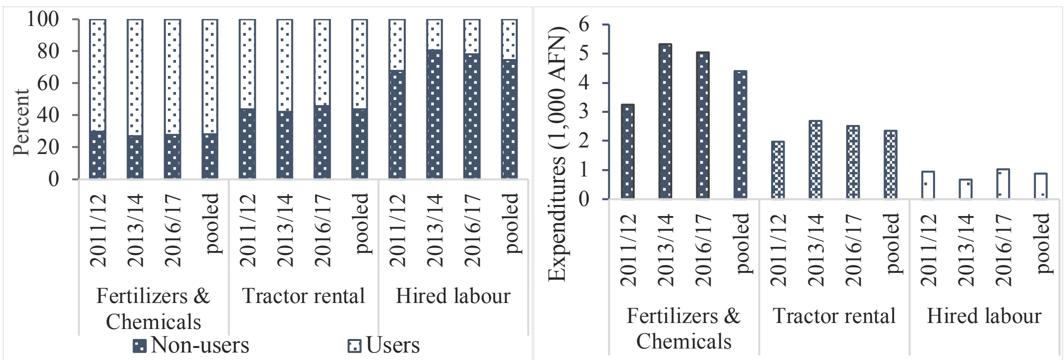


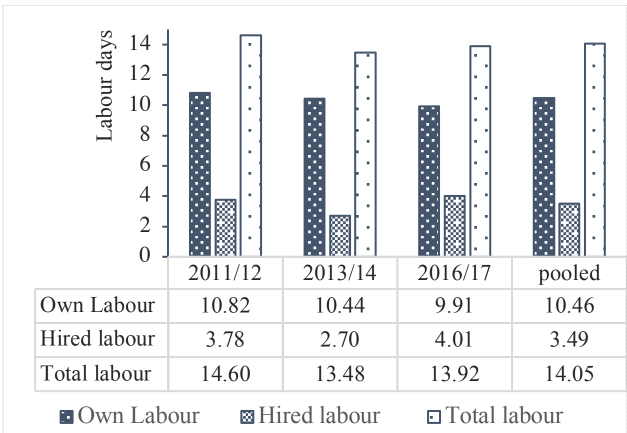
Figure 3: Percent of users and non-users and expenditures (AFN) by the type of input

Source: Author's calculation of the ALCS Data

The use of ICT equipment is quite common across the country, almost all the districts in the sample appear to be under the coverage of telecommunication facilities; 83% of farmers reported the use of ICT equipment such as TV, radio, mobile phones, and internet services (and roughly 50% used mobile phones). Average use of ICT varies slightly from year to year (by about 1-3%), possibly because the sample size (the subsample of the agricultural households) and the geographical coverage changed over the years. The percentage owning transport equipment is relatively low at about 48%.

The majority of households are located close to markets: about 64% stated that market was easily accessible (within community or less than one hour drive), 20% reported markets are within 1-4 hours of drive, but for the remaining 16% markets are not easily accessible (i.e. more than 4 but up to 12 hours of drive). While average distance to the nearest all-season road is about 2.56 km for the overall sample, average of distance to roads is consistently lower (1.28km) in 2016/17 compared to the average of 2.53 km in 2013/14 and 3.40 km 2011/12. This is an indication that road density and accessibility increased over time because there are intensive road development projects underway across the country, as about 23% of the household in the pooled sample reported that there is a road/bridge construction or rehabilitation project being implemented within the community.

Turning to the farm labour demand, we plotted the major types of labour applied by the farm households across different survey years to show the composition of total labour days employed over the years. As in Figure (4), household own labour comprises the major portion (75%) of the total labour days in our pooled sample. It can also be noted from the data that own or family labour and hired labour are somehow substitutes, as higher number of hired labour was reported when lower number of own labour is employed and vice versa. While household own family labour stays relatively constant across the years, the average of hired labour fluctuates more, particularly in the year 2013/14. This could be due to the year-to-year differences in the geographical coverage of the survey or the outcome of other socio-economic and agro-climatic conditions.



	2011/12	2013/14	2016/17	pooled
Own Labour	10.82	10.44	9.91	10.46
Hired labour	3.78	2.70	4.01	3.49
Total labour	14.60	13.48	13.92	14.05

Figure 4: Composition of labour in different survey years

Source: Author's calculation of the ALCS Data

With regard to socio-demographic characteristics, the household size is relatively large in Afghanistan and variable (overall average of 8.4 persons per household with a standard deviation 3.5), rising from 8.19 in 2011/13 to 8.48 in 2016/17. The composition of household shows that the share of prime male age demographic group (47.4%) and prime female group (47.3%) are equally distributed and consistent and stable across the years. The prime age-sex demographic groups are defined as household members between the age of 15-64 years. The average age of the household head is about 44 years in the pooled sample. Almost all households are headed by males, for this reason we excluded the household head gender variable from our analysis.

About 30% of the household heads in the pooled sample are literate meaning that they can read and write, although only 24% of the household heads have attended any formal schooling (i.e. primary, secondary, and tertiary education). The remaining 6% (out of the 30% that are literate) have received literacy training at home (i.e. home-based schooling). The mean years of education completed by the head of the household is two years, with a very slight increase over time.

The average size of the total land cultivated is considerably low (8 Jeribs equivalent to1.6 ha), with a slight increase over time, implying small landholdings per capita. The landholding shows high variability as the estimated standard deviation is 21.5 Jeribs, ranging from a minimum of 0.1 Jeribs to a maximum of 1,500 Jeribs per household. About 50% of the farm households reported some involvement in non-agricultural activities. While the overall mean of the off-farm income in the pooled sample is 4.5K Afghani with a standard deviation of 9K Afghani, it is much higher (8K Afghani) for the subsample of the farm households who actually reported a positive off-farm income.

The average number of livestock (including cattle such as cows, sheep, goats, donkeys, and horses, but not oxen) owned by the farm households in the pooled sample is 14 per household. Given the nature of our analysis, we separated oxen from the rest of the livestock and included it as a separate variable in our regression, as ownership of oxen not only proxy for the household wealth but also contributes towards land preparation and ploughing. On average, about 19% of households in the pooled sample reported that they own oxen. Average number of tractors/threshers owned by the household is about 3.6.

Next, we further break down our variables to compare the mean differences in selected household characteristics among users (market participants) and non-users (non-participants). A two-sample mean comparison t-test show that there are significant differences in selected household characteristics among participants and non-participants in all three input markets (Table 5).

Table 5: Mean difference in selected household characteristics by input use

	Non-participants	Participants	Two-sample t-test	
VARIABLES	Mean	Mean	Difference	t-statistic
Fertilizers and chemicals				
Distance to road (km)	3.520	2.180	1.34***	10.39
Total Land (Jeribs)	9.830	7.240	2.60***	8.43
Off-farm income (10K AFN)	3.250	4.950	-1.70***	(15.51)
Livestock owned (N)	18.08	12.53	5.55***	13.17
Tractors/threshers (N)	0.030	0.040	-0.017	(0.60)
HH size (count)	7.520	8.630	-1.11***	(22.55)
HH head age (years)	43.91	43.79	0.12	0.55
HH head education (years)	1.210	2.450	-1.25***	(22.75)
Farm income (10K AFN)	4.480	5.550	-1.08***	(11.62)
Total Revenue (10K AFN)	4.530	8.130	-3.60***	(13.81)
Observations	5,990	15,188	21,178	
Tractor rental				
Distance to road (km)	2.460	2.640	-0.18	(1.81)
Total Land (Jeribs)	6.330	9.260	-2.93***	(10.48)
Off-farm income (10K AFN)	4.220	4.670	-0.44***	(3.69)
Livestock owned (N)	17.26	11.63	5.63***	14.52
Tractors/threshers (N)	0.020	0.050	-0.03***	(12.03)
HH size (count)	7.850	8.680	-0.83***	(17.70)
HH head age (years)	44.23	43.51	0.73***	3.85
HH head education (years)	1.860	2.290	-0.43***	(7.50)
Farm income (10KAFN)	4.310	5.980	-1.68***	(18.57)
Total Revenue (10K AFN)	4.740	8.970	-4.22***	(12.80)
Observations	9,287	11,891	21,178	
Hired labour				
Distance to road (km)	2.620	2.380	0.24*	2.15
Total Land (Jeribs)	6.720	11.660	-4.94***	(11.41)
Off-farm income (10K AFN)	4.350	4.830	-0.48***	(3.36)
Livestock owned (N)	13.98	14.47	-0.49	(1.11)
Tractors/threshers (N)	0.030	0.050	-0.01***	(3.94)
HH size (count)	8.370	8.170	0.19***	3.52
HH head age (years)	43.83	43.81	0.010	0.07
HH head education (years)	1.930	2.620	-0.69***	(9.88)
Farm income (10KAFN)	4.930	6.190	-1.26***	(10.05)
Total Revenue (10KAFN)	6.180	9.870	-3.69***	(9.38)
Observations	15,816	5,362	21,178	

Source: Author's calculation of the ALCS Data

Except for the household head age, the mean differences for all household characteristics reported in Table (5) are statistically different among users and non-users. Surprisingly, households with smaller landholdings reported higher participation in fertilizer and chemical markets. This could be due to the resources needed to purchase sufficient fertilizers and pesticides to cover a larger area, or households with small landholdings may use more fertilizer to increase per unit production, given that they cannot expand their scale of operation. In addition, it could also be the case if small farmers have access to more manure or grow different types of crops. Households that reported participation in factor markets are generally in communities with better access to roads and markets. Similarly, farmers who participate in the fertilizer and chemical markets and those that hire tractors own less livestock (i.e. implies less manure).

Mean farm income and total revenues[6] for users is significantly higher than non-participants. Summary statistics on the ownership of tractors do not provide any statistically significant differences among participants and non-participants. Similarly, there are no significant age differences among participants and non-participants. Average years of education completed by the household head is higher among participants than non-participants as expected. Highly educated individuals may have more information on the benefits of inputs and are therefore using more inputs.

For categorical variables, we carried out a Pearson chi-squared test to compare whether the observed differences in selected characteristics associated with a change from 0 to 1 in inputs are significantly different among users and non-users (Table A2 in the appendix). The mean differences in these variables are all significant among users and non-users for all inputs as expected, however they do not imply a causal relationship.

As for the fixed transaction costs, market participants own significantly more communication and transport assets, such as TV, radio, mobile phones, bicycle, and motorbikes which could indicate that farm households who participate in the market may be facing lower costs to access market information. In general, a higher percentage of the non-participants are located farther away from the nearest market and possess fewer assets such as transport equipment (see table A2 in appendix).

We further illustrate the differences in household expenditures on inputs with respect to the ICT use and plot expenditures against the ICT use status across different years (Figure 5). While averages of expenditures on inputs slightly increase over time, there are significant differences in expenditures among farm household who own/have access to the ICT equipment (radio, TV, mobile phones, and internet) and household that don't. This may suggest that households with more information on factor markets and benefits associated with the input use are spending more money on inputs. The average expenditure on fertilizers and chemicals is about 1.95K Afghani for households that do not own ICT, whereas for households that own ICT the average expenditures on chemicals and fertilizers are 4.91K Afghani (about 2.5 times higher). Similarly, tractor rental and expenditures on hired labour is about 1.2K and 0.54K Afghani for farmers that don't own ICT equipment, whereas these expenses are 2.6K and 0.95K Afghani for tractor and labour hire respectively for households with access to ICT equipment (about 2.15 and 1.77 times higher). This is an indication that ownership of ICT equipment enables

[6] Note that data on farm income is directly collected in the survey. Revenues are calculated for each crop using district price data and then aggregated.

farm households to participate in the market, perhaps through provision of reliable and timely information on market prices and other services.

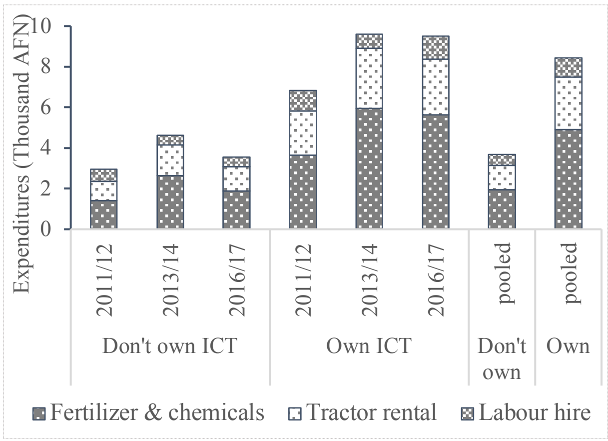


Figure 5: Input expenditures (AFN) by the ICT status over years

Source: Author's calculation of the ALCS Data

Likewise, there are significant mean differences in input expenditures with respect the ownership of transport assets (Figure 6). Farm households that own transport assets spend significantly more on inputs. Ownership of transport equipment facilitates the input delivery from market to the farm and therefore may mitigate transport costs as private transport could be a cheaper option then the public transport. However, since farm household that own transport equipment can avail themselves of cheaper transportation equipment, they are likely to participate more and use larger quantities of input factors as compared to their counterparts who may use other means of transportation which is generally a more expensive option.

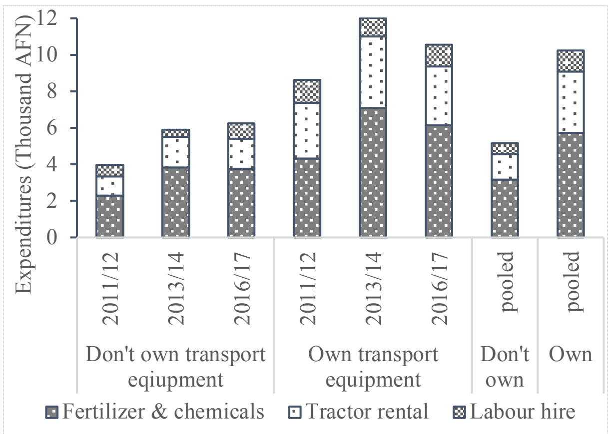


Figure 6: Input expenditures (AFN) by the transport equipment status over years

Source: Author's calculation of the ALCS Data

Distance to market is another key variable in our analysis that is used to proxy for proportional transaction costs. The longer the distance to markets, the higher the transportation costs from the market to the farm. It is also possible that households within a close proximity to market may avail of other possible services (e.g. extension services, price information, etc.) available in the district market centres. For this reason, we plotted expenditures on each input against the time taken to the nearest market (Figure 7) to illustrate the distribution of inputs with respect to the distance from markets.

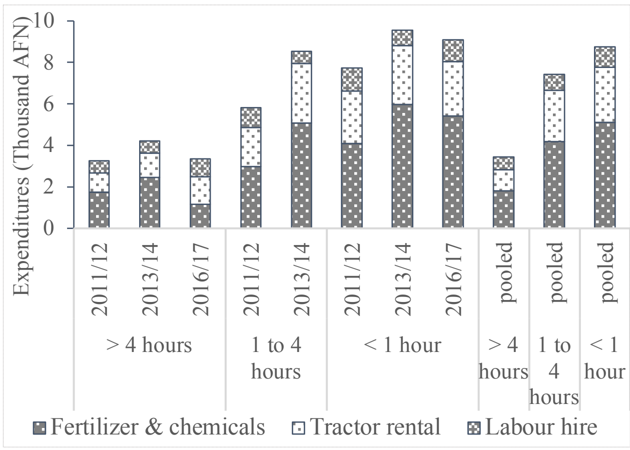


Figure 7: Input expenditures (AFN) over time taken to the market in different years

Source: Author's calculation of the ALCS Data

The statistics reveals that farm households located within a relatively closer proximity to permanent markets spend substantially more to purchase inputs from the market as compare to the households that are were located further from the market. It can be noted that the average expenditures do not fluctuate much throughout time. Note that time taken to reach the nearest market was originally reported as time taken to reach the nearest permanent market by private vehicles/car.

V. Econometric Results and Discussion

We present empirical results in the following two sections: the estimation of household labour demand and test of separation in section 5.1, and the results for assessing the impact of transaction costs on market participation for labour, fertilizer and chemicals, and tractor rental markets in section 5.2.

5.1. Labour demand estimation and testing of the hypothesis of separation

Before we formally test separability by running a multivariate regression of total labour demand over the household labour endowments (i.e. household size), we present Kernel-weighted regressions to show patterns and direction of linear relationship between household labour demand and endowments. Figure 8 illustrates the descriptive local polynomial regression of the household labour demand by the type of labour (i.e. household own labour, hired labour, and total labour demand) on the household labour endowments (e.g. household size). Even though the household own labour employed on the farm is variable when the household size exceeds 20 persons, with a default Kernel (Epanechikov) distribution and 95% confidence interval bands, the overall trend of the smooth polynomial shows that household own labour employed on the farm significantly increases in household size (Figure 8a), implying that larger households supply more labour to the farm work. In contrast, labour hiring decreases in household size (Figure 8b). Total labour demand (both own and hired labour) is also highly variable when the total household size is beyond 20 persons (Figure 8c), although overall demand for labour increases in household size.

If the separation holds (under perfect and competitive markets), we should not be able to observe a clear relationship between the total labour demand and household size (Dillon and Barrett, 2017). While this relationship does not formally signify rejection of the separation hypothesis, because underlying results are not conditioned on other covariates, it does signify that there exists a strong linear relationship between household endowments and the application of labour on the farm.

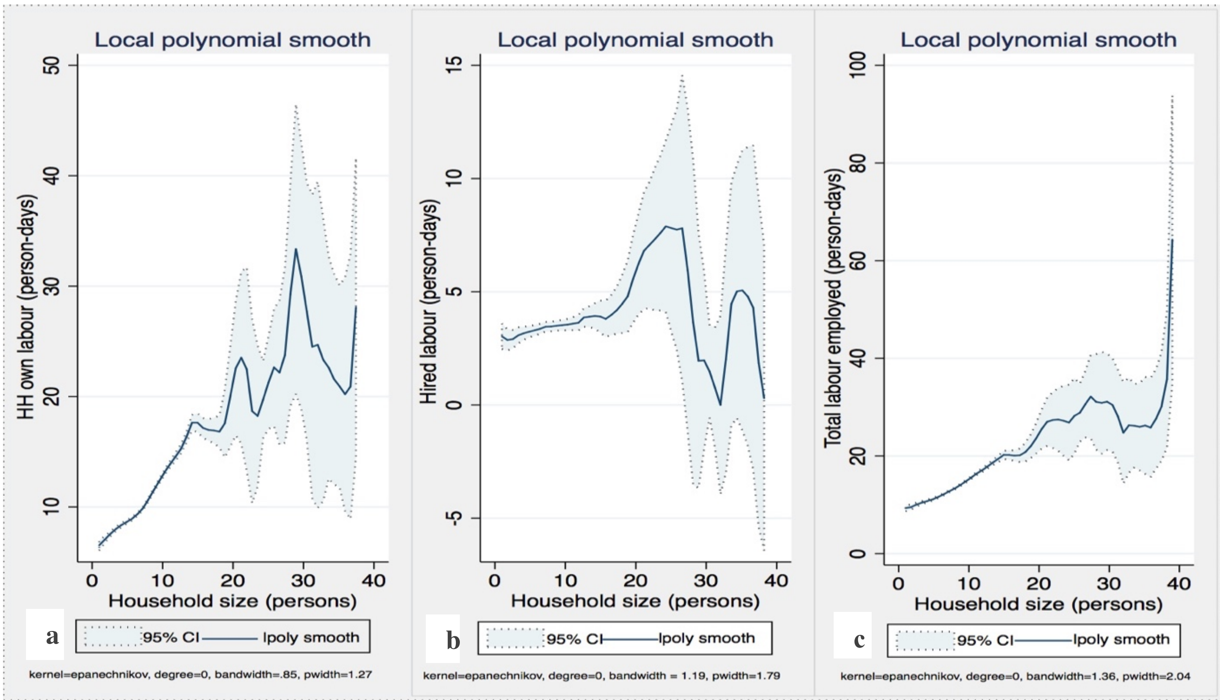


Figure 8: Local polynomial regression of a). HH own labour, b). hired labour, and c). total labour (person-days) on household size (persons)

Source: Author's calculation of the ALCS Data

Table 6 reports the result of simplified Benjamin test (Equation 18) of the separation hypothesis with different specifications. The first column presents the simplest specification with household preference shifters such as the size of the household, and household composition variables along with the landholding. Columns 2 and 3 of Table 6 condition on other covariates such as transaction costs, household socio-demographic and socioeconomic characteristics, and interaction terms to pick up some essential elements of the labour demand and examine their implications on the separation hypothesis. All regressions control for geographical variations by including district fixed effects and standard errors clustered at the district FE level.

Table 6: Regression results of the household demand for farm labour

	(1) Model 1	(2) Model 2	(3) Model 3
Dependent variable: Log of total (own and hired) labour in person-days			
Log. HH size[7] (adults) [A]	0.411***	0.449***	0.517***
	(0.018)	(0.020)	(0.042)
Prime HH male share [B]	0.119*	0.196**	0.203**
	(0.071)	(0.079)	(0.079)
Prime HH female share [C]	-0.161**	-0.110	-0.105
	(0.081)	(0.091)	(0.091)
HH elderly female share [D]	-0.286**	-0.268**	-0.268**
	(0.123)	(0.134)	(0.134)
Log total land (Jeribs)	0.231***	0.199***	0.198***
	(0.014)	(0.013)	(0.013)
ICT equipment (1=own/access)	-	0.080***	0.060
		(0.019)	(0.049)
Transport equipment (1=own/access)	-	0.029**	0.007
		(0.015)	(0.040)
Time taken to reach nearest market (1-4 hours)	-	-0.064*	-0.038
		(0.035)	(0.059)
Time taken to reach nearest market (<1 hour)	-	-0.032	0.148***
		(0.030)	(0.052)
Log. distance to road	-	-0.021**	-0.029
		(0.011)	(0.022)
Log off-farm income (AFN)	-	-0.027***	-0.027***
		(0.002)	(0.002)
HH head literacy (1=can read & write)	-	-0.040*	-0.038*
		(0.023)	(0.022)
Log. HH head education (years)	-	0.0001	-0.0001
		(0.011)	(0.011)
HH head age (years)	-	0.001	0.001
		(0.001)	(0.001)
ICT equipment (access=1) # Log. HH adults	-	-	0.015
			(0.036)
Transport equipment (access=1) # Log. HH adults	-	-	0.017
			(0.026)
Time taken to market (1-4h) # Log. HH adults	-	-	0.022
			(0.042)
Time taken to market (<1h) # Log HH adults	-	-	-0.136***
			(0.036)
Log. Distance to road # Log. HH adults	-	-	0.007
			(0.015)
Wave 2 (2013/14)	-0.204***	-0.183***	-0.183***
	(0.032)	(0.032)	(0.032)
Wave 3 (2016/17)	-0.083***	-0.085***	-0.084***
	(0.029)	(0.029)	(0.029)
District FE	yes	yes	yes
Constant	1.791***	1.901***	1.815***
	(0.077)	(0.100)	(0.102)
F-test: [A]+[B]+[C]+[D]=0, t-statistic	132.83	127.10	51.85
F-test: [A]+[B]+[C]+[D]=0, p-value	0.000	0.000	0.000
R-squared	0.244	0.265	0.266
Observations	21,189	21,189	21,189

*Note: Omitted categories for factor variables are: HH elderly male share for the HH composition, no access to ICT & transport equipment, 4 and more hours for time taken to reach market, cannot read & write for literacy, and 2011/12 for wave. Standard errors are clustered at districts FE level (in parentheses). Significance is indicated by *** p<0.01, ** p<0.05, * p<0.1.*

[7] We also regress the total labour demand on the full household size (including 0-14 age-sex group) and redefine the HH sex-age groups; the results presented in appendix Table A3 remain largely similar (separation rejected).

The estimated elasticity of household size with respect to the total labour days is 0.41 in the basic simplified specification, which is significantly different from zero at 1% significance level. A 1% increase in the household size increases total labour employed on the farm by 41%. The significance of household size implies the rejection of the hypothesis of separation that household production and consumption decisions are made independent of each other and that farmers treat all prices as given (under complete and competitive markets).

The magnitude of this elasticity can be interpreted as a rough indication of market failures that create dependency on household labour endowments. However these results cannot be interpreted as a test of the labour market failure specifically, as multiple failures are required to generate distortions in factor markets because relative (not absolute) prices determine allocation of resources (Dillon and Barrett, 2017).

The shares of prime female and elderly female (relative to the excluded group of elderly males) in household composition are negatively associated with labour demand, indicating that labour demand is decreasing in the share of females and elderly female. The share of age-sex groups and the log of household size jointly capture the composition and scale effects. As expected, the aged members of the household contribute less (or nothing) to the farm labour requirement (with aging their productivity may depreciate). The significance of household structure or composition variables is further confirmed by the F-test for joint significance. The calculated test statistic is $F(4, 385) = 132.83$ with a probability of zero (reported at the bottom of Table 6) rejecting the null hypothesis that the household size and composition variables are simultaneously zero. Based on the joint significance of the household size and composition variables, the separation hypothesis is still rejected.

As expected, the impact of land size on household labour demand is positive and highly significant: a 1% increase in the Jeribs farmed would increase the total household labour requirements by about 23%. Other studies that found a significant relationship between the landholding and the total labour demand are Dillon and Barrett, (2017) for Ethiopia, Malawi, Niger, Tanzania, and Uganda, and Benjamin, (1992) for Indonesia.

Columns 2 and 3 include other controls (both independently and interacted with the household size), to assess if these additional controls diminish the magnitude or eliminate the statistical significance of the estimated relationship between log household size and labour demand estimated by the basic model in column 1. The null hypothesis of separation is rejected in all three cases (bottom of Table 6). We find that only ownership of ICT by farm households and the log of off-farm income and distance to road were found to have significant positive and negative impact on the total labour days employed on farm respectively. In general, the insignificance of the interaction terms implies that there are no meaningful differences in transaction cost variables (i.e. ICT equipment, transport equipment, and distance to road) in the way that household endowments relate to the labour demand. Therefore, rejection of the separation hypothesis is not driven by the heterogeneities in these variables.

Our results on rejecting the hypothesis of separation are in agreement with Dillon and Barrett (2017), LaFave and Thomas (2016), and Grimard (2000) for five Sub-Saharan countries (Ethiopia, Malawi, Niger, Tanzania, and Uganda), Java, and Côte d'Ivoire respectively using the same theoretical and empirical strategy. In contrast, Bowlus and Sicular (2003) for China, and Benjamin (1992) for Java do not reject separation.

5.2. Market participation under transaction costs

Use of ICT services is rapidly growing in Afghanistan. Even though the telecommunication services coverage may differ throughout the country, roughly 82% of the households in the sample reported that they own at least one piece of ICT equipment (i.e. mobile phone, TV, Radio, and internet). On the other hand, the use of transportation assets is relatively more restricted among farm households as just under half of the households in the sample reported that they own transport equipment. We assume that the ownership or use of ICT and transport equipment is correlated with household unobservable characteristics that influence market participation decisions. Thus, the use of ICT equipment in our structural model could suffer from endogeneity due to the omitted variable bias. We allow ownership of ICT and transport equipment to be endogenous to control for such unobserved heterogeneity using a control function approach. Table 7 presents the results of the reduced form regressions from a Probit of the endogenous variables on the instrumental variables (IVs) conditional on other covariates. The first column presents the reduced form results for ICT equipment and the second column the results for transport equipment. All estimates in Table 7 are Average Partial Effects (APE), with standard errors in parentheses, controlling for provincial fixed effects and standard errors are clustered at the FE level.

All instrumental variables (indicated by the star sign in Table 7) have the expected significant impact on the endogenous variables. They satisfy the orthogonality conditions, implying that IVs are directly and significantly correlated with the endogenous variables but affect dependent variables in the structural models only through the inclusion of the endogenous variables and the computed generalized residuals from the reduced form. Thus, they are not directly in the estimation of our structural equations. Recall that in the Control Function (CF) approach, the analysis involves the estimation of the generalized residuals from the reduced form which are then included in the estimation of structural equations. It is plausible to believe that any leftover endogeneity after using the CF approach will be uncorrelated with the other covariates in the structural model (Ricker-Gilbert et al., 2011).

The APE associated with the access to electricity IV could be interpreted to mean that a shift of 1 (from having no access to having access to electricity) increases the probability to use ICT equipment by about 6 percentage points. An increase of 10,000 Afghani in the off-farm income of other farmers in the community (a proxy for off-farm employment opportunities) is associated with an increase of 0.4 percentage points in ICT use, a very small effect, given that over 80% own ICT.

Table 7: Average Partial Effects (APE) from the Reduced form estimation of endogenous variables (Ownership of ICT and transport equipment)

VARIABLES	*ICT equipment (1=own, 0=otherwise)*	*Transport equipment (1=own, 0= otherwise)*
*Electricity (1=access, 0 otherwise) **	*0.057****	-
	(0.017)	-
*Road/bridge Project (yes=1, 0 otherwise) **	-	*0.033***
	-	*(0.014)*
*Neighbour off-farm income (10K AFN) **	*0.004***	*0.003***
	(0.002)	*(0.001)*
Time taken to reach market (1-4 hours)	*0.004*	*0.005*
	(0.011)	*(0.020)*
Time taken to reach market (<1 hour)	*0.032****	*0.038*
	(0.011)	*(0.025)*
Log. distance to road (km)	*-0.009**	*-0.017*
	(0.005)	*(0.014)*
Log. off-farm income (AFN)	*0.004****	*0.006****
	(0.001)	*(0.001)*
Log. total land (Jeribs)	*0.036****	*0.061****
	(0.007)	*(0.009)*
Log. HH size (persons)	*0.060****	*0.128****
	(0.010)	*(0.011)*
HH head literacy (1=can read & write)	*0.061****	*0.085****
	(0.009)	*(0.018)*
Log. HH head education (years)	*0.018****	*0.009*
	(0.005)	*(0.008)*
Log. HH head age (years)	*0.069***	*-0.011*
	(0.001)	*(0.002)*
HH head age squared	*-2e-5***	*--8.4e-06*
	(0.000)	*(0.000)*
Log. livestock (number)	*0.007***	*0.025****
	(0.003)	*(0.005)*
*Log. electricity cost (AFN)**	*0.007****	-
	(0.002)	-
Wave 2 (2013/14)	*-0.067****	*-0.005*
	(0.016)	*(0.031)*
Wave 3 (2016/17)	*-0.018*	*0.019*
	(0.018)	*(0.031)*
Province FE	*yes*	*yes*
Pseudo R-square	*0.210*	*0.234*
Observations	*19,042*	*19,042*

*Note: Omitted categories for factor variables are: no access to electricity, no road/bridge rehabilitation/recondition projects in the community for road/bridge projects, cannot read & write for literacy, more than 4 hours for time taken to reach the nearest permanent market, and 2011/12 for wave. Provincial fixed effects are included in the regression to control for regional variation. Significance is indicated by *** p<0.01, ** p<0.05, * p<0.1 and robust standard errors in parentheses. Variables labelled with stars indicate that they are instrumental variables.*

Households in communities where road or bridge reconstruction and rehabilitation projects were implemented appear more likely to own transportation equipment: construction or rehabilitation projects within the last 12 months in the community increase the probability of owning transport assets by 3.3 percentage points. Improved roads and bridges are likely to improve access and increase the benefits of owning transport equipment. An increase of 10,000 Afghani in the off-farm income of other farmers in the community has a much smaller effect, associated with a 0.3 percentage points increase in probability. Other standard variables that are statically significant have the expected effect on the ownership or use of ICT and transport equipment.

Farm households living in communities less than one hour drive from the market are more likely to have ICT equipment. The APE associated with wave 2 (year 2013/14) is negative and significant, perhaps due to the differences in the coverage of the survey (some districts or communities surveyed in one year are left out of the survey in other years).

Results of the structural equations estimated by the Lognormal Double Hurdle (LDH) model, with a Probit of the decision to participate in input markets and a truncated regression for the extent of expenditures, are reported in Tables 8 for participation in hired labour markets and Table 9 for fertilizers and chemicals, and tractor rental markets. Column 1 of Table 8 reports non-instrumental variable estimation of hired labour while column two reports instrumental variable estimation of the hired labour with endogenous transaction costs. The estimated APE of the explanatory variables from the first hurdle of LDH model presents the probability of participation in the hired labour markets (Table 8) and fertilizer and chemicals, tractor rental (Table 9) respectively. The estimated conditional APE of explanatory variables from the second hurdle of the LDH model present the marginal effects of the explanatory variables for the extent of expenditures on hired labour (Table 8), fertilizers and chemicals, and tractor hire (Table 9) respectively, given a strictly positive participation in the input markets.

Given the dependent variable in the first tier (Probit) is binary, the APE for the log-transformed variables is interpreted as a change of 1 in the log of the independent variables is associated with an increase/decrease of the dependent variable equivalent to the estimated average partial effects, whereas for discreet variables APE measure percentage changes in the dependent variable when the variable shifts from zero to one, ceteris paribus. Because the dependent variable in the second hurdle is in logarithmic form, the conditional APE can be interpreted as elasticities for log-transformed continuous variables when participation in the input market is strictly positive, whereas for discreet variable the APE measure percentage changes in the dependent variable when they shift from 0 to 1, ceteris paribus.

Endogeneity is detected if the generalized residuals are statistically significant in the structural regressions (presented in Table 8 and 9). The estimates on the generalized residuals for both ICT and transport equipment turn out to be negative and significant for participation in fertilizer and chemical markets, confirming that both are endogenous. The negative sign on the generalized residual implies that error terms of the two models (reduced form and structural) are negatively correlated with each other. This implies that the unobserved factors captured by the generalized residuals increase the probability of owning ICT and transport equipment but reduce the probability of participation in the market. Similarly, with a negative and significant estimate of the generalized residual for ICT, endogeneity of ICT is detected for the probability of hiring tractor. However, endogeneity was not detected in the regression analysing the probability of households participating in the labour market, we therefore treat our non-IV estimates for the hired labour (Table 8) as our primary results to avoid concerns that performing IV estimation may inflate the asymptotic variance of the estimator when endogeneity is not detected as stated in Wooldridge (2002) and Tadesse and Bahiigwa (2015).

Since the reduced form Probit is a nonlinear model, we are unaware of any methods to test for the strength of IVs in this context. Following Ricker-Gilbert et al., (2011), Liverpool-Tasie (2014), and Amankwah et al., (2016) we rely on the partial correlation between the IVs and the endogenous variables in our reduced form model. All the IV's are significant at 5% implying they are partially correlated with the endogenous variable of ICT transport equipment. It is, as discussed in Section 2.4 (under estimation strategy), unlikely to be directly correlated with our dependent variables in the structural models. Controlling directly for household characteristics and district fixed effects in our structural models, we believe the only remaining pathway that the instruments (household access to electricity, implementation of road and bridge construction/rehabilitation projects and off-farm income of other farmers in the community) can affect participation in the market is through the channel of IVs. Thus, we feel confident that the instruments are exogenous in the structural model and their strong partial correlation with the endogenous variable reveal their strength.

The results in Table 8 and 9 reveal that household's possession of the ICT equipment (i.e. mobile phone, TV, radio, and internet services) significantly increases the likelihood of hiring labour, purchasing fertilizers and chemicals, and hiring tractor by 3.3, 22 and 21 percentage points respectively suggesting that the ownership of ICT as a fixed transaction cost helps facilitate entry in markets by providing new and timely information that can reduce search and information costs. Search and information costs are often considered to be fixed transaction costs that influence market entry decisions (Goetz, 1992; Alene et al., 2008; Omiti et al., 2009). Similar findings are also observed by Randela et al., (2008) who concluded that the more information on marketing available to households, the lower are transaction costs hence a higher rate of market participation. Chowdhury (2006) finds a strong connection between household use of mobile phones and their marketing decisions and suggests that a reduction in information cost in the form of access to a telephone may change the functioning of markets and market participation. On the contrary, Alene et al., (2008) and Ouma et al., (2010) found that access to communication assets have positive but insignificant effects on market participation in Kenya and Central Africa (Rwanda and Burundi) and argued that communication assets are perhaps less useful in facilitating transactions if there is no viable market information service. In assessing the impact of mobile phones on farmers' marketing decisions in Ethiopia, Tadesse and Bahiigwa (2015) find mixed results; ownership of mobile phones may be useful for certain farmers in making marketing decisions in some circumstances, while in other areas mobile phones do not seem to be an important channel to access price information

Table 8: Factors influencing household participation and extent of expenditures: hired labour

	Non-IV estimation		*IV estimation*	
	Hurdle 1: Probit (1=use, 0=otherwise)	*Hurdle 2: Truncated reg Log. Expenditures*	*Hurdle 1: Probit (1=hire, 0=otherwise)*	*Hurdle 2: Truncated reg Log. Expenditures*
VARIABLES	*APE*	*APE (conditional on y>0)*	*APE*	*APE (conditional on y>0)*
Generalized Residuals (ICT)	-	-	*0.015*	-
			-0.028	
Generalized Residuals (TE)	-	-	*-0.064*	-
			(0.044)	
ICT equipment (1=own)	*0.033****	-	*0.007*	-
	-0.01		*(0.050)*	
Transport assets (1=own)	*0.044****	-	*0.147***	-
	-0.007		*(0.068)*	
Log. distance to road (km)	*-0.006*	*-0.022*	*-0.005*	*-0.022*
	-0.007	*-0.023*	*(0.007)*	*(0.023)*
Time to market (1-4h)	*0.020*	*-0.069*	*0.021*	*-0.069*
	-0.018	*-0.066*	*(0.018)*	*(0.066)*
Time to market (<1h)	*0.037***	*0.013*	*0.034***	*0.013*
	-0.016	*-0.049*	*(0.017)*	*(0.049)*
Log. total land (Jeribs)	*0.066****	*0.444****	*0.060****	*0.444****
	-0.006	*-0.024*	*(0.009)*	*(0.024)*
Log. off-farm income (AFN)	*0.004****	*-0.011****	*0.003****	*-0.011****
	-0.001	*-0.003*	*(0.001)*	*(0.003)*
Log. household size (count)	*-0.031****	*0.164****	*-0.044****	*0.164****
	-0.009	*-0.032*	*(0.013)*	*(0.032)*
HH head literacy(1=literate)	*0.037****	*-0.072*	*0.029***	*-0.072*
	-0.011	*-0.044*	*(0.014)*	*(0.044)*
Log. head education (yrs)	*0.011***	*0.051***	*0.010**	*0.051***
	-0.005	*-0.021*	*(0.005)*	*(0.021)*
Land type (1=all irrigated)	*0.023**	*0.226****	*0.023**	*0.226****
	-0.012	*-0.043*	*(0.012)*	*(0.043)*
Landscape 2 (valleys)	*-0.025*	*-0.063*	*-0.024*	*-0.063*
	-0.019	*-0.056*	*(0.019)*	*(0.056)*
Landscape 3 (open plain)	*0.008*	*-0.052*	*0.008*	*-0.052*
	-0.014	*-0.049*	*(0.014)*	*(0.049)*
Log. No of livestock (N)	*-0.003*	*0.019*	*-0.006*	*0.019*
	-0.004	*-0.014*	*(0.004)*	*(0.014)*
Oxen (binary, 1=own)	*-0.011*	*0.046*	*-0.011*	*0.046*
	-0.012	*-0.033*	*(0.012)*	*(0.033)*
Log. tractor/threshers (N)	*0.038*	*0.298****	*0.039*	*0.298****
	-0.027	*-0.103*	*(0.027)*	*(0.103)*
Wave 2 (2013/14)	*-0.129****	*0.057*	*-0.129****	*0.057*
	-0.016	*-0.064*	*(0.016)*	*(0.064)*
Wave 3 (2016/17)	*-0.109****	*0.356****	*-0.112****	*0.356****
	-0.018	*-0.058*	*(0.018)*	*(0.058)*
District FE	✓	✓	✓	✓
Pseudo R-Square	*0.236*	-	*0.236*	-
Observations	*20,436*	*5,334*	*20,436*	*5,334*

*Notes: Omitted categories for factor variables are: no access to ICT and transport equipment, more than 4 hours for time taken to reach market, irrigated and rain-fed combined for land quality, cannot read and write for HH head literacy, hills and valleys for landscape, and 2011/12 for wave. All regressions are controlled for district FE. Standard errors (in parenthesis) are clustered in districts and significance is indicated by *** p<0.01, ** p<0.05, * p<0.1.*

Table 9: Factors influencing household participation and extent of expenditures: fertilizer and chemicals, and tractor rental

	Fertilizer & chemicals		*Tractor Hire*	
	Hurdle 1: Probit	*Hurdle 2: Truncated reg*	*Hurdle 1: Probit*	*Hurdle 2: Truncated reg*
	(1=use, 0 otherwise)	*Log. Expenditures*	*(1=use, 0 otherwise)*	*Log. Expenditures*
VARIABLES	*APE*	*APE (conditional on y>0)*	*APE*	*APE (conditional on y>0)*
Generalized Residuals (ICT)	*-0.083***	*-*	*-0.110****	*-*
	(0.033)		*(0.031)*	
Generalized Residuals (TE)	*-0.068**	*-*	*0.045*	*-*
	(0.035)		*(0.040)*	
ICT equipment (1=own)	*0.224****	*-*	*0.214****	*-*
	(0.070)		*(0.059)*	
Transport assets (1=own)	*0.140***	*-*	*-0.031*	*-*
	(0.057)		*(0.065)*	
Log. distance to road (km)	*0.005*	*-0.063****	*-0.021****	*0.003*
	(0.007)	*(0.017)*	*(0.006)*	*(0.014)*
Time to market (1-4h)	*0.002*	*-0.059*	*0.008*	*0.129****
	(0.019)	*(0.051)*	*(0.019)*	*(0.038)*
Time to market (<1h)	*0.015*	*-0.05*	*0.065****	*0.056*
	(0.015)	*(0.049)*	*(0.018)*	*(0.037)*
Log. total land (Jeribs)	*0.036****	*0.538****	*0.080****	*0.600****
	(0.008)	*(0.023)*	*(0.009)*	*(0.022)*
Log. off-farm income (AFN)	*-0.003****	*-0.016****	*-0.003****	*-0.008****
	(0.001)	*(0.002)*	*(0.001)*	*(0.002)*
Log. household size (count)	*0.003*	*0.142****	*-0.009*	*0.123****
	(0.012)	*(0.023)*	*(0.011)*	*(0.021)*
HH head literacy(1=yes)	*-0.003*	*0.044*	*0.004*	*0.065****
	(0.012)	*(0.028)*	*(0.012)*	*(0.025)*
Log head education (yrs)	*0.005*	*0.013*	*0.010***	*-0.02*
	(0.005)	*(0.014)*	*(0.005)*	*(0.013)*
Land type (1=all irrigated)	*0.168****	*0.413****	*0.045***	*0.096****
	(0.018)	*(0.045)*	*(0.018)*	*(0.032)*
Landscape 2 (valleys)	*-0.002*	*0.035*	*0.004*	*-0.008*
	(0.017)	*(0.034)*	*(0.019)*	*(0.041)*
Landscape 3 (open plain)	*0.0314**	*0.128****	*0.103****	*0.022*
	(0.017)	*(0.037)*	*(0.022)*	*(0.031)*
Log. No of livestock (N)	*0.007**	*0.002*	*0.003*	*0.003*
	(0.004)	*(0.010)*	*(0.005)*	*(0.010)*
Oxen (binary,1=own)	*0.036****	*0.120****	*-0.141****	*-0.090****
	(0.010)	*(0.030)*	*(0.017)*	*(0.033)*
Log. tractor/threshers (N)	*-0.043*	*0.355****	*-0.192****	*0.126***
	(0.031)	*(0.059)*	*(0.039)*	*(0.054)*
Wave 2 (2013/14)	*0.011*	*0.222****	*-0.012*	*0.224****
	(0.019)	*(0.045)*	*(0.015)*	*(0.047)*
Wave 3 (2016/17)	*0.031***	*0.278****	*-0.041***	*0.237****
	(0.015)	*(0.045)*	*(0.016)*	*(0.040)*
District FE	✓	✓	✓	✓
Pseudo R-Square	*0.394*	.	*0.401*	.
Observations	*19,042*	*13,133*	*19,443*	*11,079*

*Notes: Omitted categories for factor variables are: no access to ICT and transport equipment, more than 4 hours for time taken to reach market, irrigated and rain-fed combined for land quality, cannot read and write for HH head literacy, hills and valleys for landscape, and 2011/12 for wave. All regressions are controlled for district FE. Standard errors (in parenthesis) are clustered in districts and significance is indicated by *** p<0.01, ** p<0.05, * p<0.1.*

The likelihood of households to hire labour increases with ownership of transport equipment by 4.4 percentage points (Table 8). Perhaps own transport provides cheaper opportunity to farm household to pick labourers from the market or district centres and transport them to their farms Similarly, ownership of transport equipment is associated with a higher propensity of market participation in hire labour and fertilizer and chemicals market. Similarly, a shift from no transport equipment to owning transport equipment increases the likelihood of hiring labour and fertilizers and chemicals use by 14 percentage points (Table 9). Household endowments of transport assets mitigate transportation, communication and information costs (i.e. own transport equipment is maybe more cost effective compared to public transport) and reduce obstacles to entering the market (Goetz, 1992; Key et al., 2000). Our findings agree with those of Alene et al., (2008) who found significant impact of transport assets on the probability of fertilizer use in Kenya. In contrast, ownership of transport equipment was found to have no significant impact on the probability of hiring a tractor (Table 9). This is a plausible conclusion as hiring tractor by households may not require the use of any other means of transport. We find no significance impact of owning transport equipment on tractor hire.

Even though higher transportation costs due to poor accessibility associated with larger distance of farms from the nearest all-season roads does not significantly affect the probability of household's participation in the chemical and fertilizer market, a 1% increase in distance to roads would reduce expenditures on fertilizers and chemicals by 0.06%. An increase of 1 in the log of distance to road (equivalent to an increase of 172%[8]) decreases the probability of households to hire tractors by 2.1 percent points (Table 9), holding all other variables constant. Remoteness from the roads appears to have no significant impact on labour hire in both stages (probability and expenditures). Distance from the roads may not largely vary within the districts, so controlling for district fixed effect may possibly render this variable insignificant in the case of some inputs. Most studies assessing farm marketing decisions established a negative relationship between poor road accessibility and market participation and extent of use (Ricker-Gilbert et al., 2011; Winter-Nelson and Temu, 2005).

While time taken to reach the nearest market turns out to have no significant impact on the probability of households to participate in the fertilizer and chemical markets and expenditures, a decrease in time taken to reach the nearest permanent market significantly increases the probability of households to hire labour and tractor for farming activities (by about three and seven percent respectively for closest households i.e. farms located within one or less than hours to the market). While shorter distance from the market may increase the probability and expenditures on input, there is a possibility that households located in rural areas further from the market may have larger landholdings, and therefore use more inputs. Thus, it is plausible to expect the insignificant relationship between time taken to

[8] A unit increase in log of distance to road (log of distance to road) corresponds to multiplying the land by e ≅ 2.71828, therefore the absolute change in distance to road is 2.71828, thus the net difference simplifies to 1.71828. Putting that in percentage terms, it's is about 172% increase in the distance to road variable.

market and market participation particularly in the case of fertilizers and chemicals. In addition, most local markets are located in the district centres, and since we control for district fixed effects in our regressions, there is a possibility that district level variables (such as time taken to reach market) may become insignificant. These results are consistent with Ouma et al., (2010) and Liverpool-Tasie (2014) who found negative relationship ship between time taken to reach market and market participation reinforcing the argument that poor markets access for farm households that in remote areas raises costs associated with marketing and information.

Estimated APE's and significance of the landholding size are similar for all inputs, that is larger household land endowment is associated with higher probability of the input use and expenditures for each of the three inputs. An increase of 1 in the log of land (equivalent to an increase of 172%) increases the probability of market participation by 6.6, 3.6, and 7.9 percent points in hired labour, fertilizer and chemicals, and tractor rental markets respectively, holding all other variables constant. The elasticity associated with the land variable in the second hurdle (extent of expenditures) indicate that a 1% increase in land raises expenditures by 0.44%, 0.54%, and 0.60% on hiring labour, chemical and fertilizers, and tractor hire respectively. Our conclusions that land size is associated with the use of higher input usage is consistent with most of the studies literature that assed household marketing decisions (Liverpool-Tasie, 2014; Mather et al., 2013; Ricker-Gilbert et al., 2011).

A negative and statistically significant relationship is observed between off-farm income and the probability of market participation and extent of expenditures for all three input markets. A unit increase in the log of off-farm income is associated with a decrease of 0.4, and 0.3 percentage points in the probability of participation labour and fertilizers and chemicals, and tractor rental markets respectively. Similarly, a 1% increase in off-farm income decreases expenditures on hiring labour, chemicals and fertilizers, and renting tractor for farming activities by 1.1%, 1.6%, and 0.8% respectively. Our findings of negative impact of non-farm income on market participation contradicts with those of Alene et al., (2008) in Kenya, however Verkaart et al., (2017) and Makhura (2001) find similar results to ours. Winter-Nelson and Temu (2005) found no significant impact of non-farm income on input use in Tanzania. Households with lager off-farm income may divert resources such as labour to off-farm income to diversify employment risks and thus reduces reliance on farm activities (Ahmadzai, 2017; Mishra et al., 2004). Rao and Qaim (2013) finds that household with employment outside farming sector significantly reduces the quantity of hired labour.

Except for labour hire, household size was found to have no significant effect on the probability of participation in the input markets. The probability to hire labour is decreasing in family size, suggesting that households with a larger endowment rely largely on their own labour. A change of one in the log of the household size reduces the likelihood of 3.1 percentage points. Though household size is insignificant determinant for the entry in fertilizers and tractor markets, larger households significantly spend more on inputs than smaller households (Table 8 and 9). A 1% increase in household size is associated with 0.16%, 0.14%, and 0.12% increase in expenditures on hiring labour, fertilizer and chemicals, tractor rental, and labour hire respectively. The positive and significant marginal effect of household size may imply that larger families own larger farmers and consume more, thus purchasing more inputs from the markets. Our findings that household size increases the use of inputs are in conformity with Abdullah et al., (2017) but Rao and Qaim (2013) find no significant impact of household size on the likelihood of household to hire, but find a positive and significant relationship between household size and the quantity of hired labour.

Other standard household socio-demographic and socio-economic characteristics were also found to have the expected influence on market participation and input expenditures. While age is not an important factor, household head education and literacy were found to have a significant positive influence on both the propensity of market participation and magnitude of expenditures in the case of some inputs. Our findings that education increases market participation match with those Randela et al., (2008), Martey et al., (2012) and, Liverpool-Tasie (2014).

Land characteristics such as the type and landscape are important determinants of both the decision to purchase inputs and the amount of spending on inputs. Households operating all irrigated land (relative to households that own a combination of both irrigated and rain-fed land) purchase substantially more inputs from the market and spend more money on inputs. Farmers are likely to grow different crops depending on their water requirements (some crops may require more irrigation than others that may not be planted in rain-fed lands) and therefore this limitation may cause the need for input usage to decline. Farmers purchase more inputs if they own flat or plains land as compared to farmers on slopes (i.e. hills and valleys). Altitude and slopes of the farm land affect physical conditions of the farm land and therefore may limit the application some inputs, for instance, it may not be technically feasible to use tractor in farms farm land with greater slope.

A positive and statistically significant relationship is observed between the ownership of livestock at the farm and the probability of fertilizer and chemical use, consistent with Liverpool-Tasie (2014), but is insignificant for other inputs. While ownership of oxen increases likelihood of use and expenditures on fertilizer and chemicals, it significantly reduces the probability of households to hire tractor by 14 percentage points. In addition, a 1% increase in the number of oxen owned by the farm households reduces the expenditures associated tractor rental by about 9%. This large negative effect of oxen ownership on tractor rental could be due the fact that households use oxen for farm activities such as ploughing as a substitute to tractor and therefore reduces the need to hire tractor.

Ownership of tractors/threshers by household significantly decreases the likelihood of hiring tractors but have no significant impact on the propensity to use fertilizers and chemicals or hire labour. This is not unusual as households that own tractors may not need to hire tractors. However, households that have tractors/threshers spend significantly more on all three inputs. While this is plausible for use of fertilizers/chemicals and hired labour, as such farms may be more commercial, the association with expenditure on tractor hire is difficult to explain other than as a peculiarity in the data.

In general, the time fixed effects in the model reveal lower probability of participation (except for fertilizers and chemicals) and significantly higher spending on inputs in the recent survey years. Given that we use a repeated cross-sectional survey where each farm is observed only once, it is difficult to comment on the magnitude and trend of input use over time, it is plausible to assume that this could simply be as a result of fluctuations in the inflation.

5.3. Robustness and specification tests

We carried out a number of specification tests to ensure that the statistical model is appropriately chosen to best fit our data. The most widely used statistical models for censored data are independent double hurdle and the standard tobit models which is nested in the double hurdle model. For this reasons, we first test Cragg type independent double hurdle truncated normal model against standard tobit using a Log-Likelihood Ratio (LR) by Greene (2002):

$$LR - Test\ Statistic = -2[\ln L_T - (\ln L_P + \ln L_{TR})]$$

Where L_T is the likelihood for the Tobit model under the null hypothesis, L_P is the likelihood for the Probit model, and L_{TR} is the likelihood for the truncated regression model. With independent error terms, the log-likelihood of the truncated Cragg type double hurdle model is equivalent to the sum of the log-likelihoods of the Probit and the truncated regressions (Rao and Qaim, 2013). The computed statistics of the log-likelihood ratio test for each of the three inputs reject the null hypothesis at 1% significance indicating that Cragg type double hurdle model is strictly preferred to the restricted tobit model (Table 10).

Next, we use Vuong's closeness test for non-nested or non-overlapping models to distinguish between the truncated normal double hurdle model and a log-normal hurdle[9] model. Because truncated normal and lognormal hurdle models are non-nested models (Hsu and Liu, 2008), we use the Vuong (1989)) test for non-nested models to evaluate which model provides a closer representation of the data. Vuong's test is a likelihood-ratio-based test that compares non-nested models in terms of the difference in their respective Kullback-Leibler (KL) distance from the (unknown) "true" model. Suppose the KL distance between two competing models is:

$$LR(A, B) = Log\ L(A) - Log\ L(B)$$

[9] Lognormal hurdle does not nest standard tobit model by construction, therefore we can't test lognormal model against standard tobit. We therefore use a likelihood ratio test to first test truncated normal hurdle mode against standard tobit.

The null hypothesis suggests that there is no difference between the two models. The test statistic is calculated as:

$$Z = \frac{LR(A, B)}{\sqrt{n}\ \omega}$$

where ω denotes the variance of pointwise log-likelihood ratio, and n is the sample size. Large positive (negative) values of the computed test statistics are taken as evidence in favour of model A[10].

Table 10: Robustness checks: Diagnostic/specification tests for model selection

Log likelihood-ratio test for nested models: Truncated-normal DH vs Tobit				
H0: Nested model (Tobit) Specification is valid				
H1: Double Hurdle specification is valid				
Input market	Test Stat	Critical value	P-value	Decision
Fertilizer & chemicals	16,996.16	$\chi 2$ (0.05, 310) =352.06	0.000	Reject H0, DH model is valid
Tractor rental	11,703.96	$\chi 2$ (0.05, 333) =376.55	0.000	Reject H0, DH model is valid
Labour hire	5,180.13	$\chi 2$ (0.05, 360) =405.24	0.000	Reject H0, DH model is valid
Vuong's (1989) closeness test for non-nested models: Truncated-normal DH vs LDH				
H0: Truncated-normal and Lognormal hurdle models offer an equivalent representation of the data				
H1: Lognormal double hurdle model is closer				
Input market	Ln Ratio	se	p-value	Decision
Fertilizer & chemicals	5.706	0.029	0.000	LDH is closer
Tractor rental	4.648	0.030	0.000	LDH is closer
Labour hire	1.918	0.023	0.000	LDH is closer
Vuong's (1989) closeness test for non-nested models: Sample selection vs LDH				
H0: Sample selection and lognormal hurdle models offer an equivalent representation of the data				
H1: Lognormal hurdle model is closer				
Fertilizer & chemicals	0.443	0.002	0.000	LDH is closer
Tractor rental	0.561	0.004	0.000	LDH is closer
Labour hire	0.149	0.002	0.000	LDH is closer

Based on the non-nested LR test procedure of Vuong, the computed statistics for each of the three inputs reject the null hypothesis that both truncated normal and lognormal hurdle models are an equally good fit for the data and indicates that the lognormal hurdle model is the closest true model. Even though the computed Vuong's statistics are not as large when testing the lognormal hurdle model against the sample selection model, they are significant and indicative[11]. The specification tests therefore

[10] When testing lognormal DH against truncated-normal hurdle, our model A is the lognormal and B is the truncated normal hurdle. When testing lognormal hurdle against sample selection model, our model A is the lognormal hurdle and model B is the sample selection specification.

[11] We also estimated a sample selection model (results are presented in Table A4 in the appendix). The results are largely similar to those of our main results presented in Table (8) and (9).

reveal that Cragg type truncated normal two-step specification is preferred to the standard tobit, and lognormal hurdle is preferred to the Cragg type truncated normal model and sample selection model (Table 10).

5.4. Conclusions and Discussion

We test for market failures by testing the hypothesis of separation in the household demand model for the farm labour. Our estimates of the household labour demand show that household's production and consumption decisions are not separable from each other which suggests evidence for the existence of potential market failures in Afghanistan. In theory, under complete and competitive markets separation holds. This implies that household production and consumption decisions are independent of each other and farm households act as profit maximizers such that households first aim to maximize production, and then make consumption decisions conditional on the profits and income from production. On the contrary, the farm households face imperfections if production and consumptions decisions are non-separable (i.e. labour allocations in production are significantly affected by the household preference shifters such as endowments of labour). Thus, the rejection of separation therefore implies that household labour demand is strongly influenced by its endowment of own labour (i.e. household size) which could therefore be interpreted to mean that there exist potential market failures.

Given the evidence for market failures, we then look at whether improving market access by reducing transaction costs would improve farmer's market participation as a potential strategy to address market failures. The results have revealed that transaction costs are important determinants of smallholder participation in the input markets. Ownership of ICT and transport assets by farm households reduces search and information cost and therefore significantly increase the probability of participation in input markets. Farmers with better access to markets and roads are also more likely to participate in input markets. Moreover, farmers living in communities with better road access and density and within a close radius of markets, were found to spend more on inputs. The significant impact of both fixed and proportional transaction costs in this study reveals that the existence of high transactions costs could lead to a lower use of inputs and in some instances could force remote peasant smallholders to opt for self-sufficiency instead of market participation.

Standard factors such as household socio-demographic and socio-economic factors were also observed to have an important influence on household marketing decisions. Household size, literacy and education level, land endowments, off-farm income, and ownership of farming assets such as tractors, oxen and the number of livestock at the farm are among important determinants of household's decisions to participate in market and extent of expenditures. Characteristics of farms such as the type of land and landscape were also found to have implications for market decisions.

Given that the ownership or use of ICT and transport assets by households could be associated with the household unobserved factors we allow these variables to be endogenous. Using instrumental variables through a Control Function (CF) approach, endogeneity was detected in the models analyzing household's decisions to participate in fertilizer and chemical and tractor rental markets. After correcting for the endogeneity bias due to these omitted variables, the result revealed a negative association between error terms in the reduced form and structural model (i.e. model analyzing household marketing decisions). We do not, however, observe endogeneity of the ICT and transport equipment in the model analyzing household's labour participation decisions, therefore we present non-instrumental variable estimates as our primary results for the labour to avoid concerns that performing IV estimation may inflate the asymptotic variance of the estimator when endogeneity is not detected. Moreover, we check the robustness of our statistical models to ensure our econometric specifications best fit our data, our tests supported the choice of a log-normal double hurdle model to best fit the data.

This study provides hints on the critical implication of transaction costs on market participation. One area of policy intervention that can be suggested from the findings of this study is that future policies geared towards agriculture commercialization should involve providing viable and timely information on market prices, technical advantages of using modern inputs and other important information through media, so that farmers communication assets are effectively used in accessing market information. This is particularly important as communication assets are maybe less useful in facilitating transactions if there is no viable market information service available through public or private media. Other means such as publishing price information through local newspapers may also help facilitate access to markets and mitigate search costs.

In general, a market-oriented agriculture policy would help improve farmers market participation by improving access to market information, facilitating transportation, addressing institutional weaknesses, and improve public and commercial input distribution systems. Improved access to agriculture extension services particularly in remote areas to assist farmers understand the advantages of using modern agriculture inputs and providing best practices may also enhance factor market participation. Collective action through cooperatives and farmer organizations may also enable famers, particularly resource-poor farmers, to share their resources, achieve economies of scale and increase efficiencies in accessing local markets. Another possible approach could be contract farming to ensure surplus production is sold to the market and farmers gain sufficient cash money to purchase inputs from the market. Contract farming, in some cases, can also help farmers to trade some of their surplus production for agriculture inputs that can be used in the next planting seasons. Another general recommendation is that future government policy instruments that aim to incentivize Investment in rural infrastructure development such as roads, transportation facilities, and other means to stabilize input supply chain and distribution systems can also improve market participation and avert some of the negative consequences due to market imperfections or failures.

As the findings of this study suggest that there exist potential market failures, it is critical to notice that the theoretically-grounded test carried out in this study to test separation relies on the labor market transactions and therefore it is difficult to conclude which specific input markets may actually fail. In order to better understand and address the perceived market failures, further research is required to identify precisely the drivers and sources of market failures and the specific markets that are failing.

As transaction costs are "hidden" and in many instances not directly observed, and therefore most studies including this study use proxy measures to assess their impact on the household marketing decisions. One potential area to improve this research is to collect better data on transactions to help in quantifying the actual transaction costs incurred such as search, information, transport, other costs related to bargaining and contract enforcement.

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Appendix

Table A 1: Detailed summary statistics for individual year and pooled sample

	2011/12				2013/14				2016/17				Pooled			
VARIABLES	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max
Fertilizer & chemical (1=use)	0.702	0.457	0.000	1.00	0.731	0.443	0.00	1.00	0.723	0.448	0.00	1.00	0.717	0.450	0.00	1.00
Tractor (1=hire)	0.560	0.496	0.000	1.00	0.579	0.494	0.00	1.00	0.542	0.498	0.00	1.00	0.561	0.496	0.00	1.00
Labour (1=hire)	0.323	0.468	0.000	1.00	0.194	0.396	0.00	1.00	0.217	0.412	0.00	1.00	0.253	0.435	0.00	1.00
Fertilizer expense (1,000 AFN)	3.246	5.029	0.000	80.00	5.324	9.880	0.00	129.0	5.043	8.661	0.00	150.0	4.399	7.933	0.00	150.0
Tractor rental (1,000 AFN)	1.974	3.455	0.000	60.00	2.688	5.354	0.00	98.00	2.515	4.880	0.00	99.00	2.350	4.542	0.00	99.00
Labour expense (1,000 AFN)	0.944	2.759	0.000	80.00	0.672	2.474	0.00	50.00	1.027	3.714	0.00	80.00	0.877	2.966	0.00	80.00
Total labour (days)	14.60	13.90	0.400	341.0	13.15	14.69	0.08	490.0	13.92	15.78	0.39	319	13.95	14.69	0.08	490
Own labour (days)	11.83	8.950	1.000	105.0	11.30	11.09	1.00	490.0	10.68	7.35	1.00	70.0	11.35	9.323	1.00	490
Hire labour (days)	3.777	11.04	0.000	320.0	2.704	9.953	0.00	201.2	4.01	14.49	0.00	312	3.490	11.76	0.00	320
ICT equip (own=1)	0.826	0.379	0.000	1.00	0.813	0.390	0.00	1.000	0.845	0.362	0.00	1.00	0.827	0.378	0.00	1.00
Transport equip(own=1)	0.470	0.499	0.000	1.00	0.456	0.498	0.00	1.000	0.544	0.498	0.00	1.00	0.485	0.500	0.00	1.00
Distance to road (km)	3.420	6.613	0.000	75.0	2.527	9.052	0.00	100.0	1.284	5.559	0.00	98.0	2.561	7.310	0.00	100
Time to market (>4 hrs)	0.266	0.442	0.000	1.00	0.095	0.294	0.00	1.000	0.087	0.281	0.00	1.00	0.163	0.369	0.00	1.00
Time to market (1-4 hrs)	0.201	0.401	0.000	1.00	0.354	0.478	0.00	1.000	0.000	0.000	0.00	0.00	0.197	0.398	0.00	1.00
time to market (<1hrs)	0.533	0.499	0.000	1.00	0.550	0.497	0.00	1.000	0.913	0.281	0.00	1.000	0.640	0.480	0.00	1.00
Total land (Jeribs)	7.628	24.53	0.100	1,511	8.303	23.28	0.10	1,056	8.098	12.32	0.10	500	7.972	21.50	0.10	1,511
Off-farm inc. (10K AFN)	3.527	6.744	0.000	100	5.375	11.71	0.00	480.0	4.822	8.169	0.00	90.0	4.472	9.028	0.00	480
Livestock owned (N)	15.70	30.73	0.000	860	11.84	23.43	0.00	604.0	14.40	25.67	0.00	484	14.10	27.25	0.00	860
Oxen (own=1)	0.212	0.409	0.000	1.00	0.158	0.365	0.00	1.000	0.191	0.393	0.00	1.00	0.189	0.391	0.00	1.00
Tractor/threshers (N)	0.024	0.155	0.000	2.00	0.054	0.233	0.00	3.000	0.033	0.181	0.00	2.00	0.036	0.191	0.00	3.00
Land type (1=all irrigated)	0.711	0.453	0.000	1.00	0.767	0.423	0.00	1.000	0.686	0.464	0.00	1.00	0.723	0.448	0.00	1.00
HH size (count)	8.188	3.485	1.000	36.00	8.348	3.447	1.00	36.00	8.482	3.424	2.00	39.00	8.318	3.458	1.00	39.0
Prime male share	0.474	0.144	0.000	1.00	0.476	0.149	0.00	1.000	0.473	0.147	0.00	1.00	0.474	0.147	0.00	1.00
Prime female share	0.476	0.134	0.000	1.00	0.475	0.135	0.00	1.000	0.464	0.137	0.00	1.00	0.473	0.135	0.00	1.00
Elderly female share	0.017	0.063	0.000	1.00	0.018	0.063	0.00	0.500	0.025	0.072	0.00	0.50	0.020	0.066	0.00	1.00
Elderly male share	0.032	0.084	0.000	1.00	0.032	0.082	0.00	0.500	0.038	0.088	0.00	1.00	0.034	0.084	0.00	1.00
Head literacy (1=literate)	0.280	0.449	0.000	1.00	0.318	0.466	0.00	1.000	0.309	0.462	0.00	1.00	0.300	0.458	0.00	1.00
Head education (years)	1.942	4.030	0.000	19.0	2.202	4.285	0.00	19.00	2.224	4.218	0.00	19.00	2.101	4.166	0.00	19.00
Head age (years)	42.76	13.54	11.00	99.0	44.43	13.73	14.0	95.00	44.72	13.38	14.00	92.00	43.82	13.59	11.0	99.00
Head age square	2,012	1,281	121.0	9,801	2,162	1,316	196	9,025	2,179	1,282	196	8,464	2,105	1,295	121	9,801
Electricity cost (AFN)	70.44	233.9	0.000	6,000	87.97	291.7	0.00	6,000	61.77	251.5	0.00	8,000	73.81	258.7	0.00	8,000
Electricity (1=access)	0.543	0.498	0.000	1.00	0.824	0.381	0.00	1.000	0.949	0.220	0.00	1.00	0.742	0.437	0.00	1.00
Road/bridge project (1=yes)	0.265	0.441	0.000	1.00	0.258	0.437	0.00	1.000	0.175	0.380	0.00	1.00	0.238	0.426	0.00	1.00
Off-farm inc neighbours 10K AFN	4.692	4.394	0.000	51.56	6.440	5.675	0.00	88.47	5.908	5.456	0.00	34.44	5.583	5.184	0.00	88.47
Observations				8,663				6,876				5,650				21,189

Table A2: Pearson $\chi 2$ comparison test for selected HH characteristics by input type

VARIABLE		Non-users	Users	Full sample	Pearson chi2 (p-value)
Fertilizer and chemicals					
ICT equipment	Don't own	31.74	11.63	17.32	1,215.1***(0.000)
	Own	68.26	88.37	82.68	
Transport equipment	Don't own	56.91	49.34	51.48	98.74*** (0.000)
	Own	43.09	50.66	48.52	
Time taken to reach market	>4 hours	27.75	11.74	16.27	854.56*** (0.000)
	1-4 hours	19.92	19.65	19.72	
	<1 hour	52.34	68.61	64.01	
HH head literacy	Cannot read & write	76.14	67.56	69.99	150.68*** (0.000)
	can read & write	23.86	32.44	30.01	
Land type	Irrigated & rain-fed	60.63	14.75	27.73	4,513.60***(0.000)
	All irrigated	39.37	85.25	72.27	
Landscape	Hills and valleys	61.49	27.35	37.01	2,148*** (0.000)
	Valleys only	12.52	22.45	19.64	
	Open plain	25.99	50.20	43.35	
Oxen	Don't own	73.82	83.99	81.12	290.12*** (0.000)
	Own	26.18	16.01	18.88	
Tractor rental					
ICT equipment	Don't own	25.54	10.90	17.32	780.67*** (0.000)
	Own	74.46	89.10	82.68	
Transport equipment	Don't own	66.20	39.98	51.48	1,435.23***(0.000)
	Own	33.80	60.02	48.52	
Time taken to reach market	>4 hours	25.37	9.16	16.27	1,032.54***(0.000)
	1-4 hours	19.13	20.18	19.72	
	<1 hour	55.50	70.66	64.01	
HH head literacy	Cannot read & write	71.07	69.14	66.99	9.174*** (0.002)
	can read & write	28.93	30.86	30.01	
Land type	Irrigated & rain-fed	39.22	18.75	27.73	1,062.70***(0.000)
	All irrigated	60.73	81.25	72.27	
Landscape	Hills and valleys	57.46	21.03	37.01	3,844.11***(0.000)
	Valleys only	21.73	18.01	19.64	
	Open plain	20.81	60.95	43.35	
Oxen	Don't own	66.46	92.57	81.12	2.320.35***(0.000)
	Own	33.54	7.43	18.88	
Hired labour					
ICT equipment	Don't own	17.91	15.57	17.32	15.31*** (0.000)
	Own	82.09	84.43	82.68	
Transport equipment	Don't own	53.30	46.10	51.48	83.07*** (0.000)
	Own	46.70	53.90	48.52	
Time taken to reach market	>4 hours	16.81	14.66	16.27	46.04*** (0.000)
	1-4 hours	20.48	17.49	19.72	
	<1 hour	62.71	67.85	64.01	
HH head literacy	Cannot read & write	71.38	65.89	69.99	57.42*** (0.000)
	can read & write	28.62	34.11	30.01	
Land type	Irrigated & rain-fed	25.35	34.73	27.73	175.51*** (0.000)
	All irrigated	74.65	65.27	72.27	
Landscape	Hills and valleys	37.28	36.20	37.01	425.40 *** (0.000)
	Valleys only	22.58	10.97	19.64	
	Open plain	40.14	52.83	43.35	
Oxen	Don't own	81.39	80.32	81.12	2.95* (0.086)
	Own	18.61	19.68	18.88	

Source: Author's calculation of the ALCS Data

Table A 3: Estimation of labour demand with different sex-age demographic groups

VARIABLES	*(1)* *Model 3*	*(2)* *Model 3*	*(3)* *Model 3*
Log. HH size (persons)	*0.547****	*0.517****	*0.581****
	(0.022)	*(0.025)*	*(0.054)*
Share of males (15-19 years)	*1.028****	*1.045****	*1.047****
	(0.090)	*(0.092)*	*(0.092)*
Share of males (20-34 years)	*0.924****	*0.971****	*0.974****
	(0.085)	*(0.084)*	*(0.085)*
Share of males (35-49 years)	*1.013****	*1.019****	*1.015****
	(0.126)	*(0.122)*	*(0.123)*
Share of males (50-64 years)	*1.012****	*0.935****	*0.927****
	(0.116)	*(0.122)*	*(0.123)*
Share of male (65 years & older)	*1.042****	*0.869****	*0.857****
	(0.124)	*(0.145)*	*(0.147)*
Share of females (0-14 years)	*-0.078*	*-0.066*	*-0.069*
	(0.053)	*(0.050)*	*(0.050)*
Share of females (15-19 years)	*0.419****	*0.439****	*0.443****
	(0.081)	*(0.079)*	*(0.079)*
Share of females (20-34 years)	*0.568****	*0.566****	*0.568****
	(0.082)	*(0.082)*	*(0.082)*
Share of females (35-49 years)	*0.680****	*0.668****	*0.664****
	(0.094)	*(0.094)*	*(0.094)*
Share of females (50-64 years)	*0.412****	*0.390****	*0.384****
	(0.116)	*(0.111)*	*(0.110)*
Share of female (65 years & older)	*0.391***	*0.343***	*0.328***
	(0.166)	*(0.161)*	*(0.159)*
ICT equipment (access=1)		*0.081****	*0.043*
		(0.019)	*(0.068)*
Transport equipment (access=1)		*0.029**	*0.011*
		(0.016)	*(0.062)*
Time taken to reach nearest market (<1 hours)		*-0.066**	*-0.067*
		(0.035)	*(0.103)*
Time taken to reach nearest market (1-4 hours)		*-0.034*	*0.182***
		(0.031)	*(0.084)*
Log. Distance to road (km)		*-0.020**	*0.033*
		(0.011)	*(0.033)*
Log. Total land (Jeribs)		*0.195****	*0.195****
		(0.013)	*(0.014)*
Log off-farm income (AFN)		*-0.027****	*-0.027****
		(0.002)	*(0.002)*
HH head literacy (1=can read & write)		*-0.042**	*-0.042**
		(0.023)	*(0.022)*
Log. HH head education (years)		*0.002*	*0.002*
		(0.011)	*(0.011)*
HH head age (years)		*0.001*	*0.001*
		(0.001)	*(0.001)*
ICT equipment (access=1) # Log. HH size			*0.019*
			(0.035)
Transport equipment (access=1) # Log. HH size			*0.009*
			(0.030)
Time taken to market (<1h) # Log. HH size			*-0.0001*
			(0.051)

Table A3 continued

Time taken to market (1-4h) # Log HH size			*-0.107***
			(0.042)
Log. Distance to road # Log. HH size			*-0.026*
			(0.017)
Wave 2 (2013/14)		*-0.211****	*-0.210****
		(0.033)	*(0.033)*
Wave 3 (2016/17)		*-0.097****	*-0.098****
		(0.028)	*(0.028)*
District FE	*yes*	*yes*	*yes*
Constant	*1.096****	*1.079****	*0.966****
	(0.074)	*(0.072)*	*(0.112)*
F-test for joint significance of household size and demographic composition (all groups)			
F-test: t-statistic	*66.12*	*46.10*	*32.19*
F-test: p-value	*0.000*	*0.000*	*0.000*
R-squared	*0.217*	*0.265*	*0.265*
Observations	*21,189*	*21,189*	*21,189*

*Note: Dependent variable is the log of total labour days (own and hired) employed by the farm HH. Omitted categories for factor variables are: Share of males between 0-14 years old for the HH composition, no access to ICT and transport equipment, 4 and more hours for time taken to reach market, cannot read and write for HH literacy, and 2011/12 for wave. District fixed effects are included in all regressions. All standard errors are clustered at FE level (in parentheses). Significance is indicated by *** p<0.01, ** p<0.05, * p<0.1.*

Table A 4: Sample Selection model estimation of the input market participation and extent of expenditures

Selection Equation: Probit estimates of the input market participation decision						
	Fertilizer & chemicals		*Tractor hire*		*Labour hire*	
	(1=use, 0 otherwise)		*(1=hire, 0 otherwise)*		*(1=hire, 0 otherwise)*	
VARIABLES	*APE*	*SE*	*APE*	*SE*	*APE*	*SE*
Generalized residual (ICT)	*-0.064***	*(0.029)*	*-0.092****	*(0.030)*	*0.013*	*(0.028)*
Generalized residual (TE)	*-0.064**	*(0.034)*	*0.044*	*(0.039)*	*-0.060*	*(0.044)*
ICT equip (own=1)	*0.184****	*(0.061)*	*0.200****	*(0.056)*	*0.011*	*(0.050)*
TE equip (own=1)	*0.135***	*(0.057)*	*-0.032*	*(0.065)*	*0.141***	*(0.068)*
Log. distance road (km)	*0.005*	*(0.006)*	*-0.021****	*(0.006)*	*-0.005*	*(0.007)*
Time to market (<1hr)	*0.002*	*(0.019)*	*0.009*	*(0.019)*	*0.020*	*(0.018)*
Time to market (1-4h)	*0.015*	*(0.015)*	*0.068****	*(0.018)*	*0.034***	*(0.017)*
Log total land (Jerib)	*0.036****	*(0.008)*	*0.079****	*(0.009)*	*0.061****	*(0.008)*
Log off-farm inc. (AFN)	*-0.003****	*(0.001)*	*-0.003****	*(0.001)*	*0.003****	*(0.001)*
Log HH size (count)	*0.005*	*(0.012)*	*-0.007*	*(0.011)*	*-0.042****	*(0.013)*
Head literacy (1=literate)	*-0.004*	*(0.012)*	*0.005*	*(0.012)*	*0.028***	*(0.014)*
Log. head edu. (years)	*0.006*	*(0.005)*	*0.010***	*(0.005)*	*0.011***	*(0.005)*
Land (1=all irrigated)	*0.167****	*(0.018)*	*0.046***	*(0.018)*	*0.023**	*(0.012)*
Landscape 2 (valleys)	*-0.002*	*(0.016)*	*0.006*	*(0.019)*	*-0.025*	*(0.019)*
Landscape 3 (open plain)	*0.030**	*(0.017)*	*0.103****	*(0.022)*	*0.007*	*(0.014)*
Livestock (N)	*0.008***	*(0.004)*	*0.003*	*(0.005)*	*-0.005*	*(0.004)*
Oxen(1=own)	*0.034****	*(0.010)*	*-0.140****	*(0.017)*	*-0.01*	*(0.012)*
Log tractors/threshers(N)	*-0.049*	*(0.030)*	*-0.196****	*(0.039)*	*0.037*	*(0.026)*
Wave 2 (2013/14)	*0.01*	*(0.019)*	*-0.011*	*(0.016)*	*-0.128****	*(0.016)*
Wave 3 (2016/17)	*0.031***	*(0.015)*	*-0.042***	*(0.016)*	*-0.111****	*(0.018)*
District FE	✓		✓		✓	
Observations	*19,035*		*19,395*		*20,415*	
Outcome Equation: OLS estimates of the extent of expenditures						
	ME conditional on y>0	*SE*	*ME conditional on y>0*	*SE*	*ME conditional on y>0*	*SE*
Log. distance road (km)	*-0.062****	*(0.017)*	*-0.001*	*(0.014)*	*-0.021*	*(0.023)*
Time to market (<1hr)	*-0.057*	*(0.051)*	*0.122****	*(0.039)*	*-0.071*	*(0.067)*
Time to market (1-4h)	*-0.047*	*(0.049)*	*0.064**	*(0.036)*	*0.011*	*(0.049)*
Log total land (Jerib)	*0.538****	*(0.023)*	*0.614****	*(0.022)*	*0.442****	*(0.024)*
Log off-farm inc. (AFN)	*-0.016****	*(0.002)*	*-0.009****	*(0.002)*	*-0.011****	*(0.003)*
Log HH size (count)	*0.140****	*(0.023)*	*0.115****	*(0.021)*	*0.164****	*(0.031)*
Head literacy (1=literate)	*0.042*	*(0.028)*	*0.060***	*(0.026)*	*-0.07*	*(0.044)*
Log. head edu. (years)	*0.015*	*(0.015)*	*-0.017*	*(0.013)*	*0.051***	*(0.021)*
Land (1=all irrigated)	*0.001*	*(0.010)*	*-0.002*	*(0.010)*	*0.018*	*(0.014)*
Landscape 2 (valleys)	*0.120****	*(0.030)*	*-0.103****	*(0.034)*	*0.045*	*(0.033)*
Landscape 3 (open plain)	*0.362****	*(0.058)*	*0.069*	*(0.057)*	*0.297****	*(0.103)*
Livestock (N)	*0.035*	*(0.035)*	*-0.017*	*(0.042)*	*-0.063*	*(0.056)*
Oxen(1=own)	*0.130****	*(0.038)*	*0.031*	*(0.031)*	*-0.052*	*(0.049)*
Log tractors/threshers(N)	*0.416****	*(0.045)*	*0.102****	*(0.034)*	*0.225****	*(0.043)*
Wave 2 (2013/14)	*0.223****	*(0.045)*	*0.233****	*(0.048)*	*0.061*	*(0.064)*
Wave 3 (2016/17)	*0.274****	*(0.046)*	*0.235****	*(0.040)*	*0.357****	*(0.058)*
District FE	✓		✓		✓	
Observations	*19,032*		*19,392*		*20,411*	

*Notes: Omitted categories for factor variables are: no access to ICT and transport equipment, more than 4 hours for time taken to reach market, irrigated and rain-fed combined for land quality, cannot read and write for HH head literacy, hills and valleys for landscape, and 2011/12 for wave. All regressions are controlled for district FE. Standard errors (in parenthesis) are clustered in districts and significance is indicated by *** p<0.01, ** p<0.05, * p<0.1*