DETERMINANTS OF CROP DIVERSIFICATION AMONG MOZAMBICAN SMALLHOLDERS: EVIDENCE FROM HOUSEHOLD PANEL DATA

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ABSTRACT

DETERMINANTS OF CROP DIVERSIFICATION AMONG MOZAMBICAN SMALLHOLDERS: EVIDENCE FROM HOUSEHOLD PANEL DATA

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More than half of Mozambique's population lives below the poverty line and more than a third are malnourished. Poverty and hunger are intrinsically linked to agriculture in Mozambique, a sector dominated by nearly four million smallholder families primarily growing food for themselves. As its government and international donors turn their focus to improving smallholder agriculture and nutrition, it is crucial to understand those farmers' behaviors and how they make production decisions. One such decision—how to allocate land between different crops—changes frequently between years, and there is no evidence as to what drives the changes in that decision. I use household panel data collected in 2008 and 2011 to investigate the determinants of crop diversification. Using fixed effects, I eliminate unobservable village level factors and isolate the change in diversification from year to year. I find that expected crop prices, access to roads and mobile networks, household and farm size are all significant determinants of household level diversity. I employ a two-stage decision model using correlated random effects to explore the recent upsurge in pigeon pea cultivation, finding market prices to be significant predictors of a farmer's decision to plant pigeon peas, while the presence of communication infrastructure in a village increase the amount of land allocated to pigeon peas.

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My work is largely based on the work of Samuel Benin, Melinda Smale, John Pender, Berhanu Gebremedhin, and Simeon Ehui in Ethiopia in 2004; without their model of crop diversification, mine would not exist. Finally, I would like to acknowledge Bill Burke, MSU AFRE alum and author of the program *craggit* used in my second model, and Valentin Verdier, MSU econometrics expert, without whom I could never have adapted the *craggit* Stata code for my model.

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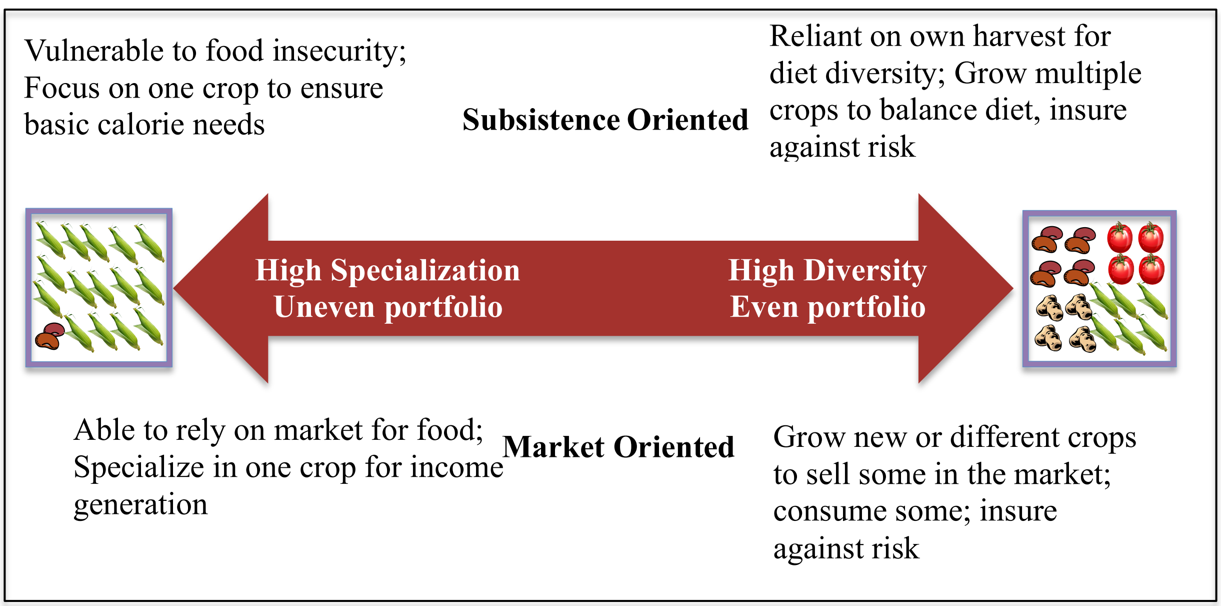
INTRODUCTION

Almost one billion people in the world currently suffer from chronic hunger, and as population growth continues to exceed food production, more and more families will find themselves without enough food in the future (WFP 2013). This issue is especially prominent in rural areas in developing countries; as such, international development organizations increasingly fund programs that target improving agricultural productivity and nutritional outcomes in rural areas.

Paramount to solving this problem is understanding the behaviors of poor households. In an agrarian society such as rural Mozambique, a family's access to food is largely dependent on what that household grows, either because they consume what they grow, or they purchase food with the income earned from what they grow. Physical access to food became a key constraint to food security following the destruction of the country's infrastructure during the civil war. Therefore, to reduce hunger in this scenario, it is essential to improve our understanding of a farmer's decision of *which crops to cultivate*. This research will focus on factors relating to that decision.

In this paper, I will refer to this decision—how a farmer allocates his or her land among different crops—as diversification. Diversification can range from complete specialization, in which a household grows only one crop and sells it to earn income, to a high level of diversity with many crops more evenly distributed over the farm. Alternatively, complete specialization could be indicative of an extreme food insecure scenario in which a family focuses on just one staple to ensure a minimum level of food from their own production. On-farm diversity is thus a spectrum, and is neither universally positive nor negative. As Figure 1 shows, farmers may engage in different levels of diversification for different reasons, and outcomes will depend on the unique situation of each farm. For example, subsistence farmers may diversify to protect themselves from risk. By growing some of everything that they need to eat, a family gains some assurance that they will be able to eat even in the event of crop failure, food price shocks, or lack of food availability in local markets. Others may diversify for income purposes; while there is no direct link proven between levels of diversification and income, some farmers may add new crops to their mix with the hope of earning more from an emerging or more marketable crop. Alternatively, farmers may choose a low level of diversity (specialize in just one marketable crop) for the same reason.

Figure 1. Motivations for Diversification



For interpretation of the references to color in this and all other figures, the reader is referred to the electronic version of this thesis.

This thesis examines farmers' behavior related to land allocation decisions in rural Mozambique, using panel household survey data collected in a Ministry of Agriculture (MINAG) and Michigan State University (MSU) survey of 1,186 households in the northern and central regions in 2008 and 2011. These regions were selected due to their relatively higher agricultural potential and productivity. The outcome is important as it has implications for total agricultural productivity, household food security and nutrition, and labor availability. For example, if a household grows only one or two crops and is dependent on its own harvest for sustenance, its members are unlikely to consume the full variety of nutrients they need. This is the case in most of rural Mozambique where low-protein staples such as maize and cassava constitute most of the diet. Alternatively, if a household grows a wide range of different crops that requires more labor, there may be less labor available for work in commercial agriculture or rural non-farm employment. Furthermore, understanding smallholders' behavior and risk attitudes related to agricultural production decisions will be useful for other potential policies or interventions that target smallholders such as technology adoption and insurance or credit markets. A farmer's decision to adopt a new crop or try a new portfolio is dependent on his or her risk preferences, and therefore similar to the decision to adopt, for example, a new higher yielding hybrid seed or purchase crop insurance, should those options become available in the future.

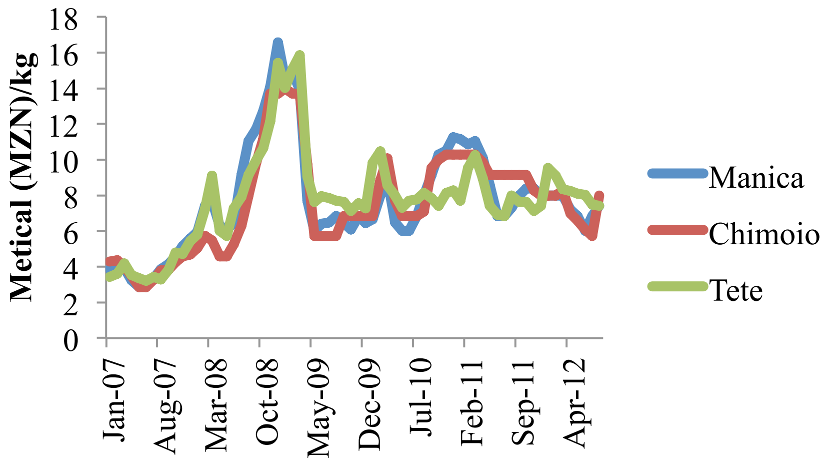
Mozambique is a fascinating place to study land allocation behavior because Mozambican smallholders regularly engage in the reallocation of their land to different crops. In some countries, land allocation decisions are a function of tradition; farmers grow maize because their fathers and neighbors only grew maize, and so on. However, in

Mozambique diversification is much more dynamic, so it is evident farmers are not just stuck in their ways. The average number of crops grown per farm doubled between 1995 and 2003 (World Bank 2006) and during the three-year duration of this study, 82% of households surveyed changed the number of annual crops they grew. Additionally, Mozambique experienced a dramatic change in diversification into pigeon peas; between 2008 and 2011 average land allocated to pigeon peas increased by over 50 percent, and the percentage of farmers growing them nearly doubled.

There is no observable causality associated with this behavior so it remains to be understood *why* farmers decide to add and remove different crops from their mixes each year. In past studies from other developing countries, researchers have found that farm size and fragmentation, market prices, productive capacity (labor and capital), farmers' age and education levels, and extension visits are all associated with higher levels of diversification. However, none of these studies has investigated changes by the same household across time. To understand why a household grows three crops one year and eight the next, as in Mozambique, we must have panel data on the same household in multiple years.

Because of the year-to-year nature of the land allocation changes, it follows that external or environmental factors—rather than characteristics of the farm itself—may be driving them. Two significant such developments affected the lives of Mozambican smallholders during our panel study. First, Mozambique was hit hard by the global food price crisis. Figure 2 shows the volatility of maize prices in Mozambique beginning in 2008. As most families are net buyers of staple foods, this left many unable to purchase sufficient food. This volatile price environment could influence a farmer's crop diversification decision as it relates to protecting his or her family from risk.

Figure 2. Monthly Retail Maize Prices, Nominal, Selected Markets in Mozambique, 2007-2012.



Source: SIMA (Sistema De Informação De Mercados Agrícolas De Moçambique/Agricultural Market Information System)

Second, infrastructure has rapidly developed in Mozambique since 2008. The government has spent over $350 million on road improvements, and cell phone coverage has expanded dramatically. Smallholders in previously isolated areas are becoming better connected to markets for inputs, information, and sales. It is unclear how this could affect land allocation decisions. Previous studies have shown a positive association between physical market isolation and overall levels of farm diversity, while access to market information is also associated with higher diversity. As one might expect, farms lacking access to transport infrastructure do not allocate land to marketable or cash crops.

Within the context of this environment, I seek to answer the following questions: What are the determinants of household-level crop diversification in Mozambique?

Specifically, what drives diversification into an emerging, mixed-purpose crop such as pigeon peas? Is improved infrastructure associated with diversification levels?

Diversity is inherently difficult to evaluate because it can be measured in so many ways, such as total quantity of crops grown, evenness of distribution, the ratio of cash to subsistence crop area, or myriad other combinations or ratios of individual crops or crop categories. I select three different indices of overall farm diversity from the literature for my analysis, and then do a crop-specific investigation into the growth of pigeon pea cultivation in recent years.

Several studies have shown associations between crop diversification and infrastructure (Ibrahim et al. 2009; Bittinger 2010; Mesfin et al. 2011; Rahman 2008). However, none measure a household's *change* in diversification level and therefore fail to account for the possibility that infrastructure—such as paved roads—actually follows agricultural productivity, in which case the error term of the estimation would be correlated with the infrastructure variables themselves. I fill this gap by using village-level fixed effects to correct for the potential endogeneity of this relationship. In so doing, I find that that expected crop prices are the strongest determinants of land allocation decisions. Infrastructure, however, is not insignificant when price variation and village-level fixed effects are controlled for; households far from paved roads are likely to grow fewer crops, and those with year round roads and mobile networks have more evenly distributed crop portfolios. Using a two stage model for my crop-specific research, I find no infrastructure variables to affect the probability of deciding to cultivate pigeon peas, but both mobile and radio coverage are associated with higher land allocated to pigeon peas, conditional on a farmer's decision to cultivate them.

The research is presented as follows: in Chapter One, I provide context for rural agriculture and nutrition in Mozambique with specific focus on recent infrastructure developments. I also provide an overview of the data used for the research. In Chapter Two, I review relevant literature on agricultural household decision-making and determinants of crop diversification. In Chapter Three, I present my models and estimation strategy. In Chapter Four, I discuss the results of my estimation. Finally, I conclude with brief comments on the implications of my study and suggestions for future research.

CHAPTER ONE: MOZAMBICAN CONTEXT

Mozambique's current economic and social conditions are largely influenced by its history of continuous conflict, first for liberation from the Portuguese and then a brutal civil war that killed over a million people (Cunguara et al. 2011). Since the peace agreement was signed in 1992, the country has remained a peaceful democracy and experienced impressive growth. Mozambique is well endowed with natural resources, has an abundance of unused land and water, and has an advantageous coastal location with major trade corridors and ports (USG 2011). Table 1 provides an overview of key demographic and economic figures. In the past 15 years the economy has grown 7.7 percent per year, driven primarily by the service sector, light industry, and agriculture, but it remains one of the poorest countries in the world (Dominguez-Torres and Briceño-Garmendia 2011).

Table 1. Mozambique at a Glance

Total Population	24,096,669
Climate	Tropical to subtropical
Population Under 14	45.5%
Population Growth Rate	2.44%
Urban Population (2011)	31.2%
Infant Mortality Rate	74.63 deaths/1,000 live births
Life Expectancy at Birth	52.29 years
Fertility Rate	5.34 children born/woman
Access to improved drinking water (2010)	77% urban/29% rural
Access to improved sanitation (2010)	38% urban/5% rural
Literacy Rate (2010)	56.1% (>15 years old)
Average schooling (Primary – Tertiary, 2011)	10 years
Gross Domestic Product (GDP) (Purchasing Power Parity/Official Exchange Rate, 2012)	$26.69 billion/ $14.6 billion
GDP Growth Rate (2012)	7.5%
GDP—service sector (2012)	46.5%
GDP—industry sector (2012)	23.9%
GDP—agriculture sector (2012)	29.5%

Source: CIA World Factbook. Figures are 2013 unless specified.

Despite its progress over the past two decades, 54 percent of Mozambicans are below the poverty line (Dominguez-Torres and Briceño-Garmendia 2011) and 46 percent of children under five years old are chronically malnourished (Cunguara et al. 2011). Access to basic infrastructure services such as water and sanitation are below average for the region (Dominguez-Torres and Briceño-Garmendia 2011). This poverty is intrinsically linked to agriculture; the sector employs most Mozambicans, yet the country is still dependent on its neighbors for food imports, leaving families vulnerable to food price volatility and often unable to meet nutritional needs. In this chapter, I provide an overview of Mozambique today, specifically its agriculture and infrastructure, to give context for my research.

1.1 Agriculture

Agriculture is the livelihood of most Mozambicans. The sector employs 80 percent of the population and constitutes 29 percent of GDP (CIA 2013). Mozambican agriculture is dominated by almost four million smallholder families; the majority grows food crops, two-thirds of which is for home consumption, and 16 percent produce cash crops such as cotton and tobacco (World Bank 2006). Crop income accounted for 73 percent of rural income in 2002 (Mather 2012). Despite its relative importance, agriculture has not received sufficient investment from the government and has not improved with the pace of population and GDP growth (Cunguara et al. 2011).

Agricultural productivity has not increased in Mozambique (Cunguara et al. 2011), despite overall agricultural growth averaging 8 percent (USG 2011). On a per capita basis, most food production has shown negative growth. Cereal production per capita has declined, leaving Mozambicans dependent on cereal imports and therefore more susceptible to global price shocks. This lack of improvement in agriculture is mainly a result of lack of access to improved technologies, markets and services (Cunguara et al. 2011). Very few smallholders in Mozambique use fertilizer, pesticides, or irrigation, and most use reserved seeds from the previous year (World Bank 2006).

In addition to low productivity, agriculture in Mozambique is also characterized by low market participation. Rural smallholders are generally subsistence-oriented, although when pressed and need cash for health or other spending, they turn to the market. Preliminary findings from the MSU/MINAG 2011 survey indicate that market participation rates have increased since international food prices began soaring in 2008 (Benfica and Tschirley 2012).

1.1.1 Crop Diversification

Maize dominates the smallholder crop portfolio in Mozambique, particularly in the central and northern provinces surveyed by MSU/MINAG. Almost every household surveyed grew maize in 2011 and on average households allocate 40 percent of their farmland to it[1]. The most important food crops in Mozambique are maize and cassava; more than 50 percent of cultivated land is devoted to these low value crops to ensure household food security (World Bank 2006). Table 2 shows the average share of land allocated to each crop at a household level in 2008 and 2011.

[1] Farmland refers to land cultivated with annual crops. See Section 1.1.3.

Table 2. Household Land Allocation by Crop

Crop	Mean Share of Farmland Allocated 2008	Mean Share of Farmland Allocated 2011
Maize	44.0%	41.2%
Cassava	10.3%	11.0%
Sorghum	8.7%	6.6%
Horticulture	5.2%	5.6%
Cowpea	4.8%	4.3%
Rice	3.7%	4.3%
Common Bean	3.4%	3.5%
Pigeon Pea	3.3%	5.4%
Groundnut (small)	3.1%	3.2%
Sesame	3.1%	2.4%
Groundnut (large)	2.4%	2.3%
Tobacco	1.6%	1.7%
Cotton	1.4%	1.6%
Non-Orange-Fleshed Sweet Potato	0.9%	1.3%
Jugo Bean	0.8%	0.9%
Potato	0.8%	1.0%
Millet	0.7%	0.4%
Soybean	0.6%	0.9%
Sugar	0.5%	0.7%
Sunflower	0.3%	0.4%
Orange-Fleshed Sweet Potato	0.2%	0.5%

N=1,175. Percentage of *every household surveyed*, including those not cultivating the crop. *Source: MSU/MINAG Survey 2008 & 2011*.

The World Bank (2006) finds evidence that crop diversification may be used as a coping mechanism for persistent low income and productivity and the high risk environment of farming in Mozambique; the average number of household crops nearly doubled from 5 to 9 between 1995 to 2003, but this did not significantly affect farm income.

Our survey shows a trend of increasing the total number of crops cultivated, however many households also decreased as well. The two other indices used to measure diversity (described in Chapter Two) show no clear trend; indeed the majority of farmers changed their portfolios between 2008 and 2011 though the average diversification levels remained very similar.

Figure 3 and Tables 3 and 4 provide a snapshot of cropping patterns by province.

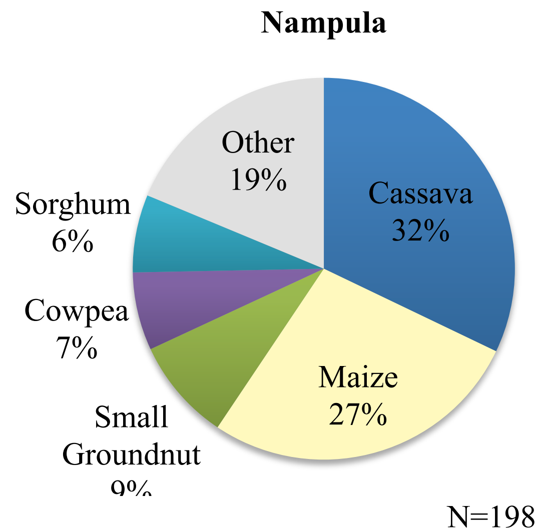
Table 3. Average Number of Crops Cultivated per Household, by Province

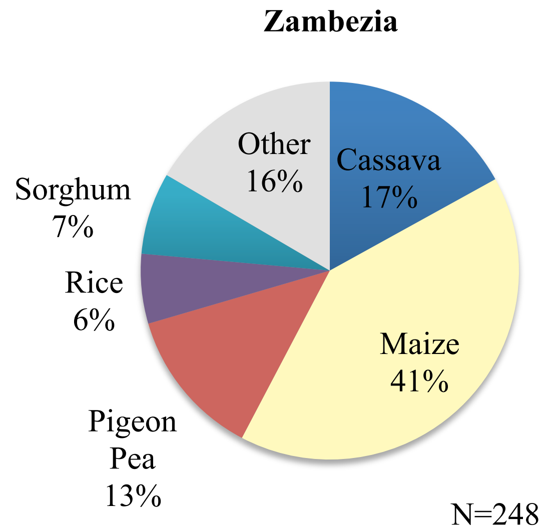
	2008	2011
Nampula	3.6	4.1
Zambezia	4.1	4.6
Tete	4.6	4.4
Manica	3.4	4.2
Sofala	4.2	6.0

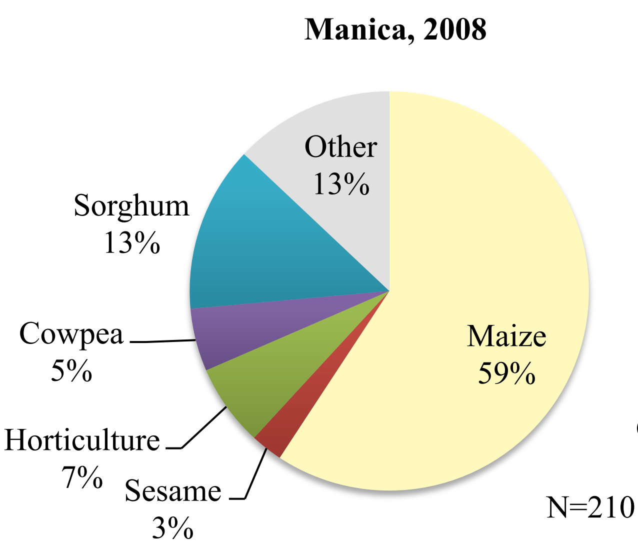
Source: MSU/MINAG Survey. N=1,186.

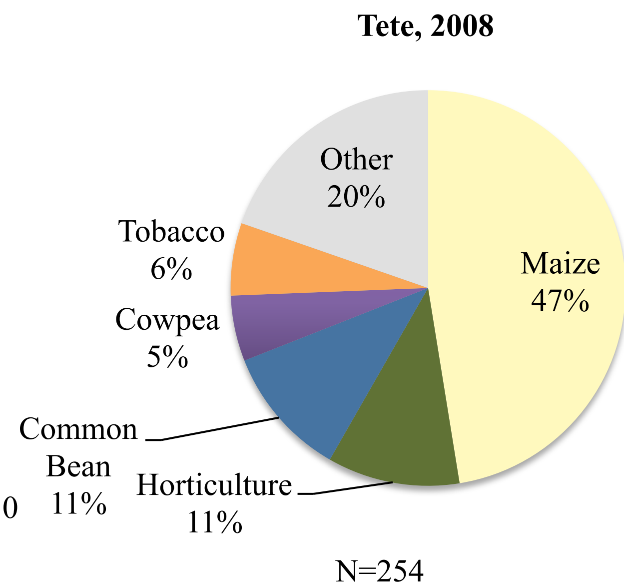
In Nampula, the northernmost province surveyed, cassava is the dominant crop in terms of land allocation, and households grow fewer total crops. Most households grow cassava and maize, as well as some integration of sesame, a cash crop (see Table 4, and next section for a description of cash crops.) Nampula also has the highest rates of child malnutrition in the country (FAO 2011). Maize is the dominant crop in the other four provinces studied. In Manica and Sofala, the southernmost provinces studied, most households grow a combination of maize and sorghum, and approximately 15 percent and 40 percent grow sesame, respectively. Pigeon peas are most frequently grown in Zambezia, where they commonly appear as one of the top three crops cultivated by households, along with maize, cassava, and sorghum. In Tete, the westernmost province, surrounded primarily by Zambia, Malawi, and Zimbabwe, maize dominates but sorghum and cassava are not common; instead households grow common beans and horticulture, and some produce tobacco, typically grown under contract as described in the following section.

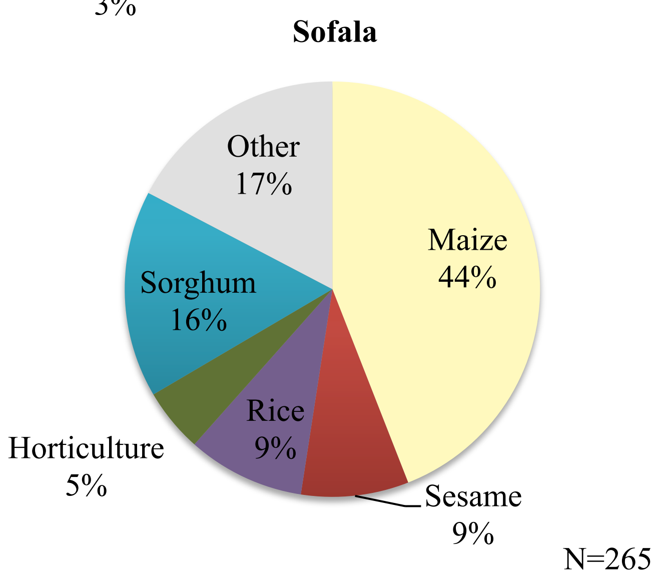
Figure 3. Average Land Allocated to Common Crops by Province, 2008











Source: TIA 2008. Information on all crops and years available in the appendix.

Table 4. Common Crop Portfolios by Province

	2008	2011
Nampula (n=200)		
Cassava, Maize	10%	5%
Cassava, Maize, Small Groundnuts	7%	7%
Cassava, Maize, Cowpea	6%	12%
Cassava, Maize, Sesame	5%	1%
Cassava, Maize, Sorghum	5%	11%
Cassava	4%	2%
Other	65%	63%
Zambezia (n=252)		
Cassava, Maize, Pigeon Pea	17%	23%
Maize, Pigeon Pea	6%	6%
Cassava, Maize, Sorghum	6%	6%
Cassava, Maize, Rice	5%	6%
Maize, Pigeon Pea, Sorghum	4%	4%
Other	62%	55%
Tete (n=256)		
Maize, Horticulture, Common Bean	11%	6%
Maize, Horticulture, Large Groundnut	10%	3%
Maize, Common Bean, Tobacco	8%	7%
Maize, Horticulture, Cowpea	6%	3%
Maize, Common Bean, Large Groundnut	5%	7%
Other	62%	74%
Manica (n=209)		
Maize, Sorghum, Horticulture	11%	9%
Maize, Sorghum	11%	3%
Maize, Sorghum, Cowpea	8%	4%
Maize	6%	3%
Maize, Sorghum, Sesame	5%	5%
Maize, Cassava, Horticulture	2%	8%
Maize, Cassava, Sorghum	5%	6%
Other	53%	62%
Sofala (n=268)		
Maize, Sorghum, Sesame	11%	3%
Maize, Sorghum	9%	1%
Maize, Sorghum, Horticulture	7%	8%
Maize, Sorghum, Rice	7%	1%
Maize, Sesame, Horticulture	4%	4%
Maize, Sorghum, Cassava	4%	6%
Maize, Rice, Sesame	3%	6%
Other	54%	70%

Percentages reflect the number of households for whom the crops listed are the three crops using the most land. Households may grow more than those crops, except in the cases when less than three are listed. Source: MSU/MINAG Survey 2008 & 2011.

1.1.2 Cash Crops

While food security and risk management often drive crop portfolio diversification, market and earnings potential could also drive diversification from subsistence into cash crops. For the purpose of this analysis, I define cash crops as those marketed by more than 75 percent of the farmers cultivating them; the World Bank (2006) identifies them as cotton, tobacco, cashew, sugar, and tea. Only five percent of cultivated land in Mozambique is devoted to cash crops (The World Bank 2006). Tea and sugar are typically grown on plantations and therefore not commonly grown by smallholders on their own plots. Households that diversify into cotton and tobacco do so under a contracting arrangement with large firms that also provide inputs and extension advice. This has increased the number of households participating in cash crops, but is limited by access to such arrangements. Cashew is a cash crop traditionally grown by smallholders, but trees tend to suffer from age (most were planted in the early colonial era) and disease, lowering yield and quality (World Bank 2006).

Although there does not exist much opportunity for the small farmer to diversify into these primary cash crops without the presence of a cotton or tobacco contractor, in the past decade Mozambique has experienced growth in the market potential of several legumes and oilseeeds that are relatively more feasible for a smallholder to adopt than the plantation crops mentioned above, but still have market potential similar to cash crops. This is due to a combination of demand and donor support. For example, Mozambican sesame exports increased from 1,500 to 36,000 tons between 1998 and 2009 with United States Agency for International Development (USAID) assistance and growth of private sector processing (USG 2011). Smallholder production of soybean has also increased recently to meet the demands of the growing poultry industry, with assistance from the Bill and Melinda Gates Foundation (USG 2011). While sesame and soy are produced primarily to sell, other crops, such as pigeon peas, are increasingly grown by smallholders for their market potential *and* for household food security. In addition, intercropping with legumes such as pigeon peas can improve soil quality and cereal yields, which can further improve a family's income, particularly in a case of little to no fertilizer use.

Unlike soybeans, which were recently introduced to Mozambican smallholders and are grown almost exclusively as a cash crop, pigeon peas are not new and have been grown as a subsistence crop for decades. However, their market potential as a cash crop is emerging which may be the reason for the substantial recent increase in cultivation (see Table 5); Mozambique's exports of dried legumes increased from 8,709 metric tons (MT) in 2007 to 128,127 MT in 2011 (UN Comtrade 2013). It is evident that there is a market for oilseeds and legumes; in my analysis, I will investigate the characteristics of smallholders that are taking advantage of the growing market for one such legume, the pigeon pea.

Table 5. Household Food and Cash Crops in Mozambique

		% Growing 2008	% Growers Selling 2008	% Growing 2011	% Growers Selling 2011
Subsistence Crops	Sorghum	37	7	35	6
	Jugo Bean	9	10	10	6
	OFSP	3	11	8	14
	Rice	14	14	14	14
	Cowpea	37	14	43	17
	Cassava	41	20	58	20
Mixed-Purpose Crops	Non-OF SP	13	22	18	25
	Groundnut Sm	20	25	26	20
	Groundnut Lg	17	27	19	27
	Maize	93	32	95	38
	Pigeon Pea	20	32	36	44
	Common Bean	23	37	26	44
Cash Crops	Sesame	16	73	16	92
	Tobacco	6	75	7	84
	Sunflower	3	84	3	93
	Soy	4	86	5	77
	Cotton	5	93	6	86

N=1,186. Source: MSU/MINAG Survey, 2008 & 2011

1.1.3 Perennial Crops

Smallholders in Mozambique also frequently cultivate tree crops, such as mango, coconut, and papaya. The nature of a farmer's decision to plant a tree crop is fundamentally different from that of annual crops; trees can take years to bear fruit, and land allocation decisions are not made on a "harvest season" basis. Therefore, for the purpose of understanding the annual land allocation decisions of a farmer, I exclude orchard crops from my analysis. When I refer to the percent or share of farmland allocated to a crop in this paper, the total farmland cultivated constitutes only that cultivated with annual crops.

1.2 Diet and Nutrition

Malnutrition is prevalent in Mozambique, and can be largely attributed to lack of dietary diversity and insufficient health services. In 2008, 44 percent of children under five suffered chronic malnutrition (FAO 2011); Table 6 provides a summary of other nutrition indicators for the population. Rural Mozambicans' diets mirror their agricultural

Table 6. Anthropometric and Nutrition Indicators, Mozambique 2008

Stunting (chronic malnutrition), rural children <5	47%
Wasting (weight-for-height), children <5	5%
Underweight, children <5	18%
Chronic energy deficiency, rural women 15-49	10%
Iodine deficiency (goitre), rural children 6-12	15.7%
Rural households with adequate iodine level of household salt (>15 ppm)	19.7%
Vitamin A deficiency , rural children 6 months – 5 years old	73.1%
Anemia/Iron Deficiency, rural children 6 months – 5 years old	80.5%

Source: FAO 2011

production. In the north, the diet is primarily composed by cassava, a low-protein staple, while households in the center rely mostly on maize. Cereals and starchy roots constitute 80 percent of the energy supply in Mozambique, making it the country with the lowest levels of dietary diversification in the region (FAO 2011). Staples are typically consumed in a porridge form and served with green leafy vegetables or bean stew, and seafood when available in coastal areas. Consumption of dairy, eggs, and meat is very low in rural areas; fruits are consumed only when in season. The per capita supply of fruits and vegetables has decreased by half since the 1970s and is the lowest in the region. As income increases, meat and fish substitute for greens and beans, while staple consumption remains the same (FAO 2011).

1.3 Infrastructure

Lack of sufficient rural infrastructure is one of the obstacles to improving the productivity, income, and food security of smallholders in Mozambique. Only 20 percent of smallholders sell in the market, and only 34 percent of those receive price information (USG 2011). Previous studies have found infrastructure to significantly impact crop diversification (see Table 8, next chapter), and the MSU/MINAG survey shows significant correlations between infrastructure variables and diversity. To provide context for the analysis of this relationship, in this section I summarize the conditions and recent development in two areas of infrastructure that may impact those statistics: roads and telecommunication, specifically mobile phones. Both have experienced recent growth and represent opportunities to connect rural smallholders to markets. Indeed, Dominguez-Torres and Briceño-Garmendia (2011) estimate that if Mozambique could improve its infrastructure to the level of middle-income countries in the region, its growth performance would increase by up to 2.6 percentage points per capita.

1.3.1 Road Infrastructure

Mozambique's road quality contrasts sharply between rural and urban areas: densely populated areas and main transport corridors enjoy good connectivity and road quality, while rural areas suffer poor quality and low connectivity. Its classified network density per land area is one of the lowest in the region (Dominguez-Torres and Briceño-Garmendia 2011) and only 18 percent of that network is paved, with many of those paved roads in terrible condition (Brouwer and Brito 2012). Only one quarter of rural Mozambicans live within two kilometers (km) of a road in the classified network, and 40 percent of rural roads are categorized as poor quality (Dominguez-Torres and Briceño-Garmendia 2011).

Nevertheless, roads constitute the only major area of transport improvement in Mozambique in recent years, and such changes have reduced travel time to cities for many (Cunguara et al. 2011). The national road connecting the north and south was completely paved in 2009 (Brouwer and Brito 2012), though rural roads improvements still lag behind. The Government of Mozambique spent approximately $347 million per year on road sector investments from 2007 to 2009, and in 2011 the World Bank extended its decade-long involvement under the Roads and Bridges Management and Maintenance Program with an additional $30 million for the objectives of increasing "(a) percentage of classified roads in good and fair condition; and (b) the percentage of the rural population within two kilometers of an all- season road" (World Bank 2009, p.2).

As such, the quality of the roads is improving and the road network is expanding. The villages in our survey reported an average decrease of 12 km to the nearest paved road, and the percent living over 50 km from a paved road dropped from 33 to 24 (see Table 10, Chapter 3). Dorosh et al. (2012) predict that reductions in travel time will lead to large increases in output; I investigate whether they are associated with diversification levels as well.

1.3.2 Telecommunications

The poor transport infrastructure makes telecommunications critical in Mozambique. Mobile networks can connect people in greater geographic areas faster and more cheaply than landlines or transport (Brouwer and Brito 2012). As in most of Africa, the expansion of mobile networks has transformed communications in Mozambique in the past decade. According to the International Telecommunications Union (ITU), the number of mobile phone subscriptions per 100 inhabitants increased from 0.28 in 2000 to 32.83 in 2011 (ITU 2012). Mobile growth between 2005 and 2008 was around 40 percent per year, and the population covered by a global system for mobile communications (GSM) increased from 14 percent in 2000 to over 80 percent in 2008 (Dominguez-Torres and Briceño-Garmendia 2011).

Since 2003, two mobile operators, MCel and Vodacom, have shared the market in Mozambique, and network rollout has generally followed economic development, beginning in Maputo and expanding main roads to provincial capitals (Brouwer and Brito 2012). A third company, Movitel, was also launched in 2012 (Zita 2012). While both MCel and Vodacom boast high coverage rates in the northern and central provinces, research has shown that operators tend to overestimate their number of users. Rural areas clearly lag behind in access to network coverage. In 2007, 32 percent of the population in Maputo (city and province) used mobile phones compared with a national average of 7.8 percent. In Zambézia, one of the provinces of focus for this study, that figure was only 1.8 percent (Brouwer and Brito 2012).

Acquiring a mobile phone in Mozambique is relatively easy since the introduction of prepaid starter packages with SIM cards, retailing for around five dollars or less. The primary obstacle is the handset itself, the cheapest of which retails for around $40 new. Because of the large market of used and stolen devices, many are able to obtain a phone more cheaply. Airtime and SMS are prepaid, unless an annual contract is signed, and callers only pay for calls or messages that they make or send (Brouwer and Brito 2012).

There is evidence that information and communication technology (ICT) drives growth; Dominguez-Torres and Briceño-Garmendia (2011) state that 0.9 of the 1.9 percentage improvement in per capita growth rates in Africa 2003-2007 were attributable to improved infrastructure, primarily from the ICT revolution, but the effect of cell phones on agriculture in Mozambique remains uncertain. Based on the 2007 census, Brouwer and Brito (2012) found that only four percent of mobile phone users work in agriculture, and the majority of those in agribusiness, not on household farms. They also found that only five percent use the phones primarily for professional needs. It is, however, worth noting that with such rapid expansion, mobile phone data quickly becomes out of date. Given the system investments in coverage outside Maputo, it is likely that much has changed since the 2007 census.

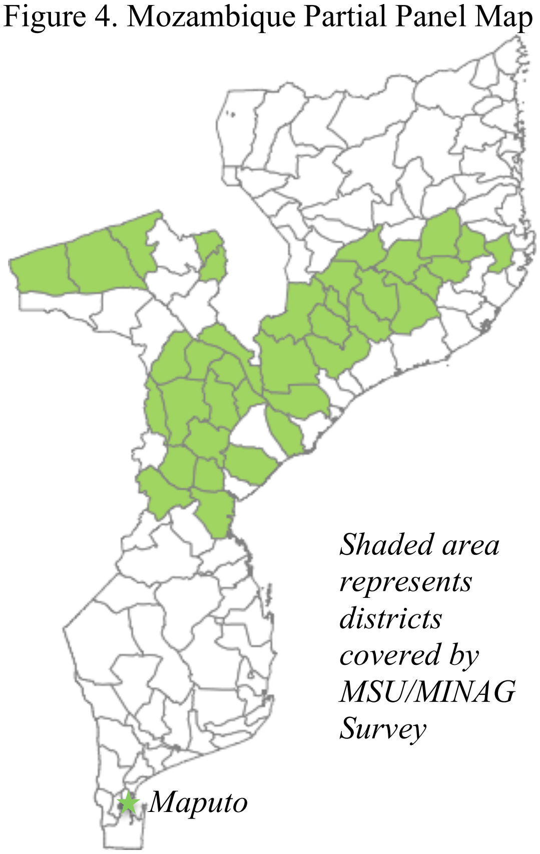
Another way in which ICT has integrated rural African farmers into markets has been through mobile banking; M-Pesa's widely celebrated popularity in Kenya has revolutionized rural finance. M-Pesa is expanding across Africa and Vodacom is launching its mobile money platform in Mozambique, which will undoubtedly change how mobile coverage impacts rural farmers. However, for the purpose of the following analysis—which spans 2008 to 2011—mobile money is not included as a component of rural market infrastructure.

1.4 Data

1.4.1 Survey

This study uses a two-year panel of rural household surveys from the north and central regions of Mozambique. The 2008 survey was conducted as part of the Trabalho do Inquérito Agrícola (TIA), implemented by the Ministry of Agriculture (MINAG) Directorate of Economics with support from MSU. The TIA 2008 sample was drawn from the listing of the 2000 agricultural census and used a stratified, clustered sampling design to form a nationally representative dataset. The 2011 survey was supported by USAID and Technoserve, implemented by MSU and MINAG, and represents a follow-up survey to TIA 2008 farmers, only in five high agricultural production provinces: Tete, Zambézia, Manica, Nampula, and Sofala (see Figure 4.) The 2008-2011 partial panel is discussed in the following section.

Figure 4. Mozambique Partial Panel Map



The household surveys cover a range of topics relating to household economic activity and wellbeing. They capture agricultural production including costs and revenues, livestock activities, land use, salaried-employment, and other income-generating activities. Household demographic information was collected in detail, including members' ages, genders, and education levels and literacy. The surveys also capture simple self-reported disease and health information. Community-level questionnaires were also administered to village leaders. These surveys included information on village infrastructure, access to input and output markets, climate, and local commodity prices.

1.4.2 Partial Panel

The 2011 survey was administered to only a subset of those households surveyed in 2008. This survey selected districts in the provinces of Nampula, Zambézia, Tete, Manica, and Sofala based on their production of maize, sesame, soybean, and sunflower. The panel data cover 1,186 farm households; only those households surveyed in both years are used for my analysis. The results are therefore not nationally representative, but rather representative of small- and medium-holders in the region specified.

1.4.3 Panel Attrition

Like most longitudinal household surveys, our panel suffered some attrition between 2008 and 2011. Eighteen percent of the households in the 2011 selected districts that were originally surveyed in 2008 did not complete the interviews. This rate is approximately what is expected for rural household surveys in sub-Saharan Africa; households move, dissolve, or become unreachable over time. In some specific cases, village chiefs declined to participate in the follow up due to conflicts resulting from cholera riots. Refusal is rarely a bias for attrition in this context. Attrition can bias results if it is not random; for example, if households dissolve because the head dies, attrition could be strongly correlated with other characteristics, such as family health status or the age of the head, which may also be correlated with farming behaviors. Summary statistics for the attritted households (see Table 7) show that wealthier or more advanced farms, as proxied by ownership of livestock, use of fertilizer, cropped area of maize, and total farm size, were less likely to be interviewed in 2011. To minimize potential attrition bias, I use inverse probability weighting (Wooldridge 2010); this predicts a household's probability of completing a second interview in 2011 based on a set of characteristics. Mather and Donovan (2007) tested this method for the TIA 2002/2005 panel and confirmed that many observable characteristics were significant predictors of the probability of re-interview, concluding that inverse probability weighting, when combined with population sample weights, is a reasonable approach for minimizing attrition bias.

Table 7. Panel Attrition Summary Statistics, 2008 Mean

	Households Re-interviewed in 2011	Households Attritted in 2011
Household head female (1=yes)	0.21	0.17
Household head's age	39.42	41.83
Maximum education in household	3.93	4.40
Household size	4.80	5.48
Cropped area of maize	0.75	1.13
Cropped area of pigeon peas	0.09	0.06
Total household landholding	2.18	2.81
Household has latrine	0.57	0.66
Household has oil lantern	0.41	0.43
Tropical livestock units (TLU)	1.57	2.73
Household uses fertilizer on any crop (1=yes)	0.02	0.10
Village has electricity (1=yes)	0.20	0.14
Village has mobile network (1=yes)	0.79	0.80
Number of Households	1,186	268

Source: TIA 2008.

1.5 Research Questions

Between 2008 and 2011, Mozambique experienced improvements in road quality, expansion of paved road networks, and a rapid increase in mobile network coverage and mobile phone users. Over the same period, smallholders in the northern and central provinces changed their land allocation strategies and overall levels of on-farm crop diversity. However, we do not know whether the infrastructure itself has affected cropping practices. I hypothesize that infrastructure may be associated with crop diversification patterns via three pathways: 1) price changes, by decreasing transportation and/or transaction costs, 2) access to information, such as market prices, crop information, or agricultural extension, and 3) access to inputs, such as seeds for crops previously unavailable in isolated villages. The survey data indicate evidence for improved access to information; the number of households receiving price information increased from 37 percent in 2008 to 57 percent in 2011 and is significantly correlated with radio and mobile coverage.

My paper will seek to answer the following research questions: What are the determinants of household crop diversification in Mozambique? More specifically, is improved infrastructure associated with changes in crop diversification patterns? Additionally, I will do a crop-specific investigation of which factors determine a household's probability of cultivating pigeon peas, an emerging mixed-use crop, and what factors are associated with the amount of land allocated to cultivating them. In the following section, I review literature that has investigated these and similar questions around farm household decision-making.

CHAPTER TWO: LITERATURE REVIEW

The body of literature on crop diversification has grown over the past decade; however it builds on literature about agricultural household theory and decision-making that has formed the basis of most studies and policy decisions relating to small farmers in developing countries in the last half century. In the following sections, I trace the origin of the agricultural household model in the literature and its extensions into farm decision-making, particularly with respect to crop choice decisions. I then summarize literature relating infrastructure and market access to household decisions, and conclude with a review of empirical works that have investigated the determinants of crop diversification.

2.1 Agricultural Household Decision Models

The agricultural household requires a unique theoretical model because it combines producer and consumer theory. The farm simultaneously behaves both as a profit-maximizing firm and a utility-maximizing household. Farm profits include explicit profits from selling products in the market and implicit profits of consuming some of some of those products, while consumption includes that of both purchased and self-produced goods (Taylor and Adelman 2003). Singh et al. (1986) formalized the agricultural household model, which I use as the basis of my own model in Chapter Three, to understand agricultural household behavior and its implications for policy. They noted that any exogenous shock such as a price policy or change in the market would simultaneously affect production, consumption, and labor supply, and therefore any attempt to estimate the impact of such a shock must recognize the interdependence of these components.

This integration of producer and consumer theory explained two fundamental paradoxes experienced in developing agricultural areas: first, the positive own price elasticity of demand for food in farm households, and second, the lower-than-expected supply responses to food price changes (Taylor and Adelman 2003). Taylor and Adelman (2003) credit agricultural household models as a fundamental component of research on developing countries and the "building block of economy-wide models," but also recognize some limitations. For example, such models assume preferences and income are shared by household members (though alternatives to the unitary decision-making model have been developed and are becoming more commonly used in research), and their micro-focus can fail to capture indirect or linkage effects between households and in villages. Additionally, de Janvry et al. (1991) note that agricultural household models often postulate the existence of markets for all of a farm's choice variables. This is explored further in section 2.2.

One component of the agricultural household model that is crucial to the discussion of crop diversification is uncertainty and risk aversion. A farm household's expected utility is dependent on its attitude toward risk. Even in a one-season model, a farm household's utility is subject to uncertainty in, inter alia, levels of rainfall, output prices, and consumption prices. A farmer's production decisions—including optimal crop allocation—are therefore dependent on that farmer's attitude toward risk (Fafchamps 1992) as well as the presence of markets for risk (de Janvry et al. 1991). For example, markets for price information or crop insurance would decrease a farmer's perceived level of risk, affecting crop allocation decisions. The literature suggests that farmers in developing countries tend to be risk averse and crop diversification may be a strategy to insure against production and price risk. Indeed, Bezabih and Sarr (2012) find that both rainfall risk and individual risk aversion lead to higher levels of crop diversity among farmers in Ethiopia.

2.1.1 Crop Choices

The agricultural household model explains farmers' production decisions and therefore can be extended to the decision of which crops to produce. The literature often postulates a simple two-good production function of cash crops, which are sold in the market, and food or staple crops, which are consumed by the household and sold in the market if a functioning market exists (de Janvry et al. 1991; Deboer and Chandra 1978). In the absence of a food market, a household must first be subsistent before allocating land to a cash crop (de Janvry et al. 1991). It then follows that larger farms will allocate a higher percentage of land to cash crops (Fafchamps 1992). Fafchamps (1992) showed that even when food markets do exist, small farmers are unlikely to diversify into cash crops because farmers prefer to protect themselves against food price risk by remaining self-sufficient in staple crop production. In order for a household to diversify into cash crops, it must feel secure in its ability to obtain staple foods elsewhere. This can be achieved by integrating food markets by investing in roads and transportation and removing policies that hinder trade (Mellor 1985; Fafchamps 1992).

2.2 Markets, Infrastructure and Agricultural Household Decisions

Infrastructure is widely acknowledged to be crucial for poverty alleviation (Antle 1983); basic water and sanitation infrastructure are essential for improving health, schools are required for improving education, and transport for trade, and so forth. In the case of agriculture, much research has been done to identify what kind of infrastructure improvement best supports agricultural development. Antle (1983) used country level data to estimate total agricultural output and found infrastructure, as measured by the GDP of the country's transportation and communication industries, to be a significant contributor to agricultural production. Binswanger et al. (1993) investigated the interrelationships of financial institutions, government investment, and agricultural output in India and found that improved road investment, electrification, and primary education enhanced agricultural output between 1960 and 1980.

While the above literature estimates the effects of infrastructure at a macro level, my research will explore the relationship between infrastructure and farmer decision-making at a household level. The existence and quality of markets for inputs, outputs, and information affect a household's decision to produce and to sell certain goods. De Janvry et al. (1991) explained the paradox of low market participation through their analysis of market failure, namely that if the cost of market participation exceeds the value generated by participation, farmers will consume instead of sell their goods. Poor infrastructure, lack of information, transaction risk, and uncompetitive marketing systems decrease the likelihood of a farmer selling in the market (de Janvry et al. 1991). This analysis was focused on market participation given that a household was already producing a specific good, but is easily extended to the decision to produce a crop for the purpose of selling it.

Several researchers have investigated the relationship between infrastructure—such as transport and information—and agricultural household decision-making and production. There is further evidence that improved road connectivity positively affects agricultural productivity and income levels by reducing travel time and transaction costs (Arndt et al. 2012A; Dorosh et al. 2012; Stifel and Minten 2008). To be sure, the causality in this relationship could be in both directions; roads are likely placed in regions with higher productive potential. Jacoby (2000) uses regional fixed effects to eliminate such "unobserved regional productivity" and finds that providing road access to markets increases plot values in rural Nepal, indicating welfare benefits for poor households. Dercon et al. (2009) use household fixed effects and instrument for household income to address the same problem and conclude that access to all weather roads reduces poverty by 6.9 percent.

Information—often made available through mobile phones—can also affect farm decisions and therefore income. Mittal et al. (2010) argue that the "next great evolutionary step in agriculture" will require an information-based, decision-making agricultural system and will depend on mobile-enabled information systems. The authors categorize information required by small farmers into (A) know-how, such as crop choice and seed varieties, (B) contextual information, such as weather and best practices for cultivation, and (C) market information. Improved information can reduce costs and improve returns for farmers (Muto and Yamano 2009) and mobile phones significantly reduce the cost of obtaining that information (Aker 2011). Research in this area has focused on the impact of access to market price information via mobile phones (Aker 2010; Bizimana et al. 2013; Jensen 2007; Muto and Yamano 2009) or the impact of specific ICT-based extension programs (Fafchamps and Minten 2012; Mittal et al. 2010). I am not aware of any empirical studies that have linked mobile phone coverage specifically to crop diversification, though some test extension contact and access to market information as potential determinants (Rahman 2008; Mesfin et al. 2011). These works are explored further in the following section.

2.3 Determinants of Crop Diversification

Several recent studies have attempted to identify household and village level characteristics that affect crop diversification. These studies range in their definitions of diversification and in their empirical methodologies. This section will summarize the methods used.

Immink and Alarcon (1993) first went beyond the traditional crop commercialization studies, which examined the complete substitution between cash and food crops, to investigate changes in crop mix patterns observed during the commercialization of subsistence farms in Guatemala in the 1980s. Using cross-sectional data, they classified households into four categories (traditional, potato-growing, wheat-growing, and vegetable-growing) and estimated the probability of a farmer selecting each portfolio, finding access to credit and geographic location to be significant determinants of diversification out of the traditional portfolio of maize and beans and into cash crops.

More recent studies tend to use indices as measures of crop diversification. The simplest index is a count of the number of crops or varieties cultivated (Benin et al. 2004; Ibrahim et al. 2009; Van Dusen and Taylor 2005). This provides a general level of overall diversity on a farm, but gives no insight as to whether the farm is growing cash or staple crops, and what percentage of resources are allocated to which. In the common example of a farm dominated by maize or another staple grain, a family often has a kitchen garden, or small plot used to grow vegetables or other crops for home use, the count index would fail to accurately capture the diversity of that farm.

A variety of other indices are used in the literature to address this problem. Most commonly used are the Simpson index of proportional abundance (Ibrahim et al. 2009; Ndhlovu 2010; Aneani et al. 2011) and the Herfindahl index of concentration (Rahman 2008; Bittinger 2010) which both employ a summation of the share of total farmland allocated to each crop squared. Other indices employed include Margalef (Benin et al. 2004; Rahman 2008), Shannon (Benin et al. 2004; Rahman 2008), Entropy (Mesfin et al. 2011), and Berger-Parker (BP) (Benin et al. 2004), all of which use some variation of the share of land allocated to each crop. For my analysis, I select two of the above indices and define them in the following section.

Another common method for measuring the determinants of crop diversification is to examine the share of total land allocated to each individual crop as its own dependent variable. This allows for the targeted investigation of what characteristics are associated with diversification into and expansion of that crop in particular and can be done with independent ordinary least squares (OLS) regressions (Ndhlovu 2010) or simultaneously via multinomial logit regression (Allen 2012). Bittinger (2010) uses a similar method to predict the share of land allocated to a particular category of crops, rather than an individual crop.

Although no studies have explicitly tested the relationship between mobile phones and crop diversity, many have tested infrastructure and market access. In Table 8, I summarize the results of these studies. Results vary widely across the literature, in part because of the range of indices used to capture diversity and the range of measures of infrastructure. Additionally, none of these studies addressed the potential endogeneity between infrastructure placement and crop diversity. Roads may be better in regions with higher agricultural potential and diversity, and farmers may engage in higher levels of diversification for the same reason. As such, there is no conventional wisdom in the literature about the relationship between infrastructure and diversification. My research will contribute to filling this gap.

Table 8: Selected results from the literature

Study	Infrastructure Measure	Diversity Measure	Result
Benin et al. 2004	Walking time to nearest all-weather road	Margalef Index; Shannon Index	Not Significant
Benin et al. 2004	Distance to nearest district town	Margalef Index; Shannon Index	Not Significant
Ibrahim et al. 2009	Road network condition (1=good)	Count	Negative
Ibrahim et al. 2009	Distance to local market	Count	Not Significant
Bittinger 2010	Travel time to population of 50,000	Share of land allocated to crop categories	Positive (cereals/pulses, fruits/vegetables) Negative (oils/spices, cash crops)
Bittinger 2010	All-weather road density	Share of land allocated to crop categories	Positive (cash crops, fruits/ vegetables) Negative (cereals/pulses, oils/spices)
Mesfin et al. 2011	Distance to market	Entropy Index	Not significant
Mesfin et al. 2011	Access to market information	Entropy Index	Positive
Rahman 2008	Infrastructure Index	Margalef Index; Shannon Index; Herfindahl Index	Negative (Margalef & Shannon) Positive (Herfindahl)

CHAPTER THREE: EMPIRICAL MODEL

3.1 Agricultural Household Model

Smallholder behavior cannot be understood via producer or consumer theory independently. The agricultural household is simultaneously both, and therefore decisions are not as simply profit- or utility-maximizing as those theories assume. As such, the agricultural household model was developed (Singh et al. 1986) to explain the decision-making of smallholder families, and has been the foundation of most such research in the past three decades. I use this model as the theory for my analysis.

3.1.1 Single Crop Model

The agricultural household is both a producer and consumer. Its objective is to maximize expected utility from self-produced goods, purchased goods, and leisure subject to several constraints. Below, I develop a simplified static agricultural household model based on the work of Singh et al. (1986):

The household is assumed to maximize a utility function $U = U(G_a, G_m, G_l)$ where G_a is a consumed agricultural product, G_m is a good purchased in the market, and G_l is leisure. The household also faces three constraints:

(1) Cash income constraint:

$$p_m G_m = p_a(Q_a - G_a) - p_l(L - F) - p_v V + E \qquad (1)$$

This constraint simply explains that a household can only purchase in the market what it earns from its production. The prices of purchased goods and produced agricultural products are p_m and p_a are, respectively; Q_a is the quantity of agricultural products produced by the household; p_l is the market wage; L is total labor input; F is family labor input; and V and p_v are the variable input and its price, respectively. E is any income earned not via the farm or via labor.

(2) Time constraint:

$$G_l + F = T \tag{2}$$

where leisure plus family labor cannot exceed total time available, T.

(3) Technology constraint:

$$Q_a = Q(L,V,A,K) \tag{3}$$

Where A is the fixed amount of land belonging to the household and K is the stock of capital.

These three constraints can be substituted to form a single constraint:

$$p_m G_m + p_a G_a + p_l G_l = p_l T + \pi + E \tag{4}$$

where π represents firm profits and equals $p_a Q_a (L,V,A,K) - p_l L - p_v V$.

3.1.2 Multiple Crop Model

The model above assumes that a household only produces one crop, *a.* To examine how a household chooses to allocate its land between multiple crop choices, I will use the model employed by Benin et al. (2004) in which a farmer produces a vector of outputs, *Q,* using a vector of inputs, *X*.

Let the farmer's production function for each crop *j* be:

$$Q_j = f(\boldsymbol{X}_{jk}, \alpha_j \mid A, Z) \tag{5}$$

A remains the fixed amount of land and *Z* represents farm and household characteristics. α_j is the share of *A* allocated to crop *j*. Therefore, the profit of the farm is given by the sum of the outputs of each crop less the costs of the inputs used:

$$\pi = \sum_{j=1}^{J} p_j Q_j - \sum_{k=1}^{K} w_k X_{jk} \tag{6}$$

where p_j is the vector of output prices and w_j is the vector of input prices.

The household maximizes the expected utility of its profits, EU($\pi(Q, X, p, w \mid A, Z)$ and via first order conditions defines optimal input levels:

$$X^*_{jk} = X^*_{jk} (p_j, w_k, U \mid A, Z) \tag{7}$$

Then, the optimal output level of each crop *j* depends on (X^*_{jk}) and is defined by:

$$Q^*_j = f(X^*_{j1} \ldots X^*_{jk}) \mid A, Z \tag{8}$$

To express the demand for crop diversification, *D*, on the farm, I then use the conceptual form from Benin et al. (2004). They argue that prices are endogenous to the household and depend on the cost of market transactions, and therefore exclude prices from the model. I instead use market prices, *P,* which capture exogenous price variation because they are observed at large, regional markets and therefore unlikely to be affected by the behaviors of an individual farmer, in addition to the exogenous market characteristics, *M,* used by Benin et al. to capture transaction costs. Then, the household's optimal choice can be expressed as a function of farm size, market prices, household, farm, and market characteristics, and initial wealth, W_0:

$$h^* = h^*(A, P, Z, M, W_0) \tag{9}$$

Letting α_j equal the share of farmland allocated to crop j so that $\sum_j^J \alpha_j = 1,\ j = 1,2 \ldots J$. Then, a farmer's optimal α is $\alpha^*_j = f(A, P, Z, M, W_0)$ so total farm diversification, D, can be expressed:

$$D = D(\alpha_j^* (A, P, Z, M\ W_0)). \tag{10}$$

3.2 Dependent Variables

3.2.1 Aggregate measures of farm diversification

The dependent variables in my fixed-effects estimation of farm diversification approximate the total level of diversification undertaken by a household farm. Following my review of those indices employed in the literature in Chapter Two, I select three measures to evaluate different aspects of total farm diversity (defined in Table 9). The first, D_C, represents the total number of different annual crops cultivated by a household in a single year. In this measure, individual horticultural crops are counted as separate crops. D_C is a very general measure of diversity, but will capture a household's propensity to increase or decrease the level of on-farm diversification.

Table 9. Dependent variables used in analysis of aggregate crop diversity

Dependent Variable	Definition	Explanation	Mean 2008	Mean 2011
Crop Count	$D_C = J$	J = total number of annual crops cultivated	4.04	4.72
Herfindahl Index	$D_H = \sum_j^J \alpha_j^2$	α_j = share of farmland allocated to the jth crop	0.42	0.38
Berger-Parker (BP) Index	$D_{BP} = 1/\max(\alpha_j)$	α_j = share of farmland allocated to the jth crop	2.10	2.22

N=1,186. *Source: MSU/MINAG Survey, 2008 & 2011.*

The second aggregate measure is the Herfindahl Index—a widely used measure of market concentration, in the context of industrial organization or antitrust (Herfindahl 1950)—applied to crop diversification, as defined by $D_H = \sum_j^J \alpha_j^2$. As in the conceptual model outlined above, α_j represents the share of total farmland allocated to crop *j.* The Herfindahl index can range from zero to one, where a zero value represents perfect diversification and one indicates perfect specialization. This index captures the overall level of concentration on a farm. For both D_H and the following index, horticultural crops are grouped together in a single share of the farm, α_j.

The final aggregate measure used as a dependent variable is the Berger-Parker (BP) index, $D_{BP} = 1/\max(\alpha_j)$ (Parker and Berger 1971). The BP index measures inverse dominance, or proportional abundance, by capturing the share of farmland allocated to the crop with the largest share. D_{BP} takes on values greater than or equal to one, with higher values indicating greater—or more even—diversification. Values closer to one denote higher relative abundance of the dominant crop.

3.2.2 Individual crop analysis

The second model will investigate the determinants of diversification into pigeon peas. I use a two-stage model to estimate the two stages of a farmer's decision. The first dependent variable is a dummy variable to indicate cultivation of pigeon peas. The second stage measures the amount of land allocated to pigeon peas, given that a farmer has decided to grow them. The model is described in detail in section 3.3.2.

3.3 Estimation Strategy

3.3.1 Indices of Diversity: Fixed Effects Model

To investigate the determinants of each of the three indices, I estimate the following fixed-effects model:

$$D_{it} = \beta_0 + \beta_1 P_t + \beta_2 M_{vt} + \beta_3 Z_{it} + \lambda_t + \varepsilon_{it} \qquad (11)$$

where $\mathrm{P_t}$ is a vector of regional market prices, M_{vt} represents the village-level market constraints and Z_{it} represents farm-level characteristics of household *i* in time period *t.*

λ_t represents a dummy variable for 2011 to allow for time-varying intercepts.

Household-level fixed effects capture village level fixed-effects given that no households moved villages between the panel years. This will yield the same results as the first-differencing model, or regressing the change in diversity on the change in explanatory variables (Wooldridge 2010).

The estimation method I use does not account for unobserved factors that affect crop diversification, influence decisions on road access and also change over time. For instance, if new roads systematically targeted areas where there are local initiatives to increase productivity and crop diversification, the FE estimator would be positively biased. However, road improvement decisions are much more likely to follow past agricultural performance than anticipated future initiatives. Therefore, most change in road access over time should be exogenous to changes in other unobserved factors so that bias in the FE estimates I present, if any, should be small.

The fundamental assumption of this model is that the unobserved heterogeneity in question is time constant. I argue that this is a function of a region's inherent agroecological potential and is therefore unchanging between 2008 and 2011. One limitation, however, is that the direct effect of that agroecological potential cannot be estimated in the model, only eliminated. Additionally, all explanatory variables in the model must be strictly exogenous and time-varying in order to be identified. I discuss each explanatory variable in section 3.4.

3.3.2 Pigeon Pea Cultivation and Land Allocation: Two Stage Decision Model

A farmer deciding to cultivate pigeon peas actually faces two decisions: first, whether to grow them at all, and second, how much land to allocate to them. Some studies of crop diversification have used the share of land allocated to a given crop as the dependent variable (Allen 2012; Ndhlovu 2010); however in the case of Mozambique, only a minority of cases grows pigeon peas and therefore the distribution of land allocation is lumped at zero. Hence I model these two decisions separately as part of a two-step process using Cragg's double-hurdle (DH) model (1971), commonly referred to as the tobit alternative model. This method is used to measure the two stage decision of selling a product and then, conditional on selling, what quantity to sell (Burke 2009; Mather et al. 2011; Cairns 2012; Reyes 2012). One limitation to the DH model is the assumption that the error terms in each stage are independent; this could be unrealistic because the decisions are in fact similar. However, the two stages still provide more accurate estimates than modeling them as a single outcome.

Cragg's DH is a favorable alternative to the Heckman two-step approach used by Goetz (1992) because it does not treat the high frequency of zero responses as a censored sample problem; a zero value is a decision made by the farmer, and therefore constitutes a valid economic choice, or "corner solution" (Wooldridge 2010; Mather et al. 2011). Below, I adapt the model employed by Mather et al. (2011) to estimate the factors determining farmers' land allocation decisions conditional on the decision to grow pigeon peas.

The structure of the two decisions is as follows. The probability of household *i* planting pigeon peas in time period *t* is represented by:

$$p_{it}^{*}=\gamma^{1}x_{it}^{1}+c_{i}^{1}+e_{it}^{1} \qquad e_{it}^{1}\sim(0,1) \qquad (12)$$

where $p_{it}=1$ if $p_{it}^{*}>0$, otherwise $p_{it}=0$.

The land allocated to pigeon peas is then:

$$\alpha_{it}^{*}=\gamma^{2}x_{it}^{2}+c_{i}^{2}+e_{it}^{2} \qquad e_{it}^{2}\sim TN\left(-\left(\gamma^{2}x_{it}^{2}+c_{i}^{2}\right),0,\sigma^{2}\right) \qquad (13)$$

where $\alpha_{it}=\alpha_{it}^{*}$ if $p_{it}=1$, otherwise $\alpha_{it}=0$.

Where TN denotes the truncated normal with lower bound $-(\gamma^2 x_{it}^2 + c_i^2)$, mean 0, and variance σ^2, and e_{it}^1 is independent of e_{it}^2 conditional on the explanatory variables and the unobserved heterogeneity terms. The superscripts denote the stage of the decision.

The variable p_{it}* represents the unobservable latent variable that determines whether a farmer plants pigeon peas or not which is observable and captured by p_{it}. The variable α_{it}* is how much land would be allocated to growing pigeon peas by a farmer if the decided to plant pigeon peas and is observable only when p_{it} =1, and α_{it} is the observed amount of land allocated to growing pigeon peas. $x_{it} = \{ x_{it}^1, x_{it}^2 \}$ is a vector of observable explanatory variables assumed to be exogenous. Unobserved heterogeneity that may be correlated with the explanatory variables and affect farmers' decisions is captured by c_i^1 and c_i^2. In my previous set of models, c_i was eliminated through the use of fixed effects. However, as shown by Wooldridge (2010) and Greene (2004), fixed effects estimation is not typically available for non-linear models; in particular, there is no fixed effects estimator available for Cragg's two stage model.

Instead, to address the problem of unobserved heterogeneity, Mather et al. (2011) employ a correlated random effects (CRE) probit (stage 1) and lognormal (stage 2) using the Mundlak version of the Chamberlain device (Mundlak 1978; Chamberlain 1982). The Chamberlain device is an estimation method that postulates that a linear projection of time constant unobserved factors on strictly exogenous explanatory variables is sufficient to account for all endogeneity due to these unobserved factors. The Mundlak device is a restricted version of the Chamberlain device that imposes that the coefficients of covariates in that linear projection be equal across time so that only averages of the covariates across time need to be added to the list of covariates to account for unobserved heterogeneity.

I use the same method employed by Mather et al. (2011), with instead a truncated normal regression for stage two, assuming that the correlation between the unobserved heterogeneity and the explanatory variables takes the form:

$$c_i{}^1 = \tau^1 + \vartheta^1 \bar{x}_i^1 + \varepsilon_{it}^1 \qquad \varepsilon_i^1 | \overline{x_i}^1 \sim N(0, \sigma_1^2) \tag{14}$$

$$c_i{}^2 = \tau^2 + \vartheta^2 \bar{x}_i^2 + \varepsilon_{it}^2 \qquad \varepsilon_i^2 | \overline{x_i}^2 \sim N(0, \sigma_2^2) \tag{15}$$

where $\bar{x}$ is the household specific time-mean of each explanatory variable. In addition, in order to use Cragg's double hurdle model I assume that ε_i^1 and ε_i^2 are independent conditional on the explanatory variables, which means that unobserved heterogeneity terms that affect the two decisions are not correlated after conditioning on the explanatory variables. This is the same kind of assumption is made for the standard Cragg double hurdle model without CRE where noise terms affecting the two decisions are not correlated after conditioning on the explanatory variables. This assumption is parallel to that made for the two stages of the model, and also may not be likely in a case where the decisions are so closely related. Additionally, the Mundlak device requires the assumption that all variation in the error term that is correlated with the explanatory variables is captured in c_i. This is the same assumption made in a fixed effects model, and allows the model to account for as much of the endogeneity due to unobserved factors as possible.

This specification is then added to the right-hand side of the estimation equations for p* and q*. I add $\bar{x}$ to the set of explanatory variables, and the error terms are transformed to $u_{it} = \varepsilon_i + e_{it}$.[2] The final estimations are as follows:

$$p_{it}^{*} = \tau^{1} + \gamma^{1} x_{it}^{1} + \vartheta^{1} \bar{x}_{i}^{1} + u_{it}^{1} \qquad u_{it}^{1} | x_{it}^{1} \sim N(0, \sigma_{u1}^{2}) \tag{16}$$

where p_{it} =1 if $p_{it}^{*}>0$, otherwise p_{it}=0.

$$\alpha_{it}^{*} = \tau^{2} + \gamma^{2} x_{it}^{2} + \vartheta^{2} \bar{x}_{i}^{2} + u_{it}^{2} \qquad u_{it}^{2} | x_{it}^{2} \sim N(0, \sigma_{u2}^{2}) \tag{17}$$

where $\alpha_{it} = \alpha_{it}^{*}$ if p_{it}=1, otherwise α_{it} = 0.

Because the values of $\bar{x}$ vary only across households, but are time constant, this method controls for any time-constant heterogeneity.

To interpret the results of these two estimations, I calculate the average partial effects (APE) across all households and time periods. Following Cairns (2012) and using Burke's (2009) Stata program, *craggit*, I calculate household-specific conditional partial effects (PE) of x_m (where x_m is explanatory variable *m*) on the probability of planting using the maximum likelihood estimated coefficients from the first stage probit:

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[2] U_{it} is not independent across time; however, this does not affect the consistency of the pooled maximum likelihood estimator, and time dependence is accounted for by reporting clustered standard errors.

$$\frac{\partial P(p*_{it}>0|x_i^1)}{\partial x_m} = \gamma_m^1/\sigma_{u1}^1 \phi(\tau_1/\sigma_{u1}^1 + \gamma 1 x_{it}^1/\sigma_{u1}^1 + \vartheta^1 \bar{x}_i^1/\sigma_{u1}^1) \quad (18)$$

Where ϕ is the standard normal probability density function (PDF) and $\beta^1 x_{it}^1$ is the matrix of explanatory variables and their parameters. The variance of the error term is σ_{u1}^1 , as defined in equation (16). By calculating the partial derivative with respect to x_{it} but not $\bar{x}$, I isolate the causal effect of each explanatory variable. For binary variables, I evaluate the change in the mean outcome of p for $x_{it} = 0$ and $x_{it} = 1$.

To calculate the partial effects for the second stage truncated normal regression, I use the following equation (Wooldridge 2010):

$$E(\frac{\partial \alpha_{it}}{\partial x_{it}^m} | x_i, \alpha_{it} > 0 \frac{\gamma_m^2}{\sigma_{u^2}} \left[1 - \lambda\left(\frac{\tau^2+\gamma^2 x_{it}^2+\vartheta^2 \bar{x}_i^2}{\sigma_u^2}\right)\left(\frac{\tau^2+\gamma^2 x_{it}^2+\vartheta^2 \bar{x}_i^2}{\sigma_u^2}\right) + \lambda\left(\frac{\tau^2+\gamma^2 x_{it}^2+\vartheta^2 \bar{x}_i^2}{\sigma_u^2}\right)\right]) \quad (19)$$

where $\frac{\partial \alpha}{\partial x}$ denotes the partial effect of x on α, λ is the inverse mills ratio (PDF/cumulative density function) and σ is the estimated variance from the second stage regression. (Again, for binary variables I calculate the change rather than partial derivative.) From these two equations, I obtain the partial effect of each explanatory variable on each household in both stages. APEs are then calculated by taking the mean across the sample.

3.4 Explanatory Variables and Hypotheses

Following Equation 10, diversification is a function of land endowment, household and farm characteristics, market prices and constraints, including infrastructure, and initial wealth. This section will identify specific variables in those categories that could impact a household's decision to alter its crop mix. Descriptive statistics for all explanatory variables are listed in Table 10.

3.4.1 Market Prices

For Mozambican smallholders, expected market prices are the key determinant in a farmer's expected profits from growing any given crop and therefore crucial in the decision to diversify. To capture variation in expected prices across villages and years, I use market prices collected by the Agricultural Market Information System of Mozambique (SIMA) in seven major markets. I calculate expected price using the average monthly price from the previous year. Households are assigned the expected prices of the market nearest to them. I include prices for three crops commonly grown by farmers in our sample—maize, common beans, and cowpeas—and use natural logs so that changes can be interpreted as percentages. Maize prices are much lower than bean prices per kilogram, therefore to compare them it is more useful to interpret percentages.

Table 10. Summary Statistics, Explanatory Variables

Variable	Definition	2008 Mean	2011 Mean
Expected Maize Price	Log monthly average price/kg at regional market, previous year	1.399 (.141)	2.058 (.133)
Expected Common Bean Price	Log monthly average price/kg at regional market, previous year	3.280 (.238)	3.664 (.199)
Expected Cowpea Price	Log monthly average price/kg at regional market, previous year	2.474 (.177)	2.849 (.276)
Pigeon Pea Price	Log district median producer price/kg, previous year	1.636 (.249)	1.971 (.172)
Paved Road, Mid-Distance	= 1 if nearest paved road between 10-50 km from village	0.387 (.487)	0.403 (.491)
Paved Road, Far-Distance	= 1 if nearest paved road > 50 km from village	0.333 (.472)	0.241 (.428)
Year Round Road	= 1 if road to nearest town is accessible during rainy season	0.778 (.415)	0.783 (.413)
Market	= 1 if village has a market	1.697 (.460)	1.612 (.487)
Mobile Network	= 1 if village has mobile phone network	0.621 (.485)	0.813 (.390)
Radio	= 1 if village has radio coverage	0.735 (.442)	0.835 (.371)
Household Size	Number of people in household	5.478 (2.516)	6.640 (3.043)
Proportion Male	Proportion of household members >14 years that are male	0.502 (.134)	0.494 (.173)
Land Size	Total size of land owned by household (ha)	2.813 (4.037)	3.618 (5.865)
Asset Index	Household ownership of basic assets, max score = 1	0.502 (.306)	0.565 (.307)

N=1,186. Standard deviation listed in parentheses. Source: MSU/MINAG Surveys, 2008 & 2011.

For the pigeon pea model, I incorporate the market price of pigeon peas, expecting that higher prices would be a key determinant of the decision to cultivate. Unfortunately, the SIMA price data do not include pigeon peas. Instead, I use district-median post-harvest prices from the preceding year as expected market price, as reported in the TIA 2007 and agricultural census of 2010. I recognize the potential endogeneity in this relationship; median reported prices depend on local production and therefore the same farmers' behavior as those the model attempts to predict, albeit in the prior year. I was unable to access regional market price data for this specific crop, but I believe including them in the model is still better than the alternative, in which the coefficients on the infrastructure variables could also be picking up the effects of prices. By using the district median, I minimize the potential endogeneity of an individual household's behavior on sales price, but I still expect some bias given the small number of households per district selling pigeon peas.

As noted previously, Mozambican smallholders rarely use inputs. Most seed is retained from previous harvests, and fertilizer use is scarce. Therefore, I do not include input costs in my model. Expected profits are represented by expected output prices.

3.4.2 Market Constraints

The explanatory variables selected at the village level will attempt to capture major changes in infrastructure that occurred between 2008 and 2011 and may change the market constraints faced by farm households. As noted by Rahman (2008), infrastructure can affect diversification both directly, and indirectly through its impact on prices. However, in my model, because prices are included at a regional market level, they are unlikely to be correlated with village-level infrastructure. Therefore village-level infrastructure may capture variation in expected prices for farmers that are not captured in the regional market prices.

At a village level, *distance from a village to the nearest paved road* and *year round road accessibility* may lower market constraints for farmers by lowering the transaction costs of acquiring inputs or selling their harvests. It could also improve the market for information relating to crops and prices, because easier transportation implies more travel between villages and more efficient agricultural extension. However, in Mozambique it is also possible that isolation (higher market constraints) encourages higher diversification because households are required to be self-sufficient (Benin et al. 2004). In a simple t-test (see Table 11), the data show that households farther from paved roads tend to grow fewer crops, which contradicts this hypothesis. In addition to the transportation infrastructure, the lack of a *market within the village* represents a market constraint for similar reasons. It could mean lower transaction costs for acquiring inputs and selling outputs, and it could influence a farmer's decision to diversify into new crops simply by increasing his awareness of different crops. Indeed, we see significantly higher levels of diversity in those villages with markets, as measured by the Herfindahl and BP indices, but not a significantly higher average crop count (Table 11.)

Table 11. Correlations between Infrastructure and Diversification

Village or Household Level Characteristic	Diversity Measure	Mean (households with characteristic)	Mean (households without characteristic)	Pr(|T|>|t|)
Village >50 km from paved road	Crop Count	4.22	4.44	0.0149
Mobile network coverage	Crop Count	4.46	4.14	0.0003
Radio Coverage	Crop Count	4.44	4.15	0.0037
Market in village	Herfindahl Index	.394	.409	0.0600
Market in village	Berger-Parker Index	2.22	2.13	0.0077
Year round road accessibility	Crop Count	4.31	4.56	0.0114

Two-sample t-tests with equal variances. Source: MSU/MINAG Surveys, 2008 & 2011. Means are pooled from both years.

Insufficient communication infrastructure is also a constraint in the market for information, which I capture through the presence of mobile *phone network* and *radio coverage* in a village. Farmers with access to information may be more likely to diversify into new crops if they learn about prices or technology via agriculture radio programming or simply by calling friends or family in other villages or districts. Indeed we see higher crop counts in villages with radio and mobile coverage (Table 11.) Alternatively, access to information could lower the risks faced by a farmer; diversification is a coping strategy for some farmers against price or climate risk, so guaranteed access to market prices could actually lower their need for diversification.

Simple, time-averaged correlations show that smallholders with local markets tend to allocate their land more evenly among different crops, while those in more isolated areas grow lower total numbers of crops. However, the presence of markets and roads may also be correlated with unobservable characteristics of the region; they are likely to target areas with better agricultural production, and mobile networks follow. By using fixed effects, I minimize potential endogeneity of infrastructure and diversification. I argue infrastructure development may depend on a regions inherent agroecological potential, and therefore is time-invariant between the two survey years. Therefore, the agroecological potential is captured by village fixed effects.

3.4.3 Household and farm-level characteristics

Following Benin et al. (2004), I include gender composition of the household measured by *proportion of males* within the household. This may affect diversification via labor availability. *Household size* is also an indicator of labor availability and heterogeneity of preferences (Benin et al. 2004).

Finally, the physical characteristics of a farm may affect crop diversification. Benin et al. (2004) use slope, erosion, fertility, and distance to plots to capture this; however with a panel dataset, these features should drop out assuming they remain constant over the three-year period. I include *total landholding* as we do see some variation in this variable across the panel. Total land available should affect the level of diversification as farmers with a greater amount of land have a greater ability to diversify.

To capture initial wealth of a household, I cannot use income, as that is clearly a function of a household's land allocation. Instead, I construct a basic *household asset index;* households are scored based on how many of five basic assets they possess (oil lantern, radio, bicycle, latrine, and table.) A zero value means they own none; a value of one means they own all five.

CHAPTER FOUR: RESULTS AND DISCUSSION

4.1 Determinants of Crop Diversification

Employing a fixed effects regression with robust standard errors clustered by household, I predict farm levels of crop diversification based on expected market prices, village-level infrastructure, and household characteristics. Regression results are listed in Table 12 and described below.

4.1.1 Infrastructure

Households in villages located over 50 kilometers from a paved road are likely to grow fewer total crops than those close to a paved road (see Table 12.) This result is inconsistent with the hypothesis that households more isolated from the market tend to have higher levels of diversity in order to be self-sufficient. That isolated farms grow fewer crops suggests that either they are self-sufficient, but consume less diverse diets (possible given that such farms allocated an average of over 50 percent of land to starches, but would require consumption data to confirm), or that these more isolated farms lack access to information about different crops; farmers in areas gaining access to paved roads may also be gaining access to traders or extension workers that encourage diversification. Therefore, one possible method for improving the diversity of production in remote areas could be to better connect farmers to traders or extension that are not typically present in the absence of a paved road; however, more research would be required to ascertain the nutritional status of such families.

Households with year round road access to the nearest town have a lower Herfindahl index (see Table 12), which represents a more even distribution across

Table 12. Household Fixed Effects Regression Results, 2008 - 2011

	Crop Count	Herfindahl Index $^{\Psi}$	BP Index
Expected Maize Price	0.574	0.106	-0.394
	(1.127)	(0.113)	(0.570)
Expected Common Bean Price	-1.739***	0.099*	-0.554**
	(0.602)	(0.060)	(0.268)
Expected Cowpea Price	3.965***	-0.351***	1.724***
	(1.239)	(0.125)	(0.631)
Paved Road, Mid-Distance	-0.243	0.012	-0.086
	(0.184)	(0.019)	(0.083)
Paved Road, Far-Distance	-0.501**	0.003	-0.032
	(0.208)	(0.023)	(0.088)
Year Round Road	0.200	-0.026*	0.073
	(0.172)	(0.014)	(0.078)
Market	0.062	0.004	-0.085
	(0.164)	(0.015)	(0.070)
Mobile Network	0.211	-0.031*	0.100
	(0.172)	(0.016)	(0.077)
Radio	-0.005	0.015	-0.061
	(0.154)	(0.015)	(0.080)
Household Size	0.145***	-0.013**	0.033
	(0.053)	(0.006)	(0.026)
Proportion Male	0.164	-0.038	-0.146
	(0.496)	(0.062)	(0.362)
Land Size	0.046*	-0.002	0.018**
	(0.027)	(0.002)	(0.009)
Asset Index	0.466*	-0.027	0.158
	(0.546)	(0.025)	(0.116)
Year 2011	-0.852	0.011	-0.134
	(0.546)	(0.053)	(0.265)
R-Squared (within)	0.1100	0.0559	0.0439

*N=1,130. Robust standard errors reported in parentheses, clustered at household level; *** (p<.01), ** (p<.05), * (p<.10). Weighted by population sample weights and inverse probability weighting for attrition.* $^{\Psi}$*Lower value indicates more even portfolio/ higher diversity. Higher BP index indicates more domination by one crop.*

different crops. Lack of year round road access is also a measure of isolation, but the index provides more information about the farming behavior than just the crop count. As expected, this result is similar to that of the paved road and is inconsistent with the hypothesis that isolation can lead to greater self-sufficiency and affect diversity levels.

Instead, it supports the hypothesis that in scenarios of high food insecurity and risk aversion, families may focus on just one crop to ensure that their staple is available from their own production.

Households that do not have year round road access allocate their crops less evenly than those that do. This result indicates one of the following possibilities: (1) farmers can sell staple crops within their own village, and therefore lack of year round road access does not affect their ability to sell; (2) farmers only sell once per year, or during the season in which they have road access; or (3) that they do not sell at all, but simply grow and consume an uneven distribution of crops. To test (1), I generated an indicator variable for those villages with no year round road access but with a market in the village; the coefficients on this variable when included in the estimation were not statistically significant. However, it is possible that the ability to sell a staple, such as maize or cassava, exists in villages that do not have a formal market captured by the survey. Possibilities (2) and (3) are both likely; the harvest typically continues up to two months after the rainy season ends (FEWSNET 2013), so isolation during the rainy season would not necessarily prevent a farmer from traveling to market with his or her harvest. Additionally, many Mozambicans' diets consist primarily of one staple, such as maize or cassava, and therefore more land allocated to one crop could be indicative of the family's diet or risk profile.

Mobile network coverage is also associated with a lower Herfindahl index, or a more even allocation of land among different crops (see Table 12.) I hypothesized that mobile network coverage is a proxy for access to information, but that different information could affect a farmer's cropping decisions in different ways. First, mobile phones could provide smallholders with information about current market prices, which in turn, shape their price expectations in the following year. This could affect their perceived risk or profitability of diversification and therefore their planting decisions. For example, if a farmer learns via cell phone that the price of a crop he or she intends to sell is high, he or she might perceive a lower risk of allocating more land to that crop, and therefore have a lower measure of on-farm evenness. Alternatively, a farmer could learn via cell phone that the price of a food he or she plans to *purchase* is high or very volatile, and therefore decide to grow everything he or she plans to consume in order to insure against price risk. My results indicate that the latter is a more likely explanation, if mobile phones are indeed serving to communicate market price information. However, there could be a time lag in this relationship, because farmers' decisions to plant would be based on expected and not current prices; therefore having cell phones in the previous year or at the time of planting would be more important than at harvest time.

In addition to market price information, farmers can also benefit from information relating to know-how, such as crop, seed, and input choices, and context-specific knowledge such as weather and climate (Mittal et al. 2010). Mobile phones could provide access to such information; many countries are exploring the effectiveness of mobile-based agricultural extension, but information can also be communicated informally via phone calls to friends or family outside the village. For example, a household could learn from a family member about a new crop or a new way to grow a crop, and that could affect the household's decision-making around land allocation. Depending on the nature of the information, this could either increase or decrease diversification. The regression results show that mobile coverage is associated with more diversity, suggesting the addition of new crops but only as a small fraction of the total cropped area. Additionally, mobile phone coverage could reduce diversification risk, as phones can connect farmers with market agents with whom they would not otherwise be in communication.

My model isolates five different infrastructure variables (see Table 11) as independent features of a village; however, it is also possible that the components of infrastructure when interacted may have a different coefficient from when they are isolated. For example, access to information via cell phone *and* access to markets via year round roads could have more impact on a farmer's cropping decisions than each alone. I therefore tested several combinations of those variables. First, I use a basic index of the five components where a village can score between zero and one depending on how many of the components it has. This infrastructure index is a significant predictor of crop count, indicating that households in villages with better infrastructure—regardless of type—grow more crops. The other results in the model do not change (see appendix for full results.)

4.1.2 Prices

Prices are the strongest determinants of crop diversification, as expected; it is surprising, however, that the expected price of maize—the crop most commonly grown in our sample—does not have a significant coefficient (see Table 12.) This could be because the majority of households in the surveyed regions grow maize no matter what the expected price, so it does not affect their cropping behavior, although it may be very important in their marketing behavior. The expected price of cowpeas has a positive association with crop diversity as measured by all three indices and has the highest magnitude of coefficient. Cowpeas are grown by almost half of our sample, yet marketed by very few. I therefore interpret the decision to grow cowpeas as generally a subsistence-oriented decision; they are grown primarily to feed the family. It follows, then, that when the price of such a subsistence crop increases, it represents a threat to food security and farmers diversify to manage their risk.

Higher expected prices of common beans have the opposite effect; they are negatively associated with crop diversity levels as measured by both the crop count and BP index (see Table 12.) This could be because of the three crops with prices included in this model, common beans are the most likely to be marketed by the farmers that grow them. Therefore, higher prices represent a market opportunity rather than a threat to food security, incentivizing farmers toward specialization. It must be noted, however, that farmers are more likely to specialize in *any crop*, not common beans in particular, when common bean prices rise.

4.1.3 Household and Farm Characteristics

Additionally, I find that land size and household size have positive associations with diversification levels (see Table 12.) This follows the hypotheses that greater land and labor availability enable higher farm diversity. The proportion of adult males in the household—another indicator of labor availability—however has no significant association with diversification. Finally, a higher asset index is associated with a higher crop count, indicating that wealthier families grow more crops. This is also inconsistent with the subsistence hypothesis; wealthier households ought to be able to purchase food to eat and therefore more likely to specialize for the market. It may be the case, however, that even those families with higher wealth indices do not have such security; the assets are very basic items such as lamps and tables, so these families could still be vulnerable to food insecurity, despite having relatively more income than their neighbors.

4.2 Pigeon Pea Two Stage Model

To estimate the probability of a household cultivating pigeon peas and the land allocated to pigeon peas based on prices, village-level infrastructure, and farm-level characteristics, I use Cragg's double hurdle model with correlated random effects and bootstrapped standard errors. Results of this estimation are presented in Table 13 and described in the following section.

4.2.1 Infrastructure and prices

No infrastructure variables were significant determinants of a household's binary decision of whether or not to plant pigeon peas. This is consistent with my hypothesis that pigeon peas are a "multi-use" crop—ie. in some cases, they are planted only for home consumption, while in other cases they are grown for the emerging market opportunities they offer. Therefore, modeling only this first stage of the decision, I would not expect to detect a significant effect of infrastructure. The two-stage approach allows for interpretation of this first decision separately from how much land a farmer allocates to pigeon peas, which may be more indicative of a farmer's intent to market the crop.

Access to both communication infrastructure variables—mobile network and radio coverage—positively affect the amount of land that a farmer allocates to pigeon peas, conditional on deciding to grow them. This indicates that access to information is also central to a farmer's decision to grow pigeon peas for the market; the information could be market prices, linkages with traders, or simply the knowledge that pigeon peas are becoming tradable and are therefore deserving of more land than a pure subsistence crop. As explained in Chapter 1, pigeon peas have recently become an exportable commodity in Mozambique, though they have always existed as a subsistence crop. So, these results indicate that mobile phones and radio coverage may be the channel that informs farmers of this new market.

The expected price of pigeon peas is only a significant predictor of the first stage of a farmer's decision. Higher prices increase the probability that a farmer plants the crop, as expected, but are not associated with the amount of land allocated. This is surprising, as I would hypothesize a strong, positive effect as more farmers perceive pigeon peas as marketable when the price is high, and therefore allocate more land. The coefficient is indeed positive but is not statistically significant. This could be a result of the data used to estimate expected prices; as previously explained, these prices are district medians and are therefore dependent on how much was produced and sold in the district the previous year.

4.2.2 Household and Farm Characteristics

Household size is strongly associated with both stages of the decision, confirming that labor availability is a key factor in a family's decision to grow and market a new crop. The asset index is also positively associated with both stages, indicating that wealthier families are more likely to take on a new and market-oriented crop. Finally, the results confirm that greater total landholdings allow farmers to adopt new crops.

Table 13. Household Two-Stage Regression Results, 2008-2011

	Pr (Cultivate Pigeon Peas)	Land Allocated (Conditional)
Paved Road, Mid-Distance	0.022 (0.020)	0.023 (0.033)
Paved Road, Far-Distance	0.005 (0.017)	-0.047 (0.030)
Year Round Road	0.022 (0.015)	0.020 (0.032)
Market	-0.038 (0.030)	-0.018 (0.032)
Mobile Network	0.016 (0.015)	0.063** (0.028)
Radio	0.015 (0.012)	0.068*** (0.021)
Pigeon Pea Price	0.039** (0.017)	0.028 (0.036)
Household Size	0.013*** (0.005)	0.034*** (0.009)
Proportion Male	0.063 (0.047)	-0.025 (0.088)
Total Landholdings	0.007** (0.003)	0.004 (0.003)
Asset Index	0.047* (0.025)	0.075* (0.045)

*Coefficients represent average partial effects (APE). Bootstrapped standard errors in parentheses, clustered at the household level. *** (p<.01), ** (p<.05), * (p<.10). N=1,186.*

4.3 Conclusions

Agriculture defines Mozambique; employing 80 percent of the population and constituting 24 percent of GDP (USG 2011), it has the attention of international donors and Mozambique's own government as a lynchpin for alleviating poverty. Indeed, stakeholders are spending millions to improve the sector and enhance food security; the Government of Mozambique recently borrowed $150 million from the World Bank "to promote private sector-led agriculture in order to improve access to food and better nutrition" (World Bank 2013) and USAID has budgeted \$18 million for agricultural development and \$5.1 million for nutrition in Mozambique in 2013 (Department of State 2013).

With so much global interest in improving Mozambican smallholder-dominated agriculture, it is crucial to understand how smallholders make their production decisions in order to affect change. One decision every smallholder must make is how to allocate his or her land among different crops, or at what level of diversification to operate. Under some conditions, greater crop diversification can improve smallholder welfare by insuring against price and weather risks and improving nutrient intake via higher dietary diversity. Many agriculture initiatives in Africa, including USAID's strategy for Mozambique (USG 2011), promote diversification for these reasons. In other scenarios, lower diversity—or greater specialization—can improve smallholder welfare by enabling economies of scale in both the production and marketing of crops. In either case, before encouraging a shift in diversification, we must understand what drives the decision.

My research contributes to the understanding of smallholder decision-making around total crops cultivated and crop portfolio evenness, specifically within the context of Mozambique's rapidly expanding infrastructure and food price volatility. The conclusions are based on literature and data alone; I expect that our understanding of smallholder behavior around this decision could be greatly enhanced through qualitative research. Interviews and focus groups were not possible for this study, but could illuminate different farmers' rationale their changing cropping patterns.

From my quantitative analysis, I find that improved infrastructure is associated with crop diversification, though the effect of changes in infrastructure is relatively less important than changing prices. Farmers far from paved roads grow fewer crops, suggesting that if they are growing for their own consumption, they have less diverse diets than households in areas with better transport connectivity. This finding is inconsistent with results from the literature; Ibrahim et al. (2009) found that good road network conditions decreased the number of crops grown and Rahman (2008) found that an index of improved infrastructure measures was associated with lower diversity as measured by three indices, including the Herfindahl index. This could be indicative of farmers specializing for commercial reasons rather than for basic food security, as I predict is the case in Mozambique. I also find that those with year round road access to neighboring towns allocate their land more evenly among crops, or have a higher level of diversity, which is consistent with the above finding that less isolation from the market leads to more diversity. Both results indicate that in the case of subsistence farmers, improving access to the information and trading opportunities typically enabled by infrastructure could also improve diversity of production. In order to confirm these results, further research should be done with more precise indicators of market access and isolation, so that households' ability to cross the border on foot—or to connect with the market in other ways—is captured.

The percentage of households in our survey growing pigeon peas nearly doubled between 2008 and 2011. This represents a promising opportunity to improve smallholders' income by connecting them to the growing export market for legumes. The USAID Feed the Future strategy for Mozambique does not specifically mention pigeon peas, but its focus is linking smallholders to markets for exportable oilseeds and pulses (USG 2011). I investigate the characteristics of the farmers that have already decided to adopt pigeon peas and find that those in areas with the highest market prices for pigeon peas are most likely to grow them, as is expected and consistent with the basic microeconomic theory that supply is positively dependent on price. I also find that farmers with greater access to information—as proxied by communication infrastructure—allocate more land to pigeon peas. As such, programs seeking to encourage smallholder cultivation of pigeon peas and similar crops for export should investigate promotion and extension via mobile and radio networks.

For further research, I would suggest the incorporation of pigeon pea processors into a model of pigeon pea adoption. I did research in this area and confirmed that new processing plants have opened since 2007, however I was not able to obtain their exact locations or dates of inception and therefore did not use them as explanatory variables. I would hypothesize proximity to a pigeon pea processor to be a strong, positive predictor of both the probability of planting and the amount of land allocated to pigeon peas.

Similarly, I do not incorporate the presence or magnitude of input markets in either of my models. This is based on the assumption that very few Mozambican smallholders purchase inputs, which from the literature I conclude to be true. However, there could be anomalies in the data; for example, if a program or private company begins promoting fertilizer or improve seeds in certain villages, this would have an impact on those farmers' land allocation decisions and therefore affect both models. Since it would likely be at a village level, such an impact could be picked up by other village level characteristics, such as infrastructure.

Additionally, I predict that environmental factors such as rainfall, temperatures, or pests in one year could influence a farmer's decision to plant different crops in the following year. For example, if a drought ruined the horticulture harvest, farmers might be more likely to allocate more land to a drought-tolerant crop such as cassava the next season. I did not have appropriate data to include these factors in my model; I expect that significant variations in yields due to such events would be captured by the market prices, but a useful extension could be to use rainfall variability at the village level to predict cropping decisions.

My results also show that wealthier families with larger farms and more household members are more likely to adopt pigeon pea cultivation. This is consistent with the theory; wealthier households are less vulnerable to crop and price risk (or less risk averse in general), and therefore more likely to take on a cash crop (Fafchamps 1992). This would be important to consider if a program were designed to promote pigeon pea cultivation, and could be extended for other marketable crops such as groundnuts, sesame, and soy that the Gates Foundation and USAID, inter alia, are encouraging for smallholders. In order for such programs to be successful with small, poorer farms, they would first need to address vulnerability, risk attitudes, and access to land.

My research also shows that high prices of staple crops encourage subsistence farming, if overall crop portfolio evenness is a proxy for subsistence farming. This is important if we expect that specialization can yield efficiency gains, and therefore would contribute to growth. Price stabilization—and access to markets—would lower the risk smallholders take on when they decide to rely on the market for food instead of their own cultivation, which is required in order for them to expand into more market-oriented and income-generating crops. However, overall evenness could also be indicative of innovative or market-oriented farmers taking on new crops.

Additionally, my conclusions assume a certain relationship between diversification and market participation, but I do not use data on market participation itself because it was not available at the time of the analysis. To gain a more accurate understanding of the relationship between diversification levels and subsistence or market-oriented farming, market participation data could be employed using similar models to those used in this paper. Understanding the relationship between market participation and land allocation is very difficult because while a farmer has some plans for the market when he or she decides to allocate land, the decision to participate is ultimately made after harvest and therefore affected by land allocation.

The use of diversity indices is somewhat limiting as it fails to provide insight on shifts between different crops or crop categories; for example, a farmer could grow half groundnuts and half maize one year, then half vegetables and half pigeon peas the next, and none of the three measures used here would detect a change, though such a change would have very serious implications for that household's income, nutrition, and workload. While there is no simple measure available in the literature that would capture this, a comprehensive analysis could be done using my model to estimate the probability of growing each individual crop, crop category, and the land allocated to each. This would provide a more complete understanding of behaviors as they relate to specific crops.

Diversity indices are also limiting because diversification itself is ambiguous. Indices assign a scale with low to high values, however those values still require interpretation. As noted in Figure 1 in the introduction, farmers on the subsistence-oriented spectrum are motivated differently than those on the market-oriented spectrum, though they may have similar “scores” as measured by any of the three diversity indices. Diversification is a much more nuanced concept than is generally understood by the development community; in scenarios of extreme poverty and high risk, “specializing” is more likely to indicate a family striving to reach a minimal caloric threshold than specialization for the market. As such, an interesting extension of diversification research could be to assign households to one of the two spectrums (based on historical market participation data, consumption, or qualitative interviews) and conduct the analysis for the two groups separately.

This paper contributes to the understanding of smallholder behavior in Mozambique, specifically what drives diversification on small farms. Policies that expand information and market access to isolated farms have the potential to change cropping behaviors . However, we must also understand the *impact* of changes in land allocation. The World Bank found no relationship between diversification and income in Mozambique (2006), and there is very little in the literature that attempts to estimate it. We also do not know how crop diversification affects the diet diversity of individuals within a household, although many development policies postulate a linkage. This would be the logical next step for further research, as the nutritional impacts are likely to differ based on a family’s motivation for diversification (ie. subsistence or commercial.)

APPENDIX

Table 14. Average Household Land Allocated to Crops by Province

	Nampula		Zambezia		Tete		Manica		Sofala	
	2008	2011	2008	2011	2008	2011	2008	2011	2008	2011
Maize	27%	25%	41%	35%	47%	51%	59%	55%	44%	38%
Sorghum	7%	9%	7%	6%	0%	0%	13%	9%	16%	9%
Rice	2%	3%	6%	6%	0%	0%	0%	1%	9%	10%
Sesame	3%	3%	1%	0%	0%	0%	3%	2%	8%	6%
Horticulture	2%	1%	1%	3%	11%	7%	7%	9%	5%	8%
Cowpea	7%	8%	4%	3%	5%	3%	5%	4%	3%	4%
Cassava	32%	29%	17%	17%	1%	1%	2%	6%	3%	6%
Cotton	2%	3%	1%	1%	1%	1%	0%	0%	3%	3%
Millet	0%	0%	0%	0%	0%	0%	1%	0%	2%	1%
Small Groundnut	9%	7%	2%	1%	3%	4%	2%	2%	2%	2%
Sweet Potato	0%	0%	0%	1%	2%	1%	1%	3%	1%	2%
Large Groundnut	3%	3%	2%	1%	5%	5%	1%	1%	1%	1%
Common Bean	0%	0%	2%	2%	11%	11%	2%	3%	1%	1%
Pigeon Pea	2%	3%	13%	18%	0%	0%	0%	2%	1%	4%
Jugo Bean	2%	2%	0%	0%	0%	1%	1%	1%	1%	1%
Orange Sweet Potato	0%	0%	0%	0%	0%	0%	0%	0%	0%	1%
Potato	0%	0%	0%	0%	4%	4%	0%	0%	0%	0%
Sugar	1%	0%	1%	2%	0%	0%	0%	0%	0%	1%
Tobacco	0%	0%	1%	2%	6%	6%	0%	0%	0%	0%
Sunflower	0%	0%	0%	0%	1%	0%	1%	1%	0%	0%
Yam	0%	0%	0%	0%	0%	0%	0%	1%	0%	0%
Mung Bean	1%	3%	0%	0%	0%	0%	0%	0%	0%	0%
Soy	0%	0%	0%	1%	3%	3%	0%	0%	0%	0%
Green Bean	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Paprika	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Ginger	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Sisal	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Tea	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Number of Households	198	196	248	244	254	256	210	206	265	264

Source: MSU/MINAG Survey 2008, 2011.

Table 15. Household Fixed Effects Regression Results with Infrastructure Index, 2008 - 2011

	Crop Count	Herfindahl Index	BP Index
	0.534	0.137	-0.484
Expected Maize Price	(1.118)	(0.115)	(0.586)
Expected Common	-1.623***	0.087	-0.505*
Bean Price	(0.592)	(0.060)	(0.265)
	3.459***	-0.313**	1.530**
Expected Cowpea Price	(1.215)	(0.128)	(0.628)
	0.654*	-0.034	0.037
Infrastructure Index	(0.339)	(0.034)	(0.176)
	0.144***	-0.013**	0.038
Household Size	(0.052)	(0.006)	(0.026)
	0.149	-0.040	-0.119
Proportion Male	(0.458)	(0.061)	(0.360)
	0.049	-0.002	0.018*
Land Size	(0.027)*	(0.002)	(0.009)
	0.442	-0.022	0.133
Asset Index	(0.252)*	(0.025)	(0.117)
	-0.633	-0.023	0.000
Year 2011	(0.513)	(0.054)	(0.263)

*N=1,130. Robust standard errors reported in parentheses, clustered at household level; *** (p<.01), ** (p<.05), * (p<.10).* $^{\Psi}$*Lower value indicates more even portfolio/ higher diversity. Higher BP index indicates more domination by one crop.*

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