Capital, Scale, and Risk Constraints to Vegetable Adoption Among Smallhold Farmers in Nepal

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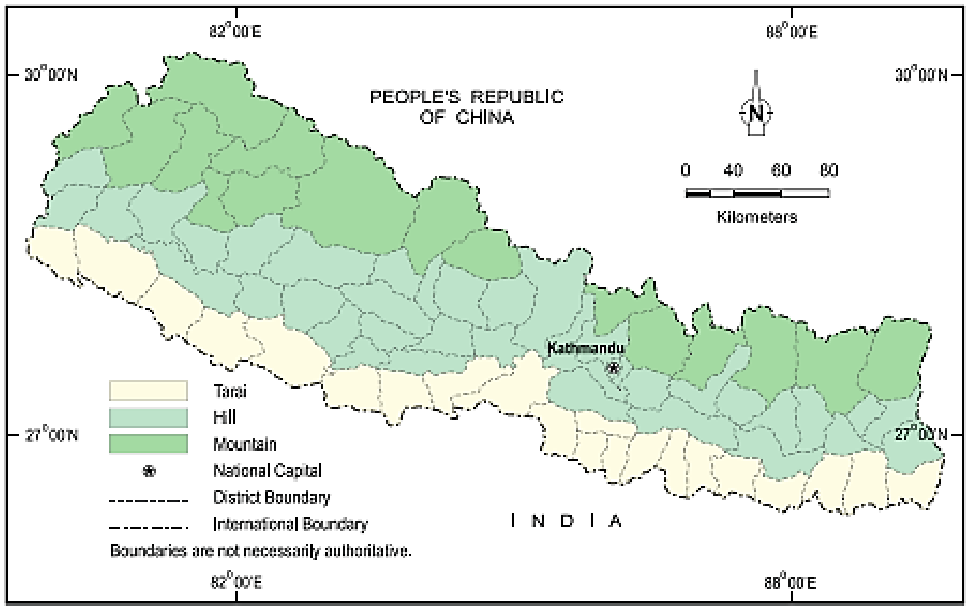
Abstract:

Nepal's agricultural productivity has stagnated in recent decades, resulting in widespread malnutrition, poverty, and civil conflict. In response, government and donor institutions have promoted high-input, high-return vegetable crops to increase earnings and productivity among smallhold farmers. This study examines the constraints limiting widespread adoption of these crops in the Mid-Western Development Region (MWDR) of Nepal. I first draw upon the technology adoption literature to generate predictions regarding potential capital, scale, and risk constraints to farmers' vegetable adoption, and then develop Logit, Probit, OLS, and Ordered Probit regression models to measure the effects of these constraints on a sample of farmers from the MWDR. The sample is drawn from a field survey I conducted in Nepal from June to July, 2014. Principal regression results show that farm area, distance to an agricultural supplier, higher caste status, and food insecurity are all significantly negatively associated with vegetable adoption, while farmers' age, agricultural training, and assets are significantly positively associated with adoption. I conclude that the surprising negative relation between farm size and vegetable adoption is the result of non-functioning labor markets, and that risk aversion is a significant barrier to vegetable adoption. More broadly, I find that vegetables are a relatively equitable instrument for poverty alleviation in Nepal.

Keywords: Technology Adoption, Nepal, Vegetables, Agricultural Development, Economies of Scale, Risk Aversion, Agricultural Productivity

Contents

Map of Nepal



Source: Asian Development Bank, 2010

Located on the Himalayan plateau between China and India, Nepal spans three distinct ecosystems. The subtropical lowlands along the Indian border, known as the Tarai, are characterized by rice cultivation, while hillier regions to the north produce wheat and millet. Beyond these agricultural belts the countryside rises rapidly into subarctic conditions near the Tibetan border.

1. Introduction and Contribution

Nepal's agricultural productivity, once the highest in South Asia, is now the lowest in the region. Agricultural productivity in Nepal has risen only 28% since 1980, while productivity rose by 82% in India and 117% in Bangladesh over the same period (World Development Indicators 2015). As a result of this stagnation, 35% of Nepal's rural population lives below the national poverty line, and 51% of rural children suffer from malnutrition (FAO 2010). In response to these devastating statistics, the Nepali government, in partnership with foreign donors, has pushed for the adoption of "high-value vegetables" among Nepali farmers. Vegetables produce higher yields and diversify farmers' diets, thus raising rural incomes and reducing malnutrition.

Nevertheless, vegetable adoption has progressed only slowly among Nepali farmers. As of 2008, only 15% of farmers were cultivating vegetable crops on at least a portion of their land, despite the significantly higher profits to be earned from vegetable production (USAID 2008). Evidently, significant constraints on vegetable adoption remain, potentially including limitations of scale (Nepali farms tend to be very small), risk (farmers often lack crop insurance), and capital (farmers face liquidity constraints and poverty traps). To the extent that these constraints limit vegetable adoption in Nepal, they also hamper rural development and nutrition.

This study employs data on farmers from Nepal's Mid-Western Development Region in order to measure factors constraining vegetable adoption. Data were collected through farmer interviews conducted by the author during June and July, 2014. Logit and Probit regression models estimate the effects of demographic and farm characteristics on farmers' likelihood of vegetable adoption. Results indicate that, contrary to the traditional assumption that large farms adopt first (due to economies of scale, access to credit, and higher levels of wealth and information), farm size actually appears to be negatively related to adoption likelihood, when controlling for other variables. Larger farms have lower family-size to land ratios and struggle to secure sufficient supplies of labor to produce labor-intensive vegetables, whereas smaller farms optimize their limited supplies of land through vegetable cultivation.

Contribution

Many studies of technology adoption in agriculture estimate either the binary adoption decision, or the share of adoption, but not both. Furthermore, studies using Logit and Probit regression models to model adoption behavior often neglect to calculate marginal effects, and especially the effects of increasing scales of adoption (Suman 2011; Paudel 2009; Zeller et al. 1998). The models employed in this study bridge these divides by calculating marginal effects both for binary Logit and Probit models and by computing an Ordered Probit model with marginal effects. The use of a range of comparative models provides a fuller understanding of the magnitude of variable trends in adoption decisions.

More broadly, the measurement in this study of a negative relation between farm area and vegetable adoption suggests that agricultural development analysts must adapt their understanding of technology adoption according to the particular characteristics of the technology at hand, specifically its level of labor-intensity. In Mid-Western Nepal, microcredit schemes reduce credit constraints, farmers' groups and marketing collectives reduce information asymmetries, and the communal sharing and renting of mechanical inputs improves access to capital. These conditions diminish the importance of scale-biased constraints and highlight the decisiveness of labor constraints, suggesting that contemporary agrarian systems may no longer follow the traditional theories and predictions of agricultural economics.

Finally, the negative relationship between farm size and vegetable adoption indicates that vegetables are a progressive rather than regressive technology. That is, smaller farmers adopt first. Vegetables thus prove to be a relatively equitable instrument for poverty alleviation when compared to scale-biased technologies such as tractors.

The remainder of this study is organized as follows. **Section 2** describes trends in Nepal's recent agricultural development and highlights the importance of agricultural productivity growth in the reduction of rural poverty and malnutrition.

Section 3 offers a broad review of agricultural development as a discipline, and then explores the ways in which farm scale, risk, and capital shape farmers' technology adoption decisions. The focus of this section is on generating testable predictions of adoption behavior.

Section 4 describes the design and implementation of my field survey in Mid-Western Nepal, and describes the dataset used in this study.

Section 5 uses the dataset to establish a series of empirical facts about vegetable production. I later draw upon these facts to facilitate the interpretation of regression results.

Section 6 reviews the empirical modeling of agricultural technology adoption behavior, and then develops Logit, Probit, OLS, and Ordered Probit regression models to measure farmers' vegetable adoption behavior in Mid-Western Nepal.

Section 7 presents principal regression results of the models developed in Section 6, and interprets the signs, coefficient magnitudes, and marginal effects of these models.

Section 8 offers a broader-level discussion and interpretation of the results.

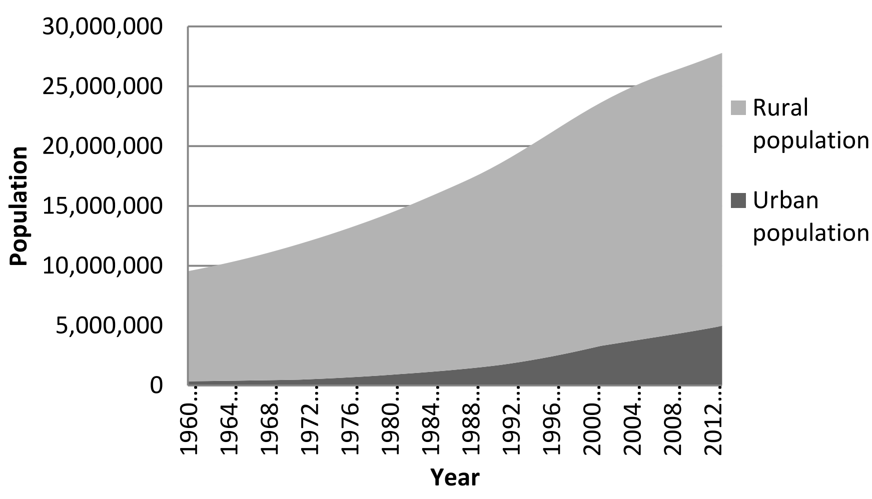
Section 9 concludes the study by reviewing its principal findings and contribution and offering policy recommendations to policy-makers in Nepal.

The Appendices that follow detail methods used to calculate farmers' costs and returns in the dataset (**Appendix A**), measure an inverse relationship between farm size and productivity (**Appendix B**), and present the questionnaires used in my field survey (**Appendix C**).

2. Agricultural Development in Nepal

Despite the steady growth of urban populations over the last three decades, Nepal's economy and demography remain fundamentally agrarian (**Figure 1**). Sixty six percent of the country's population is directly employed in agriculture, and nearly 90% live in rural areas (IRIN 2012). Agricultural production is predominantly subsistence-oriented: seventy eight percent of farm households produce primarily for family consumption, while only one percent produce entirely for sale (USAID 2008). Farmers generally practice traditional low input agricultural methods and participate in communal labor sharing networks. Most grow subsistence crops such as rice, maize, and lentils, and trade mostly through local marketing channels. Road connections have reached many parts of the country only recently, while other areas still lack any road access whatsoever.

Figure 1. Nepal: Population (1960-2012)



Source: World Development Indicators, World Bank, 2015

Regardless of the predominance of traditional farming practices, however, many Nepali farmers are finding it increasingly difficult to subsist. Rapid population growth and stifled land reform have led to a significant fragmentation of farmers' land holdings: from 1961 to 2001, the average farm size fell by 28%. Nearly half of all farmers now have access to no more than 0.5 hectares of land, while a further 23% work as landless rural laborers (**Table 1**) (USAID 2008). While traditional farmers employ advanced terrace farming and water diversion methods to maximize yields under severe resource constraints, further gains to be had from the current methods are minimal.

The fragmentation of land holdings is only one of many factors constraining rural development in Nepal. Fragile mountain ecosystems suffer from frequent landslides, and weather patterns are growing more irregular and destructive as climate change alters glacial melt and weather formation in the Himalayas (Gentle and Maraseni 2012). Rural development has been consistently neglected in development and aid initiatives (Sharma 2006). Finally, political instability has disrupted development across much of the country. A peasant-backed Maoist insurgency–itself a product of rural stagnation and impoverishment–waged war against the Nepali state from 1996 to 2006, leaving 15,000 Nepalese dead and over 100,000 internally displaced (Jha 2014).

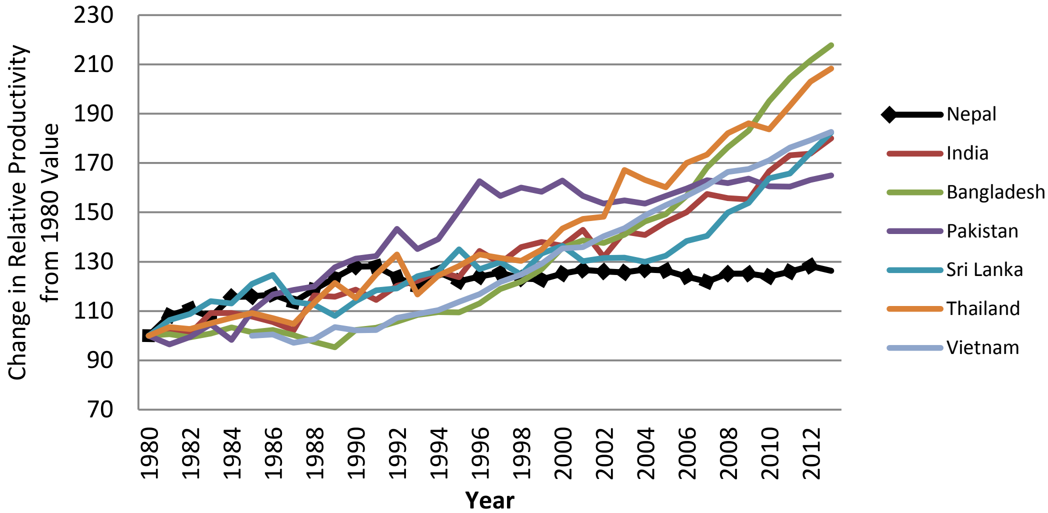
Table 1. Nepal: Average Land Holdings

Size of Holding (Hectares)	**Percent of Population**
< 0.2	18.2
0.2-0.5	29.1
0.5-1.0	27.4
1.0-2.0	17.6
2.0-3.0	4.7
3.0-4.0	1.5
4.0-5.0	0.6
5.0-10.0	0.6
> 10.0	0.1

Source: Central Bureau of Statistics, 2006

The result of these demographic, environmental, and political forces has been the flat-lining of agricultural productivity since the 1980s (**Figure 2**). While Nepal enjoyed the highest levels of agricultural productivity in South Asia during the 1960s, it has since fallen behind its neighbors and now has the lowest agricultural productivity in the region (Dhakal 2011).

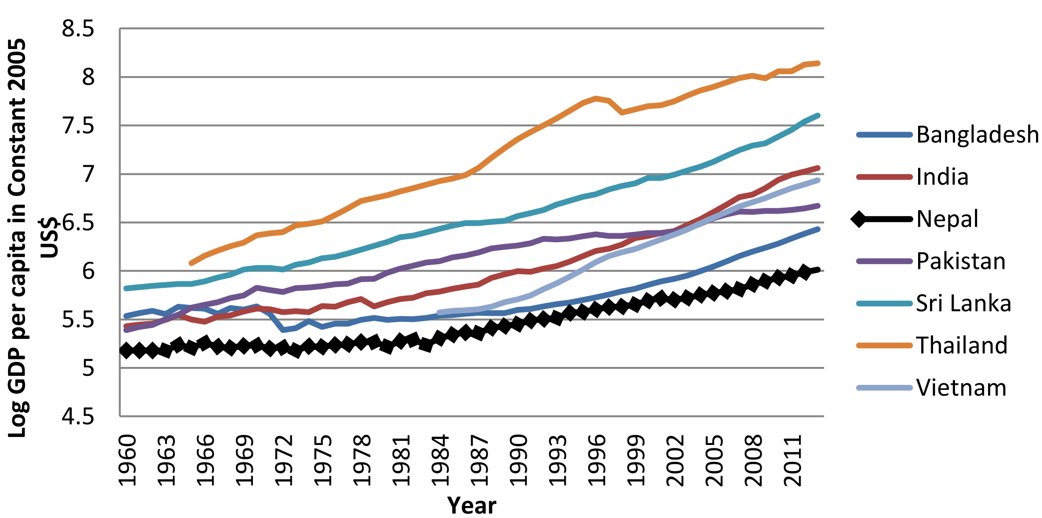
Figure 2. South and Southeast Asia: Agricultural Productivity from 1980-2013 (Value-added per Agricultural Worker in Constant 2005 $US, Indexed to 1980)



Source: World Development Indicators, World Bank, 2015

High rates of population growth (2.3% annually), coupled with stagnating agricultural productivity, have dragged down overall economic growth and complicated efforts to reduce poverty and malnutrition in the Nepali countryside (FAO 2010). The country's poor growth outcomes are clear when compared with other South Asian and comparable Southeast Asian countries. Although Nepal has experienced positive growth in per capita GDP since 1960, it remains the poorest country in one of the world's poorest regions (**Figure 3**)

Figure 3. South and Southeast Asia: GDP per capita (1960-2013)



Source: World Development Indicators, World Bank, 2015

Furthermore, this poverty is not evenly distributed. Rates of growth in urban areas have more than kept pace with growing urban populations, leading to increasing levels of wealth and conspicuous consumption in larger cities. At the same time, limited infrastructure and commercial opportunities, as well as lack of access to agricultural inputs or extension services, has hampered rural development (Deraniyagala 2005). Reflecting these limitations, growth in real GDP for Nepal's agricultural sector averaged only 2.6% annually between 1966 and 2002, while growth in the non-agricultural sector averaged 4.9% (**Table 2**).

Table 2.

Nepal: Real Growth in GDP (at 1985 prices)

Sector	1966-70	1971-75	1976-80	1981-85	1986-90	1991-95	1996-2000	2001-02
Agriculture	2.9	1.7	-1.3	5.2	4.1	1.5	3.6	2.9
Non-Agriculture	2.6	2.2	7.5	4.9	5.5	8.1	6.0	2.6

Source: Deraniyagala, 2005

Beyond this rural/urban divergence, regional disparities remain large as well. Nepal is divided administratively into five "development regions," each encompassing a north-to-south slice of the country. Poverty is highest in the Mid-Western Development Region, where 45% of the population lives below the poverty line, and lowest in the Central and Western Development Regions, where 27% live in poverty (**Table 3**) (Central Bureau of Statistics 2006).

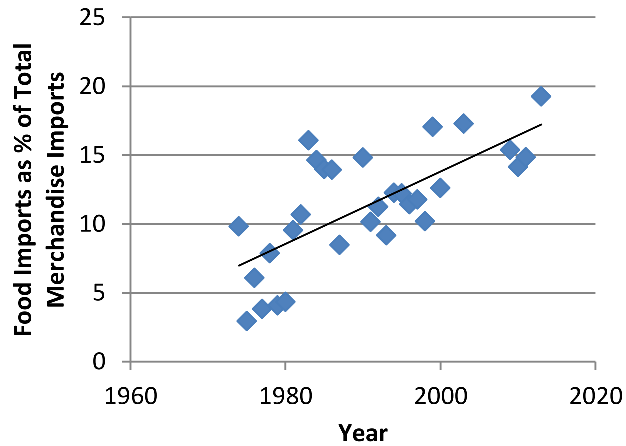
Table 3. Nepal: Poverty by Region

Region	% of Population under National Poverty Line
Eastern Development Region	29
Central Development Region	27
Western Development Region	27
Mid-Western Development Region	45
Far Western Development Region	41
Urban	10
Rural	35
Total	31

Source: Central Bureau of Statistics 2006

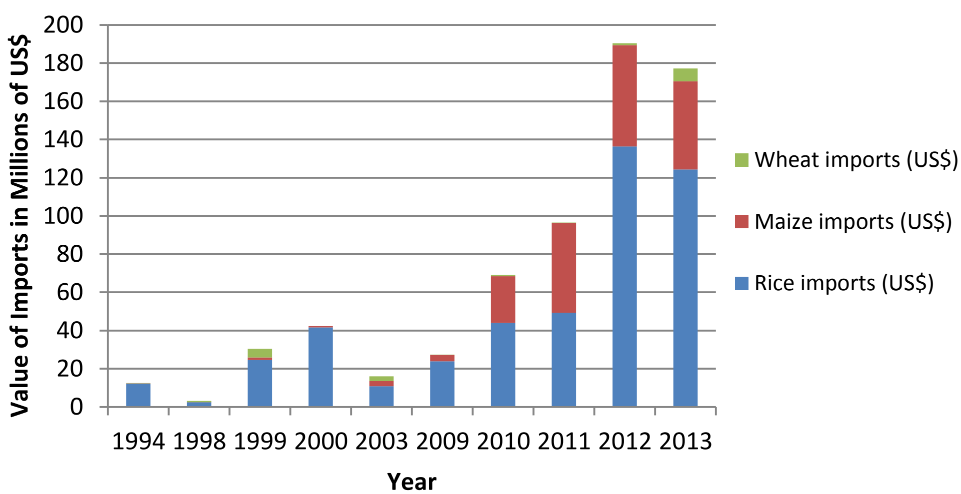
A growing population that is not accompanied by growing agricultural productivity will result inevitably in food shortages, as has been the case in Nepal. A structurally food deficit country, Nepal imported $US 177 million worth of staple agricultural products in 2013 (UN Comtrade 2015). These imports contributed to an increasing trend of food imports from abroad to make up for stagnating national production. As illustrated in **Figure 4**, food imports as a percentage of Nepal's total merchandise imports have been rising steadily over the last fifty years, and in 2012 food imports constituted nearly 20% of the country's total imported goods Imports of staple crops (rice, maize, and wheat) have increased by a factor of ten since 1994 in response to growing internal demand and stagnant national production (**Figure 5**) (UN Comtrade 2015).

Figure 4. Nepal: Food Share of Total Merchandise Imports



Source: World Development Indicators, World Bank 2015

Figure 5. Nepal: Staple Food Imports (US$ Millions)

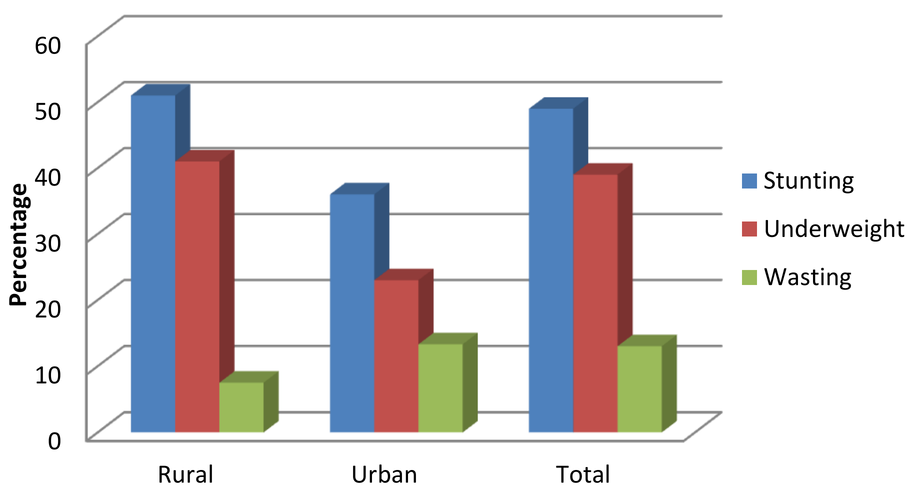


Source: UN Commodities Trading Database, 2015

Under competitive market conditions, increased demand for agricultural products should raise prices enough to incentivize farmers to produce more, thus realigning supply and demand. In Nepal, however, structural limitations (such as a very limited supply of arable land) largely prevent farmers from responding to market signals in their production decisions (USAID 2008). Furthermore, functioning factor markets would allow unprofitable farmers to transition into non-farm occupations, thus shifting land into the hands of more productive farmers. Nevertheless, many rural areas cannot provide non-farm employment at wages high enough for laborers to be able to afford the food imports that have replaced local production (FAO 2010). Consequently, while imports have substituted for declining domestic food supply at the national level, the micro-level distribution of this supply has been uneven and exclusive.

As a result of this rural market failure, rates of malnutrition in Nepal are strikingly high (**Figure 6**). Among children aged 0 to 5, 49.3% suffer from stunting due to severe malnutrition. This early-childhood malnourishment leads to diminished lifetime earning and learning potential, thus constituting a significant handicap to future development in Nepal (FAO 2010).

Figure 6. Nepal: Malnutrition in Rural and Urban Areas



Source: FAO 2010

In short, current socioeconomic conditions in rural Nepal are unsustainable. Development failure has already led to a civil war (1996-2006) that left nearly 15,000 Nepalese dead and over 100,000 internally displaced. And persistent malnutrition is stunting the life-possibilities of the next generations of Nepali farmers. Due to increasingly irregular weather, degraded environmental conditions, and the fragmentation of land holdings, even traditional subsistence farmers are increasingly unable to produce sufficient quantities of food to support themselves.

Introducing Innovations: High Value Vegetables

In the context of this flat-lining agricultural growth and increasing population pressure, numerous governmental and nongovernmental organizations (NGOs) are working to introduce new innovations into Nepal's agrarian economy. The government's Agricultural Perspectives Plan, first published in 1996, outlined a broad agenda of trade liberalization, commercialization, infrastructure expansion, and public-private partnership (Sugden 2009). Since this time, prominent NGOs including the World Bank and the US Agency for International Development (USAID) have focused on–among other approaches–diversifying farmers' crop portfolios through the promotion of "high value vegetables" for commercial sale and export. According to a USAID country analysis of Nepal:

"The main focus of USAID's agricultural programs has been to contribute to the strategic objective of increased sustainable production and sales of high-value agricultural products. A shift to high value agriculture uniquely matches the need to take pressure off the intensively irrigated cereals and enlarging small holder farmers' opportunities to benefit from expanding domestic and export markets (USAID 2008)."

Similarly, the World Bank's country report on Nepal notes that it aims to integrate farmers into "profitable market-oriented agricultural activities… targeted towards export (World Bank 2014)."

According to this analysis, Nepal (due to its unique geography) possesses a comparative advantage in the production of vegetable crops relative to the growing Indian market to its south. These crops, if marketed effectively, can yield higher profits on smaller landholdings, thus improving both agricultural productivity and standards of living. Up to 15% of farmers in some districts are now coupling small-scale commercial vegetable production with their staple crop production (USAID 2008).

Nevertheless, the approach faces significant obstacles to broader adoption. Limited access to roads and markets makes the production of vegetable crops (which are especially vulnerable to spoilage and damage) difficult and risky. Furthermore, these high-value crops require increased inputs, including chemical fertilizers and improved irrigation equipment, thus creating potential barriers to entry for farmers without the ability to access credit or capital. Overdependence on commercial farming could leave farmers at the whim of international price swings, making the adoption of vegetables a risky endeavor. Finally, the small scale of most Nepali farms could mean farmers are unable to take advantage of economies of scale in their commercial production.

The degree to which these limitations (of scale, risk, and physical and human capital) affect the adoption of high-value vegetable crops will determine the prospects of these new "technologies" in improving agricultural productivity and rural livelihoods in Nepal. Therefore, building a robust empirical understanding of the ways these constraints shape the adoption and effectiveness of vegetable cropping is integral to improving the country's development outcomes. To this end, the remainder of this study focuses on applying methods from the literature on technology adoption to evaluate current constraints on the adoption of vegetable cultivation in Nepal's Mid-Western Development Region.

3. Theories of Agricultural Development and Technology Adoption

I begin this section by exploring some of the foundational ideas and debates in the field of agricultural development. This brief review is intended to contextualize and justify my focus on farmers' micro-level adoption decisions. I follow this review with a discussion of the economics of technology adoption itself, and I conclude by analyzing the effects of scale economies, risk aversion, and capital constraints on the adoption process.

Agricultural development first received serious attention from economists in the 1950s and 60s, as independence movements across Africa and Asia brought issues of global poverty and development into focus (Barrett, Carter, and Timmer 2010). Early scholarship during this period, characterized by the work of W. Arthur Lewis, focused on the "modernization" of traditional farming (Ellis and Biggs 2001). Lewis argued that traditional agriculture–typified by small landholdings, labor-intensive inputs, and production for subsistence–was irrational and backwards, and that the transition to large-scale mechanized monoculture would precipitate the "structural transformation" of a developing nation's economy. This transformation would occur through what came to be called "Lewis linkages," by which the scaling-up of farm production would free labor to move from the low-productivity agricultural sector to higher-productivity manufacturing (Lewis, 1954). In 1961, Johnston and Mellor posited further linkages between agricultural and industrial development (Barrett, Carter, and Timmer 2010). Through "Johnston-Mellor linkages," a country's agricultural sector provided raw materials to supply urban workers, a domestic market for industrial output, and agricultural exports to earn the foreign exchange necessary to fund capital imports. Thus, agricultural and industrial development went hand in hand, each fortifying the other and lifting the country out of poverty (Johnston and Mellor 1961).

Both Lewis and Johnston and Mellor based their analyses of structural transformation upon the assumption of increasing returns to scale in developing country agriculture. They assumed that larger farms would deploy capital-intensive technological inputs more often and more effectively than smaller farms, bringing about the type of productivity gains seen previously in the United States and Western Europe. Challenging this assumption of increasing returns to scale, Theodore Schultz's 1964 work, *Transforming Traditional Agriculture*, argued that, contrary to Lewis' assumption, small farmers were in fact highly rational and efficient users of scarce inputs. According to Schultz, decisions that initially appeared irrational (such as traditional farmers' reluctance to adopt profitable technologies) could in reality be optimal under conditions of constrained credit and food insecurity. Farmers, he concluded, were risk averse and "poor but efficient (Schultz 1964)."

Schultz's theory repositioned small farmers at the center of efforts to increase agricultural productivity and foster industrialization (Ellis and Biggs 2001). Rather than working to phase out traditional farmers in favor of larger commercial enterprises, policymakers now sought to remove constraints on small farm productivity growth in order to propel farmers out of potential "poverty traps" by providing credit, crop insurance, and subsidized inputs (Azariadus and Stachurski 2005; Barrett 2005). Schultz's later work highlighted the role of human capital development in agriculture, emphasizing the importance of education (whether through formal schooling or on-the-job training) for productivity gains (Schultz 1975, 1978). Critically, however, economists following Schultz's framework have noted that, given the *a priori* efficiency of small farmers, improvements in education may fail to revolutionize productivity without accompanying improvements in technology and infrastructure (Huffman 2001; Norton 2010).

Schultz's "poor but efficient" hypothesis supported the empirical findings emerging from Amartya Sen's contemporary research on Indian agriculture (Sen 1962, 1966). Analyzing the relationship between yields per hectare and farm size among Indian farms, Sen had detected an "inverse relationship" (IR) between farm size and land productivity.[1] That is, small farmers appeared to produce more per hectare than did large farmers. Sen posited that smaller farms using primarily family labor avoided the costly supervision of less-efficient hired labor, and had a tendency to work their limited land holdings more intensively due to the low opportunity costs of their labor (Thapa 2007). Sen's findings had clear implications for the debate over land reform that was sweeping Latin America and South Asia at the time. Proponents of pro-poor land reform seized upon Sen's conclusion as evidence that redistribution would improve land productivity, while early proponents of the coming Green Revolution countered that the IR would reverse as farmers adopted scale-biased and capital-intensive technologies such as tractors (Lipton 1993; Dyer 2003). While economists remain undecided over the status of the IR in the post-Green Revolution era, Sen's findings still have relevance in countries such as Nepal where traditional agriculture remains the norm.

"Poor but efficient" theories, otherwise referred to as "small farm first," fit well into the pro-market development paradigm that reigned supreme during the 1980s and 90s and that continues to exert a strong influence on policy to this day (Ellis and Biggs 2001). Pushed most prominently by the World Bank and other international donor institutions, the "neoliberal" development agenda conceives of small farmers as micro-entrepreneurs who can lift themselves

[1] The Russian economist Aleksandr Chayanov (1888-1937) was the first to develop a coherent model of farm household decision-making, from which he derived a prediction of the inverse relationship (Barrett, Carter, and Timmer 2010). Chayanov argued that households with smaller land endowments faced a lower shadow price of labor and thus "purchased" labor more intensively in proportion to land, yielding higher production outcomes (Chayanov, 1965). Sen's later empirical work in India confirmed Chayanov's theorization.

out of poverty if only markets are made to function properly (Sugden, 2009). The Bank argues that, at the macro level, agricultural commercialization for export will allow poor agrarian countries to exploit their comparative advantages in labor-intensive goods and generate foreign exchange with which to offset structural debt imbalances. At the micro level, the facilitation of market participation through infrastructure improvements, microcredit, and trade liberalization will incentivize farmers to invest in productive technologies, thus spurring development (World Development Report 2007). Central to the World Bank's market-driven approach is the introduction and effective adoption of improved techniques and technologies in developing country agriculture.

Critics of the neoliberal approach counter that, in practice, the commercialization of traditional agriculture removes valuable farmland from domestic food production in precisely those countries most often suffering from food insecurity (Akram-Lodhi and Kay 2010). Particularly in South Asia, troubled memories of colonial-era policies that enforced grain exports even during times of devastating internal famine complicate and color the otherwise cold economic logic of the reformers (Davis 2000). Furthermore, critics argue that the World Bank's one-size-fits-all application of the Heckscher-Ohlin theorem commits the "fallacy of composition" by urging all developing countries to export similar low-value primary products, resulting in falling prices and evaporating markets (Glenn 2008). Finally, the World Bank's critics contend, marketization's reliance on scale-biased technologies could inadvertently favor larger farmers and exacerbate rural inequalities and landlessness (Barrett, Carter, and Timmer 2010).

In sum, the field of agricultural development economics has been characterized by vibrant experimentation and debate over the last half century. Despite the volume of evidence and arguments produced across the board, major areas of contention remain, including:

- The role of backward and forward linkages between agriculture and industrialization, and the ways (if any) in which agricultural development fosters “structural transformation.”
- The existence of an inverse relationship between farm size and land productivity, and the implications of this relationship for land and market reform.
- The relative merits and disadvantages of agricultural commercialization and liberalization versus state-led development, and the role that political and social discourses may have to play in the realm of the “economic.”

Superseding the divisions in current agricultural development scholarship, however, is a broad consensus on the importance of rural technology transfer as a means of stimulating agrarian economies, improving access to food in areas suffering from malnutrition, and targeting benefits to marginalized populations (Godfray 2009). Accordingly, I turn in the following section to a description of the economics of technology adoption in developing country agriculture.

3.1 The Role of Technology Adoption

Modern growth theories identify technological progress (whether exogenous or endogenous) as the engine of growth (Solow 1956; Romer 1994; Jones and Vollrath 2013). But agriculture, by its nature as a geographically dispersed, low-density activity, does not typically generate high rates of technological innovation on its own. University, government, and private-sector research services are the primary sources of agricultural innovations, which they then market to farmers through extension services. In the case of developing countries, however, research institutions may be poorly funded or nonexistent. Innovations imported from abroad may not be locally appropriate. And even where appropriate, extension services may not effectively transmit innovations to farmers (Norton 2010).

As a result, technological progress–the engine of growth–is irregular and unpredictable in rural economies, characterized by incomplete adoption of new technologies and partially functioning markets and price mechanisms (Barrett, Carter, and Timmer 2010). The stochastic arrival of foreign technologies in agricultural areas creates a constant disequilibrium in which farmers struggle to stay on the "technology treadmill." Coined by Willard Cochrane in 1958, the "treadmill" refers to the dynamic effects of an exogenous technology shock on farmers' wellbeing. Farmers, Cochrane argued, are distributed across three categories: "early adopters," "followers," and "laggards (Sunding and Zilberman 2001)." The relatively small group of early adopters is predisposed (whether through lower risk profiles, superior information, etc.) to adopt a new cost-cutting or return-increasing technology, and thus earns large profits. But as the large group of followers catches on and adopts the new innovation, the market price falls (especially for products will low elasticity of demand), reducing their profits. Followers, therefore, may gain or lose from the innovation. Finally, the laggards adopt last (after prices have fallen due to increased supply) or do not adopt at all. In either case, they earn lower returns on their output and are worse off because of the new technology. Thus, on the whole, Cochrane predicted that technological innovations may have limited or no benefits to farmers. The reduction in prices due to the innovation ultimately benefits consumers, who face lower prices at the food market (Cochrane 1979; Sunding and Zilberman 2001). Since the wealthiest farmers are likely to be early adopters while marginalized producers may be laggards, the logic of the technology treadmill suggests that technological innovations may increase rural inequalities (Feder 1985).

In cases where farmers' final output good enjoys perfectly elastic demand, however, Cochrane's pessimistic prediction may not hold. Perfect elasticity implies that the increase in supply resulting from the technology shock would not reduce prices and undercut profits among followers and laggards as it does in Cochrane's model. This may be the case if a relatively small producer country has access to a large export market able to absorb nearly any quantity of the good with minimal effect on prices (Sunding and Zilberman 2001). This result is significant in the context of the current study. Due to Nepal's privileged access to the enormous market for vegetables in northern India, broad expansion of vegetable production among Nepali farmers is unlikely to cause significant reductions in export prices (USAID 2008). Consequently, all three categories of farmers (early adopters, followers, and laggards) stand to benefit from the adoption of high value vegetables, and the negative inequality effects may be less pronounced than would otherwise be the case.

In the developing country context, Cochrane's simple technology adoption framework is further complicated by incomplete markets, inaccessible inputs, and information asymmetries. Small farmers may be efficient maximizers of yields under severe resource constraints, but their technology adoption behaviors often contradict simple market logics and reveal market failures. These contradictions are both what make farmers' decision-making interesting, and what make this decision-making an essential element of policy analysis. To implement effective rural development policy, we must first untangle the complexities of farmers' technology adoption decisions at the micro level.

Studies attempting to untangle this adoption process focus on explanatory variables that generally fall into three broad categories. First, many studies follow in Sen's footsteps by examining the impacts of farm size and economies or diseconomies of scale on the adoption of new technologies (Croppenstedt, Demeke, and Meschi 2003; Adesina, Baidu-Forson 1995; Feder 1982). Secondly, researchers draw upon behavioral models and rural sociology to measure the impacts of risk aversion and behavior under uncertainty on technology adoption (Dercon and

Christiaensen 2007; Abadi Ghadim et al. 2003; Feder 1985). Thirdly, many studies follow Schultz's emphasis on the importance of human capital by measuring the impacts of education, extension, and learning by doing, as well as physical capital and credit, on overcoming or creating barriers to adoption (Abdulai and Huffman 2005; Abadi Ghadim et al. 2003; Hojo 2002; Sunding and Zilberman 2001; D'Souza, Cyphers, and Phipps 1993)

The majority of the studies cited above employ regression analysis to isolate associations between focus variables and adoption behavior in farm-level data sets. More recent scholarship on technology adoption, however, has critiqued this reliance on regression analysis due to its inability to establish causal links between dependent and explanatory variables (Angrist and Pischke 2009). Contemporary analysts have thus turned to instrumental variable methods, natural experiments, and randomized controlled trials to isolate causal relationships between farmer characteristics and adoption behavior (Dupas 2014; Devoto and Duflo et al, 2012).

Despite differences in methodological approach, however, contemporary technology adoption studies continue to focus on the three categories outlined above–scale, risk, and capital. The following sections explore the economic dynamics of these three phenomena in turn.

3.1.1 Economies and Diseconomies of Scale

Farm size is often a central variable of focus for studies of technology adoption in agriculture. A farm's size typically reveals important information regarding the farmers' wealth, education, and access to resources and information. However, the nature of the technology being introduced (whether it is lumpy or divisible, scale-neutral or scale-biased, etc.) can also affect adoption in significant ways, thus producing potentially confounding effects (Feder 1985). In this section I first explore the effect of large and small farmers' personal characteristics on the adoption decision, and then examine the ways in which the nature of the technology itself may complicate the decision-making process.

Large farmers tend to be wealthier than small ones. Large farmers can leverage landholdings as collateral for loans, enabling them to overcome high fixed costs of adoption (the purchase of a tractor, for example). On the contrary, smaller farmers' lack of land and other assets may prevent them from obtaining credit. Thus, wealth-biased access to capital may lead to differential rates of adoption between large and small farms (Barrett, Carter, Timmer 2010).

Furthermore, large farmers may have larger food reserves or savings, giving them increased capacity for risk. They may also (due to differential levels of wealth and access) have more education than small farmers. Due to their larger size and market share, they may possess improved market information and marketing contacts (Feder 1985). As a result of these advantages, larger farmers are often more likely to adopt new technologies than are smaller farmers.

On the other hand, small farmers typically have higher ratios of family labor to land area (more people packed on to little land) and thus have a comparative advantage in labor-intensive, high-returns products. In contrast, larger farmers have a lower family-size to land ratio, and thus have a comparative advantage in land-intensive products. By this argument, smaller farmers are more disposed to adopt a labor-intensive innovation than are large farmers (Ellis and Biggs 2001). Large farmers would optimally adopt the labor-intensive, high returns product as well, but may be limited by failures in the labor market that create labor bottlenecks (Feder 1985). For instance, Harriss' 1972 study of Indian farmers found that labor shortages explained much of the failure to adopt a new high-yielding crop variety.

Evidently, the nature of the new technology plays a decisive role in defining patterns of adoption. The labor-intensiveness of new crop varieties may shape which farmers find it optimal to adopt. Similarly, technologies that enjoy economies of scale will favor adoption by large farmers, while technologies exhibiting decreasing returns to scale may favor small farmers.

Lumpy technologies, such as tractors or irrigation systems, require a significant fixed cost of adoption and cannot be phased in gradually. In this case, Weil (1970) predicted that credit constraints could prevent smaller farmers from adopting, even if they wished to. Alternatively, divisible technologies such as high-yielding crop varieties can be adopted gradually and for low fixed costs. Thus, divisible technologies allow small farmers to overcome both credit and risk constraints, since they can adopt only as much of the technology as their liquidity allows and use trial plots to assess risk without overexposing themselves (Sunding and Zilberman 2001). Nevertheless, some economists argue that even divisible technologies may require substantial fixed startup costs, including the cost of learning new methods and locating new markets. These factors may reduce small farms' adoption rates (Feder 1985).

Empirically, Schluter (1971) and Sharma (1973) found that smaller farmers in India adopted high-yielding varieties more readily and in larger proportions than did large farmers, and Adesina and Baidu-Forson (1995) found that farm size had a negative impact on adoption rates of improved sorghum varieties in West Africa. In contrast, Zeller, Diagne, and Mataya (1998) found that rates and proportions of hybrid maize production in Malawi increased with farm size. In sum, the effects of farm size on technology adoption depend on the specific nature of the technology and the characteristics of the farmers in the study sample.

The preceding theoretical review yields a number of conditional predictions of the effects of farm size on vegetable adoption. These predictions are summarized in **Table 4** below.

Table 4. Predictions of Scale Effects on Vegetable Adoption

Conditional upon whether vegetables in Nepal:

- Are a lumpy or divisible technology
- Are more or less labor-intensive than staple crops
- Produce higher or lower yields and profits than staple crops
- Are more or less risky than staple crops (exhibit larger or smaller variance in input requirements and returns)
- Exhibit increasing, decreasing, or neutral returns to scale

Two contradictory predictions emerge:

- Larger farmers will be more likely to adopt high yielding vegetables because of differential access to capital, markets, information, liquidity, food security, education, and other resources

Or

- Smaller farmers will be more likely to adopt labor-intensive vegetables in order to optimize the use of their limited land and relatively large family labor supply, while large farmers will find themselves constrained by labor shortages

3.1.2 Uncertainty and Risk Aversion

Farming in developing countries is typically a risky business. Access to crop insurance is often limited or nonexistent. Unpredictable weather patterns and faulty infrastructure make crop production and marketing anything but certain. Supply prices (seeds, fertilizers) vary dramatically between growing seasons. Hired labor supplies can evaporate at critical moments such as planting and harvest times. Some of these sources of risk (such as adverse weather conditions) affect farmers whether or not they adopt new technologies. In other cases, the new technology brings new risks and uncertainties of its own (Barrett, Carter, and Timmer 2010).

High yielding varieties (HYVs) often present higher risk and higher reward than staple crops such as rice or maize. That is, average profits are higher with HYVs, but variance in profits is higher as well (Zeller et al., 1998). Thus, farmers may be hesitant to adopt new crops until they are able to observe the outcomes on neighboring farms or on a demonstration plot. This suggests that agricultural training may be a key element in reducing farmers' perceptions of risk from new crop varieties (Feder 1985).

A central source of new risk from HYVs emerges from farmers' increased exposure to the market upon adoption. Developing country farmers typically produce to meet family needs, and engage only in small-scale marketing of their surplus production. In contrast, HYVs are typically cash crops that require farmers to commercialize their production in return for higher earnings (Norton 2010). The result is that an increased proportion of the farmer's crop portfolio is exposed to market uncertainties. Particularly in isolated rural areas with limited transportation infrastructure and communications technology, crop retail markets are likely to be fragmented and incomplete. The result is that prices vary wildly from season to season and even hour to hour, and are often entirely uncorrelated with national or global commodity prices (USAID 2008). Furthermore, if HYV supply chains are designed for export, farmers are held hostage to international prices, which may be much lower due to competition from more competitive agricultural sectors in other parts of the world (Norton 2010).

Farmers' marketing situation may be further complicated by the nature of the high value crop. In the case of vegetables, spoilage can occur within a few days of harvest, meaning that farmers must sell their crop almost immediately upon harvest, regardless of prevailing prices. In contrast, rice and maize can be stockpiled until prices are favorable. Vegetable buyers, aware that farmers' products will spoil rapidly if unsold, can extort abusively low prices. Farmers typically respond by forming marketing collectives in which entire villages elect a representative to bargain for them, thus achieving a more even bargaining position vis a vis buyers (Norton 2010). However, when a HYV is new to an area and still has few adopters, farmers suffer from a first adopter's disadvantage: adopters cannot form a marketing collective until a critical mass of farmers have adopted, but no farmers wish to adopt until that critical mass has already formed. This coordination failure means that adoption often follows spatial patterns, with certain villages exhibiting nearly universal adoption while others exhibit none (Feder 1985).

A final crop-specific risk factor plaguing high value vegetables is that their input-intensive nature means farmers must invest more labor and capital upfront, before knowing what the price will be at the point of sale. Growing less input-intensive crops would be safer since investment is reduced relative to an unpredictable payoff.

As a result of such significant risk from market exposure and the lack of insurance products to address it, risk averse farmers may find themselves locked into "poverty traps" in which their optimal risk-adjusted decisions involve avoiding new technologies and continuing less-productive traditional subsistence practices. In the event of a poverty trap, improved training and education and improved access to credit and crop insurance can change farmers' incentive structures and increase adoption (Dercon and Christiaensen 2007).

While most farmers in the developing country context are risk averse, specific levels of risk aversion may vary according to farmer characteristics. Farmers with access to credit, large food reserves, or opportunities for off-farm income (proxied by education) may be more disposed to take risks than farmers lacking these advantages. Since many of these characteristics often coincide with large farms, large farms are typically considered to be less risk averse than smaller farms (Feder 1985). Alternatively, if profits from the new technology are sufficiently higher than the increased variance in returns, smaller farmers may adopt more quickly than large farmers in order to diversify their production portfolios (Just and Zilberman 1983).

Empirical studies have employed a range of models and methods to assess the role of risk in technology adoption. Lindner (1980) employed a Bayesian learning model to assess adoption over time and found that farmers often first adopt small trial plots before adopting on a larger scale. Demir (1976) reported that farmers in Turkey were more likely to adopt if they had previously interacted with extension agents, which reduced their levels of uncertainty. Abadi Ghadim et al. (2005) surveyed farmers in Western Australia and found that farmers' perceptions of a new technology's (in this case, chickpeas) riskiness was a strong explanator of adoption behavior. Finally, Dercon and Christiaensen (2007) searched for risk-driven poverty traps in Ethiopia and found that risk aversion among small farmers did, in some cases, result in sub-optimal decision-making.

The theoretical and empirical findings discussed above generate a number of predictions for the adoption of vegetables in Nepal:

Table 5. Predictions of Risk Effects on Vegetable Adoption

- Larger or wealthier farmers may be less risk averse and thus more disposed to adopting riskier vegetables
- Farmers with better access to education and agricultural training will be more likely to adopt, since information reduces uncertainty
- Farmers with better access to markets and agricultural suppliers will be able to produce and market vegetables more easily, thus reducing the risk of production for the market

3.1.3 Physical and Human Capital

Beginning with Schultz's original work on human capital in the 1960s (Schultz 1964), many studies of technology adoption have focused on the role of education, experience, training, and other forms of human capital in the adoption process. Additionally, many studies search for the presence of credit and capital constraints, especially in the context of lumpy technologies such as tractors or irrigation pumps. In this section I will evaluate both human and physical capital as determinants of technology adoption.

Education is essential to understanding adoption behavior. Farmers with higher levels of education strategize more effectively, take advantage of new technologies and methods, and make sounder farming decisions. The majority of farmers in the developing country context may not receive education beyond primary school. Thus, primary school–which teaches essential skills such as literacy and numeracy–is the key threshold education level (Huffman 2001). Higher education, especially university education, may or may not contribute directly to increases in farm productivity, but does typically give farmers useful business contacts and a better understanding of the broader regional or national economic climate (Huffman 2001). Thus, education is likely to be positively associated with technology adoption.

Experience is also an essential component in farming practice. Nevertheless, it is unclear whether older farmers (using age as a proxy for experience) would be more likely to adopt due to a fuller understanding of agricultural practice, or younger farmers, who may be more disposed to change and who have a longer time to enjoy the increased profits from any new technological innovation (Becker 1993).

Foster and Rosenzweig (1996) posit that changing farming conditions (irregular weather patterns, new technologies, etc.) increase the returns to education, since educated farmers are more able to adapt to dynamic challenges and opportunities. Their work parallels Cochrane's theory of the "technology treadmill" by predicting that more educated farmers may be the "early adopters" who most benefit from technological change.

Education may also raise the opportunity cost of a farmers' on-farm employment, potentially drawing off the most productive workers through migration. This has been the case in Nepal, where educated rural workers travel to urban centers or migrate internationally in search of better wages and mobility. These labor flows could result in a "brain drain" from the countryside, or a key skill-upgrading process if migrant workers return to their farms with knowledge and contacts from the outside world (Norton 2010).

Physical capital is essential to reduce labor bottlenecks in areas where labor markets are incomplete (Feder 1985). However, limited liquidity and credit may constrain farmers wishing to purchase new capital technologies, especially if these technologies are indivisible. Nevertheless, Schutjer and Van der Veen (1977) argue that the potential profits from HYVs are often high enough to convince the smallest farmers to phase into adoption of this divisible technology.

Ram's research in India (1976) confirmed the importance of human capital in agriculture by measuring a positive relationship between education and productivity and a negligible relationship between labor inputs and productivity while controlling for education. Furthermore, Rosenzweig (1978) reported that the likelihood of HYV adoption in the Punjab was positively related to level of education (Feder 1985). More recently, Abdulai and Huffman (2005) found a positive relationship between adoption of cross-bred cow technology in Tanzania and schooling, access to credit, and access to agricultural training services.

The evidence above suggests the following predictions regarding vegetable adoption:

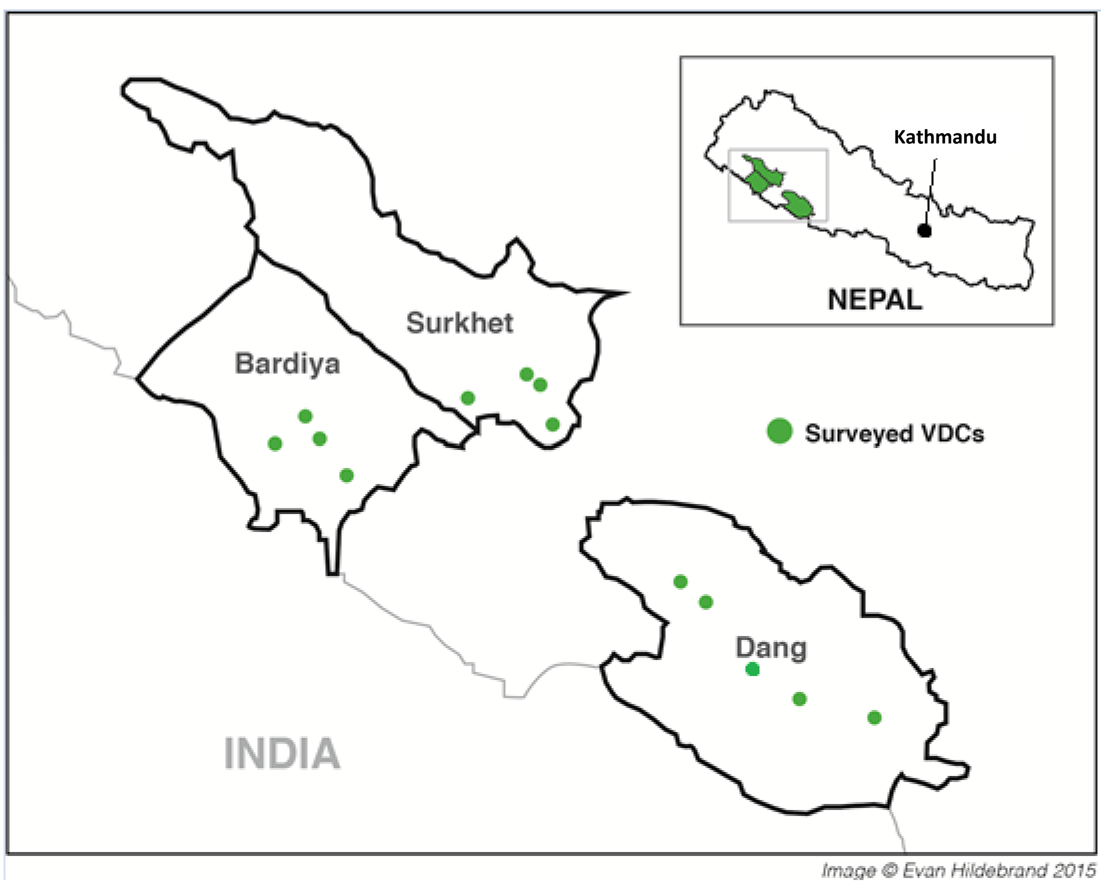
Table 6. Predictions of Capital Effects on Vegetable Adoption

- Education will be positively associated with vegetable adoption, since educated farmers possess superior information and improved understanding of technological possibilities
- Farmers controlling more physical capital will be more likely to adopt input-intensive vegetable crops, since physical capital relieves labor bottlenecks
- Agricultural training should increase adoption rates

4. Data and Definition of Variables

The dataset employed in this study comes from a survey conducted by the author in Mid-Western Nepal during the months of June and July, 2014. Surveys were administered individually to 83 farmers across 13 Village Development Committees[2] (VDCs) in the Mid-Western districts of Surkhet, Bardiya, and Dang (**Figure 7**). Five observations were found to be statistical outliers and were removed from the dataset before analysis. The district of Surkhet is in the mid-hills region, whereas Bardiya and parts of Dang lie in the Tarai lowlands. Together, these three districts offer a representative sample of environments and agricultural systems in Nepal's Mid-Western Development Region (MWDR).

Figure 7. Research Sites in Nepal's Mid-Western Development Region



[2] Village Development Committees are the smallest administrative unit in Nepal. Each VDC contains numerous villages. Thus, each surveyed VDC in our sample represents a snapshot of multiple villages.

The survey was conducted under the auspices of Winrock International and USAID's Knowledge-based Integrated Sustainable Agriculture and Nutrition (KISAN) project. All surveyed farmers were voluntary participants in the KISAN agricultural training program. Thus, while farmers were selected randomly from among the pool of KISAN participants, the underlying decision to participate in the program may correlate with farmers' decision-making as revealed in the survey. This non-random selection could potentially result in a "simultaneity bias," as postulated in Zeller et al. (1998). Consequently, descriptive statistics from the survey sample may not necessarily reflect the statistics of the region's general population as a whole. We can partially control for this selected sample bias by controlling for the variable "agtraining," which measured survey participants' degree of participation in KISAN agricultural trainings. Levels of participation ranged from 0 to 10 trainings among surveyed farmers. Presumably, controlling in regressions for the degree of farmers' participation in the KISAN program will reduce the biasing effect of a selected sample.

The survey (see **Survey Appendices** for full reproductions of the field surveys in both English and Nepali language) focused on measuring farmers' costs and returns to production for specific crops over a single growing season.[3] The survey decomposed costs of production into labor costs, capital costs, costs of credit, and opportunity costs of land and investment. Revenues and profits were calculated using the retail price obtained by the farmer at the point of sale (see **Appendix A** for a detailed accounting of the calculations involved in arriving at farmers' costs and returns to crop production). Each observation in the survey details the costs and returns for a single crop grown by the farmer over a single growing season. All farmers growing vegetable crops were surveyed about the vegetable crop they were growing. Thus, those farmers appearing

[3] Surveyed vegetable crops included: Tomatoes, Cauliflower, Cucumber, Bitter Gourd, Cabbage, Onion, and Chili. Surveyed staple crops included: Maize, Lentils, and Rice.

in the survey as cultivators of maize, lentils, or rice were not involved in vegetable cultivation. Farmers reporting vegetable cultivation in the survey, however, were nearly always cultivating a staple crop as well. Because of this mutual exclusivity, the survey data can be used to analyze the factors influencing a farmer's decision of whether or not to adopt vegetables.

The survey also collected data on the characteristics of participants' farms, as well as demographic and geographic information. Data on farm characteristics included farm size, crop portfolios, tractor and pump use, and organic and chemical fertilizer application. Demographic data included farmers' age, gender, ethnicity, level of education, family size, level of agricultural training, food security, access to credit, and household assets. Geographic information included district, VDC, ward, village, distance from drivable road, distance from market, and distance from agricultural supply store. Additional variables were calculated using the base variables described above. Additional variables included measures of farm productivity, costs, returns, and profits per hectare, and vegetable adoption behavior. **Table 7** on the following page describes selected variables from the survey and shows basic descriptive statistics.

When evaluating the data that follow, a number of considerations should be made regarding potential sources of bias. First, the small sample size (n=83) suggests that random variation could skew the outcomes. Nevertheless, the Law of Large Numbers typically begins taking effect around n=40, implying that n=83 should be sufficiently large to draw meaningful conclusions. Secondly, some estimation error appears in the data as a result of farmers' mis-estimation. Many farmers in the survey had little formal education and found it difficult to give precise numerical estimates. This measurement error may cause attenuation bias, but there is no reason to believe that farmers consistently over- or under-estimated. Thus, estimation errors should cancel out, minimizing bias from this source.

Table 7. Variable Names, Definitions, and Descriptive Statistics

Variable Name (regression variable)	Variable Description	Sample Mean	Standard Deviation
Districts:			
Bardiya	1 if farmer in Bardiya, 0 otherwise	0.36	
Dang	1 if farmer in Dang, 0 otherwise	0.37	
Surkhet	1 if farmer in Surkhet, 0 otherwise	0.27	
Age (age)	Head of Household's years of Age	36.8	11.98
Gender (gender)	Head of Household's gender, 1=male, 0=female	0.35	
Family Size (familysize)	Number of Family Members in Household	6.69	3.14
Education (education)	1=illiterate, 2=informal, 3=primary, 4=secondary, 5=SLC, 6=higher	3.50	1.69
Ethnicity (highercaste)	1=member of higher caste group, 0 otherwise	0.31	
Agricultural Training (agtraining)	Number of agricultural training sessions attended	4.12	2.20
Number of Assets (assets)	Accumulation of assets including bullock, stove, electricity, etc.	6.27	2.17
Distance to Road (distroad)	Kilometers to nearest drivable road	1.16	1.59
Distance to Market (distmarket)	Kilometers to nearest market for goods being produced	5.35	4.73
Dist. to Ag. Supplier (distagrovet)	Minutes required to reach nearest agricultural supply store	62.9	68.41
Farm Area (farmarea)	Cultivable area of farm in ropani (1 ropani = 0.051 hectares)	11.84	11.26
Food Security (foodsupply)	1=sufficient food for 0-6 months, 2=food for 6-9 months, 3=food for 9-12 months, 4=food for >12 months	3.05	0.90
Crop under Cultivation (crop)	Crop being cultivated for which survey data was collected		
Area of Crop Cultivated (croparea)	Ropani under cultivation of surveyed crop	6.06	10.30
Tractor in Use (tractor)	1=tractor rented or owned by farmer, 0=otherwise	0.26	
Motor Pump in Use (pump)	1=pump rented or owned by farmer, 0=otherwise	0.58	
Revealed Access to Credit (credit)	1=farmer currently has loan, 0=currently without loan	0.62	
Labor Cost per Ha. (laborcosthect)	Labor hrs. expended in 1 season's cultivation of surveyed crop multiplied by local labor cost	82,013.9	86,985.50
Capital Cost per Ha. (capitalcosthect)	Cost of capital inputs for 1 season's cultivation of surveyed crop	49,360.9	39,030.90
Total Cost per Ha. (costperhectare)	Total cost for 1 season's cultivation of surveyed crop	144,444	120,483
Cost per Kg. (costperkg)	Total cost to produce one kg. of surveyed crop	19.74	12.25
Capital Share of Total Cost (capshare)	Proportion of total cost going to capital expenditures	0.39	0.17
Labor Share of Total Cost (laborshare)	Proportion of total cost going to labor expenditures	0.61	0.17
Revenue per Ha. (revenuehect)	Total earnings per hectare for surveyed crop	315,357	353,025
Profit per Ha. (profithect)	Gross margin per hectare for surveyed crop	170,784	285,163
Labor Hours per Ha. (laborhrshect)	Hours of labor invested in 1 season's production of surveyed crop (including both family and hired labor)	2,550.1	2,834.54
Retail Price of Crop (retailprice)	Price per kg. for surveyed crop received by farmer at point of sale	31.27	16.44
Yield (kilos)	Total kilograms of surveyed crop produced in season of survey	25,357.8	33,425.5
Yield per Ha. (yieldhect)	Kgs. of surveyed crop produced per hectare for surveyed season	9,065.44	7,537.56
Yield per Expenditure (yieldcost)	Kgs. of surveyed crop produced per 100 NRs invested	6.84	3.64
Yield per Labor Hours (yieldhrs)	Kgs. of surveyed crop produced per labor hour invested	5.63	5.24
Fertilizer Use per Ha. (fertilizerperhect)	Kgs. of chemical fertilizer applied per hectare for surveyed crop	204.14	665.8
Physical Capital Index (physcapindex)	Index ranging from 0 to 2 measuring intensity of physical capital use, 0=no physical capital use, 2=significant physical capital use	1.97	1.19
Adoption of Vegetables (vegadopt)	1=vegetables adopted on farm, 0=vegetables not adopted	0.55	
Share of Vegetables (shareofveg)	Share of cultivable farm area dedicated to vegetable cultivation	0.08	0.14
Price Differential (pricedifferential)	Difference between veg. and staple retail prices in farmer's VDC	13.19	9.23
Total Factor Productivity (tfp)	Residual derived from Cobb-Douglas Production Function	2,425.63	2,487.65
Relative TFP (relativetfp)	Difference between farmer's TFP and TFP of other farmers in sample growing same crop type	0	1,538.6

Table 8 shows selected comparative descriptive statistics for farms growing vegetables versus staple crops.

Table 8. Comparative Statistics between Farms Growing Vegetables and Farms Growing Staple Crops

Variable	Crop Type									
	Staple					Vegetable				
Farm Characteristics	**Min.**	**Max.**	**Mean**	**S.D.**	**C.V.**	**Min.**	**Max.**	**Mean**	**S.D.**	**C.V.**
Farm Area (Ropani) (farmarea)	3.3	51.0	14.9	14.4	96.4	1.7	39.9	9.3	7.1	76.2
Crop Area (Ropani) (croparea)	2.0	53.3	12.1	13.0	107.5	0.3	5.3	1.1	1.1	99.0
Distance to Road (km.) (distroad)	0.1	5.0	1.4	1.8	125.6	0.1	5.0	0.9	1.4	145.5
Distance to Market (km.) (distmarket)	1.0	17.0	5.5	4.9	87.9	0.1	17.0	5.2	4.7	89.8
Distance to Agricultural Goods Supplier (min.) (distagrovet)	5.0	300.0	79.9	73.3	91.8	2.0	300.0	49.1	61.6	125.5
Use of Fertilizer (kg./ha.) (fertilizerperhect)	0.4	1,523.2	65.7	255.9	389.5	5.9	5,323.3	316.8	854.8	269.8
Use of Tractor (tractor)	0.0	1.0	0.3	0.5	149.9	0.0	1.0	0.1	0.4	251.3
Use of Pump (pump)	0.0	1.0	0.2	0.4	202.9	0.0	1.0	0.4	0.5	119.2
Use of Credit (credit)	0.0	1.0	0.6	0.5	82.8	0.0	1.0	0.6	0.5	77.9
Producer Price (NRs) (retailprice)	17.0	60.0	24.6	13.0	52.8	15.0	100.0	36.7	17.1	46.4
Head of Household's Age (yrs.) (age)	18.0	68.0	36.0	14.0	38.8	18.0	60.0	37.5	10.2	27.3
Head of Household's Gender (gender)	0.0	1.0	0.2	0.4	186.4	0.0	2.0	0.4	0.5	124.0
Number Family Members (familysize)	2.0	17.0	7.3	3.3	45.6	2.0	15.0	6.2	2.9	47.4
Head of Household's Level of Education (level) (education)	1.0	6.0	3.5	1.7	48.5	1.0	6.0	3.5	1.7	48.6
Agricultural Training (classes) (agtraining)	0.0	7.0	3.5	2.3	65.6	1.0	10.0	4.7	2.0	43.5
Household Assets (# of assets) (assets)	1.0	12.0	5.5	2.1	38.9	2.0	12.0	6.9	2.0	29.3
Household Food Supply (foodsupply)	1.0	4.0	2.8	1.0	34.4	1.0	4.0	3.3	0.8	24.3

The comparative statistics presented in **Table 5** illustrate some basic differences between the average vegetable producer and average staple crop producer. Farmers producing vegetable crops tend to have smaller farm sizes (mean=9.3 ropani) than do farmers producing only staple crops (mean=14.9 ropani). Furthermore, vegetable producers dedicate much smaller plots to vegetable production than staple producers dedicate to staple crop production (1.1 ropani for vegetables versus 12.1 for staples). Vegetable producers are, on average, approximately one half hour closer to an agricultural supply store than are staple crop producers. Vegetable producers apply more fertilizer to their land (316.8 kg/hectare versus 65.7 kg./hectare for staples). Vegetable producers also earn on average 12.1 NRs more per kilogram at the point of sale. Finally, vegetable producers have on average attended one more agricultural training session than have staple producers.

These findings suggest that substantial differences exist in the characteristics of vegetable and staple crop producers. The following section (**Section 5**) sets the stage for the analysis of these underlying patterns by evaluating the nature of vegetable crops according to the criteria identified in **Section 3, Table 4**. This section uses the survey data to establish a series of empirical facts that will serve to confirm or reject hypothetical explanations for the regression results presented in **Section 7**.

5. Vegetable Crops: Empirical Facts

As described in **Section 3, Table 4**, our predictions of vegetable adoption behavior are conditional upon qualities of the vegetable "technologies" themselves. Whether vegetables are lumpy or divisible determines whether access to credit is a significant constraint to adoption. And vegetables' labor requirements, profitability, risk, and returns to scale relative to staple crops determine what type of farmer is likely to adopt them. In the following section I draw upon the dataset described in **Section 4** above to derive six "empirical facts" regarding vegetable crops. These facts will condition and refine the hypotheses laid out in **Tables 4, 5, and 6** of **Section 3**, and will sharpen the specificity of my predictions regarding vegetable adoption behavior.

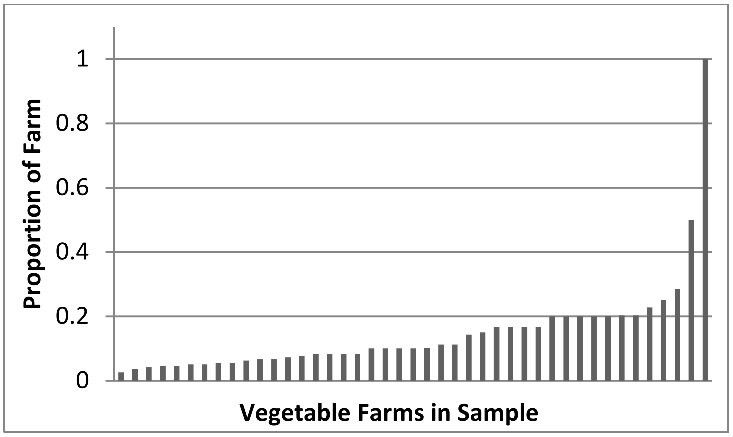
Fact 1. Vegetables are a Divisible Technology

Farmers cannot purchase technologies such as tractors or pumps in stages, but rather must have the liquidity or credit to overcome the large initial fixed cost of purchase. Thus, tractors and pumps are referred to as "lumpy" technologies. In contrast, hybrid seeds are a "divisible" technology since farmers can adopt any volume of them, from one seed to an entire field. In the case of divisible technologies, credit limitations are much less of a barrier to adoption.

Are vegetables a divisible or lumpy technology? At first glance, vegetables are akin to hybrid seeds in that farmers can adopt them at graduated scales. If, however, vegetable production requires the corresponding adoption of a fixed-cost technology such as an irrigation system, then vegetable crops could in fact be a "pseudo-lumpy" technology (Feder 1985). Thus, it is not immediately obvious whether vegetables should be a lumpy or divisible technology.

Figure 8 illustrates the proportion of vegetable farmers' farms dedicated to vegetable crops in the dataset. If vegetables were a lumpy technology, shares of vegetable cultivation should exhibit a stepwise pattern across farms. Nevertheless, the share of farm area dedicated to vegetable crops rises smoothly, suggesting that vegetables are indeed a divisible technology.

Figure 8. Proportion of Farm Area Dedicated to Vegetable Cultivation



The divisible nature of vegetable crops suggests that, while these crops may benefit from corresponding fixed-cost inputs such as irrigation, this correspondence does not appear to be a determining factor in the share of farmland that farmers dedicate to vegetable crops. Furthermore, vegetable divisibility suggests that access to credit should be a much less significant factor in predicting vegetable adoption than standard technology adoption theory would suggest.

Fact 2. Vegetables are more Labor-Intensive than Staple Crops

The quantity of labor required to produce a crop is a key constraint on farm production in Mid-Western Nepal. Labor markets are incomplete, and, in some areas, non-existent, as revealed by the very low use of hired labor in the sample (6 out of 78 farmers hired labor in 2014). Consequently, severe labor bottlenecks appear around labor-intensive periods such as planting and harvest. Farmers often participate in intra-family and intra-village labor sharing to overcome these bottlenecks. Nevertheless, if large farmers elect to plant too labor-intensive of a crop, they will be unable to volunteer sufficient quantities of labor on neighboring farms during down times to secure their neighbors' labor during their own harvesting and planting periods. Thus, the relative labor-intensity of vegetable crops relative to staple crops could affect which size of farmer is more likely to adopt which type of crop.

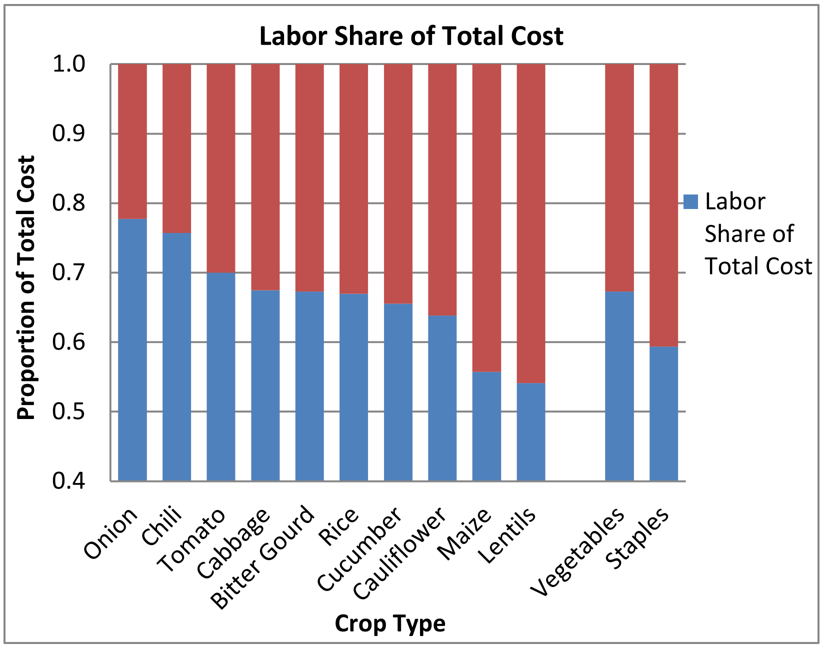
As illustrated in **Table 9**, staple and vegetable crops are relatively even in terms of labor hours required to produce one kilogram of output (with staple crops requiring, on average, 5.7 hours per kg. and vegetables requiring 5.54 hours per kg.). Nevertheless, this apparent equivalency disguises the much higher labor investment required by vegetables. On average, the sample reveals that vegetables required an average of 3,989 labor hours per hectare of cultivation, while staple crops required only 782 hours per hectare. Vegetables' much higher yield per hectare explains the rough equivalency of labor input requirements on the hours per kilogram basis. Thus, vegetables required over five times more labor input than did staple crops.

Table 9.

	Crop Type							
	Staple				Vegetable			
Variable	**Min.**	**Max.**	**Mean**	**C.V.**	**Min.**	**Max.**	**Mean**	**C.V.**
Labor Hrs. per Kg.	1.5	24.7	5.7	90.6	0.68	29.9	5.54	96.2
Labor Hrs. per Ha.	128.6	1,736	782.4	63.6	433.8	15,339	3,989	78.5

Figure 7 illustrates another aspect of the relative labor-intensity of staple and vegetable crop production. The figure charts the labor proportion of total production cost of each surveyed vegetable and staple crop. For the most labor-intensive vegetable crop, onions, 78% of total production cost goes to labor. In contrast, labor's share of the total cost for lentils (a staple crop) was just 54%. Averaging vegetable and staple crops, the labor share of total cost for vegetables was 67.3% in the sample, while the labor share of total cost for staple crops was 59.4%. Thus, using either method of measurement (total labor-input requirements or relative proportion of labor to other costs) vegetables are more labor-intensive than are staple crops.

Figure 9.



Fact 3. Vegetables are More Productive than Staple Crops

Yield per hectare is the standard measure of farm productivity, but since vegetables and staple crops bring significantly different retail values, revenue per hectare is a more informative measure. Due to their input-intensive nature, vegetable crops produce significantly larger revenues per hectare than do staples, and are thus more productive. As illustrated in **Table 10**, the mean revenue per hectare for vegetable crops in the sample was 513,179 NRs, while mean revenue per hectare for staples was 72,318 NRs, or less than one fourth of the vegetable mean.

Table 10.

	Crop Type									
	Staple					Vegetable				
Variable	**Min.**	**Max.**	**Mean**	**S.D.**	**C.V.**	**Min.**	**Max.**	**Mean**	**S.D.**	**C.V.**
Revenue per Hectare (NRs/hect.)	10,474	135,821	72,318	31,087	43	115,588	1,489,977	513,179	372,036	72
Revenue per Cost (NRs earned/100 NRs spent)	56	233	133	41	3,078	65	651	258	169	6,549
Revenue per Labor Hour (NRs/hr.)	31	482	123	97	79	31	748	190	170	89
Total Factor Productivity	70	1,344	309	220	71	72	9,791	4,148	2,130	51

Nevertheless, revenue per hectare is only one measure of farm productivity. Crops that are less productive on a revenue per hectare basis may still be more productive on a revenue per cost or revenue per labor hour basis. In the case of our dataset, mean revenue per cost for staple crops is 133 NRs per 100 NRs invested, while mean revenue per 100 NRs invested for vegetables is 258 NRs. Thus, vegetables are still more productive than staple crops when compared on a revenue per expenditure basis. When comparing crop types based upon revenue per labor hour invested, mean revenue for staples is 123 NRs per hour, and mean revenue for vegetables is 190 per hour. Thus, across all measures of productivity, vegetable crops appear to be more productivity than do staple crops.

Using a Cobb-Douglas Production Function (see **Fact 6**) we can derive residual the Total Factor Productivity (TFP) of vegetable and staple crops from the sample. The last row of **Table 10** summarizes the results of this calculation. Mean TFP for vegetable crops is 4,148, three times higher than the mean TFP value of 1,344 exhibited by staple crops. This suggests that, accounting for all factor inputs, vegetable crops are a more productive use of available resources than are staple crops.

Fact 4. Vegetables are, on average, more profitable than staple crops

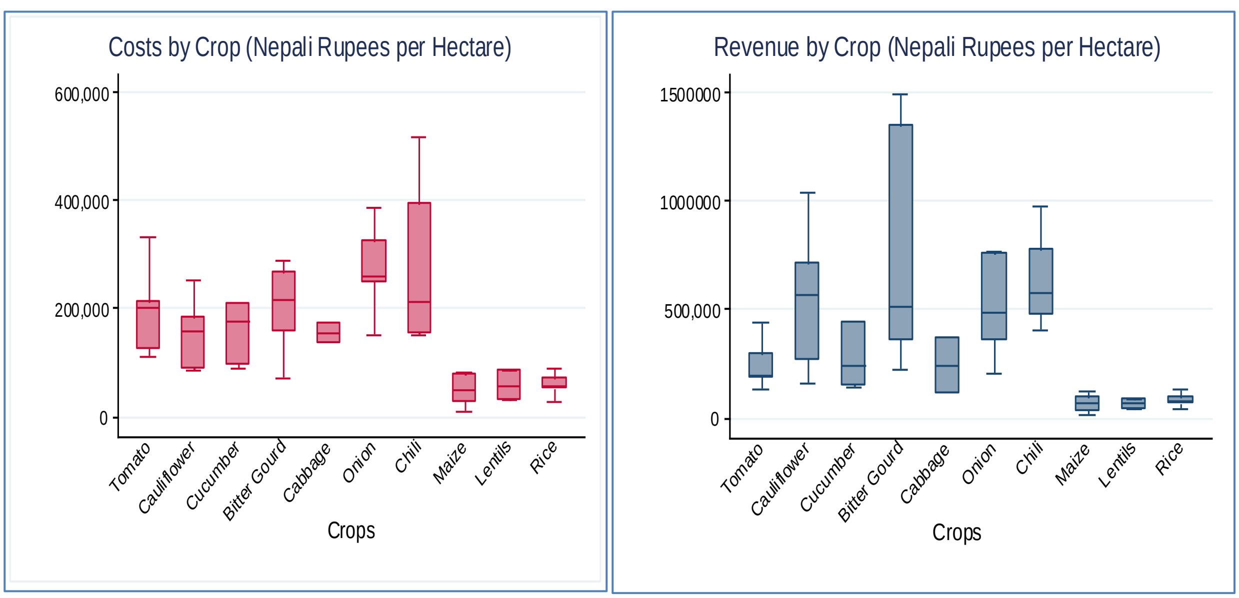
As demonstrated in **Fact 2**, vegetables require higher labor inputs than do staple crops. Therefore, to be worthwhile, vegetables must yield higher returns as well. Due to increasing demand from urban centers and export markets in India, vegetables command significantly higher retail prices than do staple crops. In the sample, the average price received by farmers for vegetable crops was 36.7 NRs per kg., while the average retail price for staple crops was only 24.6 NRs per kg. Furthermore, as demonstrated in **Fact 3**, vegetable crops exhibit notably higher yields than staple crops. Thus, not only do vegetables garner higher prices on a per kilogram basis, but they also yield more kilograms per land unit and per rupees invested. The resulting statistics for gross revenue, expenditure (cost) and gross margin (profit) among surveyed farmers in Mid-Western Nepal are reported in **Table 11** below.

Table 11.

	Crop Type							
	Staple				Vegetable			
Variable	**Min.**	**Max.**	**Mean**	**C.V.**	**Min.**	**Max.**	**Mean**	**C.V.**
Gross Revenue (NRs)	10,474	135,821	72,318	43.0	115,588	1,489,978	513,179	72.5
Expenditure (NRs)	9,203	88,143	55,764	37.6	71,536	594,535	216,626	55.3
Gross Margin (NRs)	-17,603	63,925	16,268	126.7	-88,703	1,261,216	296,553	113.2

On average, revenue from vegetables is NRs 513,179 per hectare (all values in **Table 10** are in per hectare terms) and NRs 72,318 for staple crops. Thus, revenues are over seven times higher for vegetables. However, costs are almost four times higher for vegetables as well. On net, vegetable profits were on average *eighteen times higher* than staple crop profits. **Figure 12** decomposes sample farmers' costs, revenues, and profits by crop.

Figure 12.



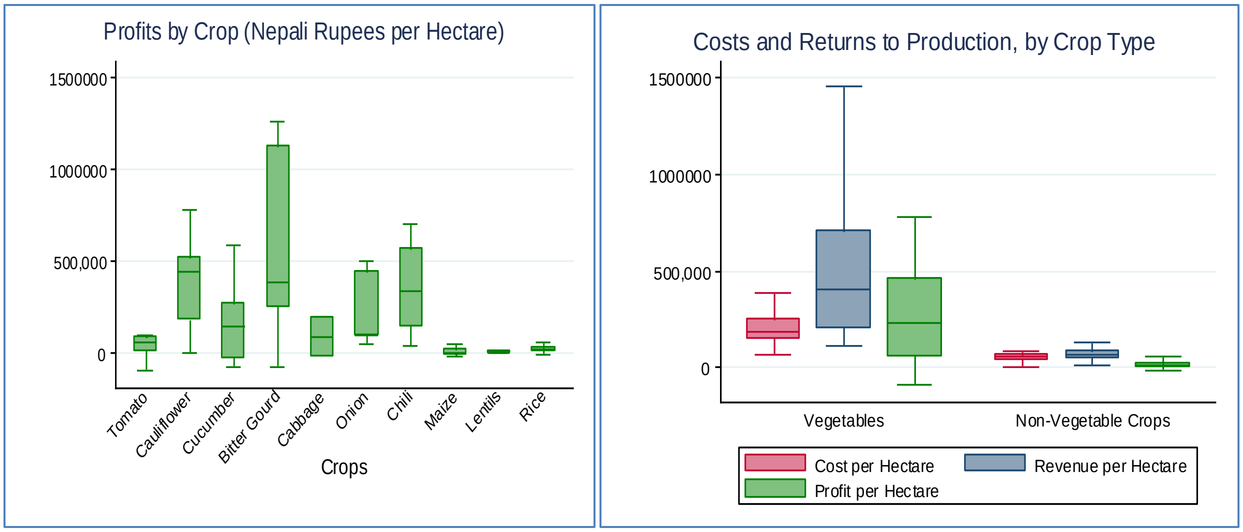


Figure 12 illustrates both the higher returns exhibited by vegetable crops, and the notably higher variance of these crops, both in terms of input costs and returns. Traditional staple crops such as rice, maize, and lentils, are low-risk, low-return products, as evidenced in the charts above. They are subsistence-level crops that mostly guarantee a return but do not yield a profit much above zero. These crops are often grown by farmers who are only marginally integrated into markets or commodity chains. In contrast, vegetable crops are typically grown as cash crops. They offer the potential for much higher returns, but also present the risk of negative profits and high variance in outcomes. The implications of this variance are discussed in **Fact 5** below.

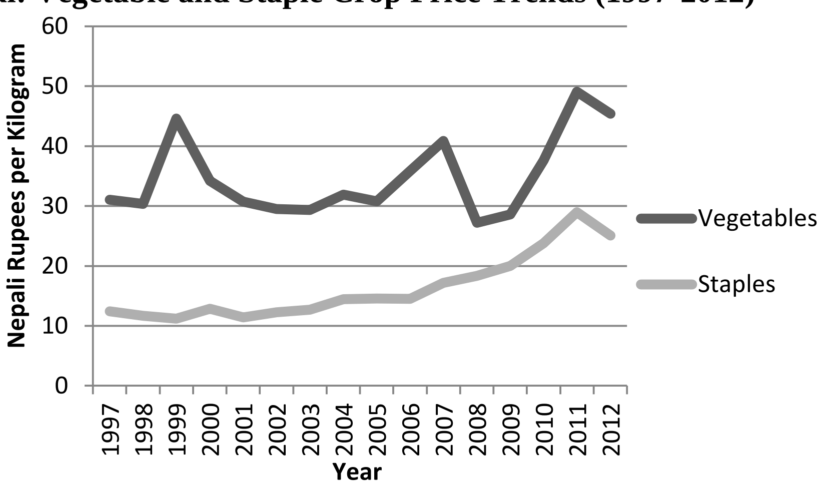
In sum, vegetables are significantly more profitable than staple crops, but require much higher inputs and exhibit greater variance in outcomes.

Fact 5. Vegetables are Riskier than Staple Crops

As illustrated visually in **Figure 12** and numerically in **Tables 9, 10, and 11**, vegetables exhibit greater variance in input requirements and outcomes, relative to staple crops. The Coefficient of Variance (CV) of labor hours per hectare for staple crops is 63.6, while the equivalent value for vegetables is 78.5. Evidently, the labor requirement for vegetables varies more than that for staples, thus introducing risk and uncertainty into farmers' production decisions. Furthermore, the coefficients of variance for revenue and expenditure per hectare are significantly higher for vegetable crops than for staple crops, suggesting that inputs and outputs from vegetables are more unpredictable. This unpredictability, as detailed in **Section 3.1.2**, may motivate more risk averse farmers to avoid adopting vegetable crops.

Furthermore, producer prices for vegetables exhibit much greater variability than do prices for staple crops. As illustrated in **Figure 13**, annual producer prices for vegetables in Nepal are significantly more unstable than staple crop prices (FAOSTAT 2015). While staple crop prices have followed a predictable trend since 1997, vegetable prices have fluctuated widely over this same time period. If seasonal price data were available for Nepal, the variation in intra-annual vegetable prices would be even more striking than the variance depicted in Figure 13.

Figure 13. Nepal: Vegetable and Staple Crop Price Trends (1997-2012)



Source: FAOSTAT 2015

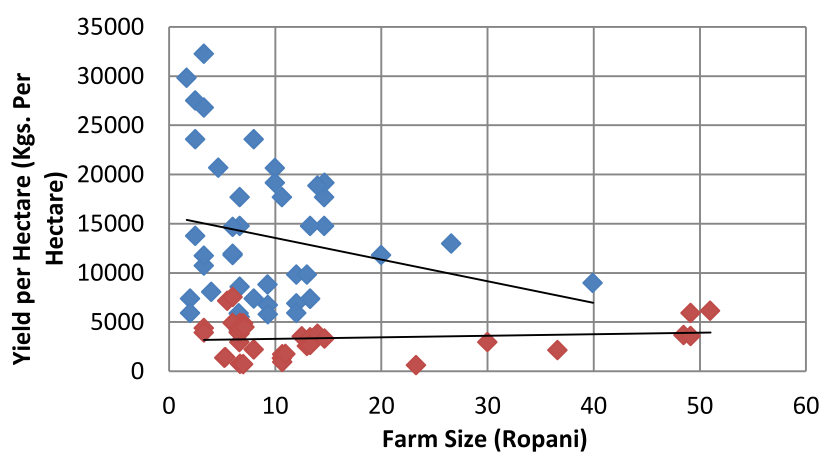
Thus, vegetables not only require more unpredictable levels of labor and cash inputs, but also present more unpredictable returns at the point of sale. As a result, we should expect that measures of risk such as food security and assets will be strongly associated with vegetable adoption. We would predict that improved food security is positively associated with adoption, and that increased quantity of assets is positively associated with adoption as well.

Fact 6. Vegetables Exhibit Decreasing Returns to Scale (DRS) whereas Staple Crops Exhibit Increasing Returns to Scale (IRS)

Whether or not vegetable crops enjoy economies of scale could determine the size of farm that finds adoption to be optimal. In particular, larger farms will be more inclined to adopt vegetables if they exhibit increasing returns to scale, since larger farmers can capitalize upon the larger scale of their production facilities and out-compete smaller farmers. On the contrary, if vegetables exhibit decreasing returns to scale, then smaller farmers will be more likely to adopt since the advantages of adoption would decrease in proportion to the size of the production area. In either case, understanding the returns to scale exhibited by vegetable crops is integral to disentangling farmers' adoption behavior.

From **Figure 14** below, it is apparent that, on the level of correlation, vegetable yields per hectare decrease as farm size increases, while staple yields per hectare increase slightly as farm size increases. Nevertheless, moving beyond correlation and measuring the effect of a particular factor input (in this case, land) on production can be difficult due to the confounding effects of other inputs. For instance, farm size may have a negative impact on land productivity, but if larger farmers employ productivity-boosting tractors and fertilizers, then these additional scale-correlated inputs may offset the negative effect of farm size and make the correlation between overall productivity and farm size positive.

Figure 14. Yield per Hectare by Farm Size (blue=vegetables, red=staple crops)



To isolate the effects of each factor of production on final output, economists often use a Cobb-Douglas Production Function, which allows for increasing, decreasing, and constant returns to scale among factors of production. The Cobb-Douglas production function can be written in general form as:

(5.1) $$Y = A(X_1^{\alpha 1} X_2^{\alpha 2} \dots X_n^{(1-\alpha 1-\alpha 2-\cdots-\alpha n)})\varepsilon$$

Where Y is total output (yield (kg.)), A is total factor productivity (the Cobb-Douglas residual, or OLS intercept), X_1 is the first factor of production and X_n is the nth factor of production. α_1 is the weight that X_1 carries, or the share it constitutes, in the production of final good Y. ε is random error term.

In the case of crop production in Mid-Western Nepal, vegetable and staple crops constitute distinct production technologies, and are not comparable to each other. However, we can divide the sample into vegetable and staple crop producers, and within each group, describe the effects of factor inputs on final production using the two specified production functions below:

(5.2) For Staple crops: $(stapleyieldperhect) =$

$$A((croparea)^{\alpha 1}(laborhrshect)^{\alpha 2}(capitalcosthect)^{\alpha 3}(fertilizervolhect)^{\alpha 4})\varepsilon$$

(5.3) For Vegetable crops: $(vegetableyieldhect)$ =

$$A((croparea)^{\alpha 1}(laborhrsect)^{\alpha 2}(capitalcosthect)^{\alpha 3}(fertilizervolhect)^{\alpha 4})\varepsilon$$

Where *stapleyieldhect* and *vegetableyieldhect* measure total kilograms of output per hectare from the respective staple or vegetable crop field, *croparea* gives the area of that field in hectares, *laborhrshect* measures the number of labor hours invested per hectare, *capitalcosthect* measures the cost of all capital inputs per hectare, and *fertilizervolhect* measures the kilograms of fertilizer applied per hectare. As before, ε is a random error term.

The production function can be log-linearized as follows:

(5.4) $$ln(Y) = ln(A) + \alpha_1\, ln(X_1) + \alpha_2\, ln(X_2) + \alpha_3\, ln(X_3) + \alpha_4\, ln(X_4) + \varepsilon$$

Equation 4.4 is now suitable for regression analysis using Ordinary Least Squares (OLS).[4]

In order to interpret OLS coefficient estimates, I solve a specified version of the CD production function. Both Equations 5.2. and 5.3 above may be written symbolically as:

(5.5) $$\frac{Y}{L} = \frac{L^{\alpha}N^{\beta}K^{\gamma}F^{\delta}}{L}$$

(5.6) $$= \frac{L^{\alpha}N^{\beta}K^{\gamma}F^{\delta}}{L^{1-\beta-\gamma-\delta}L^{\beta}L^{\gamma}L^{\delta}}$$

(5.7) $$= L^{\alpha+\beta+\gamma+\delta-1}(\frac{N}{L})^{\beta}(\frac{K}{L})^{\gamma}(\frac{F}{L})^{\delta}$$

Where L is land area, N is labor, K is capital, and F is fertilizer. From Equation 5.7 it is clear that, after log linearization, returns to land are characterized by the sum $(\alpha + \beta + \gamma + \delta - 1)$. If this sum is greater than zero, then the production function exhibits increasing returns to scale. In contrast, if this sum is less than zero, the function exhibits decreasing returns to scale.

Results of the OLS regression of the Cobb-Douglas production function for staple and vegetable crops are presented in **Table 12** below. Coefficient estimates for vegetable and staple crops indicate that the sum $(\alpha + \beta + \gamma + \delta - 1)$ = -0.687 for vegetables and 0.143 for staples. Thus, returns to scale for vegetables appear to be decreasing (since -0.687$<$ 0) and returns to scale for staples appear to be increasing (since 0.143 $>$ 0). A joint significance test of the hypothesis that $(\alpha + \beta + \gamma + \delta - 1) > 0$ is significant at the 5% level for vegetables (F=4.89). This joint significance test is not significantly different from zero for staples.

[4] The estimated OLS coefficients of Equation 5.4 may be biased since factors of production are endogenous to the production function. That is, capital, labor, etc. are not randomly selected, but are instead themselves functions of output. Nevertheless, while endogeneity means the absolute magnitudes of the OLS coefficients may not be interpretable, they are still roughly comparable.

Table 12. Regression Results of Cobb-Douglas Production Function for Vegetable and Staple Crops

	Coefficients	
Explanatory Variables	**Vegetables**	**Staples**
Log of crop area	-0.073	0.179
	(0.157)	(0.106)
Log of labor hrs/hectare	-0.311	0.155
	(0.242)	(0.172)
Log of capital input/hectare	0.686	0.722
	(0.332)	(0.255)
Log of fertilizer kilos/hectare	0.011	0.087
	(0.067)	(0.057)
Constant	3.479	-1.445
	(2.664)	(2.222)
R-Squared	0.153	0.500
Returns to Scale	DRS	IRS

Standard errors are reported in parentheses

Vegetables likely exhibit DRS because farmers, due to vegetables' input intensive nature, find it difficult to scale up labor and capital inputs in proportion to increases in land. Staples, in contrast, likely exhibit IRS because they require much less individualized attention (weeding, cross-pollination, etc.) than do vegetables and thus enable economies of scale for larger plantings. Consequently, staples deliver disproportionately higher per unit yields for large farmers.

Further manipulation of Equation 5.1 allows us to calculate the TFP of sampled farmers. Comparative TFP values between staple and vegetable crops were reported in **Table 10.**

In sum, vegetable crops exhibit decreasing returns to scale, whereas staple crops exhibit increasing returns to scale. This makes intuitive sense, given that vegetables require higher individual attention and specialized conditions, whereas staple crops are more uniform and less demanding of individualized care.

Summary:

Fact 1. Vegetables are a divisible technology

This suggests that smaller farmers will face less fixed-cost barriers to adoption. Credit should therefore *not* appear to have a significant negative impact on adoption.

Fact 2. Vegetables are more labor-intensive than staple crops

Due to this fact, larger farms may find it difficult to secure sufficient supplies of labor to grow large plots of vegetables. Smaller farmers, however, have a high enough family size to land size ratio to grow vegetables.

Fact 3. Vegetables are more productive than staple crops

Farmers who are able to overcome barriers to the adoption of vegetables will see higher yields per hectare relative to staple crop farmers. This creates an incentive for vegetable adoption.

Fact 4. Vegetables are, on average, more profitable than staple crops

Vegetables are, on average, 18 times more profitable than staples in the sample. This fact undergirds our assumption that optimizing farmers would adopt vegetables if they were able to overcome extant barriers and constraints.

Fact 5. Vegetables are riskier than staple crops

While returning higher yields and profits, vegetable crops also exhibit higher variance in input costs and returns (including more unpredictable retail prices) than staples. Furthermore, vegetable cultivation resulted in negative profits for some farmers in the sample due to poor harvests or faulty marketing. This increased variance in costs and returns introduces additional uncertainty into vegetable production, perhaps dissuading more risk averse farmers from adopting. Consequently, we should expect to find that variables proxying risk aversion have statistically significant effects. The food insecurity dummy should have a negative effect, while the assets variable should have a positive effect. Due to risk effects, credit (which allows consumption smoothing in the case of a failed harvest) may appear to have a significant positive effect, confounding the irrelevance of this variable a measure of the impact of scale.

Fact 6. Vegetables exhibit DRS while staple crops exhibit IRS

This fact suggests that larger farmers may find vegetables less attractive than do small farmers. Large farmers may be able to exploit sufficient quantities of scale on their large plots to increase staple crop profits to the point where they are unwilling to substitute these stable (albeit low) profits for the uncertainty and increased intensity of vegetables.

The following section reviews a range of limited dependent variable regression models, and then develops empirical methods to estimate the effects of farmers' characteristics on their vegetable adoption behavior.

6. Model Development and Specification

The nature of the technology under analysis can determine whether it is appropriate to model farmers' adoption decisions as binary choices or as continuous or graduated choices. For instance, the adoption of a tractor would require a binary choice model, such as logit or probit, since the farmer's adoption decision can only assume two forms–adopt or do not adopt. In contrast, when analyzing divisible technologies such as vegetables, researchers often wish to model not only the either-or adoption decision, but the scale of adoption as well (Feder 1985; Sunding and Zilberman 2001).

In the case of vegetable adoption in my sample, both the binary adoption decision and the scale of adoption decision are of interest. First of all, we are interested in the absolute question of which characteristics influence farmers to adopt or not adopt vegetables. This question lends itself to binary decision model. Furthermore, we are interested in what factors affect the magnitude or scale of adoption. As argued in **Section 5**, farmers in the sample exhibit a wide range of adoption commitments, from dedicating just 2.5% of their land to vegetables, to dedicating 100% to vegetables. In short, understanding both what prevents many farmers from adopting vegetables, and, upon adoption, what influences farmers' choices of the scale of adoption, could improve policy implementation and vegetable cultivation practices in the field.

Linear Probability Model (LPM)

The first response to modeling a binary dependent variable model is often the Linear Probability Model, or LPM. The LPM simply applies Ordinary Least Squares (OLS) to the situation in which a vector of explanatory variables predicts the binary (0 or 1) outcome of the dependent variable. The model can be described by:

(6.1) $$Y_i = \alpha + \beta X_i + \varepsilon_i$$

Where Y_i equals either 0 or 1, and where ε_i is independent with mean 0 (Wooldridge 2012). However, this model suffers from a number of limitations. First, the predicted coefficients are unbounded. That is, they can (and often do) assume values outside of the zero to one range. Since the model is nominally predicting the probability of Y_i, a coefficient outside of the 0 to 1 range is difficult to interpret. Furthermore, the error term ε_i is heteroskedastic, meaning that variance in the error is inconstant and potentially correlated with explanatory variables in X_i (Davis, 2015). For these reasons, the LPM is not the most compelling approach to modeling limited dependent variables. We thus look to Logit and Probit models for better estimates.

Logit and Probit Models

In both the Logit and Probit models, we assume that a continuous but unobserved "latent" variable underlies decision makers' behavior. In the case of farmers in my sample, this latent continuous variable can be thought of as an expected utility function, in which farmers' characteristics and characteristics of the technology combine to produce an expected utility from vegetable adoption. Nevertheless, the survey could not observe this continuous variable, and instead observed a limited-information "indicator" variable, that is, revealed vegetable adoption. Farmers' latent expected utility, Z_i, can be described by:

(6.2) $$Z_i = \alpha + \beta X_i + \varepsilon_i$$

Where ε_i is a random error term following either the Standard Normal or Standard Logistic distribution. The observed variable, Y_i, takes binary values 0 or 1, according to:

(6.3) $$Y_i = \begin{cases} 1 \; if \; Z_i > Z_i^* \\ 0 \; if \; Z_i \leq Z_i^* \end{cases}$$

Where Z_i^* is the threshold expected utility above which the farmer will optimally choose to adopt vegetables (Wooldridge 2012).

We can safely normalize Z_i^* to 0, indicating that the farmer will adopt vegetables if her expected utility from vegetable adoption is positive, and will not adopt if her expected utility is negative. Thus, Eq. 6.3 becomes:

(6.4)

$$Y_i = \begin{cases} 1 \; if \; Z_i > 0 \\ 0 \; if \; Z_i \leq 0 \end{cases}$$

In this case,

(6.5) $$P(Y_i = 1) = P(Z_i > 0)$$

$$= P(\alpha + \beta X_i + \varepsilon_i > 0)$$

$$= P(\varepsilon_i > -(\alpha + \beta X_i))$$

$$= 1 - P(\varepsilon_i < -(\alpha + \beta X_i))$$

$$=1 - G(-(\alpha + \beta X_i))$$

Where X_i is a vector of explanatory variables and G is a cumulative distribution function of ε_i that follows either the standard normal or standard logistical distribution (Wooldridge 2012). We can assume that G is symmetric about 0. Thus,

(6.6) $$P(Y_i = 1) = 1 - G(-(\alpha + \beta X_i))$$

$$= G(\alpha + \beta X_i) = G(Z)$$

Where again, G is a cumulative "link" function ranging between o and 1 (Davis 2015).

In the case of the Logit model,

(6.7) $$P(Y_i = 1) = G(\alpha + \beta X_i) = \lambda(\alpha + \beta X_i) = \frac{1}{1+e^{-(\alpha+\beta X_i)}}$$

Or, alternatively,

(6.8) $$P(Y_i = 1) = \log\left(\frac{P_i}{1-P_i}\right) = \alpha + \beta X_i$$

In other words, the dependent variable of the Logit Model is the logarithm of the odds that a specific choice will be made.

In the case of the Probit model, $\varepsilon_i \sim N(\mu, 1)$ and:

(6.9) $$P(Y_i = 1) = G(\alpha + \beta X_i) = \Phi(\alpha + \beta X_i)$$

Probit models are estimated using non-linear maximum likelihood methods.

Since Logit and Probit model results are not nested, likelihood ratio tests or Wald tests cannot provide comparable measures of goodness of fit (Wooldridge 2012). Studies often report pseudo-R^2 values, which themselves imply additional problems in interpretation. Nevertheless, as developed by Hagle and Mitchell (1992), the McKelvey-Zavoina and Aldrich-Nelson pseudo-R^2 values exhibit the best results among possible values, and will be reported in the results section below.

Interpretation of Logit and Probit Model Results

The coefficients derived from Logit and Probit regressions are equivalent to coefficients derived from a standard OLS model. They measure the degree of unit-to-unit change between explanatory variables and the latent continuous expected utility function. Thus, the signs and significance levels of Logit and Probit coefficients are indeed interpretable (Wooldridge 2012). Nevertheless, because this latent utility variable is unobserved in the data, the coefficients cannot measure the actual magnitude of effect between the explanatory variables and the revealed binary dependent variable. In order to interpret the magnitude of the effect of each explanatory variable, we need to find the marginal effect of that variable on Y_i (Greene 2009).

To calculate the individualized marginal effect of a specific continuous X on $P(Y_i = 1)$, that is, $P(Y_i = 1|X_i)$, we take the partial derivative of P with respect to X:

(6.10) $$\frac{\partial P}{\partial X_i} = g(Z)\beta_i$$

Where g(Z) is the probability distribution function corresponding to G(Z)'s CDF. Using Eq. 6.10, we calculate the marginal effect of each X_i in the sample, and then calculate the mean of these marginal effects to arrive at the average partial effect. The resulting *average partial effects* are interpretable, and measure the effect of increasing X_k by one unit (or 1% if X_k is a logged value) on the probability that Y_i crosses the threshold from 0 to 1 or vice versa. For those explanatory variables that are binary in nature, the marginal effect is calculated as the change in the probability of the dependent variable flipping from 0 to 1 given a change from 0 to 1 in the explanatory variable (Davis 2015).

Discrete Choice with More than Two Options: Ordered Probit

Farmers not only make a binary vegetable adoption decision, but, conditional upon choosing to adopt, they also decide how much of their farm to dedicate to vegetable cultivation. Using the *shareofveg* variable that measures the proportion of total available farm area dedicated to vegetables, I can estimate an OLS regression to determine the effect of explanatory variables on the continuous share of adoption variable. This method is widespread in the technology adoption literature (Feder 1985; Zeller et al., 1998). I estimate an OLS model of this nature in the results section below. Nevertheless, using OLS to estimate farmers' share of adoption decision imposes a linear relationship on what is, in reality, a graduated and censored decision structure. Farmers' decision making process is graduated because the change in share of adoption from 0 to 0.001 is modeled linearly with OLS and registers the same effect as the change from 0.001 to 0.002. Nevertheless, these two gradations are fundamentally different. The decision to adopt vegetables in the first place is a much larger decision than that of deciding to marginally increasing cultivation area. In other words, the assumption of the Independence of Irrelevant Alternatives (IIA) does not hold (Davis 2015). Secondly, OLS ignores the censored nature of the sample since it fails to disentangle the variance within non-adopting observations.

Alternative models of discrete adoption behavior may therefore be preferable. The two available models in this category are the Multinomial Logit model and the Ordered Probit model (Greene 2009). Since the IIA assumption has already been thrown out, the Multinomial Logit model must be discarded as well. In contrast, the Ordered Probit model does not rely on the independence of irrelevant alternatives. Ordered Probit allows the error term to be correlated across alternatives, and accounts for the fundamental differences between different categories in the estimated order (Davis 2015). Thus, the Ordered Probit model and its accompanying marginal effects are estimated along with OLS in the results section below.

Model Specification

The binary adoption decision is modeled in **Section 7** with *vegadopt* as the dependent variable. *Vegadopt* assumes a value of 1 when the observed farmer has adopted vegetable cultivation and a 0 when she has not. Logit and Probit models are estimated using the explanatory variables given in the equation:

(6.11) $(vegadopt) = \beta_1(farmarea) + \beta_2(familysize) + \beta_3\ln(distagrovet) + \beta_4(education) + \beta_5(age) + \beta_6(agtraining) + \beta_7(assets) + \beta_8(credit) + \beta_9(highercast) + \beta_{10}(foodinsecure) + \varepsilon$

The explanatory variables included in Eq. 6.11 are drawn from predictions made in **Tables 4, 5, and 6** of **Section 3.** Farm area is included to assess the impact of farm size on vegetable adoption. From **Fact 2** of **Section 5**, I hypothesize that farm area will be negatively associated with vegetable adoption since vegetables require input intensity beyond what large farmers can supply under existing market conditions. The family size variable is included to assess the farm's labor supply. I hypothesize that family size will thus have a positive effect on probability of vegetable adoption. Distance from Agrovet (agricultural supply store) measures the farmers' degree of market access. I hypothesize that this variable will be negatively associated with vegetable adoption likelihood, since farmers who are farther away from markets will face greater challenges in transition to market-dependent production. Education measures the levels of schooling reached by farmers. I hypothesize that this variable will be positively associated with vegetable adoption, since, in line with scholars of the human capital school, I predict that education leads to more effective information gathering and farm-level decision making. I hypothesize that the age variable will be positively associated with adoption since older farmers possess superior information and experience. However, it could be the case that younger farmers adopt earlier due to increased comfort with new technologies and methods. Similarly to my reasoning regarding *education*, I predict that the next variable, agricultural training, will also be positively related to rates of vegetable adoption. The *agtraining* variable also controls for the selected sample effects of the non-random selection process. Thus, while this estimate may be biased, it serves to reduce bias on other coefficient estimates. Variables measuring farmers' assets and access to credit proxy farmers' wealth and risk aversion. Farmers with credit and significant assets will be more likely to take on the risk of growing vegetables. Thus, I hypothesize that both assets and credit will be positively associated with vegetable adoption. Finally, higher caste and food insecurity dummies are included to measure the effects of belonging to a higher caste group or being food insecure. Much of the political economy literature on Nepal highlights the importance of ethnicity, or caste, to the access of resources, extension services, and other benefits (Thapa, 2007). I control for the effect of this differential resource access by including a dummy registering 1 if the subject identified as Brahmin or Chhetri, and 0 if the subject did not. I hypothesize that this variable is positively associated with vegetable adoption. The food insecurity dummy registers a value of 1 if the family does not have enough food reserves to last 9 months (is market dependent, in other words) and a 0 if the family has sufficient food supplies. This variable is another proxy for risk aversion, since food insecure families are much more risk averse than families with surplus food supplies. Thus, I hypothesize that the food insecurity dummy will be negatively related to vegetable adoption likelihood.

I evaluate the stability of the Logit Model's findings by systematically adding and removing extraneous variables to gauge the effects of different model specifications on core variable magnitudes and levels of significance.

Furthermore, I measure the scale of vegetable adoption using both standard OLS and an Ordered Probit model. Both estimate models similar to that given in Eq. 6.11. My predictions of the coefficient signs remain the same as they were for the standard Logit and Probit models.

Finally, I verify the reliability of the dataset as a whole by calculating a Logit model for farmers' binary tractor adoption decisions. I predict that a similar range of explanatory variables as those used in Eq. 6.11 will again be influential on tractor adoption, except that farm area will have a positive effect. This is because of the lumpy nature of tractor technology (See **Section 5, Fact 1**). The possibility exists that the data collection (detailed in **Section 4**) was flawed and that all technologies will exhibit an erroneously negative association with farm area. If, however, tractor adoption is positively associated with land area while vegetable adoption is negatively associated, the (surprising) negative association between vegetable adoption and farm size is less doubtable.

In the following section I present regression results from the models developed above.

7. Results

Results from the regression models developed in **Section 6** are presented in the tables below. For non-logged explanatory variables, marginal effects are interpretable as the change in probability (in percentage points) that a farmer adopts vegetables, given a one unit increase in the explanatory variable.[5] For logged explanatory variables, marginal effects give the change in probability that a farmer adopts vegetables, given a 1% increase in the explanatory variable. Standard errors are reported in parentheses and levels of significance are indicated with asterisks.

As noted in **Section 3**, recent econometrics scholarship has trended toward the use of instrumental variables and randomized controlled trial methods to establish causal links between dependent and explanatory variables. Due to limitations on data collection and research design, this study relies instead on more traditional regression techniques. Thus, the following results indicate correlations between farmer characteristics and vegetable adoption behavior, *controlling for other relevant variables*. Results do not indicate causal effects.

7.1 Logit and Probit Regression Results on Binary Vegetable Adoption Decision

Table 13 presents results from Logit and Probit regressions of the farm-level dataset. I analyze the Logit model results in the text. Probit model results are presented for comparison. Both models find Farm Area, Distance to Agrovet (agricultural supply store), Age, Agricultural Training, Assets, Higher Caste Status, and Food Insecurity to be statistically significant explanators of farmers' vegetable adoption decisions.

[5] There is a subtle difference between a "change in percentage" and a "change in percentage points." Given a 10% *increase in percentage*, a likelihood of 60% would increase to 66%. In contrast, given a 10% *increase in percentage points*, a likelihood of 60% would increase to 70%, that is, would see an increase of 10 percentiles. In the marginal effects computed below, all changes are given in terms of *percentage points*.

Table 13. Logit and Probit Regression Results: Effects on Binary Vegetable Adoption Decision

	Logit Model		**Probit Model**	
Variable	Coefficient	Marginal Effects	Coefficient	Marginal Effects
Farm Area	-0.1862***	-0.0194	-0.1041***	-0.0198
	(0.0549)		(0.0278)	
Family Size	-0.1156	-0.0120	-0.0673	-0.0128
	(0.1265)		(0.0716)	
Dist. to Agrovet	-0.6668**	-0.0800	-0.3257**	-0.0749
	(0.3287)		(0.1728)	
Education	0.1549	0.0161	0.1333	0.0253
	(0.2570)		(0.1399)	
Age	0.1168**	0.0122	0.0626**	0.0119
	(0.0491)		(0.0252)	
Ag. Training	0.3759*	0.0392	0.2363*	0.0450
	(0.2239)		(0.1258)	
Assets	0.5162**	0.0538	0.2454**	0.0467
	(0.2304)		(0.1159)	
Credit	-1.0200	-0.1013	-0.6291	-0.1013
	(0.9859)		(0.5368)	
Higher Caste	-1.8366**	-0.2203	-0.8874*	-0.2203
	(0.9076)		(0.4802)	
Food Insecure	-2.5808***	-0.2176	-1.4033**	-0.2176
	(1.2267)		(0.6551)	
Constant	-4.0293		-2.1660	
	(2.3064)		(1.2452)	
Goodness of Fit:				
McKelvey-Zavoina	0.8681		0.8402	
Aldrich-Nelson	0.3836		0.4125	

Standard errors are reported in parentheses
*** = significant at 1% level
** = significant at 5% level
* = significant at 10% level

Farm area is negatively associated with vegetable adoption at the 1% level of significance, and the marginal effect of -0.0194 indicates that a 1 ropani increase in farm area is associated with a 1.9% decrease in the probability of vegetable adoption, holding other variables constant. This surprising result contradicts standard theories of technology adoption, which predict that larger farmers will adopt new technologies first, and suggests instead that smaller farmers in the sample are significantly more likely to adopt vegetables than are larger farmers.

Distance to Agrovet is negatively associated with vegetable adoption at the 5% level of significance. Its marginal effect is -0.08, indicating that a 1% increase in the distance from farm to an agricultural supply store (which proxies distance to road and market is well) coincides with an 8% decrease in the likelihood of adopting vegetables. This result suggests that transportation costs and the increased risk and uncertainty that come with distance from agricultural supplies and markets is a significant barrier to vegetable adoption.

Farmers' Age is found to be positively associated with vegetable adoption at the 5% level of significance. Its marginal effect is 0.0122, indicating that a one year increase in age coincides with a 1.2% increase in the probability of vegetable adoption. Thus, a farmer who is ten years older than another appears 12% more likely to adopt vegetables, holding other variables constant.

Agricultural Training sessions (which measures the number of KISAN program training sessions attended) is found to be positively associated with vegetable adoption at the 10% level of significance. The marginal effect of 0.0392 indicates that, for each additional training session attended, farmers appear 3.9% more likely to adopt vegetables. This suggests that agricultural trainings and extension services have a positive impact on vegetable adoption in the sample.

Farmers' Assets are found to be positively associated with vegetable adoption at the 5%

level of significance. The large marginal effect of 0.0538 indicates that an additional “asset” held by the farmer is associated with a 5.4% increase in her probability of adopting vegetables.[6]

Farmers’ membership in a higher caste group is a significant predictor of vegetable adoption at the 5% level of significance. The marginal effect of -0.2203 suggests that changing from a low to high caste group is associated with a 22% decrease in the likelihood of vegetable adoption. This result is surprising, and will be discussed further in the discussion section below.

Finally, Food Insecurity is negatively associated with vegetable adoption at the 1% level of significance. The marginal effect is -0.2176, indicating that a food-insecure farmer appears 21.8% less likely to adopt vegetables than a food-secure farmer. Evidently, food insecurity (as a measure of risk aversion) is a significant barrier to vegetable adoption.

7.2 Sensitivity Analysis of Logit Regression Results

The variables included in the Logit and Probit regressions above were selected based on their relevance to economic theories and predictions drawn from the agricultural technology adoption literature. Thus, even though variables such as education, credit, and family size are found to be insignificant in the regressions, they are retained in the model because the underlying theory of technology adoption suggests we should control for them nonetheless.

The dataset includes a number of additional variables that could feasibly affect farmers’ vegetable adoption decisions but are either marginal to the predictions derived from economic theory or are largely collinear with already-included variables. These include farmers’ gender, and the retail price differential between vegetable and staple crops in individual villages. These variables are rarely discussed in the literature.

[6] Measured “assets” included cellphone, radio, TV, electricity, motorcycle, bicycle, cart, tractor, livestock, poultry, agro. Machinery, gas stove, and biogas. Each recorded asset was given a value of one, and the sum of total assets was treated as a rough measure of each farmer’s material wealth (not including land)

Furthermore, the dataset includes measures of each farmer's distance from nearest market and distance from nearest main road. These two measures are largely collinear with Distance from Agrovet. Finally, the dataset includes information on each farmer's ownership of a tractor or a motor pump, which are closely collinear with measures of Assets.

Table 14 below presents a "sensitivity analysis" of the Logit Model of vegetable adoption.[7] Each column represents a unique regression, beginning with a model that includes all core and additional variables discussed above. Gender, Price Differential, Distance to Market, Distance to Road, and Pump are found to be insignificant. Tractor is found to be weakly significant. Each regression to the right of this baseline regression drops insignificant variables until only core variables remain. The insignificance of distance to road and market, pump, and tractor is a likely result of the collinearity of these variables with Distance to Agrovet and Assets, respectively. Choosing core regression variables through this method (known as data fishing or data mining) is frowned upon for violating the random selection assumption underlying all regression models. However, by maintaining my selection of theoretically derived core variable regardless of their significance and winnowing out insignificant additional variables, I am able to evaluate the stability of my core variable regression results. If adding or removing additional variables radically changed the level of significance or sign of my core variables, this would suggest that my core regression results were more the product of luck than of real trends in the data. In contrast, as illustrated in **Table 14**, core variable signs and levels of significance are remarkably stable over a range of alternative specifications.

[7] The Logit model used in Table 14 is described by $(vegadopt) = \beta_2 ln(farmarea) + \beta_2 ln(familysize) + \beta_3 \ln(distagrovet) + \beta_4 ln(education) + \beta_5 ln(age) + \beta_6 ln(agtraining) + \beta_2 ln(assets) + \beta_8 (credit) + \beta_9 (highercast) + \beta_{10} (foodinsecure) + \beta_n (additional\ variables) + \varepsilon$. Thus, the coefficients are slightly different than those reported in Table 13, but the stability of results holds for Table 13 nonetheless.

Table 14. Sensitivity Analysis of Logit Regression

Variables	Coefficients					
Constant	-2.9049	-1.7569	-3.3904	-4.7008	-5.7193	-4.0484
	(7.0356)	(6.2111)	(5.8732)	(5.5006)	(5.3250)	(4.8178)
Farm Area	-2.3313***	-2.2478***	-1.9525**	-1.9244**	-2.0422***	-2.6218***
	(0.9014)	(0.8449)	(0.7727)	(0.7549)	(0.7528)	(0.7374)
Family Size	-1.4305	-1.4215	-1.2827	-1.4727	-1.2832	-0.8583
	(1.1668)	(1.1519)	(1.1010)	(1.0566)	(1.0072)	(0.9414)
Dist. to Agrovet	-1.0642*	-0.9844**	-0.7904**	-0.8466**	-0.8129**	-0.6054*
	(0.5725)	(0.4927)	(0.3783)	(0.3697)	(0.3610)	(0.3282)
Education	1.0556	0.8860	0.6572	0.5879	0.6422	0.6298
	(1.0184)	(0.8730)	(0.7737)	(0.7595)	(0.7546)	(0.7213)
Ag. Training	0.4958	0.5552	0.7567	0.8605	0.9746	0.4567
	(0.7750)	(0.7673)	(0.7678)	(0.7559)	(0.7428)	(0.6473)
Assets	2.5990*	2.5047*	2.6346*	2.8310**	3.0571**	3.1074**
	(1.3654)	(1.3303)	(1.3447)	(1.3320)	(1.3303)	(1.2720)
Credit	-1.1809	-1.1574	-0.6568	-0.7357	-0.7225	-0.8401
	(1.1215)	(1.1108)	(0.9698)	(0.9718)	(0.9571)	(0.9499)
Higher Caste	-1.5882	-1.5231	-1.5538	-1.7124*	-2.0110**	-2.1549**
	(1.0511)	(1.0404)	(0.9974)	(0.9732)	(0.9321)	(0.9358)
Food Insecure	-3.7151**	-3.6557**	-3.4860***	-3.2788***	-3.2602***	-3.4669***
	(1.5493)	(1.5030)	(1.3109)	(1.2626)	(1.2506)	(1.2402)
Age	3.4290	2.9634*	2.9560**	2.9544**	3.1051**	2.6332**
	(2.0967)	(1.5412)	(1.4731)	(1.4352)	(1.4057)	(1.2942)
Tractor	-2.9948*	-2.8509*	-2.1660	-2.1260*	-2.1051	
	(1.5592)	(1.4770)	(1.2978)	(1.2125)	(1.2118)	
Pump	1.2282	1.1902	1.0446	0.8246		
	(1.1168)	(1.1122)	(1.0516)	(0.9855)		
Price Differential	-0.8448	-0.7940	-0.6469			
	(0.7261)	(0.7005)	(0.6683)			
Dist. to Road	-0.3203	-0.3012				
	(0.3532)	(0.3490)				
Dist. to Market	0.6997	0.6546				
	(0.6372)	(0.6108)				
Gender	-0.4242					
	(1.2629)					
Goodness of Fit:						
McKelvey-Zavoina	0.9162	0.9123	0.8981	0.8977	0.8961	0.8727
Aldrich-Nelson	0.4224	0.4218	0.4135	0.4090	0.4058	0.3894

Standard errors are reported in parentheses; *** = significant at 1% level; ** = significant at 5% level; * = significant at 10% level

Farm area, Family Size, Distance to Agrovet, Education, Agricultural Training, Assets, Credit, Higher Caste, Food Insecure, and Age all exhibit similar levels of significance and uniformity in sign and magnitude of parameter estimates across all regressions. This suggests that the model specification computed in **Tables 13** and **16** is indeed stable and descriptive.

7.3 OLS Regression Results on Intensity of Vegetable Adoption

Beyond the binary decision of whether or not to adopt vegetables, farmers also face the more complex decision of how much of their farm area to devote to vegetable production. **Section 6** discussed a variety of approaches to modeling the intensity of vegetable adoption. This section employs an OLS model to estimate farmers' share of vegetable adoption (a measure running from 0 to 1 that reports the proportion of a farmers' field area dedicated to vegetable cultivation). The following section uses an Ordered Probit model.

Table 15 reports results from the OLS estimation of farmers' Share of Vegetables. Farm Area, Family Size, Age, Assets, and Higher Caste status are found to be significant explanators of the proportion of farm area farmers choose to dedicate to vegetables. Farm area is negatively associated with Share of Vegetables at the 1% level of significance. The elasticity of this effect is -0.0044, suggesting that a 1 ropani increase in farm area is related to a decrease of 0.004 in the proportion (out of 1) of a farmer's field dedicated to vegetables. Thus, a 10 ropani increase in farm size would coincide with a farmer dedicating 4% less farm area to vegetables, when controlling for all other variables.

Family Size is significant at the 10% level and its elasticity of -0.0122 suggests that a 1 person increase in family size is associated with a 0.012 reduction in the share of farm area dedicated to vegetables.

Table 15. OLS Regression Results: Intensity of Vegetable Adoption

(Dependent Variable = *shareofveg*, measuring proportion of farm area dedicated to vegetables)

Explanatory Variables	Coefficients
Farm Area	-0.0044***
	(0.0018)
Family Size	-0.0122*
	(0.0057)
Dist. To Agrovet	-0.0001
	(0.0002)
Education	-0.0003
	(0.0108)
Age	0.0017*
	(0.0015)
Ag. Training	0.0035
	(0.0079)
Assets	0.0177***
	(0.0088)
Credit	0.0225
	(0.0385)
Higher Caste	-0.1044***
	(0.0652)
Food Insecure	-0.0257
	(0.0460)
Constant	0.0363
	(0.0858)
Goodness of Fit:	
R-Squared	0.2762
Adj. R-Squared	0.1682
F(10,77)	2.5600

Standard errors are reported in parentheses
*** = significant at 1% level
** = significant at 5% level
* = significant at 10% level

Age is positively associated with Share of Vegetable at the 10% significance level, with a coefficient of 0.0017, suggesting that a 1 year increase in age coincides with a 0.0017 increase in share of farm area dedicated to vegetables. Assets are positively associated with vegetable share at the 1% significance level, and with a coefficient estimate of 0.018, a 1 asset increase is related to a 0.018 increase in share of farm area dedicated to vegetables. Finally, Higher Caste is negatively associated with Share of Vegetables at the 1% level of significance. A shift from lower to higher caste group coincides with an approximately 0.1 decrease in share of vegetables.

Thus, the results of the OLS regression on Share of Vegetables roughly mirror the results found in the Logit and Probit models reported in **Table 13**. Farm Area, notably, is again found to be negatively associated with vegetable adoption.

7.4 Ordered Probit Regression Results on Intensity of Vegetable Adoption

The OLS model in **Section 7.3** offers a rough estimation of the explanators of farmers' vegetable adoption intensity decisions, but fails to capture the necessarily stepwise pattern in adoption intensity. That is, the shift from no adoption (share = 0) to adoption (share = 0.001) is significantly different than the shift from share = 0.001 to share = 0.002. As detailed in **Section 6**, an Ordered Probit regression model can capture this stepwise pattern, and in effect estimate a series of nested binary decisions. **Table 16** presents the results of the Ordered Probit regression on the dataset. The dependent variable employed in the model is a constructed dummy variable that assumes the value of 0 when the farmer has not adopted vegetables, 1 when the farmer has adopted vegetables but dedicates less than 8% of farm area to them, 2 when the farmer dedicates 8-15% of farm area to vegetables, and 3 when the farmer dedicates more than 15% of farm area to vegetables. For each explanatory variable, marginal effects are calculated to measure the marginal change in probability between each category and the next.

Table 16. Ordered Probit Regression Results: Effects on Intensity of Vegetable Adoption

Explanatory Variables	Ordered Probit Estimates	Change in Predicted Probabilities (Marginal Effects): Do Not Adopt Vegetables	Dedicate 0-8% of Land to Vegetables	Dedicate 8-15% of Land to Vegetables	Dedicate >15% of Land to Vegetables
Farm Area	-0.0824*** (0.0220)	0.0195	-0.0233	-0.0732	-0.2563
Family Size	-0.0993 (0.0546)	0.0235	0.0007	-0.0048	-0.0195
Dist. to Agrovet	-0.1853 (0.1228)	0.0453	-0.0030	-0.0094	-0.0329
Age	0.0874* (0.0992)	-0.0304	0.0020	0.0063	0.0221
Education	0.0262 (0.0153)	-0.0059	0.0004	0.0012	0.0043
Ag. Training	0.0794 (0.0780)	-0.0188	-0.0006	0.0038	0.0156
Assets	0.2814*** (0.0912)	-0.0666	-0.0020	0.0135	0.0551
Credit	-0.1520 (0.3545)	0.0627	-0.0041	-0.0130	-0.0455
Higher Caste	-0.9985*** (0.3840)	0.1443	-0.0161	-0.0507	-0.0775
Food Insecure	-0.3107*** (0.4275)	0.0736	-0.0185	-0.0582	-0.2035
Constant	-1.1108 (0.8764)				
Goodness of Fit:					
N =	78	36	13	13	16
Log Likelihood	-74.5889				
McKelvey-Zavoina	0.8079				
Aldrich-Nelson	0.4013				

Standard errors are reported in parentheses
*** = significant at 1% level
** = significant at 5% level
* = significant at 10% level

Table 16 indicates that Farm Area, Age, Assets, Higher Caste status, and Food Insecurity are statistically significant explanators of the intensity of farmers' vegetable adoption.

Farm Area is again negatively associated with vegetable adoption at the 1% level of significance. A one ropani increase in farm area coincides with farmers being 1.9% more likely to not adopt any vegetables, 2.3% less likely to dedicate 0-8% of their fields to vegetables, 7.3% less likely to dedicate 8-15% of their fields to vegetables, and 25.6% less likely to dedicate more than 15% of their fields to vegetables. Evidently, larger farmers not only adopt vegetables less often, but they dedicate smaller portions of their fields to vegetables even when they do adopt.

Age is positively associated with vegetable adoption at the 10% level of significance. A one year increase in farmers' age coincides with that farmer being 3% less likely to not adopt vegetables, 0.2% more likely to dedicate 0-8% of her fields to vegetables, 0.6% more likely to dedicate 8-15% of her fields to vegetables, and 2.2% more likely to dedicate more than 15% of her fields to vegetables. Older farmers appear to adopt vegetables to a greater extent and in higher shares than do younger farmers.

Assets are positively associated with vegetable adoption at the 1% level of significance. A one asset increase is related to a farmer being 6.6% less likely to not adopt vegetables, 0.2% more likely to dedicate 0-8% of her fields to vegetables, 1.4% more likely to dedicate 8-15% of her fields to vegetables, and 5.5% more likely to dedicate more than 15% of her fields to vegetables. This suggests that farmers with more material wealth (and capital) are more likely to adopt vegetables and dedicate larger share of their fields to them (likely because they have the capital inputs necessary to cultivate more of these labor-intensive crops).

Higher caste status is negatively associated with vegetable adoption at the 1% level of significance. A shift from low to high caste status is related to a farmer being 14.4% less likely to not adopt vegetables, 1.6% less likely to dedicate 0-8% of her fields to vegetables, 5.1% less likely to dedicate 8-15% of her fields to vegetables, and 7.8% less likely to dedicate more than 15% of her fields to vegetables. Members of less privileged ethnic groups tend to adopt vegetables to a greater extent than do members of more privileged ethnic groups.

Finally, Food Insecurity is negatively associated with vegetable adoption at the 1% level of significance. A shift from food security to food insecurity (not having sufficient food stores to last at least 9 months) is related to a farmer being 7.4% less likely to not adopt vegetables, 1.8% less likely to dedicate 0-8% of her fields to vegetables, 5.8% less likely to dedicate 8-15% of her fields to vegetables, and, strikingly, 20.3% less likely to dedicate more than 15% of her fields to vegetables. Farmers who are food insecure are more risk averse, and will not over-expose themselves to market uncertainties by dedicating too large a share to vegetables, for reasons described in **Section 3.1.2.**

7.5 Logit Regression Results on Tractor Adoption

The surprising finding that farm area is consistently negatively associated with vegetable adoption (as seen in Logit, Probit, OLS, and Ordered Probit models) contradicts the orthodox predictions of the technology adoption literature. The majority of this literature predicts that larger farmers will adopt new technologies first because they tend to be more educated, have more capital, have better access to credit and market information, and enjoy economies of scale. However, as demonstrated in **Section 5**, which presented facts about high value vegetables, the nature of the technology being adopted can greatly influence the degree to which these scale-biased factors play a role.

To test whether the nature of the technology being modeled can shape the effects of explanatory variables, I next compute a Logit model regression of tractor adoption in the dataset.

Tractors are a lumpy technology and exhibit increasing returns to scale. Thus, they fit the standard assumptions underlying technology adoption predictions. Tractors should be adopted most readily by large farmers who have access to credit and who suffer from labor shortages. If the Logit regression of tractor adoption again shows a negative relation between farm size and adoption, we may suspect that the data itself may be flawed and biased towards atypically adoption-prone small farmers. If, on the other hand, we find a positive relation between probability of tractor adoption and farm area, we should be more confident in the surprising negative relationship observed between probability of vegetable adoption and farm area. **Table 17** presents the Logit Model regression results for the probability of tractor adoption among farmers in the dataset.

Table 17. Logit Regression Results: Effects on Tractor Adoption Decision

	Logit Model	
Variable	Coefficient	Marginal Effects
Farm Area	0.2004*** (0.0567)	0.0211
Family Size	-0.4318** (0.2087)	-0.0454
Dist. to Agrovet	-0.0116 (0.0095)	-0.0012
Education	-0.1515 (0.2571)	-0.0159
Age	-0.0470 (0.0396)	-0.0049
Ag. Training	0.4677** (0.2019)	0.0492
Assets	-0.2921 (0.2230)	-0.0307
Credit	0.4257	0.0448

	(0.9813)	
Higher Caste	-0.3896 (1.4077)	-0.0410
Food Insecure	2.1205 (1.3957)	0.2231
Constant	0.5777 (2.0762)	
<u>Goodness of Fit:</u>		
McKelvey-Zavoina	0.8150	
Aldrich-Nelson	0.2707	

Standard errors are reported in parentheses
*** = significant at 1% level
** = significant at 5% level
* = significant at 10% level

Results in **Table 17** indicate that indeed, the standard technology adoption predictions do hold true when the technology analyzed is the tractor. Farm area is positively associated with probability of tractor adoption at the 1% level of significance, and the marginal effect of 0.0211 indicates that a one ropani increase in farm area is related to a 2.1% increase in the probability of tractor adoption. A twenty ropani increase in farm area thus coincides with a 42% increase in the likelihood of tractor adoption.

This divergence in results (a positive relation between farm size and adoption for tractors, a negative relation between farm size and adoption for vegetables) supports this study's thesis that the characteristics of the technology being analyzed are essential to our understanding of what constraints limit adoption and what types of farmers are favored.

The following section (**Section 8**) offers analysis and discussion of the results revealed through the models developed above.

8. Discussion of Results

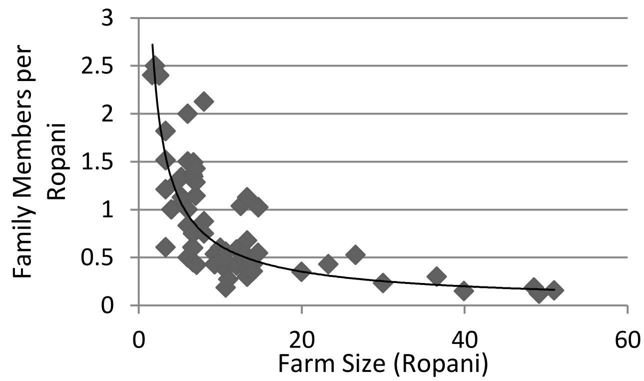
The results reported in **Section 7** largely coincide across alternative regression models. It is evident that, broadly speaking, farm area is negatively related to the probability of vegetable adoption, and particularly negatively related to the likelihood of dedicating larger proportions of farm area to vegetables. Distance to an agricultural supply store likewise is negatively related to likelihood of vegetable adoption. Age, Agricultural Training, and Assets have broadly positive associations with the likelihood of adoption, with Assets having a considerably large positive association with the probability of adopting larger proportions of vegetables as well. Higher Caste status and Food Insecurity have strongly negative relations to both adoption likelihood and the likelihood of dedicating larger shares of one's farm to vegetables. Family size has a mostly statistically insignificant effect in the dataset, as do education and credit. Nevertheless, theoretical models of technology adoption suggest that we must still control for these variables.

These regression results, taken alongside the empirical facts about vegetables that were developed in **Section 5**, allow us to answer the fundamental question that has driven this study: *Given that vegetables yield significantly higher returns than do staple crops, why are so many farmers in Mid-Western Nepal not adopting them?* If farmers are indeed rational agents, as I argue they are in **Section 3**, then they will not be restrained by tradition or custom and *will* adopt more profitable agricultural practices if external scale, capital, and risk constraints do not impede them. What constraints, then, could be distorting Nepali farmers' household economies in such a way as to make the choice of low-value staples over high-value vegetables an optimal one?

The Impact of Farm Size on Vegetable Adoption

One of the principle factors constraining vegetable adoption is their labor-intensity. Vegetables require approximately five times more labor per hectare than do staple crops. For small farms with large families, the high labor requirement of vegetables is actually an advantage: since small farms are comparatively land poor and labor rich, they find it optimal to produce labor-intensive crops to maximize the returns from their limited land.[8] In contrast, large farms are comparatively land rich and labor poor, and find it difficult to exert enough family labor or hire enough contract labor to produce labor-intensive vegetables. **Figure 15** illustrates the declining ratio between number of family members and land area among farmers in the dataset.

Figure 15. Family to Land Ratio on Farms in Mid-Western Nepal



As farms increase in size, they have proportionately less family members per land unit than do smaller farms. They therefore have less family labor available to produce crops. Since vegetables are more labor-intensive than staples, large farms face a severe labor constraint on vegetable adoption and production. It is for this reason that regression results in **Section 7** show a significant negative relation between farm size and likelihood of vegetable adoption.

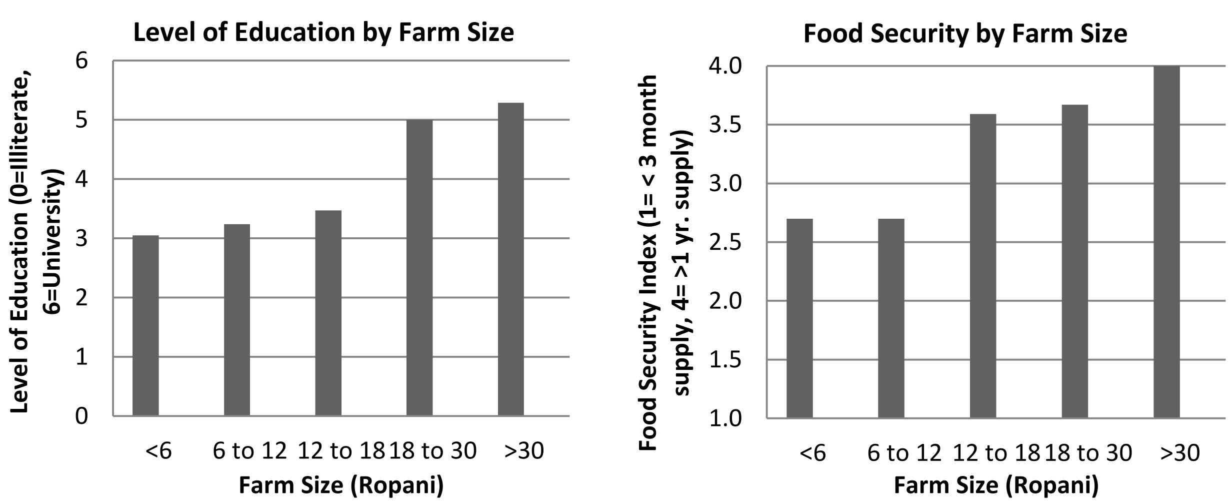
Given the significantly greater profits to be made from vegetables, however, large farms should still optimally grow vegetables and hire labor to produce them. Nevertheless, very few

[8] Given this analysis, Family Size should theoretically be positively associated with vegetable adoption. The regression models nevertheless found Family Size to be either insignificant or weakly negatively related to adoption. This is likely because the measure for family size did not break number of family members down into working members and non-working members. The fact that some families could have many young children or elderly members, while others could be predominantly of working age, adds significant noise to the data, making the variable mostly insignificant. Furthermore, Family Size could show a negative correlation because larger families have more members depending on them and thus be more risk averse, avoiding vegetables due to uncertainty and increased inertia.

farmers (6 out of 78) had actually hired labor in the sample. This dearth of hired labor, in the face of such significant gains to be had from hiring labor, suggests a severe labor market failure in Mid-Western Nepal. Larger farmers would presumably hire labor to produce vegetables if they could, and their failure to do so suggests that, at least during the season of the survey, this labor was not available.

Before going further, we should perhaps ask whether the surprising negative relationship between farm size and productivity is due not to relative land/labor ratios and labor market failure, but rather to an atypical data sample in which large farmers do not happen to fit the standard assumptions. Most agricultural economists predict that larger farmers are more educated and enjoy greater food security than do smaller farmers. These factors make them more aware of new technologies and less risk averse than smaller farmers would be. **Figure 16** illustrates average levels of education and food security, as measured by farm size. Both education and food security increase as farm size increases, suggesting that farmers in the dataset do in fact fit the standard assumptions of the technology adoption literature.

Figure 16. Levels of Education and Food Security by Farm Size



Thus, it appears that smaller farmers' propensity to adopt vegetables relative to large farmers is indeed an optimal response to land scarcity and labor abundance, whereas large farmers' failure to adopt suggests a failure of regional labor markets to supply seasonal labor.

The Role of Risk and Uncertainty in Farmers' Vegetable Adoption Decisions

As established in **Section 5**, vegetables are not only much more profitable than are staple crops, they are also much riskier. That is, they are high-risk, high-reward crops. And as explained in **Section 3.1.2**, farmers in a developing country context such as Nepal are often averse to risk and uncertainty for highly rational reasons. Being labor-intensive, vegetables require larger up-front investment, yet with more volatile market prices, they promise less predictable rewards. Vegetables' short time-to-spoilage limits farmers' ability to wait until the price is right. And perhaps most decisively, new vegetable technologies are simply an unknown variable for farmers: they have unknown consequences and require new, untested techniques.

For all of these reasons, each of the variables in my regression models that measures factors related to risk and uncertainty has a negative association with the probability of vegetable adoption. Distance to Agrovet measures both the difficulty of bringing fast-spoiling goods to market (since Agrovets are often in the same location as the local market) and the difficulty in acquiring new information regarding prices and techniques (since contact with merchants, extension agents, and other farmers occurs most often in the market). Furthermore, Distance to Agrovet measures the difficulty of repairing damaged equipment and obtaining new seeds and fertilizers–vital inputs for input-intensive vegetable cultivation. Unsurprisingly, a 1% increase in Distance from Agrovet coincides with an 8% decrease in the likelihood of adopting vegetables in the Logit model. This is the largest association found for a continuous variable in the model.

Agricultural Training is another variable that proxies farmers' access to information and new techniques. Insofar as agricultural trainings reduce farmers' uncertainty regarding vegetable cultivation techniques and production outcomes, they should reduce farmers' uncertainty and have a positive effect on the likelihood of adoption. The Logit model results corroborate this prediction by indicating that for each additional agricultural training session farmers attended, they were 3.9% more likely to adopt vegetables. Thus, trainings appear effective in reducing farmers' uncertainty regarding vegetable cultivation.

A large source of uncertainty among farmers comes from inexperience. Young farmers simply haven't lived long enough to acquire the experience necessary to understand prospective advantages and disadvantages of new technologies. Thus, age (as a proxy for experience) reduces farmers' uncertainty and increases their likelihood to adopt. We see in the data that each additional year of age is associated with a 1.2% increase in the likelihood of vegetable adoption. A 60 year old farmer is therefore 48% more likely to adopt vegetables than is a 20 year old.

A farmer with more assets has more property to use as collateral for loans, increasing her ability to smooth consumption in the event of a crop failure and thus reducing risk aversion. Assets also represent a store of wealth that can be drawn upon in times of scarcity, thus serving as a sort of insurance in areas where formal insurance schemes are not active. We should therefore expect farmers' level of assets to be positively associated with vegetable adoption. Results from the Logit model suggest that, indeed, each additional asset controlled by a farmer is related to a 5.4% increase in her probability of vegetable adoption. In this sense, wealthier farmers (not including land-wealth) adopt more often than do farmers with fewer assets.

Finally, the regression variable Food Insecure measures whether or not a farm household has a sufficient store of food to last at least nine months. Farmers without sufficient food supplies exist on a knife-edge of subsistence and cannot afford to adopt risky new products or overexpose themselves to unpredictable markets. As a result, the Logit model regression indicates that a food-insecure farmer is 21.8% less likely to adopt vegetables than is a food-secure farmer. This large association suggests that food insecurity (as a source of risk aversion) is one of the principle barriers to vegetable adoption in Mid-Western Nepal.

Farmers in the risk-averse situations described above find themselves in a “Catch-22” known as a poverty trap. They rationally avoid adopting more profitable crops and technologies because the uncertainty and risk involved in the decision to adopt outweigh the longer-term benefits of adoption. Poverty traps are especially potent where insurance and credit markets are not properly functioning, as is the case for some farmers in Mid-Western Nepal.

An alternative means of examining the negative effects of risk and uncertainty on vegetable adoption is to simulate farmers’ production outcomes over “good” and “bad” years. If farmers regularly face bad years in which low retail prices and high costs make vegetable production unprofitable, they may rationally opt for lower-return staple crops to avoid such volatility. Drawing on producer price data from FAOSTAT, **Figure 17** simulates a “bad” year for farmers in the dataset in which all producer prices assume the average value of the lowest quartile in the 1997-2012 producer price distribution, and where costs of labor are unadjusted by the wage-adjustment equation detailed in **Appendix A** (resulting in an approximately 20% increase in the cost of labor). **Figure 18** simulates a “good” year for farmers in which all producer prices assume the average value of the highest quartile in the 1997-2012 producer price distribution, and where costs of labor remain adjusted.

Comparing **Figures 17** and **18**, we see that staple crops are hardly affected by changes in crop prices and wages, since they require less labor investment and exhibit less price volatility.

Figure 17. Simulated Crop Returns in Bad Season (high labor costs, low prices)

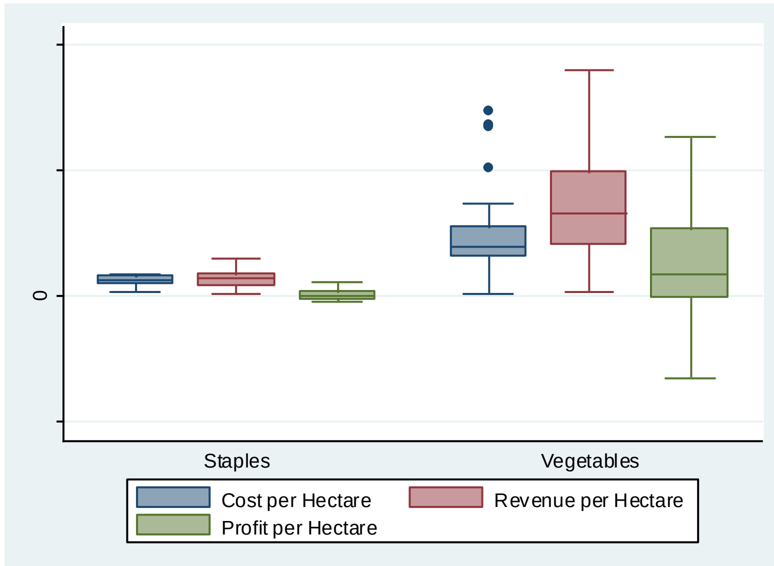
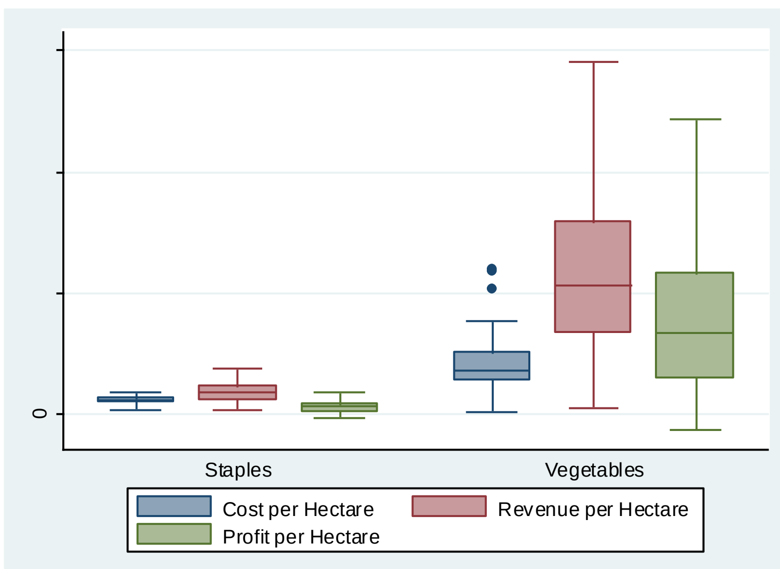


Figure 18. Simulated Crop Returns in Good Season (low labor costs, high prices)



Thus, staple crops represent a certain level of security against price swings. This is likely the reason for which even those farmers who adopt vegetables choose to devote only small portions of farm area to their cultivation. In contrast to staple crops, vegetables exhibit vastly different returns between good and bad years. In good years, 90% of vegetable farmers earn a positive profit, and approximately 80% earn more than they would have with staples. Nevertheless, in a bad year (occurring approximately once every four years) a full 25% of farmers earn negative profits, and only 50% make more than they would have with staple crops.

In an economy with functioning insurance markets these occasional losses could be smoothed over and the good years would more than compensate for the difficult ones. Without insurance, however, a single season of negative profits on a cash crop could mean starvation or severe deprivation for a farm household. In the face of this level of risk, many farmers may opt to avoid vegetables altogether. The results of the Logit and Ordered Probit regressions in **Section 7** suggest that, in practice, farmers who are susceptible to risk and food insecurity often avoid vegetable adoption altogether, while more secure farmers continue to dedicate only small portions of their farms to vegetables while maintaining a large share of staple crops as well.

Understanding the Importance of Technology-Specific Characteristics

Nearly all studies of agricultural technology adoption focus almost entirely on the effects of farmers' characteristics (such as education, farm size, age, wealth, etc.) on adoption. Studies often try to deepen their analyses by measuring more difficult-to-observe characteristics such as farmers' expectations, perceptions of risk, and learning processes. Nevertheless, many of these studies provide only glancing and perfunctory analyses of the technologies being adopted. As demonstrated in **Section 7** above however, the same model and dataset may yield drastically different results depending on which technology is being analyzed. Farm size was found to have a significantly negative effect upon the likelihood of vegetable adoption, whereas farm size had a significantly positive effect upon the likelihood of tractor adoption. The roots of this difference lie, not in the explanatory variables–which are identical–but in the nature of the technology itself. Vegetables are divisible and labor-intensive, whereas tractors are lumpy and labor-saving. Thus, in the final analysis I find that labor constraints play a much larger role than do capital constraints in limiting vegetable adoption in Mid-Western Nepal. More broadly, I find that technology-specific characteristics are an essential component in understanding farmers' adoption behavior. Future studies should place a stronger focus on analyzing this aspect.

The Equity Impacts of High-Value Vegetables in Mid-Western Nepal

Development projects and government initiatives that attempt to introduce new farming practices or alter the ways in which farms operate on a micro-level (such as USAID's effort to introduce high-value vegetables in Nepal) often provoke unintended consequences, including exacerbations of local-level inequalities. Projects may unwittingly favor larger or wealthier farmers, produce new forms of marginalization and exclusion, or alter customary agricultural practices in ways that negatively impact some groups. Examining the results of relevant variables employed in Section 7, I can evaluate the impacts of the introduction of vegetable crops on inter-farm equity in Mid-Western Nepal and answer the question: do high-value vegetables appear to be a progressive or regressive instrument for poverty reduction in Nepal?

Variables in the dataset that measure or proxy wealth or social status include Farm Size, Assets, and Higher Caste. Farmers in Mid-Western Nepal generally have few assets, and the majority of their wealth is encapsulated in their landholding. Thus, farmers with larger landholdings are presumably wealthier than farmers with smaller holdings. And while assets are not a large factor in the region, they do constitute an alternative measure of a farm household's wealth. Finally, all regressions in **Section 7** controlled for the dummy variable Higher Caste, which measured whether a farmer was Brahmin or Chhetri on the one hand, or from another group (often indigenous, such as Tharu) on the other. While ethnicity is a complex and contested topic in Nepal, there is a broad consensus in the political economy literature that belonging to one of the “higher caste” groups continues to confer social and economic benefits (Thapa 2007). Thus, the Higher Caste dummy measures the effect of these status differentials.

If vegetables were a regressive technology, we would expect Farm Size, Assets, and Higher Caste to be positively associated with vegetable adoption. In contrast, if vegetables are progressive, we would expect these variables to be negatively associated with adoption. Regression results indicate that farm size is significantly negatively associated, assets positively associated, and Higher Caste negatively associated with vegetable adoption. Explanations for Farm Size and Assets’ negative effects have been discussed above. The negative relation between Higher Caste status and vegetable adoption is strong and surprising. The Logit model suggests that moving from a low to high caste status coincides with a 22% decline in the probability of vegetable adoption. There are a number of possible explanations for this relationship. Higher caste farmers may be better networked into staple crop production systems, thus increasing their returns to scale and profits from these crops relative to lower caste farmers. They may control higher quality lands that favor staple crop production (land quality was unmeasured in the survey). Finally, they may have resided on their land longer, resulting in less of a need to attempt new techniques in order to survive.[9]

In sum, the negative relationships between Farm Size and Higher Caste and vegetable adoption suggest that vegetables are a progressive technology, while the positive relationship between Assets and adoption suggests a regressive relationship. Since much of farmers’ wealth is embodied in their land, however, the farm size effect trumps the assets effect, and vegetables appear to be a relatively progressive instrument for poverty alleviation in the region, favoring indigenous farmers with smaller landholdings over larger and higher caste farmers.

[9] Many indigenous farmers have come upon their landholdings only recently, either due to government reform measures or to unrest caused by the recent civil conflict in the region.

9. Policy Recommendations and Conclusion

Stagnation in agricultural productivity in Nepal has resulted in widespread rural poverty and malnutrition. Rural areas have seen little improvement in standards of living over the last three decades, while conspicuous consumption has become ever more visible in urban areas. This growing intra-national inequality recently contributed to a decade-long civil war that ended only in 2006. The Mid-Western Development Region, Nepal's poorest, was the epicenter of this civil war and is still struggling to realize meaningful agricultural development.

International donor institutions and the Nepali government have sought to introduce high-value vegetable crops as a means of improving agricultural productivity, increasing incomes among smallhold farmers, and diversifying diets. Nonetheless, vegetable adoption in the region has been slow at best.

Vegetables are more profitable than customary staple crops such as rice and maize. Because they require higher labor inputs and more individualized attention, they exhibit constant returns to scale, whereas staples exhibit increasing returns to scale. Vegetables exhibit greater variance in returns, and are therefore riskier than staple crops as well. Consequently, scale, capital, and risk constraints could potentially limit farmers' ability and willingness to adopt.

Analyzing a survey conducted by the author of 78 farmers from Nepal's Mid-Western Development region, this study computed Logit, Probit, OLS, and Ordered Probit regression models to measure the effects of a range of explanatory variables on farmers' vegetable adoption decisions. Regression results show that Farm Area, Distance to an Agricultural Supplier, Higher Caste status, and Food Insecurity are all significantly negatively associated with the probability of vegetable adoption, while farmers' Age, level of Agricultural Training, and number of Assets are significantly positively associated with probability of adoption. These variables have similar effects on the scale of vegetable adoption as well.

The negative relation between Farm Area and probability of vegetable adoption is likely a result of the difference in labor-intensity between vegetable and staple crops. Smaller farms optimally adopt labor-intensive vegetables to capitalize on their comparative advantage in labor, while larger farmers, being relatively labor-poor and land rich, produce land-intensive staple crops instead. Large farmers are prevented from adopting larger shares of vegetables by a revealed labor shortage in the region. Typical of developing country agrarian economies, it appears that labor markets are not properly functioning in Mid-Western Nepal.

I further find that risk and uncertainty constitute significant constraints to vegetable adoption. Variables such as Distance to Agrovet, Agricultural Training, Age, Assets, and Food Insecurity that proxy farmers' levels of risk or information-poverty are consistently negatively associated with probability of vegetable adoption. Annual country-level vegetable prices in Nepal are notably more volatile than are prices for staple products, and local-level seasonal prices are likely much more volatile still. Coupled with a lack of functioning insurance and credit markets, this volatility increases farmers' risk from vegetable adoption and prevents more marginal or risk averse farmers from adopting, potentially locking them into poverty traps.

Policy Recommendations

These results suggest a number of potential policy adjustments that could improve Nepali farmers' ability to benefit from high-value vegetables. The challenges faced by large farmers in overcoming labor shortages or bottlenecks could be reduced through government or donor-supported tractor and tiller-sharing collectives. Policy makers could lend support to local organizations that collectively purchase labor-saving mechanical inputs such as tractors and then rent or share them amongst farmers. Nevertheless, given that much of the labor required for vegetables is individualized and cannot be facilitated by mechanized inputs, this policy measure would have only a limited capacity to promote vegetable adoption among large farmers. Furthermore, this measure would reduce the currently progressive nature of vegetable crops by disproportionately aiding larger farmers.

More effective policy measures would reduce the risk farmers assume when adopting vegetables. Policymakers could facilitate the organization and implementation of village marketing collectives, which allow farmers to partially collectivize risk and improve bargaining power *vis a vis* buyers. This would reduce price volatility at the point of sale and allow farmers to more predictably plan investment and production strategies.

Furthermore, government agencies should work to roll out effective crop insurance programs in the region, and should work to regulate village-level creditors so as to avoid predatory lending. Farmers confront considerable risks when choosing to produce cash-crops for the market, and while vegetable production may be the most efficient outcome in macro-level productivity terms, individual farmers often find it unfeasible without some sort of insurance and credit support. Moreover, given the increasing volatility of weather patterns in Nepal as a result of global climate change, farmers are in ever greater need of insurance against not only price swings, but landslides, floods, and droughts.

As demonstrated in the regression analysis, each additional agricultural training that farmers attended was associated with a 3.9% increase in the likelihood of vegetable adoption. Clearly, training programs should be extended, as well as state-directed agricultural extension services and support of Agrovet-level expertise. Agricultural training diffuses information and best practices among farmers and reduces the uncertainty involved in adopting new technologies, including high-value vegetables.

Finally, given the strong negative impact of Food Insecurity on vegetable adoption, measures should be taken to improve food security exogenously to the vegetable-promotion process. While vegetable adoption itself is often intended as an instrument to improve food security, my detection of potential poverty traps suggests that additional measures must be taken to grant farmers a level of food security sufficient to allow them to assume the risks of vegetable adoption in the first place. The traditional mechanisms built into the functioning of the Nepal Food Corporation should be re-worked to better distribute internal food surpluses to food deficit regions on a seasonal basis.

Vegetables have the potential to be an effective instrument for progressive poverty reduction in Nepal. However, these crops must arrive as part of a broader, networked package of extension services, insurance and credit programs, and donor-led or government supports. Without these policy interventions, farmers may remain unable to access the potential benefits offered by high-value vegetables.

Appendix A: Calculating Farmers' Costs and Returns to Production

The field survey (see **Survey Appendices**) employed to collect the data set described in **Section 4** decomposes costs of production into labor costs, capital costs, costs of credit, opportunity costs of land, and opportunity costs of investment. The survey also collected general demographic and geographic information. The survey measured costs of one crop for one growing season.

- **Labor costs** include all payments to hired farm laborers, as well as the wage-value of all family and unpaid neighbors' labor that was invested in the production of the surveyed crop for that season. The valuation of unpaid labor is discussed in **Part A.1** below.
- **Capital costs** include the costs of all capital inputs for the production of one season of the surveyed crop. The process of valuing these inputs is discussed in greater detail in **Part A.2**.
- **Cost of credit** was measured as the cost of interest for the portion of a farmer's loan going towards the surveyed crop. Details are given in **Part A.3**.
- **Opportunity Costs of Land** and **Investment** are further discussed in **Part A.4.**

A.1 Pricing Unpaid Farm Labor

The cost of hired labor is easily calculated. Total hours of hired labor are multiplied by the local market wage to find total cost of hired labor. Farmers in Mid-Western Nepal, however, rarely hire labor. Most rely on unpaid labor from themselves, their own families, or unpaid neighbors. Communities often pool labor during periods of planting and harvest.

A sizeable body of literature exists on the pricing of unpaid farm labor. Many studies suggest that assigning a market wage to this labor will overestimate the value of unpaid farm labor, because farmers tend to "self-exploit" and work beyond the point at which the marginal returns of their labor equal the marginal costs (Huffman 1996). Because many farmers have very little opportunity cost to their time, they work for long hours on their farms, even though the value they are creating in these hours may be very low. Thus, assigning a market wage to these hours would drastically overestimate the value added to production.

Furthermore, the labor investment in a family farm's crop production may involve diverse labor inputs: men, women, and childrens' labor, as well as highly trained and untrained labor. Again, assigning a single wage to labor irrespective of gender, age, and training, ignores the complexity of agricultural practice.

The real cost of a farmer's unpaid farm labor is the opportunity cost of her off-farm employment, that is, what she could earn if she reallocated her farm-labor time to outside employment. Or, perhaps more accurately in small village settings (such as that of the Mid-Western Development Region) where off-farm employment opportunities are scarce, the real cost of the farmer's labor is the opportunity cost of her leisure (Huffman 1996). Putting a numerical value on how much each farmer values his or her leisure time is, of course, unfeasible. However, a measure of off-farm opportunity cost can be constructed. As suggested in El-Osta and Ahearn (1996), the opportunity cost of off-farm employment can be estimated as a factor of human capital variables. Age, gender, level of education, and level of agricultural training all determine the wage that could be received off-farm.

Drawing upon the results of El-Osta and Ahearn (1996), we constructed a weighted wage that adjusts the local market wage according to the individual farmer's level of human capital. The human capital variables considered were Age, Education, Number of Agricultural Trainings attended, and Gender. Education was considered the most influential variable. Many farmers in the survey area are illiterate, while others possess higher education beyond secondary school. Those with more education clearly have wider off-farm employment opportunities. The next most important variable was considered to be Number of Agricultural Trainings. Farmers with knowledge of high-value vegetable cultivation, mechanized inputs, chemical fertilizer and pesticide, and nursery or seed techniques have valuable skill sets that could confer upon them higher earning potential. Thirdly, Age is considered a decisive variable because agricultural labor in the region is physically demanding. Bending over, repetitive motions, heavy lifting, and high temperatures all mean that older laborers would be less productive than younger ones, and could thus command a lower off-farm labor wage. Furthermore, very young laborers (considered here as those under 20 years old) are less experienced, and may thus require more supervision. Finally, gender is determinative in off-farm earning capacity because the regional average market wage for men is around 300 NRs per day, while for women it is around 200-250 NRs per day. The relative importance of these four variables is encapsulated in **Equation 1:**

Equation 1. Adjusted Wage = Local Market Wage *((0.2*Age)+ (0.4*Education)+(0.25*Agro. Trainings)+(0.15*Gender))

Equation 1 adjusts the local market wage with weighted Age, Education, Agro. Trainings, and Gender components. If values of 1 were input for Age, Education, Agro. Trainings, and Gender, the equation would simply return the local market wage. If, instead of 1, the weighted values given in **Table 18** are insterted, the local market wage will be depressed to a new, adjusted wage that accounts for the farmer's level of human capital.

Table 18.

Education:

Illiterate	0.6
Informal Literacy	0.7
Primary (1-5)	0.7
Secondary (6-10)	0.8
SLC	0.9
Higher	1.0

Age:

<20 yrs.	0.8
20-45 yrs.	1.0
45-65 yrs.	0.7
>65 yrs.	0.5

Agro. Trainings

0 Trainings	0.6
1-2 Trainings	0.7
3-4 Trainings	0.8
5-6 Trainings	0.9
7-9 Trainings	1.0

Gender:

Male	1.0
Female	0.8

These values are arrived at arbitrarily, but can be calibrated using an alternative method of calculating the value of unpaid labor. This is the "consumption method." In subsistence agricultural practices, many laborers may not receive a wage, but are instead paid "in kind." They receive the value of their labor as a portion of the final harvest into which their labor was invested. Even farmers' children in a sense receive a payment in kind for their labor on the farm, in the form of their food allotment. Thus, measuring the value of the crop production consumed by the laborer gives the value of that worker's labor. The problem with this approach is that calculating the value of consumption is possible only when data exists for all the crops grown on the farm. The current study focuses on just one crop per farmer. Thus, calculating the value of tomatos consumed by the farmer would be relatively simple:

Equation 2.

(Total Tomato Yield – Volume of Tomatoes Sold) = Total Volume Tomatoes Consumed

(Total Volume Tomatoes Consumed) / (Number of Family Members) = Tomato Consumption per Family Member

(Tomato Consumption per Family Member)*Market Tomato Price = Value of Tomato Consumption

This seasonal value could be further decomposed into a daily wage.

Nevertheless, this method cannot capture the value of consumption of other crops, and is therefore not a valid estimation of total consumption. There are, however, situations in which the survey was able to measure the crop production for an entire farm. These are the cases in which the farmer was growing a single crop (usually rice) on all of her land. In these cases, the average consumption (when converted to daily wage) amounts to around 241 NRs per day. Using this approximate benchmark value, the weightings in **Table 18** can be calibrated to approximate 241 NRs. With the given weightings, the average adjusted wage for all survey data is 250.2 NRs per day. It is to be expected that the adjusted wage be slightly higher than the consumption value for the rice growers, since these 100% rice cultivation farms often represent the lowest value farms in their communities.

A.2 Depreciating Capital Costs

Capital inputs measured in the study include:

Tractor	Hoses
Motor Tiller	Pesticide
Thresher	Jhol Mol
Plow Animal	Manure
Motor Pump	Chemical Fertilizers
Water Tanks	Seeds
Irrigation Canals	Motor Transport
Sprinklers	Plastic Houses

Major capital inputs such as tractors, tillers, and pumps often last for more than one season. Since the study seeks to measure costs of production for a single crop for a single season, these long term capital inputs must be depreciated. Long-term capital inputs were considered to be: Tractors, Motor Tillers, Threshers, Motor Pumps, Hoses, and Plastic Houses. The single season, single crop value is calculated as:

Equation 3.
Single Season/Single crop value of long-term capital input =
(Initial Cost of Input)/(Estimated life-span of input)/(Proportion of total landholding dedicated to target crop)/(# of seasons that field can be planted)

Further accounting must be made for **byproduct incomes**. Many farmers use significant amounts of manure and jhol mol (a formulation of livestock urine used as fertilzer and biopesticide) on their fields, which we assess at a cost of between 35 and 50 NRs per doka (a unit of measurement referring to a traditional basket, typically holding about 10 kilograms of manure). Nevertheless, the farmers feed these livestock on byproducts from their crop production. Thus, crop byproduct value cancels out the cost of jhol mol and manure. The study accounts for this by reducing jhol mol and manure costs for those farmers growing crops with useable byproduct

A.3 Costs of Credit

Many farmers in the region have taken out loans to cover costs of crop production. Interest rates average 13%, and costs of credit can be significant for some farmers. Costs of credit are assessed according to the following formula:

Equation 4.

Cost of Credit = (Amount of Loan*Duration of Loan*Interest Rate) / (Number of Seasons Crop is Planted per year)

Note: Amount of Loan is itself adjusted. Farmers report total loan amount, and detail for which crops the loan is used. Surveyers calculated the proportion of the total loan value that went toward the specific focus crop of the survey. This reduced value is the value entered as "Amount of Loan" in the above equation.

A.4 Opportunity Costs of Land and Investment

In some communities in the MWDR most farmers own their own land and there is a very limited or non-existent rental market for land. In these communities, the opportunity cost of land leasing may be very low, or even zero. However, in communities in which at least one farmer reported leasing land, this study assessed opportunity costs of land as the per ropani lease price of land multiplied by the number of ropanis of the focus crop under cultivation.

While opportunities for non-farm investment are often low in the MWDR, farmers do have the ability to reallocate farm investment into non-farm enterprises or migration. This study assess the opportunity cost of investment as 5% of all labor and capital expenditures.

Further key results were calculated using the formulas below:[10]

Equation 5.

Labor Cost Per Ropani = Total cost of paid and unpaid labor (at adjusted unpaid labor wage) / ropani under cultivation

Equation 6.

Capital Cost per Ropani = Total cost of all capital inputs (with long-term inputs depreciated) / ropani under cultivation

Equation 7.

Total Cost per Ropani = Total labor and capital costs / ropani under cultivation

Equation 8.

Total Cost per kg. = Total labor and capital costs / number of kilograms produced

Equation 9.

Revenue per Ropani = (Total kilograms produced)*(Retail price per kilogram) / ropani under cultivation

Equation 10.

Net Profit per Ropani = (Total Revenue per ropani – Total Cost per ropani) / ropani under cultivation

Equation 11.

Cost of Land Preparation = ((Hours of paid and unpaid labor invested in the stage of Land Preparation)*(Adjusted wage)) + Tractor Cost + Motor Tiller Cost + Plough Animal Cost + Plastic Houses Cost

[10] Note: The ropani is one of the traditional land units of Nepal. One ropani is equal to approximately 0.051 hectares. Ropani are used throughout this report because they are the unit of reference in Nepali agriculture, and because they provide smaller values than per hectare terms. Given the small size of Nepali farmers, the ropani simply makes more sense.

Equation 12.

Cost of Planting = ((Hours of paid and unpaid labor invested in the stage of Planting)*(Adjusted wage)) + Seed Cost

Equation 13.

Cost of Land Maintenance = ((Hours of paid and unpaid labor invested in the stage of Land Maintenance)*(Adjusted wage)) + Pesticide Cost + Jhol Mol/Manure Cost + Chemical Fertilizer Cost + Hoses Cost + Sprinklers Cost + Water Tanks Cost

Equation 14.

Cost of Harvest **=** ((Hours of paid and unpaid labor invested in the stage of Harvest)*(Adjusted wage)) + Thresher Cost

Equation 15.

Cost of Post-Harvest = ((Hours of paid and unpaid labor invested in the stage of Post-Harvest)*(Adjusted wage)) + Transportation Cost

Appendix B: Evaluating the Inverse Farm Size–Productivity Relationship

The relative productivity of large versus small farms is one of the oldest and most thoroughly debated topics in agricultural economics. Based upon the foundational works of Chayanov (1925) and Sen (1962), economists in the 1960s began advancing the argument that small farms could in fact be more productive than large farms due to higher per unit labor and capital inputs (the so-called Inverse Relationship (IR) between farm size and productivity) (Barrett, Carter, and Timmer 2010).

The IR debate acquired heated practical significance as land reform movements swept Asia and Africa in the post-war period, with advocates of land redistribution citing Sen's findings as evidence that smaller plots would be more, rather than less, efficient than larger farms (Thapa 2007). Critics of the IR hypothesis argue that the inverse relationship disappears with sufficiently high levels of capital inputs, and is thus relevant only in traditional agricultural sectors (Fan and Chan-Kang 2005). Others point out that much of the observed IR may actually be explained by commonly unobserved farm-level characteristics such as land quality (Bhalla and Roy 1988).

The results of studies of the IR in Nepal have yielded mixed results. Bhandari (2006) used district-level data to conclude that a positive relationship exists between scale of landholdings and per-hectare productivity, contradicting the IR hypothesis. But using farm-level data from the Western hills, Thapa (2007) measured a negative relationship between farm size and per hectare, per labor hour, and per expenditure productivity, confirming the IR hypothesis.

In the case of those farmers from the Mid-Western Development Region included in my field survey, a measured inverse relationship could indicate the failure of labor and capital markets to properly proportion and allocate resources amongst farmers.

The standard OLS model used to measure the relation between farm size and productivity is given by:

Equation 1: $\ln(Y_i) = \alpha + \beta \ln(L_i) + \delta X_i + \varepsilon_i$[11]

Where Y_i is total yield per hectare, L_i measures the total area of crop land, X_i is a vector of socioeconomic variables that could affect productivity, and ε_i is the error term. Some critics of the IR have argued that while productivity may be higher on small farms in per hectare terms, it is not higher in per labor hour and per expenditure terms. To measure the effect of crop area on these alternative measures of productivity, we can also estimate:

Equation 2: $\ln(H_i) = \alpha + \beta \ln(L_i) + \delta X_i + \varepsilon_i$

Equation3: $\ln(C_i) = \alpha + \beta \ln(L_i) + \delta X_i + \varepsilon_i$

Where H_i measures yield per labor hour invested, and C_i measures yield per hundred NR invested.

The farmers' socioeconomic characteristics that may influence productivity are identified as Age, Education, Assets, and Vegetable Adoption. Dummies measuring higher caste status and district were rejected since they were insignificant in all regressions. Age should have an ambiguous relation with productivity, since older farmers are more experienced (which suggests a positive relationship), but younger farmers may be more innovative and open to new techniques and resources (also suggesting a positive effect). Education should be positively associated with productivity, as should be assets and vegetable adoption (see **Section 5, Fact 3**).

If an inverse relationship exists between farm size and productivity, coefficient β should be significantly negative. Since Mid-Western Nepal is characterized by traditional agricultural practice, I hypothesize that the IR will hold for per hectare productivity. The existence of an IR between farm size and per labor input and per capital input productivity is an empirical question.

[11] From Thapa (2007)

Table 19 below presents OLS regression results on the relationship between farm size and productivity for the three models identified in **Equations 1, 2**, and **3** above.

Table 19. OLS Regression Results: Effect of Crop Area on Returns per Hectare

Explanatory Variables	Dependent Variables		
	Log of Yield per Ha.	Log of Labor Hrs. per Ha.	Log of Capital Input per Ha.
Log of Crop Area	-0.1209*	-0.3454***	-0.2774***
	(0.0698)	(0.1107)	(0.0607)
Age	0.0262	-0.5815**	-0.1798
	(0.1885)	(0.2783)	(0.1725)
Education	0.1730*	-0.0893	0.0820
	(0.1244)	(0.1377)	(0.0893)
Assets	0.1821**	-0.0929	0.1176
	(0.0817)	(0.1256)	(0.0954)
Vegetable Adoption	1.1096***	0.8403**	0.6702***
	(0.1971)	(0.3201)	(0.1593)
Constant	8.9769***	10.1915***	12.5937***
	(0.7201)	(1.0717)	(0.6397)
Goodness of Fit:			
R-Squared	0.6439	0.6769	0.7413
Root MSE	0.5751	0.6207	0.4328
F(5,72)	25.99	36.53	39.30

Standard errors are reported in parentheses
*** = significant at 1% level
** = significant at 5% level
*=significant at 10% level

The regression results presented in **Table 19** indicate that a statistically significant and negative relationship exists between crop area and yield, labor hours, and capital input per hectare, when controlling for relevant farmer characteristics. Thus, the existence of an inverse relationship between farm size and productivity is confirmed for my dataset.

Table 19 shows that age, education, assets all appear as significant explanators of productivity as well. But even when comparing for these socioeconomic variables, the strongest effects on productivity appear to be crop area and vegetable adoption. Vegetable adoption has a consistently positive effect on productivity, while crop area has a consistently negative effect. The negative effect of crop area on productivity holds not only for productivity in per hectare terms, but for per labor hour and per capital input terms as well.

These findings confirm the results presented in Thapa (2007), which measured an IR between farm size and productivity in Western Nepal. The analysis presented here, however, could be vulnerable to criticisms presented by Bhalla and Roy (1988), since I did not control for land and soil quality variables. Nevertheless, the strong results in Table 13 suggest that indeed smaller farms in Mid-Western Nepal are more productive than larger farmers. This is likely a demonstration of the continuing prevalence of traditional, low-capital intensity farming practices in the region.

Appendix C. Field Surveys

Questionnaire to Estimate Costs of Production (English)

0. General Information

0.1 Date:____
0.2 Form #:______________________________________
0.3 District:______________________________________
0.4 VDC:____
0.5 Ward:____
0.6 Village:_______________________________________
0.7 Group Name/#:_________________________________

1. Personal Information

1.1 Name of Respondent:_______________________________________
1.2 Age:__________________________
1.3 Gender:

- ☐ Male
- ☐ Female

1.4. Number of Family Members:______________________________

1.5 Respondent's Position in Group: (Check One)

- ☐ Chairperson
- ☐ Secretary
- ☐ Member
- ☐ Other:________________

1.5 Education:

- ☐ Illiterate
- ☐ Informal (Adult Literacy)
- ☐ Primary (1-5)
- ☐ Secondary (6-10)
- ☐ SLC
- ☐ Higher

1.6 Ethnicity:

- ☐ Brahmin
- ☐ Chhetri
- ☐ Janajati
- ☐ Dalit
- ☐ Other:_________

1.7 Which KISAN trainings or demonstrations have you attended?

- ☐ Plastic Houses/Drip Irrigation
- ☐ Planting Techniques
- ☐ Storage Technologies
- ☐ Seed Varieties
- ☐ Chemical Fertilizer
- ☐ Livestock
- ☐ Jhol-Mol
- ☐ Pest Management (IPM)
- ☐ Rhizobium Culture

2. Socioeconomic Status

2.1 Primary Source of Income:

- ☐ Grain Crops
- ☐ High Value Vegetables
- ☐ Livestock
- ☐ Tourism/Business
- ☐ Business
- ☐ Government service
- ☐ Non-Timber Forest Products
- ☐ Other: ___________________

2.2 Assets (Check all that apply):

- ☐ Cellphone
- ☐ Radio
- ☐ TV
- ☐ Electricity
- ☐ Motorcycle
- ☐ Bicycle
- ☐ Bullock Cart
- ☐ Truck/Tractor
- ☐ Livestock
- ☐ Poultry
- ☐ Agro. Machinery
    - o Pump
    - o Tiller
    - o Thresher
    - o ___________________
- ☐ Gas Stove
- ☐ Multiple Water Use System (MUS)
- ☐ Solar Home System (SHS)
- ☐ Biogas

2.3 Distance to nearest road:________________________________

2.4 Distance to nearest Market:_______________________________

2.5 What is the source of wateryou're your farm:___________________________

2.6 Services Accessible:

2.6.1 Is there an Agrovet supplier near your farm?

- ☐ Yes
- ☐ No

If yes,

2.6.2 How long does it take to get to Agrovet supplier:

- ☐ Walking _______________
- ☐ Bus/vehicle __________

2.6.3 What services are available there?

- o Pump
- o Drip Hoses(pipe)
- o Sprayers
- o Seed
- o Fertilizer
- o Pesticide
- o Water Storage Tanks

2.6.4 Are any other services available near your farm?

- ☐ Agricultural Extension Services
  - o Government Services
  - o Non-Government Services
- ☐ Agro. Machinery
  - o Tractor
  - o Tiller
  - o Thresher

3. Land

3.1 Land Ownership Status:

- ☐ Farming on their own land
- ☐ Leasing land
  - o If leasing: Cost of lease:________________
  - o Lease Period:________________________

3.2 What is the area of the farm? (Specify Kattha/Ropani):___________________________________

3.3 What type of farming is practiced?

- ☐ Subsistence
- ☐ Commercial

3.4 Is your annual farm income and your food production enough to last your family:

- ☐ For 3 – 6 months
- ☐ For 6 - 9 months
- ☐ For 9 – 12 months
- ☐ More than 1 year

3.5 Crops in Production:

Crops in Production:	Area of production (specify units)	Yield (kg.)	Yield in Previous Season (kg.)	Volume sold (kg.)	Sale price (per kg.)	# of Plantings per Year
Tomatoes						
Cauliflower						
Cucumber						
Bitter Gourd						
Cabbage						
Onion						
Chili						
Maize						
Lentils						
Rice						
Other:__________						

4. Investment/Expenditure

4.1 Labor Investment/Expenditure

<table>
<tr><th rowspan="3"></th><th colspan="3"></th><th colspan="6">Hired Labor</th></tr>
<tr><th colspan="3">Family and Unpaid Neighbor's Labor</th><th colspan="3">Male Workers</th><th colspan="3">Female Workers</th></tr>
<tr><th># of Workers</th><th># of Days Worked</th><th>Hours Worked per day</th><th># of Workers</th><th># of Days Worked</th><th>Wage (+lunch)</th><th># of Workers</th><th># of Days Worked</th><th>Wage (+lunch)</th></tr>
<tr><td>Land Preparation: (getting materials/ seeds, ploughing, fertilizer, pipes, building, etc.)</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>Planting</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>Maintenance (weeding, watering, upkeep, fertilizing, pest mgmt.)</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>Harvest</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>Storage</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>Transportation</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
</table>

4.2 Capital Investment/Expenditure

1st Crop:

Type of crop (circle one):	Tomatoes	Lentils						
	Cauliflower	Rice						
	Bitter Gourd	Onion						
	Cucumber	Chili						
	Cabbage	Other:_________________________						
	Maize							
Capital Good:		**Owned (✓)**	**Rented (✓)**	**Service provider**	**Service Provider's Dist. From Farm (km.)**	**Unit**	**Cost (per unit)**	**Duration of Use**
Tools/Machinery:								
	Tractor							
	Tiller							
	Thresher							
Plough Animal								
Irrigation:								
	Pumps							
	Tanks							
	Drip Hoses							
	Sprinklers							
Pesticide:								
Fertilizer:								
	Jhol Mol/Manure							
	Chemical							
Seed								
Technical Assistance								
Transportation								
Other Inputs:								
	Fence							
	String							
	Plastic Houses							
	Planting Trays							
	Coconut Peat							
	Buildings							
Other:								

2nd Crop:

Type of crop (circle one):	Tomatoes	Lentils						
	Cauliflower	Rice						
	Bitter Gourd	Onion						
	Cucumber	Chili						
	Cabbage	Other:___________________________						
	Maize							
Capital Good:		**Owned (✓)**	**Rented (✓)**	**Service provider**	**Service Provider's Dist. From Farm (km.)**	**Unit**	**Cost (per unit)**	**Duration of Use**
Tools/Machinery:								
	Tractor							
	Tiller							
	Thresher							
Plough Animal								
Irrigation:								
	Pumps							
	Tanks							
	Drip Hoses							
	Sprinklers							
Pesticide:								
Fertilizer:								
	Jhol Mol/Manure							
	Chemical							
Seed								
Technical Assistance								
Transportation								
Other Inputs:								
	Fence							
	String							
	Plastic Houses							
	Planting Trays							
	Coconut Peat							
	Buildings							
Other:								

5 Challenges to Accessing Inputs:

5.2 From the following list, identify which are the most important to the farmer (check up to three) and comment on what the challenges are for those inputs:

Irrigation:____

Pesticide:____

Fertilizer:____

Seed:____

Equipment:____

Technical Assistance:______________________________________

Transportation:____

Structures:____

Other:____

6 Estimating Total Investment and Revenue:

6.1 (Identify Units)

Estimated total investment per crop:		**Estimated Total Invesment**	**Estimated Total Income**
	Tomatoes		
	Cauliflower		
	Cucumber		
	Bitter Gourd		
	Cabbage		
	Maize		
	Lentils		
	Rice		
	Onion		
	Chili		

7 Credit:

7.2 Are you a member of any formal or informal groups?

- ☐ Yes
- ☐ No

7.1.1 If yes, which groups?

- ☐ Forest Users' Group
- ☐ Water Users' Group
- ☐ Savings & Loan Group
- ☐ Other (NGO)

7.1.2 What services do you get from this group?

____

7.2 Do you currently have a loan?

- ☐ Yes
- ☐ No

If yes:

7.2.1 What type of loan is it?____

7.2.2 What is the amount of the loan?_____________________________________

7.2.3 What is the interest rate of the loan?_______________________________

7.2.4 What is the status of the loan?_____________________________________

Questionnaire to Estimate Costs of Production (Nepali)

साना किसान खेती उत्पाद लागत अध्ययन प्रश्नावली

मध्य -पश्चिमाञ्चल बिकास क्षेत्र

०.सामान्य जानकारी

१. मिति:________________________________
२. फार्म नं :______________________________
३. जिल्ला :______________________________
४. गा.वि.स : _____________________________
५. वडा नं:________________________________
६. गाँउ:__________________________________
७. समुहको नाम :___________________________

१. व्यक्तिगत जानकारी

१.१ उत्तर कर्ताको नाम:________________________

१.२ उमेर:__________________________

१.३ लिंग

☐ पुरुष ☐ महिला

१.४ कुल परिवार संख्या :_______________________________

१ .५ उत्तर कर्ताको समुहमा पद:

☐ अध्यक्ष ☐ सदस्य
☐ सचिव ☐ अन्य ____________________

१.५: शिक्षा

☐ निरक्षर
☐ अनौपचारिक (प्रौढ शिक्षा)
☐ प्राथमिक (१-५)
☐ माध्यमिक (६-१०)
☐ एस.एल.सी
☐ उच्च शिक्षा

१.६: जात:

☐ ब्राहमण
☐ क्षेत्री
☐ जनजाती
☐ दलित
☐ अन्य _________________

१.७: के तपाईले कुनै KISAN तालिम वा प्रदशेनमा भाग लिनुभएको छ?

- ☐ प्लास्टिक घर / थोपा सिंचाई
- ☐ रोपाइ प्रविधी
- ☐ भण्डार / थन्क्याउने प्रविधी
- ☐ बीउका प्रकार
- ☐ रासायनीक मल
- ☐ पशु पालन
- ☐ झोल मोल
- ☐ एकीकृत शत्रुजीव व्यवस्थापन (IPM)
- ☐ राइजोबियम पद्धती

२ .सामाजिक आर्थिक विवरण

२.१ प्राथमिक आम्दानीको स्रोत :

- ☐ अन्न वाली
- ☐ उच्च मुल्य तरकारी खेती
- ☐ पशु पालन
- ☐ पर्यटन
- ☐ सरकारी जागिर
- ☐ ब्यापार
- ☐ गैर काष्ठ उत्पादन
- ☐ अन्य: ____________________

२.२:सम्पत्ति:

- ☐ मोवाईल
- ☐ साईकल
- ☐ रेडियो
- ☐ टि.भी
- ☐ विजुली बत्ती
- ☐ मोटर साइकल
- ☐ गाढा
- ☐ ट्रक / टेक्टर
- ☐ पशुपालन
- ☐ कुखुरा पालन
- ☐ कृषी औजार / मेशीन
  - ○ पम्प
  - ○ टीलर
  - ○ थ्रेसर
  - ○ ______________________
- ☐ ग्याँस चुलो
- ☐ बहु उद्देश्यीय सिंचाइ प्रणली (MUS)
- ☐ सोलार घरेलु प्रणली (SHS)
- ☐ बायो ग्याँस

२.३ नजिकको बाटोको दुरी: _______________

२.४ नजिको हाटबजार/बजारको दुरी: _______________

२.५ खेतीको लागी पानिको स्रोत :_______________

२.६ उपलब्ध सेवाहरु :

२.६.१ के तपाईको नजीकै कृषी सामाग्री विक्रेता (एग्रोभेट) छ?

☐ छ
☐ छैन

एदि छ भने,

२.६.२ त्यहाँ पुग्न लाग्ने समय :

☐ पैदल ___________________
☐ बस / गाडी ____________

२.६.३ कुन कृषी सामाग्री पाइन्छ ?

○ पम्प
○ ड्रिप (पाइम)
○ स्प्रेयर
○ बीउ
○ मल
○ बिषादि
○ पानी ट्याङ्क

२.६.४: अरु कुनै सेवा पाईन्छ ?

☐ कृषी प्रसार सेवा
  ○ सरकारी सेवा
  ○ गैर सरकारी सेवा
☐ कृषी औजार / मेशीन
  ○ ट्रेक्टर
  ○ टीलर
  ○ थ्रेसर
  ○ ____________________

३. जीमन

३.१जमिनको अधिग्रहण स्थिति :

- ☐ निजि
- ☐ ठेकाबन्धक / भाडा
  - ○ भडाको लागत :_________
  - ○ ठेकाको अवधि :_________

३.२ जमिनको क्षेत्रफल (रोपनी/कठ्ठा :_______________________________________

३.३ खेती कुन किसिमको हो ?

- ☐ निर्वाहमुखी
- ☐ व्यवसायिक

३.४ खेतीको उत्पादन ,खपत र बिक्रिले तपाँइको परिवरलाई कति महिना पुग्छ ?

- ☐ ३ -६ महिना
- ☐ ६-९ महिना
- ☐ ९-१२ महिना
- ☐ १ वर्ष भन्दा बढी

३.५ उतपादन हुने बालिहरु

बालीको नाम	क्षेत्रफल (रोपनी /कठ्ठा)	उत्पादन (के.जी)	गत बालिको उत्पादन (के .जी)	बिक्रि मात्रा (के.जी)	बिक्रिदर प्रति (के.जी)	बर्षमा कति पटक बाली लगाउनु हुन्छ ?
गोलभेडा						
काउली						
काँक्रो						
करेला						
बन्दा						
प्याज						
खुर्सानी						
मकै						
दाल/दलहन						
धन						
अन्य						

४. लागत

	परिवार र छिमेकी जनशसक्ति			भाडा र किराया जनशक्ति					
				पुरुष			महिला		
	सँख्या	जन श्रमको दिन	प्रति दिन गर्ने काम (घण्टामा)	सँख्या	जन श्रमको दिन	ज्याला+ (खाजा खर्च)	सँख्या	जन श्रमको दिन	ज्याला+ (खाजा खर्च)
जमीनको तयारी(सामान /बीउ ओसार्ने, जोत्ने, सम्याउने, मल हाल्ने आदि)									
रोपाँई (छर्ने, रोप्ने सिंचाई)									
हेरचाह गर्ने(झार उखेल्ने, पानि हाल्ने,रेखदेख गर्ने,मल र विषादिको प्रयोग आदि)									
बाली काट्ने									
भण्डार/थन्क्याउने									
ढुवानी									

४.२: पुँजीगत लगत

पहिलो बाली

बालीको नाम (एक चिन्ह लगाउनु)	गोलभेडा	काउली	काँक्रो	करेला	बन्दा	प्याज	खुर्सानी	
	मकै	दाल/दलहन	धन					
	अन्य							
		निजि	भाडामा	सेवाप्रधान गर्ने व्यक्ति / सँस्था	सेवा प्रधान गर्नेको दुरी (कि.मी.)	परिमाण	लागत प्रति	प्रयोग गरेको अवधि
औजार ,मेशिन								
	ट्रेक्टर							
	टीलर							
	थ्रेसर							
जोत्ने बस्तुभाउ								
सिँचाई								
	पम्प							
	ट्याङ्क							
	ड्रिप, पाईप							
	स्प्रिंकलर							
विसादि								
मल								
	झोल मोल /गोवर							
	रासायनीक							
बीउ								
प्राबिधिक सहयोग								
ढुवानी								
अन्य लागत								
	बार							
	तार /डोरी							
	प्लास्टिक घर							
	बेर्ना सार्ने भाडा							
	नरिवल पीट							
	भवन							
अन्य								

दोस्रो बाली

बालीको नाम (एक चिन्ह लगाउनु)	गोलभेडा	काउली	काँक्रो	करेला	बन्दा	प्याज	खुर्सानी	
	मकै	दाल/दलहन	धन					
	अन्य							
		निजि	भाडामा	सेवाप्रधान गर्ने व्यक्ति / सँस्था	सेवा प्रधान गर्नेको दुरी (कि.मी.)	परिमाण	लागत प्रति	प्रयोग गरेको अवधि
औजार ,मेशिन								
	ट्रेक्टर							
	टीलर							
	थ्रेसर							
जोत्ने बस्तुभाउ								
सिँचाई								
	पम्प							
	ट्याङ्क							
	ड्रिप, पाईप							
	स्प्रिंकलर							
विसादि								
मल								
	झोल मोल /गोवर							
	रासायनीक							
बीउ								
प्राबिधिक सहयोग								
ढुवानी								
अन्य लागत								
	बार							
	तार /डोरी							
	प्लास्टिक घर							
	बेर्ना सार्ने भाडा							
	नरिवल पीट							
	भवन							
अन्य								

५.कृषी लागत प्राप्त गर्न लाग्ने चुनौतीहरु:

५.१ सुचिबाट मुख्य कृषी लागतहरुमा टिप्णी दिनुहोस् :

सचाँई:______________________________

बिषादि:______________________________

मल :______________________________

बीउ:______________________________

उपकरण:______________________________

प्राबिधिक सहयोग :______________________________

ढुवानी /यातायात :______________________________

भौतिक संरचना :______________________________

अन्य :______________________________

६. अनुमानित कुल लगानी र आम्दानी :

बलीको नाम	अनुमानित कुल लगानी	अनुमानित कुल आम्दानी
गोलभेडा		
काउली		
काँक्रो		
करेला		
बन्दा		
प्याज		
खुर्सानी		
मकै		
दाल/दलहन		
धन		
अन्य		

७. कर्जा

७.१. के तपाई कुनै औपचारीक वा अनौपचारीक समुहमा संलग्न हुनु हुन्छ ?

- ☐ छ
- ☐ छैन

यदि छ भने,

७.१.१ कुन समुह?

- ☐ वन उपभोक्ता समुह
- ☐ पानि उपभोक्त समुह
- ☐ बचत तथा समुह
- ☐ अन्य (गैर सरकारी संस्था)

७.१.२ तपाईले के कस्तो सेवा / अनुदान प्राप्त गर्नु हुन्छ ?

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७.२ के तपाँईले हाल कुनै ऋण लिनुभएको छ ?

- ☐ छ
- ☐ छैन

इदि छ भने :

७.२.१ कुन प्रकारको ऋण हो ? _________________________________

७.२.२ ऋणको रकम कति छ ?_________________________________

७.२.३ ऋणको ब्याजदर कति छ ?______________________________

७.२.४ ऋणको अवश्था(कति तिरेको र तिर्न बाँकी) कस्तो छ ?

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