Impacts and Impact Dynamics of Smallholder Participation in High-Value Markets in Kenya

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Summary

Many developing countries are experiencing a food system transformation with a rapid growth of supermarkets. This supermarket growth can be attributed to demand-side factors such as rising incomes, urbanization, and changing lifestyles, as well as supply-side factors, such as market liberalization in the food industry and greater openness for foreign direct investment. The retail revolution has also caused structural changes along the supply chains. Supermarkets try to offer their customers a consistent variety of high-quality products. To ensure continuous supply, supermarkets have established their own procurement systems, involving centralized buying points and contractual arrangements with farmers and traders. Several studies have analyzed determinants and impacts of farmer participation in these new supermarket channels, or in other emerging high-value supply chains in general, but various issues still remain under-researched.

First, past research shows that access to market information can help speed up the diffusion of technical and institutional innovations. In most rural areas of developing countries, however, smallholders have limited access to market information. Due to infrastructure and institutional constraints, the cost of searching and processing formal market information tends to be high. Informal information networks could possibly be used as an avenue to reduce transaction costs. However, so far little is known about the role of information networks for high-value market (HVM) participation.

Second, the nutrition impacts of supplying supermarkets and other emerging high-value markets remain unexplored. This is despite high rates of undernourishment among the rural population of developing countries. Given positive income effects observed in previous research, it is conceivable that supplying supermarkets can have profound impacts on the nutrition of smallholder farm households.

Third, past studies that analyzed welfare effects of participation in high-value markets used cross-sectional data, which may lead to bias in impact assessment, especially if unobserved factors affect participation, or if valid instruments cannot be found. With panel data, unobserved heterogeneity can be controlled for much better. Furthermore, panel data help to better understand possible impact dynamics.

This dissertation consists of three essays. In the first essay we investigate the role of informal information networks for HVM participation. We focus on informal farmer interactions to exchange information, what we call 'information links'. Specifically, we analyze the determinants of the existence of information links between individual farmers and effects of having information links with other farmers that previously supplied HVM on own HVM participation and participation dynamics. In the second essay, we analyze impacts and impact pathways of participation in supermarket channels on rural household nutrition. In the third essay, we analyze impacts and impact dynamics of supplying HVM on household income. All three essays utilize data from smallholder vegetable farmers in Kenya. Panel data for 2008 and 2012 are available.

Kenya is an interesting example for this type of research, because supermarkets have rapidly gained in importance there in recent years. Supermarkets in Kenya now account for about 10% of national grocery sales and over 20% of food retailing in major cities.

In the first essay, we use social network data at individual level and dyadic regressions to analyze determinants of the existence of information links between farmers. In our definition, an information link exists if farmers exchange information on possible vegetable marketing options. We find a higher likelihood of exchange of vegetable market information among farmers supplying HVM, as compared to traditional market (TM) farmers. Also, farmers supplying HVM are more likely to obtain market information from those supplying TM. Further, using household level data and probit models, we find that having an information link with at least one farmer who previously supplied HVM increases farmers' own probability of participation in HVM by at least 10 percentage points. Finally, using multinomial logit models we analyze the effect of having information links with HVM farmers on the dynamics of participation in HVM (joining and also dropping out from these markets) over two time periods. We find that having an information link with at least one farmer who previously supplied HVM increases farmer's own probability of participation in HVM in both periods by 5 percentage points or more, at the same time decreasing the probability of supplying TM in both periods by at least 9 percentage points.

In the second essay, we use household level data to analyze impacts of participation in supermarket channels on farm household nutrition. Using an instrumental variable (IV) approach to control for both observed and unobserved heterogeneity, we show that

participation in supermarket channels has sizeable positive impacts: calorie, vitamin A, iron, and zinc consumption are all increased by 15% or more. We also analyze possible impact pathways, using simultaneous equation models and find that supermarket-supplying households have higher incomes, a higher share of land under vegetables, and a higher likelihood of male control of revenues. Furthermore, income and the share of land under vegetables have positive impacts, while male control of revenues has negative impacts on dietary quality.

In the third essay, we use panel data to analyze welfare effects of participation in high value markets. Employing differencing techniques and IV models, we show that participation in HVM is associated with a 59% increase in household income. On the other hand, dropping out of HVM is associated with a significant decrease in household income. Finally, we find that the difference in income between farmers supplying HVM and those supplying TM is diverging over time.

We derive a few general conclusions from the three essays. It is certainly important that market information is disseminated to smallholders, as it increases the probability of participation and continued supply to HVM. However, farmers already supplying HVM seem to be the ones using informal social networks to assess market information. Further development of these farmers alone may create even larger disparities between farmers supplying HVM and those supplying TM. Therefore, there is need for inclusive involvement of farmers supplying both channels whenever market information is being disseminated to smallholders, as this is likely to increase participation hence improving household welfare in general. Participation in HVM has a significant effect on the dietary quality of the participating households. The effect could however, be even larger if women are supported to keep control of revenue from crops sold in HVM. Finally, participation in HVM has a positive income effect that is growing over time, whereas dropping out leads to huge income loss. Therefore, there is need to support smallholder farmers to participate and stay in HVM

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Table of Contents

List of Tables

List of Figures

1 General Introduction

1.1 Background

Agricultural food systems have been undergoing tremendous structural changes over the past decades, affecting wholesaling, processing and retailing sectors (Minten et al., 2010; Reardon & Timmer, 2012). Over the years, global food trade has sharply increased with notable changes in the structure and products being traded. High-value products such as fruits, vegetables, meat and dairy products have been gaining in importance (Maertens & Swinnen, 2009; Reardon et al., 2009). At the same time, food production and trade are increasingly being regulated through strict requirements on food quality, food safety, and environmental aspects (Henson & Reardon, 2005; Maertens & Swinnen, 2009). Investment in food processing and retail sectors is also increasing rapidly, leading to growth and modernization of supply chains in developed and developing countries. In developing countries, modern supply chains are increasing their market shares in food retailing at the expense of spot markets and traditional shops (Reardon et al., 2003).

In developing countries, the growth of the retail sector including supermarkets has been massive and rapid over the past two decades. The speed has been so fast that it has been referred to as a "supermarket revolution". Compared to developed countries, supermarkets have taken much shorter time to spread in developing countries. For example, what took the USA eight decades has taken Brazil only two decades (Reardon & Hopkins, 2006). This growth has occurred in three waves (Reardon & Gulati, 2008). The first wave took off in the early-1990s to the mid-2000s in South America, East Asia (excluding China), and South Africa, raising the share of modern retail in food markets from about 10% to 50-60%. The second wave, in the mid-1990s, took place in Central America, Mexico, and parts of Southern Asia. The share of modern retail in these countries reached 30-50% by the mid-2000s, whereas the third wave countries (China, Vietnam, and India) attained a 2-20% modern retail share in the mid-2000s. Other parts of Africa, mainly Eastern and Southern Africa outside South Africa, have also begun to experience this revolution since the past decade (Reardon et al. 2008). Among them, Kenya has been on the forefront. Supermarkets in Kenya now account for about 10% of national grocery sales and 20% of food retailing in major cities (Planet Retail, 2015).

Both demand and supply side factors have spurred the growth of modern retail in developing countries (Reardon et al., 2003; Mergenthaler et al., 2009). On the demand

side, increasing incomes, urbanization and increased number of women in the workforce are the driving factors. A substantial growth in real per capita income in developing countries has been experienced since the 1990s (World Bank, 2006; World Bank, 2014). This has led to the emergence of a large middle class, hence increased demand for processed foods (Reardon et al., 2004). In addition, increased urbanization since the 1990s has led to an increase in the number of women working away from home. Consequently, the opportunity cost of their time has increased so that they look more for shopping convenience and increased purchase of processed convenience foods to save cooking time (Reardon & Berdegué, 2002). The modern retailers offer such types of products with greater variety and lower costs than traditional retailers and shops (Rischke et al., 2015). On the supply side, the market liberalization in the food industry and openness for foreign direct investment (FDI) in the 1990s and 2000s significantly sparked the diffusion (Reardon et al., 2009). Foreign supermarkets and other modern retailers were opened in developing countries leading to their multi-nationalization. Their spread further accelerated as they sought to improve their competitive positioning.

For modern retailers to meet the requirements of the consumers such as consistency in quality and continuous supply, they have modernized their procurement systems. This translates to a shift from reliance on spot markets to sourcing from farmers through specialized and dedicated wholesalers using contractual arrangements and quality standards (Reardon et al., 2009; Reardon et al., 2010). These changes have far reaching effects on smallholders (Reardon & Berdegué, 2002; Weatherspoon & Reardon, 2003).

Given the sheer size of the market, the retail revolution brings potentially lucrative market opportunities for small and poor farmers to access high-value markets (Maertens et al., 2007). Furthermore, the emerging high-value markets are often associated with more stable output prices and guaranteed market access. This can lead to higher incomes for the supplying households compared to those supplying traditional markets, which may also contribute to reduction in poverty (Rao & Qaim, 2011). Additionally, increase in income is associated with more diversified consumption patterns hence improved household nutrition (Babatunde & Qaim, 2010). Farmers may also benefit from supplying high-value markets (HVM) by attaining improved farm productivity. To meet the quality standards required by these HVM, farmers may have to change their production systems and their input mix, adopt new farm technology such as improved seed, or invest in new farm equipment. Such changes could lead to improved farm productivity for smallholders

(McCullough et al., 2008; Rao et al., 2012). Moreover, supplying HVM may benefit smallholders through creation of employment opportunities in the community. This may result from the high usage of farm labor in production, harvesting, cleaning, and packaging of produce supplied in these modern markets (Rao & Qaim, 2013).

Despite the potential benefits of participation in the emerging HVM, there are also concerns that smallholders may be excluded from supplying these markets hence leading to further marginalization (Reardon & Barrett, 2000; Henson & Reardon, 2005). Supplying supermarkets and other HVM requires compliance with the associated quality, logistical, safety, and volume requirements (Reardon & Berdegué, 2002). However, smallholders are often poor and may lack the required resources to make changes in their production systems and investments that may be necessary to meet such requirements. Furthermore, the HVM often target farmers who have invested in non-land assets such as farm equipment and irrigation, those with access to good infrastructure, and also the farmers with larger sizes of land (Reardon & Gulati, 2008). Therefore, asset-poor smallholder farmers may face increasing challenges in accessing or continuing to supply HVM.

Farmers may also be limited from supplying these markets due to high transaction costs, such as costs of searching for market information, negotiating contracts with the buyers, and transportation among others (Blandon et al., 2009). In terms of market information, participation in HVM requires access to more information than supplying traditional markets. Farmers need diverse information, for example, regarding buyer requirements, the appropriate production methods, and the benefits of participation. This may limit smallholder participation.

1.2 Problem Statement

The transformation of agri-food systems and the increasing role of modern supply chains offer new opportunities and challenges for small farmers. Various studies have raised concerns that smallholders may be excluded from participating in these high-value markets (HVM) (Reardon & Barrett, 2000; Henson & Reardon, 2005). As a result, several studies have analyzed determinants of participation (Hernández et al., 2007; Blandon et al., 2009; Neven et al., 2009; Moustier et al., 2010; Rao & Qaim, 2011). Most of these studies show that farmer characteristics and physical capital including infrastructure, are the most important determinants of participation in HVM.

Having human and physical capital required for HVM participation does not suffice to participate in HVM: farmers may be lacking information on the existence of HVM opportunities or requirements for participation. Furthermore, before farmers can make investments that would qualify them to participate in the HVM, such as purchasing irrigation equipment, they may need to know the expected returns from participation. Such information is not always obtained from HVM buyers. Similarly, due to infrastructure and institutional constraints, smallholders are not always able to obtain such information from formal sources (Birner et al., 2009). In addition, some attributes of HVM may not be directly observed by non-participating farmers. For instance, the benefit of increased incomes that come from supplying HVM mainly results from stable prices and market assurance offered by HVM (Rao & Qaim, 2011; Michelson, 2013) and it may not necessarily be that HVM offer higher prices than traditional markets. Therefore, farmers already supplying HVM are the ones likely to know the benefits of participation in terms of incomes. Thus, informal social networks may support the spread of relevant information among smallholders, but the role of such information networks for HVM participation has never been analyzed. Having farmers who previously supplied HVM in one's informal social network could be beneficial. Farmers can learn from each other about the benefits of participation and also obtain information that one would require to participate in these HVM.

Several studies have analyzed whether smallholders benefit from supplying HVM. Results indicate that such benefits are substantial. Farmers supplying HVM are gaining as much as 48% higher household incomes on average, compared to those supplying traditional markets (Rao & Qaim, 2011). Furthermore, HVM-supplying households benefit in terms of improved productivity and employment creation for the local community. Surprisingly, however, there is no study that has analyzed impacts of modern supply chains on farm household nutrition (Popkin, 2014). This is despite the high rates of undernourishment in developing countries. Out of the 805 million people estimated to have been chronically undernourished in 2012-2014 worldwide, 791 million live in developing countries, many of them in rural areas where they depend directly or indirectly on the small farm sector for their livelihoods (FAO, 2014). At the same time, deficiencies of various micronutrients are widespread (FAO, 2013; Gómez et al., 2013). Undernourishment and micronutrient deficiencies have far-reaching health and nutrition

consequences including growth retardation in children, impaired cognitive development, and low labor productivity (Kennedy et al., 2003; Black et al., 2008).

The improved incomes resulting from supplying HVM shows that participation in these markets could have profound effects on nutrition of supplying households. For the previously undernourished households, higher household incomes may result in consumption of more calories. In addition, higher incomes are associated with consumption of more diversified diet hence leading to improved dietary quality (Ye & Taylor, 1995). Furthermore, producing crops for sale in HVM may lead to specialization (Rao et al., 2012). Specializing in a food crop, even though for commercial purpose, may lead to increased consumption of that crop by the producing household. For example, produce that does not meet the quality standards of HVM may be retained for home consumption hence increasing their intake at the household level. Supplying HVM may also affect household's nutrition through changes in gender roles and household decision making. As crops get commercialized, males tend to take over control of the crops and revenues previously controlled by females (von Braun, 1994; Fischer & Qaim, 2012). Such changes in gender roles and household decision making may have important effects on nutrition in farm households.

Most of the previous studies analyzing impacts of supplying HVM have used cross-sectional data which has some drawbacks. First, with cross-section data, only static analysis can be undertaken which does not give a complete story. Dynamic analysis with panel data would give a clearer picture of the impacts. Second, when using cross-section data, there are problems in controlling for heterogeneity arising from unobserved factors particularly if good instruments cannot be found. With panel data such heterogeneity, especially time-invariant one, can be controlled for. Empirical evidence of impacts of participation in HVM using panel data is scarce. One exception is Michelson (2013), who used a difference-in-difference estimator to analyze impacts of supplying supermarkets on household assets in Nicaragua. However, Michelson collected data only at one point in time, using recall data on past asset ownership among supermarket farmers for constructing the panel. Such data may be less accurate compared to actual data collected over two or more periods.

This dissertation seeks to address the discussed research gaps using data from smallholder vegetable farmers in Kenya. The dissertation has three essays. In the first essay, we analyze the role of information networks for dissemination of market

information regarding supplying HVM. The second essay analyzes the impacts and impact pathways of supplying HVM on farm household nutrition. Both these essays primarily use cross-sectional data. In the third essay, we use panel data collected from the same smallholder farmers to analyze the impacts and impact dynamics of participation in HVM on household income.

1.3 Research Objectives and Dissertation Outline

The focus of this dissertation is to analyze the role of information networks for high-value market (HVM) participation and the impacts of supplying HVM on farm household nutrition and income. Specifically, this dissertation has the following objectives:

1. To analyze impacts and impact dynamics of information networks on dissemination of HVM information and hence participation in HVM,
2. To analyze the impacts and impact pathways of supplying HVM on household nutrition, and
3. To analyze impacts and impact dynamics of supplying HVM on household income.

The analyses of these objectives are based on comprehensive data collected from 400 smallholder vegetable farmers in rural Kenya, consisting of farmers supplying HVM or traditional markets (TM). The first objective uses individual level social network data and household level data. The second objective utilizes household level data. Both of these objectives primarily use cross-sectional data collected in 2012. The questionnaire used for data collection is attached in the Appendix at the end of the dissertation. The third objective uses panel data from the same smallholder farmers, collected over two rounds: 2008 and 2012. The author of this dissertation was not involved in the 2008 data collection, but she planned and implemented the 2012 survey round. Kenya is an interesting case study for such an analysis because it is one of the countries in Africa where modern supply chains have rapidly gained in importance in recent years. Supermarkets in Kenya now account for about 10% of national grocery sales, and over 20% of food retailing in major cities (Planet Retail, 2015). Also, smallholders in Kenya, like in other developing countries, are faced with challenges of inadequate market information.

The rest of the dissertation is organized as follows. Chapter 2 presents the first essay analyzing the role of information networks for HVM participation using dyadic

regressions and probit models. The second essay analyzing impacts and impact pathways of supplying supermarkets on household nutrition is presented in the third chapter. We use an instrumental variable approach to control for endogeneity and simultaneous equations to analyze impact pathways. In chapter 4, we present the third essay that uses panel data to analyze impacts and impact dynamics of HVM participation on household income. We employ differencing techniques and treatment effect estimators to undertake the analysis. Chapter 5 summarizes the main findings of the dissertation, derives some policy recommendations, and discusses limitations of the study as well as important areas for further research.

2 Informal Information Networks and Smallholder Participation in High-Value Markets[1]

***Abstract*:** This paper analyzes the determinants and role of informal information networks for high-value market (HVM) participation and participation dynamics, an area that has not been explored before. Using primary data collected from smallholder farmers in Kenya who supply HVM or traditional markets (TM), we find a higher likelihood of exchange of market information among farmers supplying HVM, as compared to TM farmers. We also find that farmers supplying HVM are more likely to obtain market information from those supplying TM, but we do not find evidence that TM farmers obtain market information from HVM farmers. In addition, our results show that obtaining market information from farmers who previously supplied HVM significantly increase farmers' own probability of participation in HVM by 10% to 19%, and enhances farmers to join and continue supplying HVM. Some policy implications of these findings are also discussed.

2.1 Introduction

Access to market information is fundamental for market participation, which in turn has important implications for the rural poor, and overall economic growth (Barrett, 2008). However, smallholders in developing countries have limited access to market information limiting optimal production and marketing choices. Smallholders may not be aware of the existence of some market opportunities, such as the emerging high-value markets (HVM) including supermarkets. Alternatively, they may be lacking information on the requirements for participation, or how to successfully supply these new high-value markets.

Supermarkets in developing countries have been undergoing a massive and rapid growth since the past two decades (Reardon *et al.*, 2004; Reardon & Timmer, 2007; Neven *et al.*, 2009). Consequently, opportunities for participation in these emerging high-value markets have increased. An emerging body of literature seeks to explain the

[1] This chapter is co-authored by Theda Gödecke, Camilla Andersson, and Matin Qaim. The following roles were performed by me: conceptualization and designing the study in cooperation with Camilla Andersson and Matin Qaim; implementing the survey in cooperation with Camilla Andersson; data analysis; interpretation of research results in cooperation with all co-authors; writing of the paper; and revision of the paper with all co-authors.

determinants of participation in such high-value markets (see for example, Hernández et al., 2007; Moustier et al., 2010; Rao & Qaim, 2011; Andersson et al., 2015). Most of these studies, however, emphasize on infrastructure, organizational support, physical, and social capital as important determinants of participation. No study has analyzed impacts of information networks on HVM participation. To successfully supply HVM, farmers require more information than to supply traditional markets (TM). Lack of access to market information may limit smallholders from HVM participation. Furthermore, if only a few farmers are supplying HVM, further development of the HVM could aggravate inequality between farmers supplying HVM and those supplying TM through differential access to information.

Market information may be obtained from formal sources such as agricultural extension officers, media, or Non-Governmental Organizations (NGO). However, due to infrastructure and institutional constraints, cost of searching and processing formal market information by smallholders tends to be high (Birner et al., 2009; Feder et al., 2010). Informal information networks could possibly be used as an avenue to reduce transaction costs, but so far little is known about the role of information networks to spread market information[2]. This article addresses this research gap by analyzing effects of information networks on HVM participation, using the example of smallholder vegetable farmers in rural Kenya.

Past research shows that informal information networks can help speed up the adoption of agricultural technologies through social learning (see for example, Munshi, 2004; Matuschke & Qaim, 2009; Conley & Udry, 2010; van den Broeck & Dercon, 2011). However, there are also findings showing that informal information networks could have negative effects. In their study on effect of social networks on adoption of sunflower (a new crop) in Mozambique, Bandiera and Rasul (2006) find that information networks measured by the number of adopters among relatives and friends has a negative effect on sunflower adoption when there are many adopters. They explain that the negative effect could arise from farmers strategically delaying to adopt the technology so that they free ride on the knowledge accumulated by others. These findings therefore

[2]Some studies have analyzed effect of social capital and collective action on participation in HVM, e.g.,Kaganzi et al., (2009), Markelova, et al., (2009), and Andersson et al., (2015). However, such data are collected differently from social network data. Proxies like group membership or membership to certain project or NGO activities are often used, which do not necessarily reflect direct interaction and exchange of information between individuals.

show that the effects of information networks could differ depending on the context. Thus, general conclusions about the effect of information networks on household and agricultural decision making are not justified.

In this paper, we identify social networks by randomly matching farmers within our sample (Conley & Udry, 2010; Maertens & Barrett, 2013). Building on primary data consisting of farmers supplying HVM or TM, we analyze three main aspects. First, we analyze determinants of the existence of information links between farmers. In our definition, an information link exists if farmers exchange information on possible vegetable marketing options. Second, we investigate the effect of having information links with farmers that previously supplied HVM on farmer's own probability of participation in HVM. A recent study on participation in HVM shows that there can be significant participation dynamics, with many smallholders dropping out and others joining HVM (Andersson et al., 2015). Therefore, analyzing effects of information networks statically may not tell a complete story. In our third objective, we analyze the impacts of having information links with previous HVM farmers on farmer's own participation dynamics over a two time period.

We use the case study of Kenya because it is one of the countries in Africa that has experienced a rapid growth of emerging high-value markets such as supermarket in the past decade (Reardon et al. 2008). Supermarkets in Kenya now account for about 10% of national grocery sales, and over 20% of food retailing in major cities (Planet Retail, 2015). At the same time, smallholders in Kenya, like in many other developing countries, are faced with challenges of inadequate market information (Okello et al., 2012).

Findings of this study could have wider implications in other developing countries experiencing similar growth of supermarkets or other emerging high-value supply chains. Therefore, having a better understanding of the information networks and their effects on participation in HVM and participation dynamics is also important from a policy perspective.

2.2 Literature Review

The agri-food systems in developing countries have been facing dynamic changes in the past two decades (Reardon et al., 2009; Reardon & Timmer, 2014). Among other factors, the recent rapid growth of supermarkets is contributing to this change (Reardon et al.,

2004; Reardon & Timmer, 2007; Neven et al., 2009). Supermarkets and other emerging high-value supply chains are increasingly changing their procurement systems, from buying through traditional markets (TM) to contractual agreements with farmers, often through specialized intermediaries (Reardon & Berdegué, 2002; Rao & Qaim, 2011). This has created both opportunities and challenges for smallholder farmers. On the one hand, participation in these new high-value supply chains require farmers to meet diverse stringent requirements in terms of quality, quantity, timely supply, and product specifications (Key & Runsten, 1999; Reardon & Barrett, 2000; Weatherspoon et al., 2001). On the other hand, those who manage to participate benefit immensely in terms of increased household incomes, improved household nutrition, productivity, and employment creation (Miyata et al., 2009; Rao et al., 2012; Michelson, 2013; Rao & Qaim, 2013; Chege et al., 2015; Andersson et al., 2015).

In this paper we combine literature on emerging high-value markets (HVM) and social network to find out the role of information networks for HVM participation. Unlike supplying TM, farmers require diverse information before they can successfully supply HVM. They require information on buyer requirements in terms of product quality, quantity, and product specifications. Furthermore, farmers need information on how to best meet these requirements on a consistent basis. To fulfill the requirements may require changing production methods and/or heavily investing on farm equipment. Thus, prior to this investment decision, farmers require information on the benefits and challenges of supplying HVM. In the case of participation in some HVM like supermarkets, the actual outcome of participation may not be easily revealed in terms of significantly higher prices than in the TM, but often stems from less salient features such as less price volatility and more stable demand throughout the year (Rao & Qaim, 2011; Michelson, 2013).

Literature on social learning shows that people are likely to adopt an innovation if they see evidence from outcomes of earlier adopter that convince them that the innovation is worth adopting (Young, 2009; Conley & Udry, 2010). In the case of participation in emerging high-value markets therefore, the process of learning may be through peers. Since there are multiple farmers supplying different markets in similar circumstances, farmers can attain information on the HVM, learn the practices of other HVM farmers,

learn about the outcome of participation, and make informed decisions on whether to join the HVM or not.

Social networks may also play other roles besides dissemination of market information. Screening buyers and sellers, as well as monitoring and enforcing contracts often involves high costs (Aleem, 1990). When buyers and sellers interact frequently, patterns of expected behavior and bonds of trust are established allowing the social network to serve a screening function (Wydick et al., 2011). This consequently reduces transaction costs of market participation. Additionally, the possibility of social sanctions may lower the probability of contract breaching by either the buyer or seller. Finally, social networks can be used to reduce the burden of financial requirements among farmers. Supplying HVM may require farmers to invest in farm machinery and equipment such as those for irrigation (Rao et al., 2012). However, smallholder farmers are often poor and may lack resources to invest in such equipment. Social networks can assist such farmers to overcome this barrier by enhancing pulling of resources and making joint investments in purchasing the required equipment or using social networks as an informal source of loans. Furthermore, social networks can also be importance for credit awareness and approval (Okten & Osili, 2004).

2.3 Methodology

2.3.1 Conceptual Framework

In this sub-section, we discuss more formally how information networks are likely to affect farmers' participation decisions.

Determinants of the Existence of Information Links

Our first objective is to analyze determinants of the existence of information links between a pair of farmers (dyad). A dyad is a pair of linked actors, in which the actor whose network is being studied (actor *i*), is linked to another actor (actor *j*) (Smith & Christakis, 2008). Based on the theoretical literature on network formation, (see Jackson, (2007) for an extensive review), people form links with each other based on the cost-benefit analysis of the links. Farmers are expected to form an information link if the

benefits that accrue from the relationship outweigh the cost of forming and maintaining it. This can be represented as follows:

$$L_{ijk} = \begin{cases} 1 & if\ B_k(X_{ij}) - C_k(X_{ij}) \geq 0 \\ 0 & \text{otherwise} \end{cases} \quad (2.1)$$

where L_{ijk} denotes the directed information link indicating that farmer *i* receives information from farmer *j* with respect to activity *k*, B_k *(.)* represents the benefits of the link, and the cost of establishing or maintaining the link is represented by C_k *(.)*. The costs and benefits depend on the characteristics of individuals *i* and *j*, X_{ij}. Based on past literature on role of information networks for adoption of agricultural technology[3], X_{ij} will include social and geographical distances. Social distance refers to the similarities and differences in individual characteristics between *i* and *j* such as age, gender and education, whereas geographical distance refers to the physical distance between *i* and *j* measured in kilometers (km) or whether the two farmers are in the same neighborhood or region.

X_{ij} will also include the previous choice of the supply channel of the paired farmers. Empirical evidence shows that farmers can attain information on adoption of agricultural technology through network members who have already adopted the technology (Bandiera & Rasul, 2006; Matuschke & Qaim, 2009; Conley & Udry, 2010). Regarding participation in HVM, farmers who have already supplied HVM will be a better source of information regarding supplying HVM, as compared to those who have not. Thus, the benefits of forming an information link with these farmers may be higher. Farmers can attain market information from other sources than their informal social networks, for example traders. Therefore, X_{ij} will also include other sources of market information.

[3]Due to the lack of previous studies on determinants of information link in regard to HVM, the extensive literature on other types of information networks especially in the context of adoption of agricultural technology, offer lessons for our case.

Determinants of Participation in High-Value Markets

Our second objective is to analyze the effect of having information links with farmers that previously supplied high-value markets (HVM) on farmer's own probability of HVM participation. Supplying HVM can be modeled as a binary choice decision, assuming farm households aim to maximize their utility subject to household resource constraints (Manski, 1977). So that utility, *U*, is determined by a set of farm, household and contextual variables, *Z*, which also influence farmers' ability to adjust to the requirements of the emerging supply channels, leading to participation. Variable *Z* also includes the level of connectedness with information network members. Information networks disseminate important information among farmers hence lowering the transaction costs (Conley & Udry, 2001). We therefore model a utility maximizing farm household as:

$$MAX\ U = f(Z) \tag{2.2}$$

If we define *h* to be HVM and *t* the TM, a farmer will participate in HVM, if the utility derived from this channel, U_h^*, is greater than the utility U_t^*, from TM. However, U_h^* and U_t^* are latent variables. What we observe is the supply channel that the farmer chooses, *Y*. A farmer will choose to supply HVM, *Y*=1 or TM, *Y*=0, following the following decision rule:

$$Y = \begin{cases} 1 & if\ U_h^* \geq U_t^* \\ 0 & \text{if } U_h^* < U_t^* \end{cases} \qquad \forall h \neq t \tag{2.3}$$

2.3.2 Measuring Social Network

Different methods can be used to collect social network data. Maertens and Barrett (2013) give an excellent review of these methods. In summary, there are two main approaches: undertaking a complete village census or taking a sample of the population of interest. Undertaking a complete village census entails asking all farmers to list all their information contacts and the kind of information they share (De Weerdt & Dedrcon, 2006; Fafchamps & Gubert, 2007; van den Broeck & Dercon, 2011). This makes this method time consuming and may only be applicable in small villages (Goswami & Basu, 2010; van den Broeck & Dercon, 2011). Furthermore, some respondents may forget to

mention certain network partners. Also, data are only collected within the network boundary previously defined, for example, a village (Udry& Conley, 2004).

In the case of taking a sample of the population, several ways of sampling are documented in the literature (see Maertens & Barrett (2013) for this discussion). One sampling technique that has gained preference amongst economist lately is "random matching within sample" (Conley & Udry, 2010; Santos & Barrett, 2010; Maertens & Barrett, 2013). Each farmer is matched with a certain number of randomly drawn individual from the sample, and asked to elicit details on the kind of relationship the farmer has with each of these individuals. This method has the advantage that it can be implemented within a short period of time. Furthermore, Santos and Barrett (2008) use Monte Carlos simulation on a network of herders in Ethiopia and show that this method outperforms other methods of sampled networks. The main drawback of using sampled networks however, is that a key network member may be omitted from the sampling hence leading to a large omitted variable bias (Maertens & Barrett, 2013). In our study, we collected information network data using "random matching within sample" method. We further collected additional information about farmers' other information networks (besides those in our sample), so as to reduce the bias of omitted variable. This is explained in detail in sub-section 2.4.2.

2.3.3 Empirical Strategy

There are three issues we aim to analyze: first, determinants of the existence of information links; second, effects of having information links with farmers who previously supplied high-value markets (HVM) on farmers' own probability of HVM participation; and third, the effects of having information links with farmers who previously supplied HVM on farmer's own participation dynamics including joining and dropping from HVM.

Analyzing Determinants of the Existence of Information Links

To empirically analyze determinants of existence of information links between a dyad of farmers, we follow Fafchamps and Gubert (2007) with adjustments to suit our study, and estimate the following model:

$$L_{ij(2012)} = \beta + \alpha_1 (x_i - x_j)_{(2008)} + \alpha_2 (x_i + x_j)_{(2008)} + \gamma w_{ij(2008)} + \rho M_{ij(2008)} + \varepsilon_{ij} \quad (2.4)$$

where L_{ij} denotes the probability of existence of an information link between individuals *i* and *j*. The dyadic relationship is directional and therefore L_{ij} does not have to equal L_{ji}. x_i and x_j are characteristics of individuals *i* and *j* that are likely to influence probability of existence of a link, including the social distance characteristics. Since L_{ij} is directional, regressors $x_i - x_j$ enters the regression as such, not in absolute value (Fafchamps and Gubert, 2007). Parameter α_1 measures effect of differences in attributes on L_{ij} while α_2 measures effect of combined level of x_i and x_j on L_{ij}. Variable w_{ij} captures link attributes of dyad *i* and *j*, including geographical distance, whereas M_{ij} denotes supply channel variables. All the explanatory variables are lagged to 2008 to avoid reverse causality. Parameter ρ will show the effect of past choice of supply channel of the dyads on probability of existence of an information link (L_{ij}). Finally, ε_{ij} is the error term.

A potential problem of estimating equation (2.4) is that the error terms are likely to be inconsistent due to cross-observation correlation in the error terms involving same individuals. It is possible that at one time the respondent is the individual *i*, and in another instance the same respondent is identified as individual *j*. Therefore, there is need to correct the standard errors. Since our data were collected differently from Fafchamp and Gubert (2007), we are not able to follow their standard error correction method. Therefore, we cluster the standard errors of the probit model based on farmers *i* and *j* following Petersen (2009).

This probit model will show determinants of existence of an information link. To understand the effects of information links on HVM participation, we undertake further analysis as explained in the following.

Analyzing Determinants of Participation in High-Value Markets

As discussed in the conceptual framework, farm households' decision on the choice of the supply channel is an individual decision based on utility derived from each channel, and each household will choose to participate in the supply channel with the highest utility. Therefore, participation in HVM can be specified as follows:

$$H_{(2012)} = \beta Z_{(2008)} + \alpha N_{(2012)} + \gamma O_{(2012)} + \mu \quad (2.5)$$

where $H_{(2012)}$ is a dummy variable equal to one if the household supplied HVM in 2012, and zero otherwise; $Z_{(2008)}$ is a vector of explanatory variables that we lag to 2008 to avoid reverse causality; $N_{(2012)}$ captures "HVM information link within sample"; a binary variable which is equal to one if the main person in the household responsible for vegetable production and marketing talked to at least one social network member about vegetable marketing options, and zero otherwise. The social network member came from our sample and had to have supplied HVM in 2008. $O_{(2012)}$ denotes "HVM information link outside sample". This is also a binary variable which is equal to one if the main person in the household responsible for vegetable production and marketing talked to at least one other farmer currently supplying HVM, about vegetable marketing options, and zero otherwise. This refers to farmers other than those already randomly sampled and matched with the respondent. α and γ are the parameters of interest, which show the effects of HVM information links on participation in HVM. β is a vector of other parameters to be estimated, and μ captures stochastic disturbances, assumed to be normally distributed.

We draw on existing literature to identify explanatory variables to be included under *Z*. Previous studies have identified farmer characteristics such as age, gender, and education level; and physical capital as important determinants of supplying HVM (Hernández et al., 2007; Neven et al., 2009; Rao & Qaim, 2011; Andersson et al., 2015). We also control for traders (proxy for other sources of market information) as farmers may receive vegetable marketing information from other sources than informal social networks. We include distance to tarmac road as a measure of infrastructure conditions. Farmers who live close to tarmac roads may have easy access to transport hence easily market their produce compared to those living deep inside the villages (Hernández et al.,

2007; Michelson, 2013). Furthermore, they may also easily receive more information about other marketing options. Finally, we include the region dummies to capture possible regional effects.

Analyzing Determinants of Dynamics of Participation in High-Value Markets

Our third objective is to estimate effect of having information links with farmers that previously supplied high-value markets (HVM), on farmer's own participation dynamics. If farm households are faced with a decision to participate in HVM or traditional markets (TM) over two time period, they are likely to fall into four possible categories: Category 1=the household supplies HVM in both periods (HVM stayer); category 2=the household supplies TM in the first period and HVM in the second period (HVM newcomer); category 3=the household supplies HVM in the first period and TM in the second period (HVM dropout) and category 4= the household supplies TM in both periods (TM stayer). The probability that one alternative is chosen is the probability that the utility of that alternative exceeds the utility of all other available alternatives.

The choice of supply channel over the two time periods may be influenced by access to information on supplying HVM. As discussed in section 2.2, supplying HVM may require more information than supplying TM. We analyze the effect of having information links with previous HVM farmers on own participation dynamics using two information link variables ("HVM link within sample" and "HVM link outside sample"). All other control variables discussed under determinants of supplying HVM are also used to analyze participation dynamics. We undertake our dynamic analysis using a multinomial logit model (Greene, 2008).

2.4 Data and Descriptive Statistics

In this sub-section, we describe how the farm and information network data were collected and show some descriptive results.

2.4.1 Farm Survey

This study uses data from smallholder vegetable farmers from rural households of the former Kiambu District in the Central province of Kenya (under the new constitution Kiambu district is now in Kiambu County). The main economic activity in the region is agriculture mainly horticulture farming, dairy farming, tea, and coffee production. Due to its proximity to Nairobi city, Kiambu serves as the main source of most vegetables sold in Nairobi's supermarkets and spot markets (Neven et al., 2009).

Household data were collected from 331 smallholder vegetable farmers in 2012, 77 participating in high-value market (HVM) and 274 in traditional market (TM). These farmers were also interviewed in 2008 when the sampling was done. In 2008, farmers were selected using a stratified random sampling procedure, differentiating between HVM and TM farmers. TM farmers were randomly sampled from 31 administrative locations that mainly produce vegetables in Kiambu District. HVM farmers were selected using lists from HVM suppliers (Rao & Qaim, 2011).We use 2008 data to lag our variables so as to avoid issues of reverse causality, and to analyze dynamics of participation in HVM in our third objective.

In both years data were collected using a structured questionnaire that was carefully pretested prior to the data collection. Data collected included household characteristics, information on vegetable production and marketing, other farm and non-farm economic activities, household assets, various institutional variables, and information network data (only in 2012).

2.4.2 Information Network Data

We use three information link variables in our analysis. The first variable, "*link within sample",* is used in a dyadic regression model to elicit the determinants of existence of information links. Second variable "*HVM link within sample"* and third variable "*HVM link outside sample*" are used in the probit and multinomial logit models to analyze the effects of having information links with previous HVM farmers on farmer's own HVM

participation and participation dynamics. The three models are discussed in the methodology section.

These models have different units of analysis and therefore require different types of data. In a dyadic regression model the unit of analysis is a dyad, therefore, information on each link between the network pairs are required. On the other hand, for the probit and multinomial logit models the unit of analysis is the household, thus household level data is required.

As mentioned earlier, these social network data were collected using the "random matching within sample" approach (Maertens & Barrett, 2013). Respondent were randomly matched with a maximum of seven randomly selected farmers from our sample, including HVM and TM farmers. Of the seven matches, five were sampled from the respondent's village and two from the neighboring village. In some cases, respondents could not be matched with the two farmers from the neighboring village since our sampled villages did not have any neighboring village in our sample. Therefore, such farmers were only matched with five farmers from within the respondent's village.

All social network variables used allow for the direction of the information flow. All variables are designed in a way that farmer *i* receives information from farmer *j*. The advantage of using directed social network data is that we can account for the fact that the exchange of information is not necessarily reciprocal, meaning that even if farmer *i* receives information from farmer *j,* this does not mean that *j* also provides information to farmer *i*.

The first information network variable, which we refer to as "*link within sample",* is based on the following social network questions which were asked in the following sequence; to start with, farmers were asked about their acquaintances with the matches, by asking the questions:

"Do you know farmer *x*?" If yes, "How many times have you talked to him/her in the last month?"

If the individual farmer (farmer *i*) talked to the match (farmer *j*) at least one time, then farmer *j* is said to belong to farmer *i's* close social network that could act as a source of information. However, knowing and talking to a fellow farmer about general issues does

not necessarily mean that these farmers exchange market-related information. Therefore, to identify actual exchange of information about vegetable marketing, the following question was asked, only to farmers that know their matches:

> "Have you ever talked to farmer *x* about different marketing channels for vegetables?"

If the farmers responded with a yes, then we classify this as an information link, that is, those individuals that farmers have chosen as a source of information on vegetable marketing. This "*link within sample"* variable is binary and used in our dyadic regression model to address the first research question.

The second information network variable is referred to as "*HVM link within sample"* and we use it to address the second and third research question. This variable is based on the "*link within sample"* discussed before. However, since our interest in the second and third objective is finding out how information network affects participation in HVM, the information link farmers who previously participated in HVM would be the appropriate ones to provide information on aspects regarding participating in HVM, for example requirements and benefits of participation. Therefore, we define the "*HVM link within sample"* as a binary variable equal to one if out of the "*link within sample"* there was at least one farmer that supplied HVM in 2008, and zero otherwise. We use this variable as binary because majority of the respondents received information on marketing channels only from one HVM farmer.

The need for a third information link variable "*HVM link outside sample*" is driven by the fact that our social network data is based on sampled networks. When using such a methodology, there is the risk of getting a large omitted variable bias in case the sampled network omits an important network pair (Maertens & Barrett, 2013). Therefore, we asked further questions to capture these links. Farmers were asked the following questions:

> "Do you know any other vegetable farmers who are supplying their vegetables to HVM ?" "If yes, how many?"

"Out of these farmers that you know who supply HVM, have you talked to any of them about marketing of vegetables?" "If yes, how many?"

If the respondent talked to at least one other HVM farmer about vegetable marketing, then we reckon existence of information link. We also use this variable as binary, which is equal to one if the respondent talked to at least one other HVM farmer about vegetable marketing and zero otherwise. Additionally, we collected information on distances to these other farmers that the respondent knows.

When we multiply the 331 farmers interviewed with the number of matches given to each farmer, we arrive at 1449 pairs of farmers (dyads) that we would consider in our dyadic analysis. However, descriptive analysis shows that not everyone knows everyone else within the sampled farmers. A total of 39% of the matches are not known to the respondents, implying that these matches do not have any social relation with the respondents. Yet, there needs to be existing social relations before an information link can be formed as farmers can only contact those farmers known to them. Therefore, we restrict our dyadic analysis to the subsample of 61% of the sample that know their match (884 dyads), as suggested in the literature (Santos & Barrett, 2010).

2.4.3 Descriptive Results

The descriptive statistics of the dyads show that the links through which vegetable farmers actively acquire marketing information comprise of a subset of their social network members. In total, 70% of the known matches are selected as sources of marketing information. HVM farmers have a higher percentage of information link farmers (74%) compared to TM farmers (67%), but this difference is not statistically significant. A further analysis of the dyads that know their matches show that 79% of the farmers know the buyer of their peer's vegetables.

Turning to the analysis at the household level, Table 2.1 shows the descriptive statistics of the interviewed households, differentiated by HVM and TM. The HVM farmers in our sample sell their vegetables in supermarkets and other institutions like schools and hotels. Even though these constitute only a part of the broad high value market channels, our analyses on the role of information networks to spread market

information can also be applied to other types of HVM, such as export market and other institutions. Therefore, the use of the term HVM is justified.

The descriptive results show that on average, 23% of the sampled households supply their vegetables in HVM. HVM farmers are more connected; a higher percentage has information networks in their personal networks. In line with previous studies (e.g. Rao & Qaim, 2011 and Andersson et al., 2015), HVM farmers are more educated and they have higher physical capital and wealth endowment compared to TM farmers.

The descriptive analyses only give an overview of what we expect in our further analysis. However, these results should not be over interpreted because we do not control for other factors. In the next section we undertake econometric analysis where other confounding factors are controlled for.

Table 2.1.Descriptive statistics of sample households by marketing channel

	Full sample		HVM		TM	
	Mean	Std. Dev.	Mean	Std. Dev	Mean	Std. Dev
HVM link within sample (dummy)	0.38	0.49	0.57***	0.50	0.32	0.47
HVM link outside sample (dummy)	0.40	0.49	0.73***	0.45	0.30	0.46
Trader is source of mkt info (dummy)	0.47	0.50	0.49	0.50	0.46	0.50
Participation in NGO activities (dummy)	0.22	0.41	0.25	0.43	0.21	0.41
Age of farmer (years)	50.29	13.28	50.00	12.92	50.37	13.41
Education of farmers (years)	9.40	3.58	10.53**	3.17	9.06	3.63
Male farmers (%)	0.66	0.47	0.79**	0.41	0.62	0.49
Household size	3.52	1.78	3.86	1.83	3.41	1.76
Off farm income (dummy)	0.49	0.50	0.66***	0.48	0.44	0.50
Farm size (acres)	2.09	2.79	2.95**	3.87	1.82	2.32
Irrigation technology (dummy)	0.77	0.42	0.92***	0.27	0.73	0.45
Livestock ownership (dummy)	0.82	0.38	0.82	0.39	0.83	0.38
Owns a vehicle (means of transport) (dummy)	0.13	0.34	0.25***	0.43	0.10	0.30
Access to credit (dummy)	0.11	0.32	0.08	0.27	0.12	0.33
Electricity access (dummy)	0.74	0.44	0.91***	0.29	0.69	0.47
Distance to tarmac road (km)	2.01	2.59	1.44*	2.07	2.18	2.70
Limuru region	0.25	0.43	0.06***	0.25	0.31	0.46
Kikuyu/Westlands/Dagorett region	0.46	0.50	0.66***	0.48	0.40	0.49
Githunguri/Lower Lari/Lari region	0.29	0.45	0.27	0.45	0.29	0.46
Number of observations	*331*		*77*		*254*	

Notes: *, **, *** show statistical significance difference between HVM and TM at 10%, 5% and 1% level respectively; HVM, high-value channels; TM, traditional market; All variables are lagged to 2008 except for the two information link variables where we use 2012 values because these data were not collected in 2008

2.5 Results and Discussion

2.5.1 Determinants of the Existence of Information Links

To address our first research question, i.e., determinants of the existence of information links, we use dyadic probit model specified in equation (2.4). Table 2.2 presents the results of this estimation. Results of the social distance variables show that dyads of the same gender are more likely to exchange vegetable marketing information compared to dyads of different gender. This can be explained by higher costs of forming and maintaining a link when dyads are dissimilar. These results are in line with finding of previous studies (Conley & Udry, 2010). We also find that large vegetable farmers are less likely to exchange market information. This is plausible since the large farmers, who are mainly wealthy farmers, are often more informed about several agricultural aspects including marketing and therefore may be sharing similar ideologies, hence no need to source information from each other.

Table 2.2.Determinants of the existence of information links: Dyadic regression results

	Coefficients	Clustered std error
Both *i & j* are HVM farmers[a]	0.624***	(0.209)
Farmer *i* is HVM, *j* is TM[a]	0.364**	(0.170)
Farmer *i* is TM, *j* is HVM[a]	0.206	(0.151)
Live in same village	0.420***	(0.123)
Distance between farmer *i*&*j* (Km)	-0.131*	(0.069)
Same gender	0.173*	(0.103)
Age in years (difference)	-0.006	(0.004)
Age in years (sum)	0.001	(0.003)
Education in years (difference)	-0.012	(0.013)
Education in years (sum)	0.001	(0.013)
Veg. area in acres (sum)	-0.073**	(0.032)
Veg. area in acres (difference)	-0.037	(0.040)
Same soil quality	-0.004	(0.093)
Both *i*& *j* are in the lower 2 income quintiles(poor)	-0.045	(0.145)
Both *i*& *j* are in the upper 2 income quintiles (rich)	0.160	(0.171)
Farmer *i* is rich & farmer *j* is poor	0.139	(0.161)
Traders are main source of veg.mkt info. (for one)	-0.069	(0.090)
Both in Kikuyu/Westlands/Dagoretti region	-0.094	(0.135)
Constant	0.114	(0.525)
Number of observations	*884*	

Notes: ∗∗∗p<0.01; ∗∗p<0.05; ∗p<0.1; HVM, high-value channels; TM, traditional market; Farmer *i* is the respondent and farmer *j* is the match; *i* is obtaining information from *j;* standard errors are clustered at farmers *i's* and *j's* level; [a]base category is "Both *i & j* are TM farmers"; All variables are lagged to 2008 except for "same soil quality", where we use 2012 values, because these data were not collected in 2008

Geographical distance matters as well. The likelihood of the existence of information link increases if farmers are living in the same village, and decreases if they are living far from each other. This affirms the importance of distance in network formation as it reduces the cost of forming a link. This is also in line with findings of past research e.g. Conley and Udry (2010) and Maertens and Barrett (2013).

Farmers' previous choice of supply channel also play a role in spreading market information. Farmers who previously supplied HVM are more likely to exchange vegetable market information among themselves compared to those who supplied TM. This is not unexpected. As discussed earlier, supplying HVM requires more information than supplying TM, and farmers who have previously supplied HVM would be in the best position to offer practical information on what works in that market. Furthermore, HVM farmers are likely to have short social distance, hence lower cost of forming and maintaining a link. We also find that farmers who previously participated in HVM are likely to form a link with TM farmers. However, only HVM farmers are likely to obtain vegetable marketing information from TM farmers, but we do not find evidence of the reverse. This can be explained by the fact that HVM farmers might be dissatisfied with some aspects of supplying HVM and therefore may seek information regarding TM. During the survey, HVM farmers, especially those supplying in supermarkets, expressed dissatisfaction regarding rejection of produce by supermarkets. This may be one of the factors that would drive them to seek information regarding supplying TM.

2.5.2 Effects of HVM Information Links on Farmer Participation

To address our second research question, i.e., to find out the effect of having information links with farmers that previously supplied HVM on farmer's own probability of participation, we use probit model presented in equation (2.5), and Table 2.3 presents results from the estimation. The marginal effect of the first information link variable, (HVM link within sample), is positive and significantly correlated with participation in HVM as expected (Table 2.3). Having an information link with at least one farmer who previously supplied HVM increases farmer's own probability of participation in HVM by 10 percentage points. The second information link variable, (HVM link outside sample) also has a positive and significant effect on participation. Having an information link with

at least one previous HVM farmer outside our sample increases farmer's probability of participation in HVM by 19 percentage points.

Other factors that significantly influence participation in emerging HVM are farmer characteristics such as gender and years of education, being in off-farm employment, infrastructure related factors such as access to electricity and short distance to tarmac road. These results are in line with findings of previous studies (Hernández et al., 2007; Rao & Qaim, 2011; Andersson et al., 2015). Conversely, coming from Limuru region is negatively correlated with participation in HVM. This could be explained by two factors: two wholesale markets operate within Limuru area. Therefore, farmers in this area have an advantage over other farmers in other regions in terms of TM choices. In addition, there was an NGO that was linking farmers to supermarkets in 2008, and this NGO worked less with farmers in Limuru area compared to other regions.

Table 2.3.Effects of HVM information links on probability of supplying HVM: Probit model results

	Marginal effects	Robust std. errors
HVM link within sample	0.096**	0.039
HVM link outside sample	0.190***	0.039
Trader as source of information	0.024	0.038
Complain of vegetable rejection	-0.010	0.042
Participation in NGO activities	0.005	0.053
Male farmer	0.081*	0.045
Farmer education	0.013**	0.006
Age of farmer	-0.001	0.012
Age of farmer squared	0.000	0.000
Household size	0.005	0.012
Off farm income	0.069*	0.040
Electricity access	0.157***	0.061
Farm size (acres)	0.014	0.009
Livestock ownership	-0.019	0.052
Irrigation technology	0.064	0.064
Own means of transport	0.068	0.063
Access to credit	-0.106*	0.061
Distance to the tarmac road	-0.030***	0.009
Limuru region	-0.155*	0.091
Kikuyu/westlands/dagoretti region	0.047	0.070
Number of observations	*331*	
Chi^2	*91.57***	

Notes: * p< 0.10, ** p< 0.05, *** p< 0.01; HVM, high-value market; All variables are lagged to 2008 except for the two information link variables, where we use 2012 data, because these data were not collected in 2008

2.5.3 Effects of Information Network on Participation Dynamics

To address our third objective, i.e., the effect of having information links with other farmers that previously supplied HVM on farmers' own participation dynamics; we undertake further analysis using multinomial logit models. Results are presented in Table 2.4. Having information links with HVM farmers increases farmer's own probability of participation in HVM. Both information link variables ("HVM link within sample" and "HVM link outside sample") have a positive effect on farmers being in HVM stayers category (as opposed to being in any other category). HVM information links increase the probability of farmers staying in HVM by 5 to 10 percentage points but decreases the probability of staying in TM (TM stayers) by 9 to 16 percentage points. Also, having information links with HVM farmers increases farmers' own probability of joining HVM by 5 percentage points (for HVM link outside sample).

Table 2.4.Effect of HVM information links on HVM participation dynamics: Multinomial logit results

	HVM stayers	HVM newcomers	HVM dropouts	TM stayers
HVM link within sample	0.045**(0.021)	0.035(0.026)	0.008(0.023)	-0.088**(0.041)
HVM link outside sample	0.097***(0.030)	0.053* (0.028)	0.014 (0.026)	-0.164***(0.045)
Trader as source of information	0.015(0.019)	0.002 (0.024)	0.030 (0.022)	-0.047(0.040)
Complain of veg. rejection	0.010(0.019)	-0.019 (0.030)	0.001 (0.029)	0.008(0.046)
Participation in NGO activities	0.067**(0.033)	-0.067 (0.046)	0.131***(0.043)	-0.131*(0.069)
Male farmer	0.030(0.024)	0.039 (0.031)	-0.011 (0.025)	-0.058(0.048)
Farmer education	0.007**(0.004)	0.003 (0.004)	0.003 (0.003)	-0.013*(0.007)
Age of farmer	0.003(0.005)	-0.002(0.008)	0.005(0.006)	-0.007(0.013)
Age of farmer squared	-0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)	0.000(0.000)
Household size	-0.005 (0.006)	0.007(0.008)	-0.012*(0.007)	0.011(0.014)
Off farm income	0.053***(0.019)	0.009(0.025)	0.023(0.025)	-0.084**(0.041)
Electricity access	0.053(0.037)	0.068* (0.035)	-0.017(0.025)	-0.104*(0.058)
Farm size	0.005(0.004)	0.007 (0.006)	0.004 (0.004)	-0.015(0.010)
Livestock ownership	-0.032(0.025)	0.015(0.036)	-0.060*(0.036)	0.076(0.062)
Irrigation technology	0.015(0.038)	0.031(0.040)	-0.013(0.029)	-0.032(0.066)
Own means of transport	0.032 (0.037)	0.020 (0.042)	0.039 (0.031)	-0.090(0.071)
Access to credit	-0.059 (0.037)	0.007(0.035)	0.038 (0.028)	0.015(0.060)
Distance to the tarmac road	-0.010**(0.004)	-0.018***(0.006)	0.002 (0.003)	0.025***(0.008)
Limuru region	-0.059(0.051)	-0.067(0.049)	-0.059 (0.058)	0.185*(0.095)
Kikuyu/Westlands/Dagoretti region	0.041(0.035)	-0.003 (0.040)	0.006 (0.035)	-0.045(0.071)
Number of observations				*331*
Chi^2				*178***

Notes: *p< 0.10, **p< 0.05, ***p< 0.01; HVM, high-value market; TM, traditional market; Marginal effects (at the mean) are reported with robust standard errors in parentheses; All variables are lagged to 2008 except for the two information link variables, where we use 2012 data, because these data were not collected in 2008

We further find that infrastructure, human, and physical capital variables are important determinants of farmers' participation dynamics. Farmers with more education, off-farm employment, living near tarmac road, and those with institutional support linking them to markets are likely to be in HVM stayers category as opposed to being in any other category. On the other hand, those without institutional support, with lower education level, no off-farm employment, and poor infrastructure (electricity and tarmac road) are likely to be in TM stayers category. Infrastructure (electricity access and distance to tarmac road) turns out as important determinant of farmers being in HVM newcomers category. Probability of being in HVM dropout category decreases with livestock ownership (proxy for wealth) and household size (proxy for labor), but increases with participation in NGO market linkage program activities. These findings are in line with results of a recent study analyzing determinants of participation dynamics (Andersson et al., 2015).

2.5.4 Robustness Tests

In this sub-section, we carry out additional analyses to test the robustness of our results. To start with, we undertake further analysis to find out whether matching farmers with different number of matches could bias our results. As discussed in section 2.4, not all farmers were matched with seven matches. Descriptive statistics on number of matches randomly allocated to each farmer show that 79% of the farmers were matched with five to seven farmers, whereas 21% were matched with less than five farmers. As a robustness check, we dropped all individual farmers matched with less than five matches (21%) and undertook analysis on the remaining sample of 700 dyads. Results of the reduced sample are very similar to those of the full sample. The two information link variables that had a positive and significant effect in the full sample also have a positive and significant effect in the reduced sample. The first information link variable "Both *i*& *j* are HVM farmers" has a coefficient of 0.55 whereas "Farmer *i* is HVM, *j* is TM" has a coefficient of 0.43. The magnitudes of both coefficients are very close to those from full sample (Table 2.2).

In the second robustness test, we are interested in finding out whether there are farmers who were only matched with TM-supplying farmers and not a single HVM-supplying farmer. If there are, this could have an influence on whether such households could have HVM information links or not. But could this be driving our results on effect of HVM information links on farmer's own participation? Indeed we find 95 households

were not matched with any HVM-supplying farmer. As robustness test, we dropped these households and undertook our analysis with the reduced sample. Results of the probit model are shown in Table 2.5. Both information link variables have a positive and significant effect on participation in HVM. The magnitude of the marginal effects are also very close to those from the full sample (Table 2.3).

Table 2.5.Effect of HVM information links on probability of supplying HVM: Probit model results with reduced sample

	Marginal effects	Robust std. errors
HVM link within sample	0.118***	(0.041)
HVM link outside sample	0.183***	(0.043)
Trader as source of information	0.018	(0.038)
Complain of vegetable rejection	0.040	(0.040)
Participation in NGO activities	0.054	(0.051)
Male farmer	0.095**	(0.047)
Farmer education	0.014**	(0.007)
Age of farmer	0.014	(0.011)
Age of farmer squared	-0.000	(0.000)
Household size	0.000	(0.012)
Off farm income	0.096**	(0.041)
Electricity access	0.151***	(0.056)
Farm size (acres)	0.015*	(0.008)
Livestock ownership	-0.035	(0.055)
Irrigation technology	0.026	(0.066)
Own means of transport	-0.014	(0.060)
Access to credit	-0.119**	(0.057)
Distance to the tarmac road	-0.034***	(0.009)
Limuru region	-0.145*	(0.088)
Kikuyu/westlands/dagoretti region	0.051	(0.063)
Number of observations	*236*	
Chi^2	*80.48***	

Notes: *p< 0.10, **p< 0.05, ***p< 0.01; HVM, high-value market; Households that were not matched with any HVM-supplying households are excluded in this analysis; All variables are lagged to 2008 except for the two information link variables, where we use 2012 data, because these data were not collected in 2008

Finally, we seek to find out whether the information link variables could be endogenous hence biasing the probit model results on effects of HVM information links on farmer's own participation. One can think of various possible ways in which the information link variables could be potentially endogenous. Social interactions are symmetrical such that farmer *i's* behavior affects the behavior of the network member, and vice versa. Moreover, a farmer could get to know a network member because they share similar characteristics or they supply in the same supply channel and therefore self-select into a specific social network group. Finally, unobserved attributes such as similar

preferences and environment related factors affecting both the decision maker being modeled as well as the behavior of farmers in his/her network could also lead to biased estimates. In our probit model analysis, we have included various variables including soil characteristics, to control for such confounding factors. Nevertheless, we undertake further analysis to check for endogeneity of the information link variables as robustness check of our results.

We employ instrumental variable (IV) approach to address both observed and unobserved bias. The challenge of using IV approach is in finding valid instruments. Instruments need to be exogenous, correlated with the endogenous variable, and uncorrelated with the outcome variable, i.e., the supply channel. We use various instruments that we believe to be valid as explained below.

As instrument for the first information link variable "HVM link within sample" we use gender (male dummy) and average age (years) of the information network members. Characteristics of neighbors have recently been used as instrument for social capital (Andersson et al., 2015). In this recent article, the authors give an extensive discussion on why neighbor characteristics are not likely to affect farmers' choice of supply channel directly, but indirectly through neighbors. Previous research show that farmer characteristics influence own choice of supply channel (Neven et al., 2009). However, social network research show that characteristics of neighbors are not likely to affect farmer's own participation decision (Matuschke and Qaim, 2009; Santos and Barrett, 2010). Therefore, we expect that characteristics of information networks are only likely to have an indirect effect on farmers' participation decision through information networks.

For the second information link variable "HVM link outside sample", we use average distance to other HVM-supplying farmers that the respondent has information link with outside our sample, as the instrument. As shown in the social network literature, distance is a key determinant in existence of an information link (Conley & Udry, 2010; Maertens & Barrett, 2013). A social network link is more likely between farmers located near each other, since the cost of social interaction would be lower than when farmers are located far apart. At the same time, distance between information network members is not likely to have a direct effect on their choice of supply channel.

All our instruments are statistically significant in the first stage regression implying that they are important in explaining the specific information link variables. The test of over identifying restrictions fail to reject the null hypothesis that the instruments are uncorrelated with the error term (p-value=0.152). Furthermore, the Wald test of exogeneity fails to reject the null hypothesis that the two information variables are exogenous (p-value=0.153). Therefore, we conclude that the two information link variables are exogenous

2.6 Conclusion and Policy Recommendations

In this study, we have combined the literature on social networks and emerging high-value supply chains to elicit the importance of information networks when choosing agricultural output markets. Precisely, we focus on informal farmer interactions to exchange information, what we call 'information links'. In our definition, an information link exists if farmers exchange information on possible vegetable marketing options. In this paper, we have analyzed three aspects. First, the determinants of the existence of information links between farmers using dyadic probit models. Second, we have assessed the effects of having information links with other farmers that previously supplied HVM on farmers' own probability of participation in HVM using probit models. Finally, using multinomial logit models, we have assessed the effects of having information links with other farmers that previously supplied HVM on farmers' own participation dynamics including joining, dropping, or supplying HVM over a two time period: 2008 and 2012.

Analysis of social effects is usually beset by econometric challenges like selection bias, simultaneity and correlated unobservable variables. In our analysis, we attempted to tackle these challenges in various ways such as including several variables that would capture unobserved characteristics and lagging some variables that we had past data on to avoid simultaneity. We also undertook various robustness checks including using instruments.

Our results show that HVM farmers are obtaining vegetable marketing information from fellow HVM farmers and also from TM farmers. We however, do not find evidence that TM farmers are obtaining marketing information from HVM farmers. Further, we find that having information links with other farmers that previously supplied HVM increase probability of farmers' own participation in HVM by 10 to 19 percentage

points. Results of the multinomial logit model show that access to market information is likely to enhance farmers' participation in HVM overtime, and decrease the probability of supplying TM overtime. This is plausible because farmers would be interested to participate in the most lucrative channel.

Our results have important policy implications for dissemination of market information. To start with, it is important that market information is disseminated to farmers so that they can make informed market choice decisions. Informal information systems like social network would be a pathway to disseminate such information: our findings show that these networks have an effect on farmers' decision making on choice of marketing channel. The findings that there is flow of market information among HVM farmers and that HVM obtain market information from TM farmers and not the vice versa, has important implications. Given that HVM-supplying households are mostly the more wealthy ones and those with larger farms, further development of the HVM is likely to aggravate the inequality between small and large farmers through differential access to information. Therefore, governments need to put in place other mechanisms to support the informal information networks in spreading market information. For example, the agricultural extension officers can disseminate market information through small groups at the village level, while ensuring inclusive engagement of all farmers (those supplying HVM and TM) in such groups.

The findings that information networks increase the probability of participation in HVM, and that of staying in HVM imply that participation in HVM is likely to increase as farmers attain information about these markets. Therefore, it is vital to avail market information to farmers to increase participation. Furthermore, increased participation in HVM is likely to results in positive welfare effects in terms of household income, household nutrition, productivity, and employment creation as shown in past research, and this is likely to have an effect on overall economic development.

Our results should be taken as an analytic evidence for the important role played by information networks in choice of supply channel. Even though our study is tailored to the specific context of smallholder vegetable farmers in rural Kenya, the findings have broader applicability to other areas of developing countries experiencing rapid growth of supermarkets and other emerging high-value markets, while at the same time facing challenges of accessing market information. This study being the first to use informal

social networks data in the context of modern supply chains makes a great contribution both in the social network and HVM literature. However, more research in this direction is needed. This would for instance be a study using complete panel data on social networks and combining social network with behavioral field experiments to capture unobserved endogeneity.

3 Impacts of Supermarkets on Farm Household Nutrition in Kenya[4]

Abstract. Many developing countries experience a food system transformation with a rapid growth of supermarkets. We analyze impacts of supermarkets on farm household nutrition with survey data from Kenya. Participation in supermarket channels is associated with significantly higher calorie, vitamin A, iron, and zinc consumption. We use simultaneous equation models to analyze impact pathways. Supermarket-supplying households have higher incomes, a higher share of land under vegetables, and a higher likelihood of male control of revenues. Furthermore, income and the share of land under vegetables have positive impacts, while male control of revenues has negative impacts on dietary quality. Policy and further research implications are discussed.

3.1 Introduction

In the recent past, many developing countries have experienced a profound food system transformation with a rapid growth of supermarkets (Timmer, 2009; Neven et al., 2009; Minten et al., 2010; Reardon et al., 2012). This supermarket growth can be attributed to both demand and supply side factors (Reardon et al., 2009; Mergenthaler et al., 2009; Lakatos & Fukui, 2014). On the demand side, rising incomes, urbanization, and changing lifestyles contribute to preference shifts towards higher-value foods, including processed and convenience products, which modern retailers are better equipped to provide than traditional markets (Rischke et al. 2015). On the supply side, the supermarket growth was facilitated by policy changes such as market liberalization in the food industry and greater openness for foreign direct investment. This retail revolution has also caused structural changes along the supply chains. Supermarkets try to offer their customers a consistent variety of high-quality products. To ensure continuous supply, supermarkets have established their own procurement systems, involving centralized buying points and

[4] This chapter is co-authored by Camilla Andersson and Matin Qaim. The following roles were performed by me: conceptualization and designing of the study in cooperation with all co-authors; implementing the survey in cooperation with Camilla Andersson; data analysis; interpretation of research results in cooperation with all co-authors; writing of the paper in cooperation with Matin Qaim; and revision of the paper with all co-authors. This paper was accepted for publication in *World Development* in March 2015.

contractual arrangements with farmers and traders (Reardon & Berdegué, 2002; Reardon et al., 2009; Rao et al., 2012).

Several studies have analyzed impacts of farmer participation in these new supermarket channels on farm productivity (Hernándezet al., 2007; Nevenet al., 2009; Rao et al., 2012), sales prices (Michelson et al., 2012), household income (Miyata et al., 2009; Rao & Qaim, 2011; Michelson, 2013; Andersson et al., 2015), and labor markets (Neven et al., 2009; Rao & Qaim, 2013). Most of these studies conclude that supermarkets can contribute to rural economic growth and a modernization of the small farm sector. Strikingly, however, there is no research that has analyzed possible impacts of supermarkets on farm household nutrition (Gomez & Ricketts, 2014; Popkin, 2014). While recent research has examined how supermarkets may influence dietary habits and nutrition of urban consumers (Neven et al., 2006; Pingali, 2007; Asfaw, 2008; Tessieret al., 2008; Rischke et al., 2015; Kimenju et al., 2015), a focus on farm household nutrition is important, too. Smallholder farmers make up a large proportion of the undernourished people worldwide.

In this article, we address this research gap and analyze the impacts of supermarkets on farm household nutrition, using detailed survey data specifically collected for this purpose. We contribute to the literature in two ways. First, we add a new perspective to the existing body of literature on supermarket impacts. Second, we contribute conceptually to the analysis of agriculture-nutrition linkages. Given the persistently high rates of rural undernutrition, the international community has shown a renewed interest in better understanding the nutrition and health impacts of agricultural innovations (Dube et al., 2012; Smith & Haddad, 2015). Yet, very few studies have evaluated such impacts; identifying suitable methodologies has proven a challenge (de Haen et al., 2011; Masset et al., 2012; Kabunga et al., 2014).

Our study focuses on smallholder farmers in Kenya. Kenya is an interesting example because supermarkets have rapidly gained in importance there in recent years. Supermarkets in Kenya now account for about 10% of national grocery sales, and over 20% of food retailing in major cities (Planet Retail, 2015). Whereas this share in Kenya is still lower than in middle-income countries in Asia and Latin America, it is already higher than in most other countries of sub-Saharan Africa. Based on detailed food consumption data, we compare nutritional indicators between farm households with and without supermarket contracts. In addition to calorie intakes, we analyze levels of micronutrient

consumption as indicators of nutritional quality. Possible issues of selection bias are addressed with an instrumental variable approach. We also analyze impact pathways. Participation in supermarket channels may affect household nutrition through increasing cash incomes. Moreover, supermarket contracts may influence the farmers' choice of commodities produced, and thus the types of foods available in the household from own production. Finally, there may be changes in gender roles within the farm family that could also affect household nutrition (Sraboni et al., 2014; Imai et al., 2014). Earlier research showed that commercialization of agriculture is often associated with men taking over control of resources that were previously controlled by women (von Braun & Kennedy, 1994). We develop and estimate simultaneous equation models to analyze such impact pathways.

3.2 Farm Household Survey

In 2012, we carried out a survey of smallholder vegetable farmers in Kiambu District, Central Province of Kenya (after the constitutional change in Kenya this is now Kiambu County). Kiambu is relatively close to Nairobi and is the capital's main source of horticultural produce (Rao & Qaim, 2011). Some of the farmers in this region produce vegetables for supermarkets, while others sell their vegetables in traditional channels. The two biggest supermarket chains sourcing vegetables from Kiambu are Nakumatt and Uchumi, which are both Kenyan owned. Foreign owned retail chains so far play a much smaller role in Kenya (Planet Retail, 2015).

Based on information from the district agricultural office, four of the main vegetable-producing divisions were chosen. In these four divisions, 31 administrative locations were purposively selected, again using statistical information on vegetable production. Within the locations, vegetable farmers were sampled randomly. In total, our data set comprises observations from 384 farm households – 85 that participated in supermarket channels and 299 that sold only in traditional channels. These households were visited, and household heads were interviewed face-to-face, using a structured questionnaire that was carefully designed and pretested. The data collected include general household characteristics, details on vegetable production and marketing, other farm and non-farm economic activities, food and non-food consumption (see below for details), and various institutional variables.

Sample households are typical smallholder farmers with an average farm size of about 2 acres (0.8 hectares). These households produce vegetables that are exotic to Kenya, such as kale, spinach, and cabbage, as well as Kenyan indigenous vegetables like black night-shade and amaranth. In addition, sample households are engaged in other agricultural activities such as the production of staple and cash crops like maize, beans, tea, and coffee. Many are also involved in small-scale livestock farming. Table 3.1 shows sample descriptive statistics for a number of socioeconomic variables that are used as controls in the regression analysis below. In addition to the household head, we captured some information about gender relations within the household. Eighty-nine percent of the sample households are headed by males. Household heads have 9.6 years of formal schooling on average. In contrast, the main female in the household, who in most cases is the spouse of the household head, has a formal education of only about one year.

Table 3.1.Summary statistics of farm and household variables by marketing channel

Variables	Full sample		Supermarket channel		Traditional channel	
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
Farm land owned (acres)	2.06	2.9	2.82**	3.7	1.84	2.6
Share of area grown with vegetable (%)	53.24	29.0	60.35*	30.0	51.22	28.4
Annual household income (1000 Ksh)	471.69	737.8	938.48***	1160.4	338.99	490.2
Household assets (100,000 Ksh)	2.32	5.7	4.16***	8.6	1.79	4.5
Off-farm income (dummy)	0.70	0.5	0.82**	0.4	0.66	0.5
Annual off-farm income (1000 Ksh)	148.43	301.7	291.94***	508.2	107.64	191.4
Distance to market (km)	3.05	3.6	2.78	1.9	3.13	3.9
Credit access (dummy)	0.17	0.4	0.22	0.4	0.16	0.4
SM farmers among 5 nearest neighbors (number)	0.97	1.4	2.27***	1.7	0.60	1.0
Male household head(dummy)	0.89	0.3	0.95*	0.2	0.87	0.3
Age of household head(years)	51.75	13.5	51.12	12.8	51.93	13.8
Education of household head (years)	9.59	3.7	10.55**	3.3	9.31	3.8
Education of main female (years)	0.97	3.0	0.25*	1.4	1.18	3.3
Male control over vegetable revenue (dummy)	0.73	0.5	0.85**	0.4	0.69	0.5
Number of observations	*384*		*85*		*299*	

Notes: Ksh, Kenyan shillings; SM, supermarket. The official exchange rate in 2012 was 1 US dollar = 85 Ksh.

Table 3.1 also reveals that there are significant differences between supermarket and traditional channel farmers with respect to several socioeconomic variables. This is because farmers self-select into the group of supermarket suppliers according to their conditions and preferences, which needs to be accounted for in the impact analysis.

Supermarket farmers tend to be wealthier and more educated than farmers in traditional channels. Following Fischer & Qaim (2012a), survey respondents were also asked which household member controls vegetable production and revenue. To ensure collection of reliable information, enumerators were trained to ask these questions and confirm the responses from various perspectives. As can be seen in Table 3.1, males control the revenues from vegetable production in 85% of the supermarket-supplying households. In traditional channel households, this number is significantly lower with 69%.

Supermarket and traditional channels also differ considerably with respect to marketing conditions. Traditional channel farmers have no advance agreements with the buyers of their vegetables. They either sell to traders at the farm gate or in traditional wholesale markets without any promise of repeated transactions. There is no market assurance in traditional vegetable channels, and prices tend to be volatile. In contrast, supermarket farmers have agreements, either with the supermarkets directly or with specialized agents. These agreements are mostly verbal in nature; they specify vegetable quantities, quality, and form of supply. Prices in supermarket channels are stable and higher than in traditional channels. For actual delivery, supermarket farmers are contacted via mobile phone a few days in advance and asked to deliver a certain lot at a particular time. Farmers have to transport their produce themselves to the supermarkets in Nairobi. Vegetables have to be cleaned and bundled before delivery, ready for the supermarket shelves. Payments are usually made with a delay of one or two weeks. Hence, while supplying supermarkets is attractive in terms of price incentives, farmers with high opportunity costs of time and limited access to transportation and credit are less likely to participate. These observations are consistent with earlier research in Kenya (Neven et al., 2009; Rao & Qaim, 2011; Andersson et al., 2015).

The 299 traditional channel farmers in our sample sell their vegetables only in traditional channels. The 85 supermarket farmers sell most of their vegetables to supermarkets. Only if the quantities produced exceed the contractual agreement, supermarket farmers sell these excess quantities in traditional channels. A few households in our sample sold their vegetables under contract to hotels or schools. As the contracts with hotels and schools are similar to the agreements with supermarkets, these few households are classified as supermarket farmers for the purpose of this analysis.

3.3 Indicators of Household Nutrition

3.3.1 Measurement Approach

The main objective of this study is to analyze the impacts of supermarket participation on household nutrition. This requires identification of suitable nutrition indicators that can be used as outcome variables. Various possible indicators exist (de Haen et al., 2011). Recent studies have used data on food expenditure or households' subjective food security assessment in evaluating impacts of new agricultural technologies (Shiferaw et el., 2014; Kabunga et al., 2014). Other studies have used data on child anthropometrics (Masset et al., 2012). While these approaches are useful to capture certain dimensions of food insecurity and undernutrition, they are not suitable to analyze impacts in terms of household nutrition behavior and dietary quality. In order to examine such aspects, we collected detailed information on household food consumption.

We included a 7-day food consumption recall in the survey. To ensure accurate information, this part of the interview was carried out with the person in the household responsible for food choices and preparation. This person was mostly a female household member who often responded together with the household head. Details on food quantities consumed from own production, purchases, transfers, and gifts were collected for over 180 food items. These data were used to calculate daily calorie consumption in each household as well as consumption levels of certain micronutrients (The term "consumption" refers to everything that enters the household. Sometimes, this is also referred to as "availability", which may differ from actual intake levels, as is explained below). We concentrate on vitamin A, iron, and zinc, because deficiencies in these micronutrients are widespread and constitute serious public health problems in many developing countries (Black et al., 2008; Stein et al., 2008).

To calculate calorie and micronutrient consumption levels, reported food quantities were corrected for non-edible portions. Edible portions were converted to calorie and nutrient levels using food composition tables for Kenyan foods (FAO, 2010; Sehmi, 1993). In a few cases where individual food items could not be found, other international food composition tables were consulted (FAO, 2012; USDA, 2005). To make values comparable across households, we divided by the number of adult equivalents (AE), taking into account household size, demographic structure, and levels of physical activity. One AE is equal to a moderately active adult male. In these

calculations, it is assumed that food within the household is distributed according to individual calorie and nutrient requirements (IOM, 2000; FAO, WHO, UNU, 2001).

For micronutrients, losses during cooking had to be accounted for (Bognár, 2002). Furthermore, issues of bioavailability need to be considered. Bioavailability of iron and zinc in particular depends on the composition of meals, as body absorption is influenced by enhancing and inhibiting factors (IZiNCG, 2004; WHO & FAO, 2004). Since we do not have information on the exact composition of meals, we had to make assumptions based on the literature and knowledge about local food habits in the study region. For iron, WHO & FAO (2004) provide a bioavailability range of 5-15%; we assume low iron bioavailability of 5%. For zinc, IZiNCG (2004) differentiates between mixed/refined vegetarian diets and unrefined, cereal-based diets. We assume unrefined, cereal-based diets and low zinc bioavailability of 15%. This is consistent with assumptions made by WHO & FAO (2004) for Kenya.

To determine calorie and micronutrient deficiency, we compare amounts consumed with standard levels of requirements. For calories, a daily intake of 3000 kcal is recommended for a moderately active male adult (FAO, WHO, &UNU, 2001). Moreover, it is recommended that a safe minimum daily intake should not fall below 80% of the calorie requirement. Based on this, we use a minimum intake of 2400 kcal per AE and categorize households below this threshold as undernourished. Following WHO & FAO (2004), we use daily estimated average requirements (EAR) per AE of 625 µg of retinol equivalent (RE) for vitamin A, 18.3 mg for iron, and 15.0 mg for zinc. Households with consumption levels below these thresholds are categorized as deficient.

While our approach of using household food consumption data to measure nutrition is useful to assess possible impacts on food security and dietary quality, it also has a few limitations (de Haen et al., 2011; Fiedler et al., 2012). First, by using a single 7-day recall we cannot account for seasonal variation in food consumption. Second, we are not able to account for intra-household food distribution. Third, the 7-day recall data measure consumption levels, which are only a crude proxy of actual food and nutrient intakes. Food wasted in the household or portions given to guests or fed to pets cannot always be fully accounted for, which may result in overestimated intake levels. Furthermore, as explained above, issues of bioavailability have to be approximated. While these limitations have to be kept in mind, we do not expect a systematic bias in our

impact assessment, because the same issues hold for both supermarket and traditional channel farmers

.

3.3.2 Nutrition Indicators by Marketing Channel

Table 3.2 shows the calculated nutrition indicators for the sample of households. On average, households consume 3258 kcal, 1374 μg of vitamin A, 17 mg of iron, and 21 mg of zinc per day and adult equivalent (AE). The standard deviations in the sample are relatively high. About 21% of all households are undernourished. For vitamin A and zinc, the prevalence of deficiency is in a similar magnitude; the prevalence of iron deficiency is much higher with an estimated 64%.

Table 3.2.Nutrition indicators by marketing channel

Nutrition indicators	Full sample		Supermarket channel		Traditional channel	
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
Calorie consumption (kcal/day/AE)	3258	1081.9	3348	1206.2	3232	1044.7
Prevalence of undernourishment (%)	21	40.7	19	39.3	21	41.1
Vitamin A consumption (μg RE/day/AE)	1375	926.3	1449	825.5	1354	953.3
Prevalence of vitamin A deficiency (%)	16	37.1	14	35.0	17	37.7
Iron consumption (mg/day/AE)	17	7.2	17	7.4	16	7.1
Prevalence of iron deficiency (%)	64	48.0	62	48.7	65	47.8
Zinc consumption (mg/day/AE)	21	7.8	22	8.7	21	7.5
Prevalence of zinc deficiency (%)	24	42.9	24	42.7	24	43.0
Number of observations	*384*		*85*		*299*	

Notes: AE, adult equivalent; RE, retinol equivalent. A household is categorized as undernourished when calorie consumption is below 2400 kcal per AE and day. Micronutrient deficiencies are categorized as daily consumption levels below625μg of RE for vitamin A, 18.27mg for iron, and 15 mg for zinc. These deficiency thresholds are further discussed in the text.

The comparison between the two groups of farmers shows that supermarket suppliers have slightly higher levels of calorie and micronutrient consumption than traditional channel suppliers. Likewise, the prevalence of deficiency is somewhat lower among supermarket farmers for all indicators. However, these differences are small and not statistically significant. It is important to note that these differences should not be interpreted as impacts of supermarket participation or lack thereof. As was shown in Table 3.1, the two groups differ not only in terms of marketing channel but also in terms of several other socioeconomic characteristics. Unlike a controlled experiment with

random assignment of the treatment, we use observational data where farmers self-selected into marketing channels and therefore differ systematically in terms of observed and unobserved factors. Not controlling for these factors might lead to a serious bias in impact assessment. In the next section, we explain the approach that we use to identify unbiased treatment effects of supermarket participation on nutrition.

3.4 Supermarket Impacts on Household Nutrition

We are interested to estimate the impact of supermarket channel participation on household nutrition. This is not straightforward, however. The comparison of supermarket and traditional channel suppliers in the previous section revealed systematic socioeconomic heterogeneity, so that observed differences in the nutrition outcome indicators between the two groups cannot be interpreted as impacts of supermarket participation. Such simple comparison would be possible when using experimental data with random assignment of the treatment, but not with observational data where households have self-selected into treatment. We explain our strategy to avoid self-selection bias in the following.

3.4.1 Regression Framework

To analyze the impacts of supermarket participation on farm household nutrition, we regress the nutrition indicators discussed in the previous section on supermarket participation as treatment variable and a set of control variables as follows:

$$N = \alpha_0 + \alpha_1 SM + \alpha_2 X_1 + \varepsilon_1 \quad (3.1)$$

where N is the nutrition indicator of interest, SM is a dummy for supermarket participation, X_1 is a vector of control variables that are expected to influence household nutrition, and $\varepsilon_1$is a random error terms. α_1 represents the treatment effect. We estimate separate models for calorie, vitamin A, iron, and zinc consumption. Given that previous research showed that supermarket participation has a positive effect on household income, we expect positive treatment effects.

Control variables used as part of the vector X_1 include education, gender, and age of the household head, as well as education of the main female in the household. We also control for household size, land area owned, and the value of non-land assets (e.g.,

machinery and irrigation equipment). To avoid possible issues of reverse causality, we use lagged asset values referring to the situation before households had started to supply supermarkets. Possible issues of endogeneity are also the reason why we do not include current household income. In terms of contextual variables, we control for access to road and transport infrastructure, piped water, and distance to the nearest local food market.

3.4.2 Instrumental Variable Approach

Household nutrition is influenced by a number of factors, not all of which we are able to observe. This is unproblematic for the impact assessment, as long as these unobserved factors are not correlated with the treatment variable. However, if such correlation exists the estimated treatment effect from equation (3.1) will be biased. Due to self-selection and significant correlation between the treatment variable and observed socioeconomic factors, it is in fact likely that unobserved heterogeneity is an issue, if not controlled for. For instance, it is possible that the farmers' entrepreneurial skills jointly affect supermarket participation and household nutrition, but we are not able to observe entrepreneurial skills. We use an instrumental variable (IV) approach to control for self-selection bias. IV approaches are common techniques in the economics literature to reduce self-selection problems and other endogeneity issues in impact assessment (Imbens & Wooldridge, 2009; Deaton, 2010; Winters et al., 2011). The underlying idea is to use an instrument in a first-stage regression to obtain predictions of the treatment variable. These predictions are then used instead of the treatment variable itself in the second stage outcome regression to avoid correlation with the error term.

The challenging part is to find a valid instrument. A valid instrument has to be exogenous, correlated with supermarket participation, but not correlated with the nutrition outcome indicators, except for the indirect effect through supermarket participation (Imbens & Wooldridge, 2009; Kabunga et al., 2014). In that sense, variables such as farmers' education or asset ownership would not qualify as instruments: while human and physical capital endowments are expected to influence supermarket participation, these variables are also likely to affect household nutrition through other channels. Education may influence nutrition awareness; asset ownership may influence income and thus economic access to food in various ways. We identified "the number of supermarket farmers among the five nearest neighbors" as a valid instrument for supermarket participation, as we justify below. The five nearest neighbors are not necessarily the

immediate neighbors, but the five nearest households included in the sample based on GPS coordinates. These are usually households in the same village but can also be households belonging to the neighboring village. In most parts of rural Kenya, including Kiambu, settlements within villages are scattered because people live on the land that they cultivate (Miller et al., 2011; Fischer & Qaim, 2012b). Hence, administrative boundaries are of limited practical relevance; in some cases a household belonging to a neighboring village may be located closer than a same-village household. The average distance of farm households to the five nearest neighbors in our sample is 0.13 kilometers.

In smallholder production systems of Kenya, farms and farmland are inherited from one generation to the next. Especially in the agro-ecologically favorable areas, where land is scarce, migration within rural areas is rare (Miller et al., 2011). Hence, farm households do not actively choose who else lives in their neighborhood, which makes our instrument exogenous to farmers' decisions. Within the sampled locations in Kiambu, we do not observe significant regional clustering in the sense that only farmers with similar characteristics from specific neighborhoods would supply supermarkets. To test for this, we correlated the instrument – the number of supermarket farmers among the five nearest neighbors – with household characteristics such as education, farm size, and the value of other household assets. These correlation coefficients are all small and statistically insignificant (Table A3.1 in the Appendix). We also correlated household income with mean income of the five nearest neighbors, obtaining a small correlation coefficient of 0.09.

However, social interactions between neighboring farm households occur. Recent research showed that farmers' interactions through social networks can significantly influence agricultural technology adoption decisions (Maertens& Barrett, 2013). Similarly, collective action among farmers from the same neighborhood can reduce transaction costs and facilitate access to high-value output markets (Fischer & Qaim, 2012b). In a recent study in Kenya, Andersson et al. (2015) showed that farmers with neighbors that supply supermarkets are much more likely to supply supermarkets themselves, because logistics can be coordinated and the cost of delivering produce to Nairobi be shared. Indeed, our instrument – the number of supermarket farmers among the five nearest neighbors – is closely correlated with own supermarket supply. This

variable is highly significant in all first-stage regression models (Table A3.2 in the Appendix).

When neighboring farmers coordinate their supermarket deliveries and exchange information on marketing, it is possible that they also exchange other types of information, for instance on nutrition, so that our instrument may possibly also have a direct effect on the nutrition indicators in the outcome equations. When correlating the number of supermarket suppliers among the five nearest neighbors with calorie and micronutrient consumption levels, the correlation coefficients are small. Except for vitamin A, they are all insignificant (Table A3.3 in the Appendix). And the significant correlation between the instrument and vitamin A consumption seems to be an indirect effect through supermarket participation. Once we control for supermarket participation and other explanatory variables in a regression model, the instrument coefficient turns insignificant (Table A3.3 in the Appendix). These tests support the validity of the instrument.

We had also tested other instruments, without being able to identify alternatives that meet all criteria of instrument validity. In particular, we tried distance to supermarket, but found that this is not correlated with participation in supermarket channels. We also tried infrastructure variables, such as access to roads and public transportation. Some of these variables are correlated with supermarket participation, but infrastructure also seems to influence household nutrition through other pathways, so that the IV models with these alternative instruments are not properly identified.

We stress that impact assessment with cross-section observational data is always difficult, because perfect instruments are rarely available. Hence, some endogeneity problems might possibly remain, which is important to keep in mind when interpreting the estimates. But the chosen instrument – the number of supermarket suppliers among the five nearest neighbors – seems to be strong. The resulting IV models produce robust results, which are presented in the following.

3.4.3 Estimation Results

The second-stage of the IV models with the nutritional indicators as dependent variables are shown in Table 3.3. The estimated treatment effects are all positive and significant, implying that supermarket participation contributes to improved nutrition. Controlling for other factors, supermarket participation increases calorie consumption by 598 kcal per

adult equivalent (AE), which implies a 19% increase over mean consumption levels of traditional channel households. Iron and zinc consumption levels are both raised by around 3 mg per AE, implying increases of 15-18%. The increase in vitamin A of 1302 μg RE per AE involves almost a doubling of mean consumption levels. This large effect may be due to the specialization on vegetable production in supermarket-supplying households (Rao et al., 2012). Green leafy vegetables are an important source of vitamin A in Kenyan diets, and higher levels of production are likely to cause higher levels of consumption. Further details of impact pathways are analyzed in section 3.5.

Table 3.3.Impact of supermarket participation on calorie and micronutrient consumption

Variables	Calorie (kcal/day/AE)	Vitamin A (μg/day/AE)	Iron (mg/day/AE)	Zinc (mg/day/AE)
SM participation (dummy)	597.46**	1302.41***	3.01*	3.21*
	(244.81)	(325.79)	(1.72)	(1.71)
Male household head (dummy)	20.40	25.85	3.19*	-3.38
	(265.22)	(274.47)	(1.71)	(2.14)
Age of household head (years)	-104.29***	-88.23***	-0.40**	-0.45**
	(32.39)	(32.21)	(0.19)	(0.20)
Age squared	1.02***	0.84***	0.00**	0.00**
	(0.32)	(0.30)	(0.00)	(0.00)
Education of household head (years)	3.31	7.87	0.13	0.09
	(17.18)	(12.43)	(0.11)	(0.12)
Education of main female (years)	0.41	35.49	-0.01	-0.20
	(25.78)	(24.04)	(0.17)	(0.22)
Household size (AE)	-270.56***	-155.55***	-1.24***	-2.95***
	(39.11)	(42.57)	(0.16)	(0.38)
Farm land owned (acres)	-42.12*	-17.32	-0.11	-0.14
	(22.65)	(20.69)	(0.14)	(0.14)
Household assets (100,000 Ksh)	27.02**	4.39	0.08	0.18**
	(12.17)	(7.86)	(0.07)	(0.08)
Access to piped water (dummy)	21.47	57.11	-0.01	-0.05
	(37.49)	(50.50)	(0.23)	(0.23)
Distance to tarmac road (km)	29.18	-0.05	0.26**	0.34***
	(20.38)	(15.68)	(0.11)	(0.12)
Public transport in village (dummy)	-221.63*	-102.08	-0.40	-1.10
	(113.60)	(95.59)	(0.72)	(0.77)
Distance to market(km)	15.81	5.35	0.01	0.04
	(10.36)	(10.99)	(0.07)	(0.08)
Constant	6691.20***	3714.59***	29.49***	42.73***
	(753.61)	(862.82)	(4.80)	(5.01)
Wald chi-squared	*219.33***	*369.27***	*237.23***	*227.59***
F-test of excluded instrument	*86.95***	*86.88***	*85.63***	*87.47***
Number of observations	*384*	*384*	*384*	*384*

Notes. * denotes significance at 10% level; ** denotes significance at 5% level; *** denotes significance at 1% level; SM, supermarket; AE, adult equivalent; Coefficients of instrumental variable models are shown with robust standard errors in parentheses; Results of the first-stage equation are shown in Table A3.2 in the Appendix.

In terms of control variables, we find that households with older household heads have lower calorie and micronutrient consumption levels. Likewise, larger households have consistently lower consumption levels per AE. This is a typical phenomenon when using data from food consumption recalls (Ecker& Qaim, 2011), as larger households tend to use foods more efficiently with less waste. More household assets significantly increase the consumption of calorie and zinc, but not of vitamin A and iron. This underlines that the economic status of a household alone is not a good predictor of healthy and balanced diets. The lower part of Table 3.3 shows selected model statistics. The F-test statistics of the excluded instrument refer to the first-stage equations (Table A3.2 in the Appendix). These statistics confirm that the number of supermarket farmers among the five nearest neighbors is a strong instrument in all four models.

3.5 Analysis of Impact Pathways

3.5.1 Conceptual Framework

Results in the previous section suggest that participation in supermarket channels has positive impacts on household nutrition. So far, however, the pathways through which these impacts occur remain obscure. We hypothesize that nutrition impacts of supermarket participation will mainly occur through three closely related pathways, as shown in Figure 3.1. The first pathway is through possible changes in household income. Several studies showed that participation in supermarket channels can cause significant income gains (Reardon & Berdegué, 2002; Hernándezet al., 2007; Rao & Qaim, 2011; Andersson et al., 2015). Higher incomes improve the economic access to food, which may result in higher calorie consumption, especially in previously undernourished households. Moreover, rising incomes may contribute to better dietary quality and higher demand for more nutritious foods, including vegetables, fruits, and animal products. These changes in demand would also result in improved micronutrient consumption.

The second pathway may be through altered agricultural production choices at the farm level and thus changes in the availability of home-produced foods. Previous studies showed that the commercialization of agriculture is often associated with on-farm specialization (von Braun & Kennedy, 1994). This has also been observed for farms supplying supermarkets (Rao et al., 2012). As mentioned, the supermarket contracts in Kenya are associated with higher price stability; hence they reduce market risk and

provide incentives for farmers to specialize. Similar developments were also observed elsewhere (Michelson et al., 2012). Whether such changes in production choices influence household nutrition in positive or negative directions will depend on the types of commodities that farmers produce under contract. If farmers specialize on cash crops with no or low nutritional value – such as tea, coffee, or cut flowers – dietary quality may not improve. Yet, in our case supermarket farmers specialize on vegetables. This may lead to more vegetable consumption at the household level and thus improved dietary quality. Even if farmers produce vegetables primarily for sale, certain portions that do not meet the stipulated quality standards or that exceed the quantity agreement with supermarkets are likely kept for home consumption.

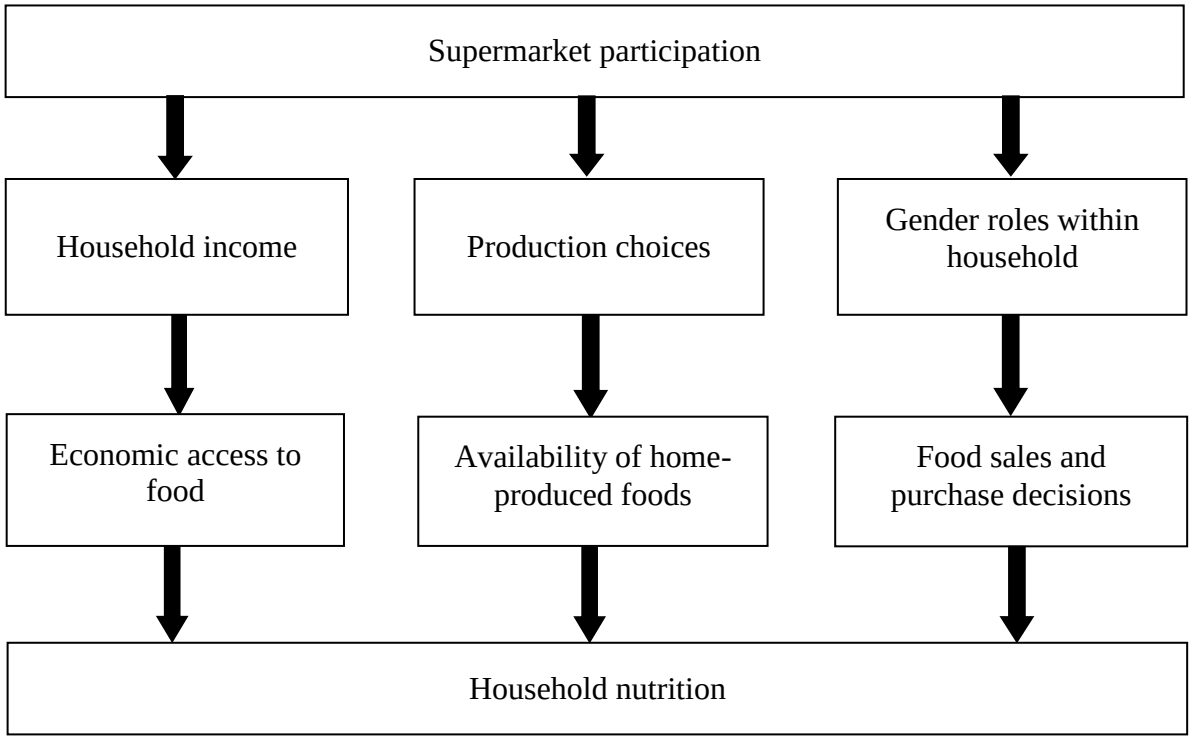


Figure 3.1.Supermarket participation and farm household nutrition: Impact pathways

The third pathway is related to possible changes in gender roles and intra-household decision-making. In many African countries, subsistence food crops are often controlled by women, whereas cash crops are predominantly controlled by men. Accordingly, the process of commercialization may be associated with men taking over domains that were previously controlled by women (von Braun & Kennedy, 1994). Such

changes in gender roles and responsibilities were indeed observed in studies on horticultural supply chains in different African countries (Ezumah & Di Domenico, 1995; Fischer & Qaim, 2012a). A possible shift from female to male control of production and revenue and a loss of women's bargaining power within the household may also have nutrition implications (Sraboni et al., 2014; Imai et al., 2014). Female-controlled income is often more beneficial for household nutrition, because women tend to spend more than men on food, health, and dietary quality (Hoddinott & Haddad, 1995). Hence, supermarket participation may have a negative partial effect on nutrition through this gender pathway.

3.5.2 Empirical Strategy

In order to test the discussed hypotheses on impact pathways empirically, we develop a model of simultaneous equations as follows:

$$N = \alpha_0 + \alpha_1 Y + \alpha_2 SV + \alpha_3 G + \alpha_4 X_2 + \varepsilon_2 \quad (3.2)$$

$$Y = \beta_0 + \beta_1 SM + \beta_2 X_3 + \varepsilon_3 \quad (3.3)$$

$$SV = \sigma_0 + \sigma_1 SM + \sigma_2 X_4 + \varepsilon_4 \quad (3.4)$$

$$G = \delta_0 + \delta_1 SM + \delta_2 X_5 + \varepsilon_5 \quad (3.5)$$

$$SM = \varphi_0 + \varphi_1 SMN + \varphi_2 X_6 + \varepsilon_6 \quad (3.6)$$

where *N* is the respective indicator of household nutrition, which depends on household income (*Y*), the share of farm land under vegetables (*SV*) that we use as a measure of specialization, the gender of the household member who controls vegetable revenues (*G*), and a vector of other control variables (X_2), including household size, education, and other socioeconomic factors. Following the discussion above, *Y*, *SV*, and *G* are influenced by supermarket participation, represented by the *SM* dummy, and additional covariates (X_3 to X_5). However, as discussed above, *SM* is endogenous itself because farmers self-select into the supermarket channel. This is modeled in equation (3.6), where *SM* is explained by the number of supermarket farmers among the five nearest neighbors (*SMN*), which was used as a valid instrument in section 3.4, and a vector of other control variables (X_6).

This system of simultaneous equations, where some of the dependent variables are binary, is estimated with a mixed-process maximum likelihood procedure (Roodman, 2011). We estimate a separate system for each nutrition indicator, namely calorie, vitamin A, iron, and zinc consumption. Except for the dependent variable in equation (3.2), these four systems are specified identically.

3.5.3 Estimation Results

Full estimation results for the four systems of equations are shown in Tables A3.4 to A3.8 in the Appendix of this chapter. Results for the main variables of interest are summarized in Table 3.4. The hypothesized impact pathways are all confirmed. The upper part of Table 3.4 shows that household income has a positive and significant effect on calorie and micronutrient consumption. Likewise, the share of the farm area grown with vegetables influences nutrition positively. Especially the effect for vitamin A is relatively large: an increase in the area share by 10 percentage points increases vitamin A consumption by almost 400 μg RE per AE, implying a 30% increase over mean consumption levels. This sizeable effect should not surprise given that vegetables are a very important source of vitamin A in the local context. The main staple food in Kenya is white maize, which does not contain vitamin A. Other sources of vitamin A are livestock products, which are only consumed in small quantities, due to income constraints. The results in Table 3.4 further show that male control of vegetable revenues has large negative effects on calorie and micronutrient consumption, which we attribute to gender differences in income use, as discussed above.

The lower part of Table 3.4 shows how supermarket participation affects these important determinants of household nutrition. Depending on the particular model, selling vegetables in supermarket channels increases annual household income by 300,000 Ksh, implying a gain of over 60%. This is consistent with earlier research on supermarket impacts in Kenya (Rao & Qaim, 2011; Andersson et al., 2015). Moreover, as expected, supermarket participation contributes to a higher degree of on-farm specialization on vegetables. On average, and controlling for other factors, the share of the area grown with vegetables is around 20 percentage points higher for supermarket suppliers than for traditional channel farmers. Finally, supermarket participation has a significant effect on gender roles within the household. Selling to supermarkets increases the likelihood of male control of vegetable revenues by over 20 percentage points. This is in line with the

existing literature on agricultural commercialization (von Braun & Kennedy, 1994; Fischer & Qaim, 2012a).

Table 3.4.Impact pathways of supermarket participation

	Calorie (kcal/day/AE)	Vitamin A (µg/day/AE)	Iron (mg/day/AE)	Zinc (mg/day/AE)
Effect on nutrition				
Annual household income (1000 Ksh)	0.501**	0.939***	0.003**	0.004**
	(0.21)	(0.23)	(0.00)	(0.00)
Share of area grown with vegetables (%)	26.769***	39.559***	0.147***	0.168***
	(8.20)	(9.35)	(0.05)	(0.06)
Male control over vegetable revenue (dummy)	-1013.312***	-1346.740***	-8.522***	-7.344***
	(285.98)	(151.24)	(1.27)	(2.09)
Constant	3774.757***	86.549	15.308**	25.227***
	(1235.63)	(1352.08)	(7.40)	(8.59)
Effect on annual household income (1000 Ksh)				
SM participation (dummy)	361.894***	297.791**	342.556***	368.007***
	(129.95)	(123.62)	(127.76)	(131.64)
Constant	-48.625	-14.868	-19.836	-16.395
	(230.85)	(227.00)	(229.49)	(225.13)
Effect on share of area with vegetables (%)				
SM participation (dummy)	20.228**	23.138***	23.144***	17.647**
	(8.89)	(7.21)	(8.43)	(8.90)
Constant	104.841***	102.606***	101.230***	106.068***
	(19.55)	(19.28)	(19.72)	(19.55)
Effect on male control over revenue (dummy)				
SM participation (dummy)	0.224**	0.379***	0.213**	0.213**
	(0.10)	(0.07)	(0.09)	(0.10)
Constant	0.602	0.596	0.365	0.563
	(0.48)	(0.45)	(0.45)	(0.48)
Effect on SM participation (dummy)				
SM farmers among 5 nearest neighbors	0.083***	0.075***	0.080***	0.086***
	(0.01)	(0.01)	(0.01)	(0.01)
Constant	-2.708*	-1.915	-2.792**	-2.319
	(1.41)	(1.19)	(1.36)	(1.48)
LR chi-squared	*507.93***	*485.04***	*520.12***	*517.00***
Number of observations	*384*	*384*	*384*	*384*

Notes: * denotes significance at 10% level; ** denotes significance at 5% level; *** denotes significance at 1% level. SM, supermarket; AE, adult equivalent. Coefficients are shown with standard errors in parentheses. Only the variables of major interest are shown here. Full results of the simultaneous equation models with all control variables are shown in Tables A3.4 to A3.8 in the Appendix of this chapter.

The overall effect of supermarket participation on household nutrition is positive. But the analysis of impact pathways reveals that this overall effect involves both positive and negative partial effects. Hence, it is of interest to know more about the relative magnitude of these partial effects. This can be calculated based on the different model

estimates. For all models, the income effect accounts for 30-40% of the overall effect. The gender effect is in a similar magnitude, but with opposite sign. Hence, the overall effects are strongly driven by the specialization of supermarket farmers on vegetables, which are a rich source of micronutrients in particular. These results are specific to the concrete case and should not be extrapolated to other situations. It is possible that the nutrition impacts would be less favorable in situations where farmers in supermarket channels specialize on producing crops with lower nutritional value.

3.6 Conclusion

Many developing countries are currently experiencing a profound food system transformation, which is associated with a rapid growth of supermarkets. The expansion of supermarkets can also have far-reaching implications for farmers. Recent research has shown that smallholder farmers can benefit in terms of higher productivity and income, provided that they can be linked to the emerging high-value supply chains. In this study, we have analyzed what participation in supermarket channels may mean for farm household nutrition. The analysis contributes to the existing literature in two ways. First, it adds to the knowledge on supermarket impacts; nutrition effects for farm households have not been studied previously. Second, it contributes conceptually to the discussion on agriculture-nutrition linkages by developing a method that is suitable to capture various nutrition dimensions and determinants.

Building on data from smallholder vegetable farmers in Kenya, we have shown that participation in supermarket channels has positive nutrition impacts. We have used detailed food recall data to derive several nutrition indicators, such as calorie, vitamin A, iron, and zinc consumption. While these are not precise measures of individual nutrition status, they provide a reasonable overview of food security and dietary quality at the household level. Controlling for other factors, participation in supermarket channels increases calorie, iron, and zinc consumption by 15-20%. The positive effect for vitamin A consumption is even higher.

In a further step, we have analyzed impact pathways, using simultaneous equation models. We could show that supermarket participation affects household nutrition mainly via three pathways, namely through (1) income, (2) crop production choices at the farm level, and (3) gender roles. The first pathway has a positive effect on nutrition. Farmers who participate in supermarket channels benefit from income gains, and higher incomes

improve the economic access to food. The second pathway has a positive nutrition effect as well. In this particular case, supermarket farmers sell vegetables under contract. As these supermarket contracts provide market assurance and price stability, farmers have an incentive to specialize on vegetable production. More vegetable production also entails higher quantities of vegetables consumed at the household level. Vegetables are an important source of vitamin A in particular, which also explains the large positive impact of supermarket participation on vitamin A consumption. In contrast, the third pathway has a negative effect on nutrition. Supermarket participation contributes to a shift from female to male control of vegetable revenues, and male household members tend to spend less on nutrition and dietary quality. Such a change in gender roles within the household is not uncommon in the process of agricultural commercialization. The total nutrition effects of supermarket participation are positive, but they could be even more positive if a loss of female control of vegetable revenues could be prevented.

These results have two broader implications. First, the food system transformation and the growth of supermarkets in developing countries can contribute to economic development and improved nutrition in the small farm sector. This is an important finding, because smallholder farmers make up a large proportion of all undernourished people worldwide. Policy support may be required in some cases to link small farms to emerging supply chains and overcome constraints in terms of underdeveloped infrastructure and weak institutions. Second, the analysis of impact pathways underlines that a good understanding of the complex interactions between agriculture and nutrition is required to promote desirable outcomes. A clear message from our findings is that the role of women should be strengthened to further improve nutritional benefits. Gender mainstreaming of programs that try to link smallholders to supermarkets and other high-value supply chains would be an important step in this direction.

In spite of the robust findings, our study also has a few limitations that should be mentioned and addressed in follow-up research. First, the analysis builds on cross-section data where farm households self-selected into the supermarket channel. We used an instrumental variable approach to reduce issues of selection bias. While we carefully selected and tested the instrument, it is possible that some endogeneity issues remain. Collecting panel data and using differencing techniques would help to increase the estimates' reliability. Second, nutrition impacts of supermarket participation might change over time, for instance because household consumption behavior is adjusted only

gradually, or because income and gender effects are subject to temporal variability. Such dynamics could not be comprehensively analyzed here. Disaggregation of our results suggests that the nutrition effects are somewhat larger for households that have supplied supermarkets for several years than for new entrants into this supply chain, although the differences are not statistically significant. Again, panel data would be useful to analyze such impact dynamics further. Third, the food consumption data used here are a good indicator of dietary quality but not a precise measure of individual nutritional status. Follow-up research might additionally include anthropometric data, especially for children, as these are more reliable indicators of nutritional status. Fourth, the results estimated here are specific to the concrete situation in Kenya and should not be generalized. Gender effects will differ by social context, and whether further specialization of farm production is good or bad for nutrition will depend on the type of crops supplied to supermarkets. More micro-level research along the lines proposed here will be useful to better understand nutrition impacts under various conditions.

Appendix A3

Table A3.1. Correlation between instrument and farm household characteristics

	Correlation coefficients	*p*-value
Education	0.078	0.130
Gender	0.069	0.177
Farm size	0.042	0.413
Household assets	0.007	0.888

Note: The number of supermarket farmers among the five nearest neighbors is used as instrument for supermarket participation.

Table A3.2. Factors influencing supermarket participation (first stage of IV models)

Variables	Calorie (kcal/day/AE)	Vitamin A(μg/day/AE)	Iron (mg/day/AE)	Zinc (mg/day/AE)
SM farmers among 5 nearest neighbors	0.50***	0.33***	0.49***	0.51***
	(0.06)	(0.09)	(0.06)	(0.06)
Male household head (dummy)	-0.75*	-0.90**	-0.70	-0.77*
	(0.45)	(0.36)	(0.45)	(0.45)
Age of household head (years)	0.03	-0.01	0.04	0.01
	(0.05)	(0.04)	(0.05)	(0.05)
Age squared	-0.00	0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Education of household head (years)	0.05*	0.03	0.05*	0.05*
	(0.03)	(0.02)	(0.03)	(0.03)
Education of main female (years)	-0.16***	-0.12**	-0.16***	-0.15***
	(0.06)	(0.06)	(0.06)	(0.05)
Household size (AE)	0.10	0.19***	0.04	0.19**
	(0.06)	(0.06)	(0.03)	(0.09)
Farm land owned (acres)	0.05	0.05**	0.05	0.04
	(0.03)	(0.03)	(0.03)	(0.03)
Household assets (100,000 Ksh)	0.02*	0.02*	0.02*	0.02*
	(0.01)	(0.01)	(0.01)	(0.01)
Access to piped water (dummy)	-0.01	-0.04	-0.01	-0.02
	(0.07)	(0.07)	(0.07)	(0.07)
Distance to tarmac road (km)	0.01	-0.01	0.01	0.00
	(0.03)	(0.02)	(0.03)	(0.03)
Public transport in village (dummy)	0.34*	0.21	0.35*	0.30
	(0.18)	(0.16)	(0.18)	(0.18)
Distance to market (km)	-0.01	-0.00	-0.01	-0.01
	(0.02)	(0.01)	(0.02)	(0.02)
Constant	-2.77**	-1.06	-2.84**	-2.28
	(1.39)	(1.13)	(1.37)	(1.39)
LR chi-squared	*120.69****	*121.37****	*119.26****	*122.62****
Number of observations	*384*	*384*	*384*	*384*

Notes: * denotes significance at 10% level;** denotes significance at 5% level; *** denotes significance at 1% level. SM, supermarket; AE, adult equivalent; VA, vitamin A. Coefficients are shown with robust standard errors in parentheses.

Table A3.3. Association between instrument and outcome variables with and without controlling for other factors

Instrument	Calorie (kcal/day/AE)	Vitamin A(μg/day/AE)	Iron (mg/day/AE)	Zinc (mg/day/AE)
Correlation coefficient	0.066	0.111	0.078	0.067
	(0.201)	(0.029)	(0.128)	(0.188)
Regression coefficient	-64.803	78.185	-0.393	-0.393
	(0.319)	(0.189)	(0.562)	(0.429)

Notes: The number of supermarket farmers among the five nearest neighbors is used as instrument for supermarket participation. *p*-values are shown in parentheses. The regression models include supermarket participation and the same control variables as those in Table 3.3, in addition to the instrument.

Table A3.4. Impact pathways: factors influencing calorie and micronutrient consumption

	Calorie (kcal/day/AE)	Vitamin A (µg/day/AE)	Iron (mg/day/AE)	Zinc (mg/day/AE)
Annual household income (1000 Ksh.)	0.501**	0.939***	0.003**	0.004**
	(0.21)	(0.23)	(0.00)	(0.00)
Share of area grown with vegetables (%)	26.769***	39.559***	0.147***	0.168***
	(8.20)	(9.35)	(0.05)	(0.06)
Male control over vegetable revenue (dummy)	-1013.312***	-1346.740***	-8.522***	-7.344***
	(285.98)	(151.24)	(1.27)	(2.09)
Household size (AE)	-303.882***	-201.013***	-1.314***	-3.338***
	(40.84)	(45.74)	(0.15)	(0.44)
Male household head (dummy)	468.183	267.478	8.109***	0.360
	(351.46)	(317.26)	(2.05)	(2.53)
Age of household head (years)	-50.627	-21.048	-0.135	-0.146
	(35.21)	(36.53)	(0.21)	(0.24)
Age squared	0.585*	0.323	0.001	0.002
	(0.32)	(0.33)	(0.00)	(0.00)
Education of household head (years)	11.445	22.031	0.084	0.119
	(23.90)	(25.77)	(0.15)	(0.16)
Education of main female (years)	-2.890	-9.527	0.055	-0.177
	(28.39)	(24.24)	(0.17)	(0.20)
Distance to market (km)	17.355	0.699	0.008	0.046
	(17.78)	(18.48)	(0.10)	(0.12)
Distance to tarmac road (km)	69.113**	70.190**	0.508***	0.612***
	(27.01)	(28.23)	(0.16)	(0.18)
Constant	3774.757***	86.549	15.308**	25.227***
	(1235.63)	(1352.08)	(7.40)	(8.59)
LR chi-squared	*507.93***	*485.04***	*520.12***	*517.00***
Number of observations	*384*	*384*	*384*	*384*

Notes: * denotes significance at 10% level;** denotes significance at 5% level; *** denotes significance at 1% level. SM, supermarket; AE, adult equivalent; VA, vitamin A. Coefficients are shown with standard errors in parentheses. The models for calories and for each micronutrient in Tables A3.4 to A3.8 were estimated jointly as simultaneous systems of equations.

Table A3.5. Impact pathways: factors influencing household income

	Calorie model Annual income (1000 Ksh)	VA model Annual income (1000 Ksh)	Iron model Annual income (1000 Ksh)	Zinc model Annual income (1000 Ksh)
SM participation (dummy)	361.894***	297.791**	342.556***	368.007***
	(129.95)	(123.62)	(127.76)	(131.64)
Wealth index	114.649***	127.732***	114.555***	109.133***
	(34.96)	(31.85)	(35.07)	(34.96)
Male household head (dummy)	91.027	92.247	121.036	59.864
	(104.35)	(104.68)	(103.02)	(105.38)
Age of household head (years)	-3.654	-3.702	-3.998	-4.404
	(2.78)	(2.78)	(2.79)	(2.79)
Education of household head (years)	2.106	0.893	2.889	2.034
	(10.93)	(10.85)	(10.98)	(10.88)
Household size (AE)	56.885***	66.141***	30.569**	97.698***
	(21.41)	(24.18)	(12.70)	(31.28)
Off-farm income (dummy)	197.106***	166.342**	193.911***	188.050***
	(69.71)	(67.61)	(69.10)	(69.22)
Farm land owned (acres)	75.003***	75.389***	76.012***	75.415***
	(12.83)	(12.22)	(12.78)	(12.75)
Credit access (dummy)	32.744	63.122	28.666	19.728
	(82.75)	(69.83)	(81.73)	(82.16)
Constant	-48.625	-14.868	-19.836	-16.395
	(230.85)	(227.00)	(229.49)	(225.13)
Number of observations	*384*	*384*	*384*	*384*

Notes: * denotes significance at 10% level;** denotes significance at 5% level; *** denotes significance at 1% level. SM, supermarket; AE, adult equivalent; VA, vitamin A. Coefficients are shown with standard errors in parentheses. The models for calories and for each micronutrient in Tables A3.4 to A3.8 were estimated jointly as simultaneous systems of equations

Table A3.6. Impact pathways: factors influencing share of area grown with vegetables

	Calorie model Vegetable area (%)	VA model Vegetable area (%)	Iron model Vegetable area (%)	Zinc model Vegetable area (%)
SM participation (dummy)	20.228**	23.138***	23.144***	17.647**
	(8.89)	(7.21)	(8.43)	(8.90)
Irrigation (dummy)	11.243***	11.593***	12.265***	11.655***
	(4.30)	(3.80)	(4.55)	(4.52)
Farm land owned (acres)	-2.221***	-1.901***	-2.083***	-2.075***
	(0.54)	(0.52)	(0.56)	(0.55)
Off-farm income (dummy)	-6.283**	-8.920***	-6.756**	-7.717***
	(2.55)	(2.36)	(2.65)	(2.60)
Household assets (100,000 Ksh)	0.388*	0.221	0.275	0.363
	(0.23)	(0.18)	(0.24)	(0.24)
Distance to market (km)	-0.000	0.014	0.046	0.001
	(0.39)	(0.39)	(0.39)	(0.39)
Distance to tarmac road (km)	-1.351***	-1.411***	-1.413***	-1.379***
	(0.51)	(0.51)	(0.51)	(0.51)
Access to piped water (dummy)	-1.268	-0.319	-1.440	-1.447
	(1.19)	(1.08)	(1.29)	(1.24)
Male household head (dummy)	5.354	4.397	4.829	5.713
	(4.41)	(4.37)	(4.42)	(4.39)
Age of household head (years)	-1.147	-1.260*	-1.139	-1.170
	(0.72)	(0.71)	(0.72)	(0.72)
Age squared	0.006	0.007	0.006	0.006
	(0.01)	(0.01)	(0.01)	(0.01)
Education of household head (years)	-2.649**	-1.012	-1.910	-2.670**
	(1.12)	(0.97)	(1.17)	(1.16)
Education squared	0.079	-0.019	0.034	0.083
	(0.06)	(0.05)	(0.07)	(0.07)
Constant	104.841***	102.606***	101.230***	106.068***
	(19.55)	(19.28)	(19.72)	(19.55)
Number of observations	*384*	*384*	*384*	*384*

Notes: * denotes significance at 10% level; ** denotes significance at 5% level; *** denotes significance at 1% level. SM, supermarket; AE, adult equivalent; VA, vitamin A. Coefficients are shown with standard errors in parentheses. The models for calories and for each micronutrient in Tables A3.4 to A3.8 were estimated jointly as simultaneous systems of equations.

Table A3.7. Impact pathways: factors influencing male control over vegetable revenue

	Calorie model Male control (dummy)	VA model Male control (dummy)	Iron model Male control (dummy)	Zinc model Male control (dummy)
SM participation (dummy)	0.224**	0.379***	0.213**	0.213**
	(0.10)	(0.07)	(0.09)	(0.10)
Member in women's group (dummy)[a]	-0.124***	-0.068**	-0.098***	-0.118***
	(0.04)	(0.03)	(0.03)	(0.04)
Male household head (dummy)	0.351***	0.399***	0.359***	0.368***
	(0.10)	(0.10)	(0.09)	(0.09)
Age of household head (years)	-0.005***	-0.006***	-0.004***	-0.005***
	(0.00)	(0.00)	(0.00)	(0.00)
Education of household head (years)	-0.015**	-0.015***	-0.013**	-0.014**
	(0.01)	(0.01)	(0.01)	(0.01)
Household head married (dummy)	0.136	0.073	0.140*	0.127
	(0.09)	(0.08)	(0.08)	(0.08)
Constant	0.602	0.596	0.365	0.563
	(0.48)	(0.45)	(0.45)	(0.48)
Number of observations	*384*	*384*	*384*	*384*

Notes: * denotes significance at 10% level; ** denotes significance at 5% level; *** denotes significance at 1% level. SM, supermarket; AE, adult equivalent; VA, vitamin A. Coefficients are shown with standard errors in parentheses. The models for calories and for each micronutrient in Tables A3.4 to A3.8 were estimated jointly as simultaneous systems of equations. [a] This refers to the main female in the household. Women's groups are involved in various activities, including savings and small-scale credit. Such activities may strengthen the role of women within the household.

Table A3.8. Impact pathways: factors influencing supermarket participation

	Calorie model SM participation (dummy)	VA model SM participation (dummy)	Iron model SM participation (dummy)	Zinc model SM participation (dummy)
SM farmers among 5 nearest neighbors	0.083***	0.075***	0.080***	0.086***
	(0.01)	(0.01)	(0.01)	(0.01)
Farm land owned (acres)	0.013	0.011*	0.015*	0.011
	(0.01)	(0.01)	(0.01)	(0.01)
Own vehicle (dummy)	0.047	0.005	0.057	0.040
	(0.04)	(0.04)	(0.04)	(0.04)
Access to piped water (dummy)	0.005	0.010	0.004	0.003
	(0.02)	(0.02)	(0.02)	(0.02)
Assets before SM (100,000 Ksh)	0.004	-0.000	0.003	0.003
	(0.00)	(0.00)	(0.00)	(0.00)
Distance to tarmac road (km)	0.004	0.007	0.006	0.002
	(0.01)	(0.01)	(0.01)	(0.01)
Male household head (dummy)	-0.148	-0.084	-0.155	-0.163
	(0.12)	(0.10)	(0.12)	(0.12)
Age of household head (years)	0.007	-0.003	0.008	0.002
	(0.01)	(0.01)	(0.01)	(0.01)
Age squared	-0.000	0.000	-0.000	-0.000
	(0.00)	(0.00)	(0.00)	(0.00)
Education of household head (years)	0.011*	0.012**	0.011*	0.011*
	(0.01)	(0.01)	(0.01)	(0.01)
Education of main female (years)	-0.029**	-0.020*	-0.031**	-0.029**
	(0.01)	(0.01)	(0.01)	(0.01)
Household size (AE)	0.013	0.019	0.005	0.031
	(0.01)	(0.01)	(0.01)	(0.02)
Regional dummies	Yes	Yes	Yes	Yes
Constant	-2.708*	-1.915	-2.792**	-2.319
	(1.41)	(1.19)	(1.36)	(1.48)
Number of observations	*384*	*384*	*384*	*384*

Notes: * denotes significance at 10% level; ** denotes significance at 5% level; *** denotes significance at 1% level. SM, supermarket; AE, adult equivalent; VA, vitamin A. Coefficients are shown with standard errors in parentheses. The models for calories and for each micronutrient in Tables A3.4 to A3.8 were estimated jointly as simultaneous systems of equations.

4 Following Up on Smallholder Farmers and Supermarkets in Kenya[5]

Abstract. In many developing countries, supermarkets are expanding rapidly. This affects farmers' marketing options. Previous studies have analyzed welfare effects of smallholder participation in supermarket channels from a static perspective, using cross-section data. We develop a conceptual framework and use panel data to better understand participation and impact dynamics. The analysis focuses on vegetable producers in Kenya. Participation in supermarket channels is associated with income gains. However, many farmers have dropped out of the supermarket channel due to various constraints. The initial income gains cannot be sustained when returning to the traditional market. Organizational support may be needed to avoid widening income disparities.

4.1 Introduction

Global food supply chains are in rapid transition. In developing countries in particular, income increases, urbanization, and globalization have contributed to changing lifestyles and dietary habits (Pingali 2007; Popkin 2014). The increase in demand for readily available food of high quality and variety, together with other factors, has contributed to a large-scale expansion of supermarkets (Reardon et al. 2003; Reardon et al. 2009; Minten et al. 2009; Mergenthaler et al. 2009; Michelson et al. 2012). In fact, the expansion of supermarkets has been of such a scale that the phenomenon is often referred to as a 'supermarket revolution' (Reardon and Gulati 2008; Reardon et al. 2009). This supermarket revolution has raised questions about the wider implications for poverty. Several recent studies have analyzed whether smallholder farmers are able to supply supermarkets, and – if so – what impacts this may have on household welfare (Hernández et al. 2007; Neven et al. 2009; Rao and Qaim 2011). Results suggest that farmers mostly benefit from supplying supermarkets, but that it is often difficult for smallholders to enter these new, high-value supply chains.

[5] This chapter is co-authored by Camilla Andersson, Elizaphan Rao, and Matin Qaim. The following roles were performed by me: conceptualization and designing of the study in cooperation with all co-authors; implementing the survey in cooperation with Camilla Andersson; interpretation of research results in cooperation with all co-authors; and revision of the paper with all co-authors. This chapter was published in the *American Journal of Agricultural Economics* in 2015

One important shortcoming of previous studies is that they mainly rely on cross-section data. This means that the reliability of estimated impacts hinges on either the assumption that supermarket participation is determined by variables that are fully observed or that the instruments employed are valid.[6] Here, we address this shortcoming by using panel data collected from smallholder vegetable farmers in Kenya. In particular, we combine differencing approaches with instrumental variable techniques to better account for possible selection bias.

A second drawback with cross-section data is that the dynamics of supermarket participation cannot be analyzed. Who joins, who stays, and who leaves supermarket channels over time? What are the determinants of these dynamics, and what are the effects on household welfare? For example, is joining the supermarket channel also associated with an income gain for latecomers? Are the early participants gaining more than the latecomers? Can higher income levels of supermarket suppliers be sustained when they return to the traditional market? Do farmers who return to the traditional market earn more or less than farmers who never entered the supermarket channel? And, are income disparities between supermarket and traditional market suppliers increasing or decreasing over time? These are important questions, because supermarkets are still on the rise in many developing countries. Using the panel data from Kenya we address such questions as well.

4.2 Literature Review

Starting from the early-1990s, supermarkets have gained market shares in many developing countries at remarkable speed. Reardon and Gulati (2008) divide this expansion of supermarkets into three distinct waves. The first wave took off in South America, East Asia, and South Africa, where supermarkets increased their market shares from a modest 10% of retail sales in 1990, to 50-60% in the mid-2000s. The second wave started in the mid-1990s in Mexico, Central America, and much of Southeast Asia, where supermarkets increased their market shares from 5-10% to 30-50% by the mid-2000s. The

[6] One exception is Michelson (2013), who used a difference-in-difference estimator to analyze impacts of supermarket participation on household productive assets in Nicaragua. However, data about past asset ownership of supermarket suppliers were collected through a farmer recall, which is less accurate than a real panel data base. Furthermore, we are aware of one recent study that used panel data to evaluate the impact of contracts on farmers' subjective wellbeing in Senegal (Dedehouanou, Swinnen, and Maertens 2013). That study in Senegal focused on the horticultural export sector, not on farmers participating in supermarket channels.

third wave began in the late-1990s in China, India, and Vietnam. By the mid-2000s, the sales of supermarkets in these countries grew at annual rates of 30-50%. Reardon et al. (2008) further recognized a fourth wave taking off in Eastern and Southern Africa, where supermarket shares are still small but growing significantly. In Kenya, the modern retail sector has grown at an annual rate of 19% over the past few years (Kenya National Bureau of Statistics 2012). Supermarkets in Kenya now account for about 10% of national grocery sales; in large cities, the share is already much higher (Planet Retail 2014).

Supermarkets differ from traditional markets in many ways that also affect procurement channels and marketing options for farmers. The basic concept is that produce of certain quality can be sold to consumers continuously. For supermarkets in developing countries, this concept is often difficult to accomplish by sourcing from traditional wholesale markets, where supply is not always reliable in terms of quantity and quality. Hence, especially for horticultural produce, new procurement systems were established, involving specialized supermarket traders, centralized procurement through distribution centers, and the use of 'preferred suppliers' who are able to meet the requirements on quality and consistent supply (Reardon et al. 2008). Often, these preferred suppliers are farmers who are contracted by supermarkets through written or verbal agreements, as is also the case in Kenya (Neven and Reardon 2004; Rao et al. 2012).

The scale of the spread of supermarkets in the developing world together with the new set of requirements for suppliers has spurred a growing body of literature studying whether or not smallholder farmers can be successfully included in these new supply chains. Of particular interest for this article are the studies about participation in the Kenyan horticulture sector by Neven et al. (2009) and Rao and Qaim (2011). Neven et al. (2009) conclude that many smallholders face a capital vector threshold that prevents them from participation in supermarket channels. This vector includes physical capital (irrigation, transport, cell phones etc.), financial capital, human capital, and social or organizational capital. In line with this, Rao and Qaim (2011) show that supermarket participants are more likely to have larger farms, own means of transportation, better education, and off-farm income sources. Many have also participated in an NGO project that specialized on linking smallholder farmers to high-value markets.

Similar results were found elsewhere. Moustier et al. (2010) acknowledge the importance of farmer organizations for supermarket participation in Vietnam. Blandon et al. (2009) highlight the key role of transaction costs and collective action in Honduras. Hernández et al. (2007) stress the importance of assets for participation in Guatemala. Michelson (2013) emphasizes the significant role of farmers' geographic location as well as access to water and transportation for supermarket participation in Nicaragua. Although these studies offer important insights about determinants of participation at one point in time, they do not provide information about participation dynamics, such as factors influencing farmers' decisions to drop out of supermarket channels or join at a later stage.

When it comes to the impact of supermarket participation on household welfare, previous studies have generally found very positive results. For Kenya, Rao and Qaim (2011) showed that participation increases average household income of vegetable farmers by 48%, resulting from higher prices and higher productivity achieved by supermarket suppliers. Michelson (2013) found significant positive impacts of supermarket participation on asset holdings in Nicaragua. Minten et al. (2009) revealed positive effects on income stability and seasonality smoothening in Madagascar. One exception to these positive results is the study by Hernández, Reardon, and Berdegué (2007), who did not find a significant difference in profits between supermarket and traditional channel suppliers in Guatemala, due to much higher expenditures for inputs in the new supply chain.

As always in impact assessment studies, researchers trying to establish the treatment effect of supermarket participation run into the classical evaluation problem: what would have been the outcome for supermarket participants if they had not participated? The mentioned studies used different approaches to address this problem. Rao and Qaim (2011) used an endogenous switching regression model, assuming that participation in a special NGO market linkage project and availability of public transport would affect income only indirectly through the supermarket participation link. Michelson (2013) employed a difference-in-difference approach, for which assumptions are less restrictive, but her data accuracy may potentially be lower due to long recall periods in the farmer survey. Minten et al. (2009) studied perceived impacts among farmers, thus using a subjective outcome measure. Finally, Hernández et al. (2007) compared net incomes between supermarket and traditional channel suppliers without

controlling for possible selection bias. In sum, the validity of previous impact results hinges on a number of assumptions. In their review paper, Reardon et al. (2009) discuss potential issues with cross-section data and suggest panel data analysis to estimate impacts more consistently.[7]

In this article, we use a panel data set collected in two rounds: 2008 and 2012. This allows us to follow the same farmers over time and study changes in income as these farmers join or leave supermarket channels. Thus, we can control for selection on unobserved time-invariant variables. We use instruments to test for possible bias through time-variant heterogeneity. Furthermore, the panel data allow us to analyze how possible income differences between supermarket and traditional channel suppliers develop over time.

4.3 Conceptual Framework

We are particularly interested in two research questions that were not sufficiently addressed in the previous literature. First, what factors influence the dynamics of smallholder participation in supermarket channels, or high-value markets more generally? Second, what are the impacts of these dynamics on household income?

4.3.1 Dynamics of Smallholder Participation

As mentioned in the literature review, previous studies suggest that participation in high-value markets (HVM) depends positively on access to various types of capital such as physical, financial, human, and social capital. To analyze the dynamics of smallholder participation, we use a diagrammatic framework with access to two types of capital on the axes, as shown in Figure 4.1. To make the description more intuitive, we can think of 'capital 1' as physical capital and 'capital 2' as social capital. Physical capital includes equipment and finance required for high-value production (such as technology, means of transportation, and credit), whereas social capital involves the farmers' social network and collective action that may be important for accessing information and reducing transportation and transaction costs. In panel (a) of Figure 4.1, farmers are uniformly distributed in the plane, depending on their individual access to the two types of capital. Farmers with low access to physical and social capital supply traditional markets (TM),

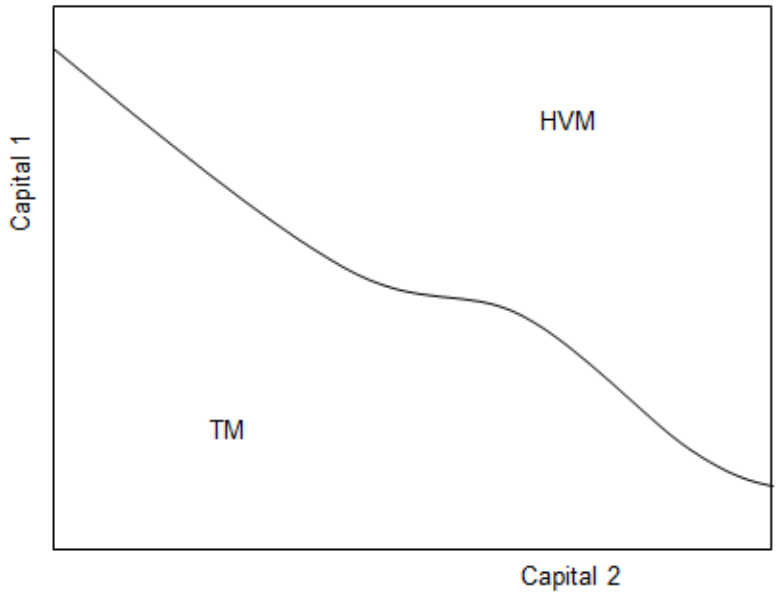
[7] Potential endogeneity problems in econometric studies were also acknowledged by Stokke (2009), who used numerical simulations in a structural framework to analyze supermarket impacts.

whereas farmers with better access are more likely to supply HVM. In the graph, farmers located on the dividing line between the HVM and TM regions are indifferent between the two marketing options.

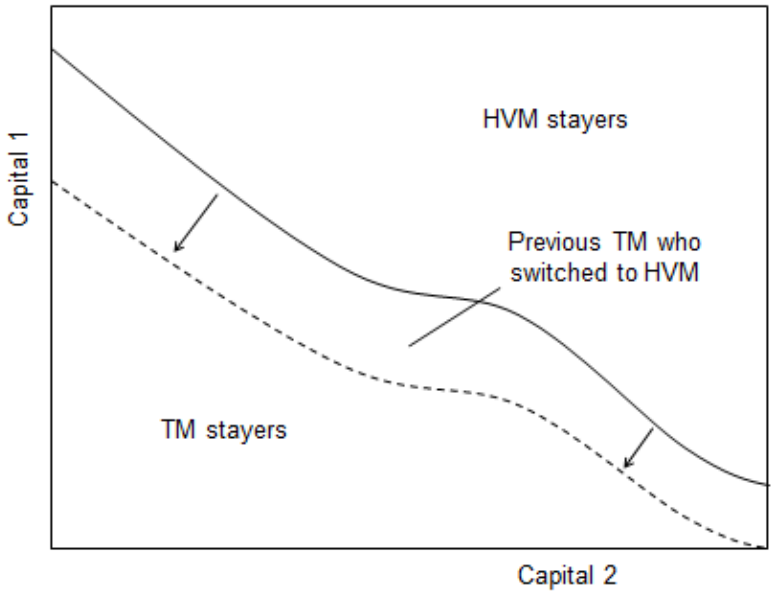
Up till here, cross-section data would suffice to analyze farmers' initial decision to participate in HVM. However, in reality conditions are not static. As various literature strands show, economic agents react to uncertainty and changing circumstances, which can lead to market entry and exit decisions over time (Dixit 1989; Hopenhayn 1992; Shen 2014). In panel (b) of Figure 4.1, the situation in a second time period is shown where a change in external circumstances occurred. This change in circumstances caused some farmers who previously supplied TM to now switch to HVM. This may be due to an increase in the price premium paid in HVM, improved transport infrastructure, increased activity by an NGO facilitating HVM access, or other types of external shocks. Of course, circumstances might also change in the opposite direction (not shown in the figure), with farmers who previously supplied HVM switching back to TM.

In panel (b) of Figure 4.1, it is assumed that the change in external circumstances affects all farmers evenly, so that HVM entry or exit decisions all occur in one direction. Yet, heterogeneous farmers may be affected differently by external shocks, as shown in panel (c). For instance, farmers with low access to physical capital may be affected more negatively by an NGO that decreases market linkage activities previously offered. It is also possible that price premiums in HVM are only offered to those farmers who are capable of meeting certain standards, which may be easier for farmers with better access to physical capital. In fact, there may be different types of external shocks that occur simultaneously, affecting farmers in different ways. In panel (c), a few additional farmers enter HVM in the second period, while others who supplied HVM previously switched back to TM. Hence – depending on the situation – theory predicts switching in both directions.

(a) First period



(b) Second period with exogenous shock



(c) Second period with different kind of exogenous shock

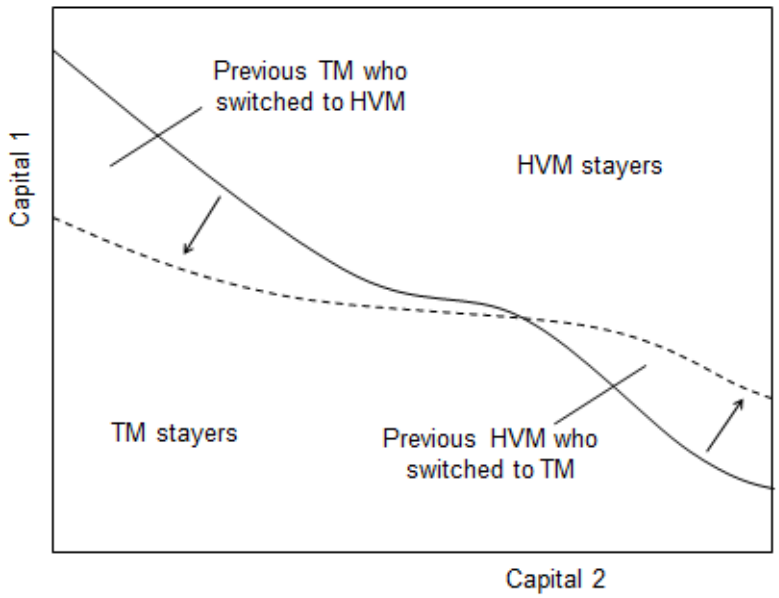


Figure 4.1.Supply channel participation dynamics for farmers with different types and levels of capital

Notes: HVM, high-value markets; TM, traditional markets.

4.3.2 Contract Offer and Impact Dynamics

So far, we implicitly assumed that all farmers who are able and willing to supply HVM would actually do so. In reality, entering HVM often requires a contractual relationship between supermarkets or other agribusiness firms and farmers. The decision to participate is therefore not made by the farmer alone, but also depends on whether he/she is offered a contract. If farmers' willingness to supply HVM is higher than the demand, supermarkets will prefer those farmers where contracts are associated with lower transaction costs. Especially in growing industries, supply and demand conditions can change rapidly, so that who is offered a contract is not a constant parameter.

These dynamics in HVM participation can also lead to dynamics in the effects on farmers' income. When farmers choose freely, they will opt for the most profitable supply channel from their individual perspective. However, when farmers are not offered a contract, they may also end up in a less lucrative channel.

Furthermore, income differences and dynamics depend on farmers' expectations, previous choice of supply channel, and the functioning of credit markets. For example, farmers that are expecting to supply HVM but, for various reasons, end up in TM, may find themselves in a situation where they have overinvested in physical capital that is not easily covered by returns in TM. Assuming naïve expectations, this could lead to a situation where farmers that dropped out of HVM suffer from large sunk costs and thus have lower income than TM stayers. Similarly, if credit markets are functioning poorly, farmers may potentially not be able to invest at once but may need some time in HVM to reach the optimal level of physical capital. Under such circumstances, new HVM suppliers may have lower income than farmers who entered HVM earlier and stayed.

In sum, participation and income dynamics can take a number of different pathways. Which of the outcomes predicted by theory really occurs is an empirical question, depending on initial conditions and developments over time in a particular context. We analyze such dynamics empirically, using panel data from Kenya.

4.4 Data and Descriptive Statistics

4.4.1 Household Panel Survey

Data for this study were collected in Kiambu District, Central Province of Kenya (in Kenya's new constitution, Kiambu is now a county). Kiambu is mainly an agricultural region with high-potential land. About 70% of the population is involved in agriculture, and the vast majority (about 90%) of the farmers are smallholders producing maize, beans, potatoes, and other food crops for subsistence. The major cash crops in the region are tea, coffee, and horticultural crops. Farmers in Kiambu produce leafy vegetables including exotic types, like kale and spinach, as well as indigenous species such as amaranthus and black nightshade. Kiambu is located in relative proximity to Nairobi. Even before the spread of supermarkets, Kiambu was one of the main vegetable-supplying regions for the capital city. The two biggest supermarket chains now sourcing vegetables from Kiambu are Nakumatt and Uchumi, which are both Kenyan owned. Foreign owned retail chains so far play a much smaller role in Kenya (Rao, Brümmer, and Qaim 2012).

The first round of data was collected in 2008. At that time, 402 vegetable farmers were interviewed using a structured questionnaire. The farmers were selected with a stratified random sampling procedure, differentiating between supermarket and traditional channel suppliers. Supermarket farmers were selected from lists of suppliers obtained from supermarkets. In order to get a sufficient number of observations, all farmers on these lists in Kiambu were selected. Farmers supplying traditional markets were randomly selected from 31 administrative locations in Kiambu. These locations were selected to cover the main vegetable-growing areas based on data from the District Agricultural Office.

The second round of the survey was conducted in 2012. Despite significant efforts, some of the farmers from the first round could not be met again. Ten households had stopped vegetable cultivation altogether. Each missing household was replaced by another randomly selected vegetable-growing household in the same village. In this article, we only employ data from farmers who were surveyed in both rounds; a balanced

panel is required for the differencing approach that is further explained below. Thus, we have a sample of 336 farm households with complete information for 2008 and 2012.[8]

4.4.2 Farm and Household Characteristics

Farm and household characteristics are shown in Table 4.1. We differentiate between HVM and TM suppliers. The majority of the farmers in HVM supply vegetables to supermarkets. This involves verbal agreements on quantity, price, and time of delivery. A few HVM farmers also sell their vegetables to companies and institutions (e.g., hotel chains). As the agreements between farmers and these companies and institutions are similar to the agreements with supermarkets, including both in the same HVM category is justified.

While the supply channel of farmers may change over time, the distinction between HVM and TM suppliers in any particular year is clear-cut. All TM suppliers sell their vegetables only in traditional markets. Most HVM suppliers sell their vegetables primarily to HVM; only when the harvested amount at a particular date unexpectedly exceeds the agreement with supermarkets or other institutions, the surplus is sold in TM. HVM suppliers tend to specialize on one HVM channel. That is, in 80% of the cases, the HVM supplier sells to only one particular supermarket, company, or institution.

Sample households are typical smallholders with an average farm size of 1-2 acres. Some of the variables shown in Table 4.1 deserve further explanation. Personal characteristics of the farmer are captured in terms of age, gender, and education. This refers to the person in the household responsible for vegetable cultivation and marketing, which may or may not be the household head. Wealth and capital endowment are captured in terms of ownership of assets, such as land, livestock, and a vehicle (means of transportation), among others. Furthermore, we look at access to certain types of infrastructure, such as piped water and electricity. Household size and off-farm employment of the farmer are proxies for labor availability and the opportunity cost of

[8] Of the 66 farmers that could not be interviewed again in 2012, 18 were supplying supermarkets and 48 traditional markets in 2008. In order to test for attrition bias we followed an approach similar to Wooldridge (2002 p. 582), using the full sample from the first round and estimating the probability that a household is also interviewed during the second round with a probit model. Based on this model, we estimated the inverse mills ratio, which was included in a first-differenced income equation for the reduced sample used in our analysis. The inverse mills ratio was insignificant in this income equation. We conclude that attrition bias is not an issue.

time. Off-farm employment may also be an important source of cash for farm investments when credit markets fail (Oseni and Winters 2009).

Table 4.1.Sample descriptive statistics

	HVM 2008	TM 2008	HVM 2012	TM 2012
Age of farmer (years)	47.24*	50.33	49.45	50.50
	(12.94)	(14.73)	(12.32)	(13.50)
Male farmer (dummy)	0.93	0.89	0.78***	0.62
	(0.26)	(0.31)	(0.42)	(0.49)
Education of farmer (years of schooling)	10.29***	8.62	10.48***	9.10
	(3.16)	(4.13)	(3.21)	(3.61)
Land size (acres)	1.99**	1.46	2.09**	1.43
	(2.34)	(1.74)	(2.74)	(2.14)
Own livestock (dummy)	0.83	0.82	0.87	0.85
	(0.37)	(0.38)	(0.34)	(0.35)
Off-farm employment (dummy)	0.61***	0.44	0.84***	0.67
	(0.49)	(0.50)	(0.37)	(0.47)
Use of advanced irrigation techniques (dummy)	0.88***	0.71	0.90***	0.73
	(0.33)	(0.45)	(0.31)	(0.45)
Household size (number)	3.47	3.52	4.62*	4.23
	(1.65)	(1.85)	(1.71)	(1.76)
Own means of transportation (dummy)	0.23***	0.09	0.19***	0.05
	(0.42)	(0.28)	(0.40)	(0.21)
Access to public transportation (dummy)	0.88*	0.80	0.94*	0.79
	(0.33)	(0.40)	(0.25)	(0.41)
Access to tarmac road (dummy)	0.46	0.50	0.60	0.45
	(0.50)	(0.50)	(0.49)	(0.50)
Access to piped water (dummy)	0.31	0.36	0.66**	0.51
	(0.47)	(0.48)	(0.48)	(0.50)
Access to electricity (dummy)	0.79	0.71	0.92**	0.81
	(0.41)	(0.45)	(0.27)	(0.40)
Kikuyu/Westlands region (dummy)	0.63***	0.37	0.68***	0.39
	(0.49)	(0.48)	(0.47)	(0.49)
Limuru region (dummy)	0.04***	0.36	0.06***	0.31
	(0.20)	(0.48)	(0.25)	(0.46)
Number of HVM neighbors	2.90***	1.02	2.31***	0.72
	(1.65)	(1.34)	(1.57)	(1.13)
Participation in NGO project (dummy)	0.36***	0.15	0.13***	0.04
	(0.48)	(0.36)	(0.34)	(0.20)
Household income (Ksh per year)	405,373***	208,983	657,947***	253,679
	(375,152)	(207,261)	(828,590)	(365,986)
Per capita income (Ksh per year)	154,352***	75,622	153,121***	71,687
	(199,666)	(94,349)	(189,710)	(130,004)
Access to credit for buying production assets [a]			0.78***	0.53
			(0.42)	(0.50)
Number of observations	*115*	*221*	*77*	*259*

Notes: *** p<0.01; ** p<0.05; * p<0.1. HVM, suppliers to high-value markets; TM, suppliers to traditional markets. Mean values are shown with standard deviations in parentheses. Monetary values for 2012 were deflated to 2008. Mean values between HVM and TM in the same year were tested for statistically significant differences. [a] This variable was measured in different ways in the two survey rounds, hence only the 2012 values are included.

In the conceptual framework we discussed the possible role of social capital to facilitate farmers' access to HVM. We proxy social capital with a variable measuring the number of farmers supplying HVM among the five nearest neighbors in terms of geographic proximity. The five nearest neighbors refer to other farmers in the sample and are derived from GPS coordinates measured at the farmers' homestead. Coordination between nearby farmers may reduce the cost of supplying HVM. In principle, clustering of HVM farmers could also be the result of supermarkets preferring to transact with farmers located in proximity to one another and therefore, as such, is not conclusive evidence that social capital matters. However, in this case the transaction costs are primarily borne by the HVM farmers themselves, as supermarkets require farmers to deliver their vegetables directly to the stores in Nairobi. Indeed, previous research in Kiambu showed that collective action among HVM farmers from the same neighborhood helps to reduce transport and transaction costs (Rao and Qaim 2011).

We also discussed the possible role of NGOs to facilitate HVM access. In the study area, an international NGO had implemented a project since the mid-2000s aiming at linking farmers to supermarkets (Ngugi, Gitau, and Nyoro 2007). This NGO promoted collective action and trained farmers to meet the supermarket standards in terms of quality, consistency, and post-harvest handling of vegetables. The NGO also helped farmers to negotiate supply conditions and provided financial assistance to bridge the time between vegetable delivery and payment by the supermarkets. These support measures seemed to be effective in linking smallholders to supermarket channels in the early period (Rao and Qaim 2011). However, farmer participation in this NGO project decreased significantly between 2008 and 2012. The reason is that the NGO had phased out most of its activities in the region by 2012.

The descriptive statistics in Table 4.1 show that farmers supplying HVM own more land, are better educated, and have better access to transportation and off-farm employment than TM farmers. HVM suppliers also have more neighbors supplying HVM and higher household incomes. The possibility to obtain credit for buying production assets such as irrigation infrastructure is significantly higher for farmers supplying HVM (around 80%) than for farmers supplying TM (around 50%). Household incomes, expressed in Kenyan shillings (Ksh), were calculated by including all farm enterprises and off-farm economic activities over a 12-months period. In the survey, output from crop cultivation was covered separately for the two seasons of the year (long rains and

short rains). For the farm income calculations, total output was valued at market prices.[9] Costs for inputs and hired labor were subtracted. Off-farm earnings of all household members were reported for the entire 12-months period. All monetary values for 2012 were deflated to 2008.[10]

4.5 Participation Dynamics

In this section, we first describe the dynamics of HVM participation in the sample and discuss reasons for supply channel choices as subjectively stated by farmers, before analyzing determinants more formally with econometric models. Figure 4.2 shows how market participation evolved between 2008 and 2012. In 2008, out of the 336 farm households, 115 had supplied HVM. Four years later, almost half of the former HVM suppliers had dropped out of this supply channel. At the same time, only 7% of the former TM suppliers had switched to HVM by 2012.

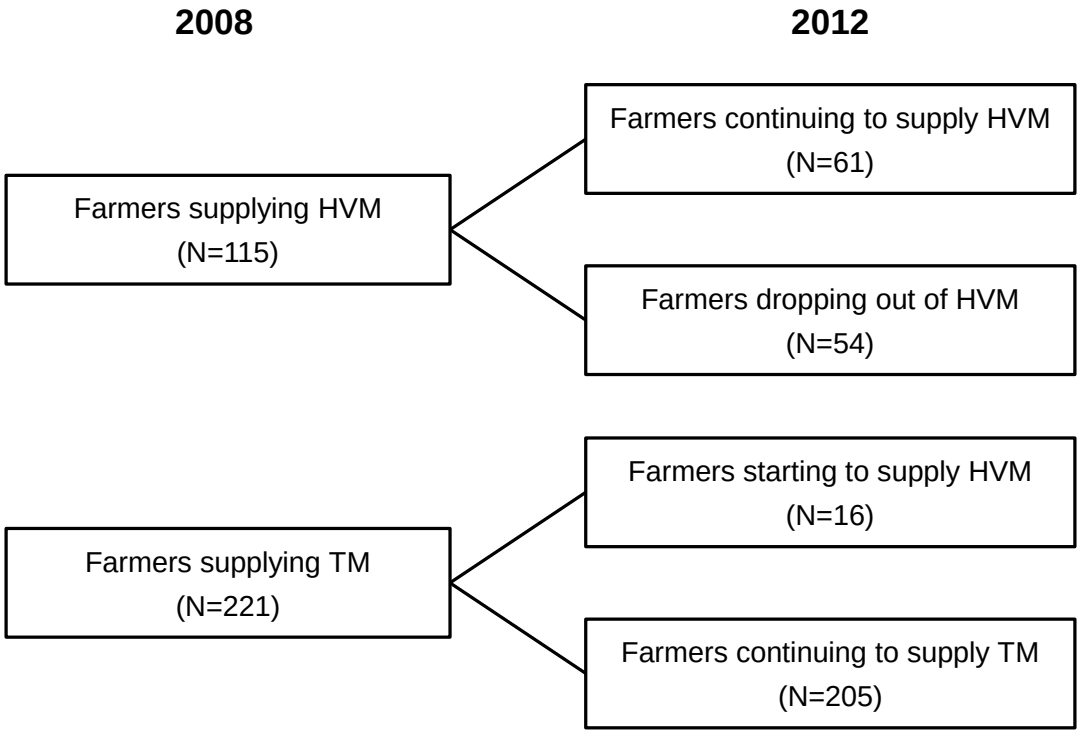


Figure 4.2.Dynamics of participation in high-value markets (2008-2012)

Notes: HVM, high-value markets; TM, traditional markets; N, number of observations

[9] For crops other than vegetables, we used the stated average seasonal price for the revenue calculations. If a crop was produced but not sold by a particular farmer, we used the average price stated by other farmers in the same village. For vegetables, we had asked the farmers more specifically for the total revenue per season.

[10] For deflating, we used the annual weighted average consumer price index obtained from the Kenya National Bureau of Statistics (http://www.knbs.or.ke/consumerpriceindex.php).

4.5.1 Reasons for Supplying Specific Markets

In order to better understand these dynamics, all farmers were asked about reasons for selling vegetables in their particular supply channel. Answers from the 2012 survey round are summarized in Table 4.2 (several answers were possible). We differentiate between HVM and TM suppliers. HVM suppliers in 2012 include HVM stayers (those that supplied HVM in both survey rounds) and newcomers (those that had switched to HVM after 2008). TM suppliers in 2012 include TM stayers (those that supplied TM in both survey rounds) and HVM dropouts. Table 4.2 reveals an interesting pattern with significant differences. Both HVM stayers and newcomers were more likely to state market assurance and price related aspects – such as high, stable, and reliable price – as reasons for supplying the HVM channel.[11] This is a first indication that this channel may indeed offer price incentives and provide market assurance. But the answers reflect personal experiences by those who supply HVM and should not be interpreted as objective descriptions of supply chain characteristics. Farmers supplying TM were more likely to mention other reasons, such as the ability to negotiate the price with their buyers, prompt payment, and lenient quality requirements. It also seems that lack of alternative marketing options and lack of means of transportation are reasons for many farmers to supply TM.

[11] Similar questions were asked in the 2008 survey round as well. HVM farmers in 2008 also mentioned higher prices and assured demand as important reasons for supplying this channel, though with somewhat lower proportions as those shown for HVM stayers in table 2. This difference could indicate that the price advantages in HVM further increased over time.

Table 4.2.Reasons stated for supplying a specific market (Proportion of farmers)

	HVM suppliers in 2012		TM suppliers in 2012		Difference in proportion between HVM and TM suppliers
	HVM stayers	HVM newcomers	HVM dropouts	TM stayers	
Buyer offers a high price	0.73	0.54	0.28	0.31	0.38***
Buyer pays a stable price	0.45	0.15	0.04	0.08	0.32***
Buyer does not change price arbitrarily	0.34	0.31	0.02	0.04	0.29***
Can negotiate price with buyer	0.09	0.08	0.44	0.43	-0.34***
Buyer pays promptly	0.48	0.39	0.57	0.67	-0.19***
Buyer provides assured demand	0.73	0.54	0.28	0.29	0.41***
Buyer is lenient on quality requirements	0.04	0.00	0.07	0.1	-0.06*
No worry about spoilage after selling	0.11	0.00	0.17	0.24	-0.14**
Have long-standing trading relationship	0.36	0.23	0.19	0.1	0.21***
Buyer is well known in the village	0.07	0.15	0.09	0.08	0.00
Have no alternative market (buyer)	0.04	0.00	0.26	0.16	-0.15***
Have no means of transportation	0.00	0.15	0.17	0.13	-0.11**
To save time	0.02	0.08	0.26	0.18	-0.16***
Number of observations	*56*	*13*	*54*	*205*	

Note: *** p<0.01; ** p<0.05; * p<0.1. A reason is only listed if at least 10% of farmers in any group mentioned this reason.

We were also interested in the reasons stated by TM suppliers in 2012 for not supplying supermarkets. These answers are summarized in Table 4.3. Farmers who had previously supplied supermarkets often stressed time, labor, and transport constraints, as well as their own inability to supply consistently, as reasons for not supplying supermarkets in 2012. In contrast, among those who never supplied supermarkets, the most frequent answer was difficulty to get the initial contract, followed by inability to supply consistently, and the high time requirements.[12] A higher labor requirement in supermarket channels was also pointed out by Rao and Qaim (2013). This is particularly

[12] In 2008, not being aware of the supermarket supply channel was an important reason mentioned by TM farmers. Transport problems and inability to supply consistently were also mentioned, yet by a lower proportion of farmers. This suggests that constraints in accessing HVM may have become more evident over time.

related to more time-intensive post-harvest operations required by supermarkets, such as cleaning and bundling the vegetables. Moreover, vegetables have to be delivered to supermarkets in Nairobi. As these transactions are usually managed by farmers themselves, the opportunity cost of own time can be sizeable.

Table 4.3.Reasons stated for not supplying supermarkets (Proportion of farmers)

	Farmers who previously supplied supermarkets	Farmers who never supplied supermarkets
They do not pay promptly	0.21	0.09
Timing of payment unreliable	0.02	0.00
High price variation	0.00	0.00
Price agreement unreliable	0.00	0.00
Price too low	0.05	0.00
They purchase too small quantities	0.14	0.02
Standards too strict	0.17	0.17
Rejection rate too high	0.07	0.02
Quality agreement unreliable	0.02	0.00
It is difficult to get the initial contract	0.07	0.82
I am unable to supply required quantity consistently	0.33	0.34
I have too much spoilage	0.33	0.02
They cheat on spoilage	0.10	0.00
Reliable means of transport required	0.43	0.26
Too time consuming / labor demanding	0.52	0.27
Too capital intensive	0.11	0.20

4.5.2 Conditional Probit Analysis

We now turn to the econometric analysis of the participation dynamics. In a first step, we study the probability of supplying HVM in 2012, conditional on the choice of supply channel in 2008. This analysis is conducted by dividing farmers into two subsamples based on their HVM participation status in 2008 and estimating a separate probit model for each subsample. These two probit models are given by:

$$P(HVM_{2012} = 1 \,|HVM_{2008} = 1) = f(\boldsymbol{x}_{2008}) \quad (4.1)$$

$$P(HVM_{2012} = 1 \,|HVM_{2008} = 0) = f(\boldsymbol{x}_{2008}) \quad (4.2)$$

where $\boldsymbol{x}$ is a vector of household specific explanatory variables. These models can provide an indication of why some farmers stayed in HVM while others dropped out, and why some farmers joined HVM while others stayed in TM. With opposite signs, the estimates also help to explain the mirror outcome, namely reasons for dropping out as opposed to staying in HVM, and for staying in TM as opposed to joining HVM. To reduce reverse causality and allow coherent interpretation of the probit estimates, all household characteristics in $\boldsymbol{x}$ are lagged one time period, that is, they refer to 2008.[13] The only exception is participation in the NGO project, where we use 2012 values, because we expect changes in NGO activity to influence farmers' decision.

Participation in the NGO project is potentially endogenous, as there may be unobserved factors that are jointly correlated with NGO and HVM participation. Similarly, the number of HVM farmers among the five nearest neighbors, which we use as a proxy for social capital, may also be endogenous. To test for endogeneity of both variables, we employed an instrumental variable (IV) approach, using neighbor characteristics as instruments. Details of the IV approach and the test procedure are provided in Appendix A4.1 of this paper. The test fails to reject the null hypothesis of exogeneity for both variables (Table A4.3.1 in the appendix).

Results of the conditional probit models are shown in Table 4.4. The probability of joining HVM in the later period as compared to staying in TM increases with off-farm employment (column 1). As mentioned, income from off-farm employment may provide cash for farm investments when credit markets fail. The probability of joining HVM also increases with use of advanced irrigation techniques, access to piped water, and the number of neighboring farmers supplying HVM. The probability of staying in HVM as compared to dropping out increases with household size, access to electricity, ownership of means of transportation, and number of neighboring farmers supplying HVM, but decreases if the farmer is a male (column 2).

It should be noted that the number of observations for these conditional probit estimates in Table 4.4 is quite small, especially for the model in column (2). This is also the reason for the low levels of statistical significance for some of the variables. We tested the robustness of the results by excluding variables that were insignificant. With

[13] The use of lagged variables for farm assets reduces endogeneity issues but may not eliminate them completely. If farmers invested in physical capital prior to HVM entry, in order to gain market access, assets might still be endogenous. This should be kept in mind when interpreting the results.

the exception of own means of transportation, the observed effects are robust to these changes.

The importance of neighbor participation in HVM for farmers' decisions confirms that social capital matters for supply channel choices. Participation in the NGO project is not significant. This does not surprise, because the effect shown in Table 4.4 refers to 2012, when the NGO had already stopped most of its activities in the region. In alternative estimates, we replaced NGO participation in 2012 with NGO participation in 2008 with different results: farmers who participated in the NGO project in 2008 were 21 percentage points more likely to drop out of HVM by 2012, when the NGO had ceased most of its activities. In yet another specification, we used the change in NGO participation between 2008 and 2012 as explanatory variable, also leading to a significant effect: losing NGO support increased the probability of dropping out of HVM by 23 percentage points.

Table 4.4.Conditional probit model estimates

	(1) Probability of HVM supply in 2012 among those who supplied TM in 2008 (HVM newcomers)	(2) Probability of HVM supply in 2012 among those who supplied HVM in 2008 (HVM stayers)
Male farmer	0.022 (0.046)	-0.260* (0.133)
Education of farmer	0.002 (0.005)	-0.022 (0.018)
Age of farmer	-0.001 (0.001)	-0.000 (0.004)
Household size	0.004 (0.008)	0.058** (0.027)
Off-farm employment	0.060* (0.034)	0.066 (0.085)
Land size	0.009 (0.009)	0.014 (0.030)
Use of advanced irrigation	0.058* (0.034)	0.169 (0.137)
Own livestock	0.015 (0.041)	0.025 (0.112)
Access to electricity	0.055 (0.035)	0.315*** (0.117)
Own means of transportation	-0.033 (0.040)	0.192* (0.111)
Access to public transportation	-0.010 (0.061)	0.118 (0.148)
Access to tarmac road	0.059 (0.040)	0.132 (0.095)
Access to piped water	0.065* (0.039)	0.089 (0.093)
Limuru region	-0.034 (0.049)	0.030 (0.218)
Kikuyu/Westlands region	-0.046 (0.043)	0.073 (0.131)
No. of HVM neighbors	0.044*** (0.013)	0.062** (0.028)
Participation in NGO project	-0.009 (0.089)	0.096 (0.137)
Number of observations	*221*	*115*
Pseudo R^2	*0.34*	*0.25*

Notes: Marginal effects are shown with standard errors in parentheses. HVM, high-value markets; TM, traditional markets. *** p<0.01; ** p<0.05; * p<0.1.

These results are consistent with our conceptual framework, predicting that physical and social capital matter for HVM participation and that exogenous shocks can contribute to additional market entry and exit decisions over time. The fact that the probability of staying in HVM (dropping out) increases (decreases) with household size may be explained by the higher time requirements in the supermarket channel. Households with more members tend to have lower opportunity costs of family labor time.

4.5.3 Multinomial Logit Analysis

The conditional probit model estimates have the advantage that they give us information about why farmers change supply channels in the second period, given their first-period choice. However, based on these models we cannot draw any generalizable inference about which types of farmers are likely to end up as HVM stayers, HVM dropouts, newcomers in HVM, or stayers in TM. To analyze these aspects further, we estimate the unconditional probability of the different decision paths simultaneously with a multinomial logit model, which is specified as:

$$p_{ij} = P(D_i = j) = \begin{cases} \frac{exp(\boldsymbol{x_i}\boldsymbol{\beta_j})}{1+\sum_{m=1}^{3} exp(\boldsymbol{x_i}\boldsymbol{\beta_m})}, if\ j = 1,2,3 \\ \frac{1}{1+\sum_{m=1}^{3} exp(\boldsymbol{x_i}\boldsymbol{\beta_m})}, if\ j = 4 \end{cases} \quad (4.3)$$

where *j*=1 for HVM stayers, *j*=2 for HVM dropouts, *j*=3 for HVM newcomers, and *j*=4 for TM stayers. As above, $\boldsymbol{x_i}$ is a vector of explanatory variables specific to each household *i*, and $\boldsymbol{\beta}$ is a vector of parameters to be estimated. We focus on the marginal effect of the change in an explanatory variable on the probability of falling into a certain category as compared to falling into any of the other categories, given by $\frac{\partial p_{ij}}{\partial x_i} = p_{ij}(\beta_j - \sum_l p_{il}\beta_l)$.

Results are shown in Table 4.5. The probability of staying in HVM increases with off-farm employment, access to electricity, and the number of neighbors supplying HVM. The probability of dropping out increases with education and the number of

neighbors supplying HVM and decreases with family size.[14] Better educated farmers and smaller families are likely to have higher opportunity costs of time. The fact that the number of HVM neighbors positively affects both the probability of staying in HVM and the probability of dropping out may surprise on first sight, but is actually plausible with this model specification. Farmers can only fall into the HVM stayer and dropout categories when they had entered HVM in the first place. As the number of HVM neighbors in 2008 is an important determinant of market entry, we expect a positive association also with staying and dropping out when the whole sample – with many farmers who never entered HVM – is included in estimation.

The probability of being a HVM newcomer increases with access to piped water, access to electricity, and the number of neighbors supplying HVM. Finally, the probability of staying in TM decreases with education, off-farm employment, farm size, access to public transportation, and the number of neighbors supplying HVM, but increases with family size. There also seems to be a regional effect with farmers in Limuru being more likely to stay in TM. This can be explained by two factors. First, the NGO that helped to link farmers to supermarkets concentrated less on Limuru than on the other regions, even in 2008. Second, due to two wholesale market centers located in Limuru farmers in that region have better traditional marketing conditions than their colleagues in other regions.

In sum, the results confirm previous studies in that farmer characteristics as well as physical and social capital endowments are important determinants of HVM participation.[15] The results add to the knowledge by showing that the same factors also play an important role in explaining participation dynamics. Furthermore, the estimation results underscore that exogenous shocks can affect farmers' ability to supply HVM differently, depending on individual endowments with different types of capital.

[14] As for the conditional probit models, we also ran an alternative specification of the multinomial logit model using lagged NGO participation. In that alternative specification, NGO participation in 2008 is highly significant in the dropout equation: it increases the probability of dropping out by 0.21.

[15] As an additional robustness test, we used a correlated random effects probit model to control for unobserved time-invariant heterogeneity. Note that such a model with observations from two time periods can analyze the determinants of HVM participation, but not the participation dynamics. Results are presented in Table A4.3.2 in the Appendix of this paper. Due to correlation between the explanatory variables, many of the coefficients are insignificant. Yet, NGO participation and the number of HVM neighbors have a positive and significant impact on HVM participation, while household size has a negative impact.

Table 4.5. Multinomial logit model estimates

	HVM stayers	HVM dropouts	HVM newcomers	TM stayers
Male farmer	-0.014	0.030	-0.000	-0.016
	(0.074)	(0.068)	(0.032)	(0.101)
Education of farmer	0.007	0.020***	0.000	-0.027***
	(0.006)	(0.007)	(0.002)	(0.010)
Age of farmer	-0.001	-0.002	-0.000	0.004
	(0.002)	(0.002)	(0.001)	(0.003)
Household size	-0.007	-0.029**	0.005	0.031*
	(0.010)	(0.014)	(0.004)	(0.018)
Off-farm employment	0.067*	0.006	0.024	-0.097*
	(0.037)	(0.042)	(0.018)	(0.059)
Land size	0.012	0.017	0.004	-0.032*
	(0.010)	(0.011)	(0.005)	(0.017)
Use of advanced irrigation techniques	0.054	-0.002	0.021	-0.077
	(0.046)	(0.057)	(0.017)	(0.074)
Own livestock	0.035	-0.000	0.004	-0.040
	(0.040)	(0.063)	(0.019)	(0.082)
Access to electricity	0.081**	-0.048	0.031*	-0.064
	(0.039)	(0.059)	(0.019)	(0.073)
Own means of transportation	0.132	0.006	-0.011	-0.127
	(0.085)	(0.063)	(0.019)	(0.108)
Access to public transportation	0.062	0.067	0.016	-0.146**
	(0.040)	(0.042)	(0.021)	(0.064)
Access to tarmac road	0.047	-0.068	0.010	0.012
	(0.040)	(0.048)	(0.019)	(0.069)
Access to piped water	0.001	-0.056	0.051*	0.004
	(0.036)	(0.045)	(0.029)	(0.068)
Limuru region	-0.106**	-0.193***	0.000	0.299***
	(0.045)	(0.042)	(0.027)	(0.064)
Kikuyu/Westlands region	0.043	-0.040	-0.013	0.010
	(0.051)	(0.055)	(0.023)	(0.080)
No. of HVM neighbors	0.062***	0.037**	0.016*	-0.114***
	(0.017)	(0.018)	(0.008)	(0.027)
Participation in NGO project (2012)	0.196	0.004	-0.007	-0.193
	(0.129)	(0.083)	(0.028)	(0.145)
Number of observations	*336*			
Pseudo R^2	*0.272*			

Notes: *** p<0.01; ** p<0.05; * p<0.1. HVM, high-value markets; TM, traditional markets. Marginal effects are shown with standard errors in parentheses.

4.6 Impact of Participation

In this section, we analyze the impacts of HVM participation on household income. We develop and estimate a number of different models to address the various questions on impact and impact dynamics. We start by estimating the average treatment effect of HVM participation with the full sample of farmers, including newcomers and dropouts.

To better understand the effects of joining and leaving HVM, we then continue by splitting the sample accordingly. In a further step, we explore income differences between farmers who stayed in HVM and farmers who recently joined, as well as between farmers who dropped out of HVM and farmers who stayed in TM. Finally, we are interested to know whether the income difference between HVM suppliers and TM suppliers is increasing or decreasing over time. A broader discussion of the results and their implications is provided in the next section.

4.6.1 Average Impact of HVM Participation

In a first model, we analyze whether HVM participation has any effect on income. Since we have panel data available, we employ a differencing technique, using the change in household income (y) between 2008 and 2012 as dependent variable, and the change in HVM participation as treatment variable. Furthermore, we include changes in relevant farm and household characteristics ($\boldsymbol{z}$) as control variables:

$$y_{2012} - y_{2008} = \alpha + \delta(\boldsymbol{z}_{2012} - \boldsymbol{z}_{2008}) + \gamma_1(HVM_{2012} - HVM_{2008}) + e \qquad (4.4)$$

This model has the advantage that all unobserved time-invariant heterogeneity is removed, because it exploits the within-household variability in the variables. The coefficient γ_1 gives the impact of HVM participation.

Descriptive statistics of the difference variables used in the impact regressions are shown in Table A4.3.3 in the Appendix of this chapter. Estimation results are shown in Table 4.6. HVM participation has a large positive and significant effect on household income. The coefficient implies that – controlling for other factors – HVM suppliers have an income that is 185 thousand Ksh higher than that of TM suppliers, equivalent to a 59% difference. However, since changes in the treatment variable may occur through both farmers entering and leaving HVM, the underlying dynamics remain unclear. This will be further analyzed below.

Table 4.6. Average impact of HVM participation on household income

	Change in household income
Change in HVM	184,589*** (59,577)
Change in age of farmer	2,064 (2,934)
Change in gender of farmer	-61,890 (59,215)
Change in education of farmer	5,579 (8,926)
Change in land size	65,119*** (18,136)
Change in livestock ownership	143,300** (66,152)
Change in off-farm employment	95,944** (43,403)
Change in use of advanced irrigation techniques	1,287 (56,782)
Change in household size	12,267 (12,714)
Change in ownership of means of transportation	-5,740 (75,601)
Constant	40,825 (33,788)
Number of observations	*336*
Adjusted R^2	*0.083*

Notes: *** p<0.01; ** p<0.05; * p<0.1. HVM, high-value markets. Coefficient estimates are shown with standard errors in parentheses. The dependent variable is change in annual household income measured in Ksh.

4.6.2 Impact of Entering and Leaving HVM

A drawback of the differencing model in equation (4.4) is that the treatment variable $(HVM_{2012} - HVM_{2008})$ takes on the value 1 for farmers that join HVM, 0 for farmers that stay either in HVM or TM, and -1 for farmers that drop out of HVM. In our case, only 16 farmers newly entered HVM between 2008 and 2012, while 54 previous HVM suppliers dropped out. This implies that the result presented in Table 4.6 is likely driven by the income loss associated with dropping out. In a different model specification, we split the sample and separately analyze the income effect of entering and leaving HVM:

$$(y_{2012} - y_{2008} | HVM_{2008} = 0) = \alpha + \delta(\boldsymbol{z}_{2012} - \boldsymbol{z}_{2008}) + \gamma_2(HVM_{2012} - HVM_{2008}) + e \quad (4.5)$$

$$(y_{2012} - y_{2008} | HVM_{2008} = 1) = \alpha + \delta(\boldsymbol{z}_{2012} - \boldsymbol{z}_{2008}) + \gamma_3(HVM_{2008} - HVM_{2012}) + e \quad (4.6)$$

where γ_2 describes the impact of joining HVM as compared to staying in TM, and γ_3 describes the effect of dropping out of HVM as compared to staying in that channel. To

facilitate interpretation, we have turned around the HVM difference in equation (4.6), so that a negative sign of γ_3 would indicate an income loss from dropping out and vice versa.

We estimate these models in equations (4.5) and (4.6) with ordinary least squares (OLS). To control for time-variant heterogeneity we additionally use a treatment-effect estimator, where the treatment variable is instrumented with the number of HVM farmers among the five nearest neighbors. This variable was shown to play an important role for farmers' participation decisions and was tested successfully for exogeneity in the participation equation. We performed additional analyses to test whether the number of HVM neighbors has a direct influence on household income. These tests are described in Appendix A4.2 of this paper; they confirm the validity of the instrument.

Results from estimates of equations (4.5) and (4.6) are shown in Table 4.7. The results suggest that joining HVM contributes to significant income gains. This holds true for both the OLS and treatment-effects results. The estimates also indicate that dropping out of HVM is associated with a significant decrease in household income.[16]

[16] As an alternative to the models in equations (5) and (6) one could analyze the effects of joining and leaving HVM in one model with the full sample and separate treatment dummies for HVM newcomers, HVM dropouts, and HVM stayers (TM stayers would form the reference). We estimated such an alternative model with OLS and obtained similar results. In order to control for selection on time-variant unobserved variables, we also tried estimating the model using a multivariate treatment regression. However, the results proved to be highly sensitive to the number of draws and are therefore not reported here. In this respect, splitting the sample is advantageous. A drawback is that the inference can only be drawn for the subsample used, not for the whole sample.

Table 4.7.Impact of entering and leaving HVM on household income

	OLS		Treatment effect	
	Impact of joining HVM (farmers who supplied TM in 2008)	Impact of leaving HVM (farmers who supplied HVM in 2008)	Impact of joining HVM (farmers who supplied TM in 2008)	Impact of leaving HVM (farmers who supplied HVM in 2008)
Change in HVM	342,861***	-233,226**	245,108*	-382,720*
	(104,960)	(117,212)	(144,944)	(221,366)
Change in age of farmer	5,601**	-7,471	5,781**	-7,670
	(2,801)	(9,685)	(2,737)	(9,202)
Change in gender of farmer	-67,910	-74,936	-65,618	-75,145
	(59,362)	(158,041)	(57,917)	(150,178)
Change in education of farmer	9,852	-8,417	10,210	-9,191
	(9,470)	(19,377)	(9,234)	(18,437)
Change in land size	37,933**	111,921***	38,358**	110,266***
	(19,129)	(41,036)	(18,649)	(39,034)
Change in livestock ownership	129,387*	186,176	131,293**	176,307
	(65,980)	(155,158)	(64,372)	(147,772)
Change in off-farm employment	91,397**	102,266	90,597**	107,017
	(44,432)	(95,297)	(43,325)	(90,688)
Change in irrigation techniques	7,557	12,337	7,146	11,002
	(55,706)	(144,697)	(54,299)	(13,7458)
Change in household size	-5,061	28,278	-5,844	29,909
	(13,426)	(27,553)	(13,116)	(26,285)
Change in transportation	-154,444*	187,217	-156,536*	194,453
	(86,483)	(141,870)	(84,249)	(135,108)
Constant	-2,664	-82,219	5,442	-162,640
	(35,169)	(111,934)	(35,394)	(148,6240)
First-stage probit: dependent variable HVM_{2008}				
No. of HVM neighbors			0.432***	0.312***
			(0.096)	(0.081)
Constant			-1.956***	-0.479**
			(0.196)	(0.186)
LR test of independent equations (p)			*0.371*	*0.474*
Number of observations	*221*	*115*	*221*	*115*
Adjusted R^2	*0.079*	*0.145*		

Notes: *** p<0.01; ** p<0.05; * p<0.1. HVM, high-value markets. Coefficient estimates are shown with standard errors in parentheses. The dependent variable in all models is change in annual household income measured in Ksh.

4.6.3 Income Differences between Farmers in the Same Channel

As discussed above, farmers in the same supply channel but with a different participation history may earn different incomes, for instance, due to sunk costs and credit market imperfections. We estimate two additional models to examine whether income

differences within one channel can be observed, depending on participation history. One of these models looks at farmers who supplied HVM and the other at farmers who supplied TM in 2012:

$$(y_{2012}|HVM_{2012} = 0) = \alpha + \delta \mathbf{z}_{2012} + \gamma_4 HVM_{2008} + e \quad (4.7)$$

$$(y_{2012}|HVM_{2012} = 1) = \alpha + \delta \mathbf{z}_{2012} + \gamma_5 HVM_{2008} + e \quad (4.8)$$

Note that we are now interested in explaining income in 2012, not income changes over time. For TM suppliers in 2012, γ_4 indicates whether there is an income difference between those that stayed in TM and those that dropped out of HVM. A negative coefficient would suggest that dropouts are worse off than TM stayers, which could be due to overinvestment in certain production equipment. For HVM suppliers in 2012, γ_5 indicates the income difference between newcomers and stayers in HVM. A positive (negative) coefficient would suggest that HVM stayers (newcomers) have an income advantage. Equations (4.7) and (4.8) are not based on differencing techniques, so both time-variant and time-invariant heterogeneity can potentially bias the results. We employ a treatment-effect estimator to control for such bias, using the number of HVM neighbors as instrument for HVM participation.

The estimation results are shown in Table 4.8. We do not find a significant income difference between stayers in TM and dropouts from HVM. Thus, dropouts do not seem to suffer from overinvestment. Likewise, we do not observe a significant difference between HVM stayers and newcomers.

Table 4.8.Difference in income between farmers in the same supply channel

	OLS		Treatment effects	
Model	Income of TM suppliers in 2012	Income of HVM suppliers in 2012	Income of TM suppliers in 2012	Income of HVM suppliers in 2012
HVM 2008	2,787	-31,435	-49,413	-645,960
	(55,004)	(183,412)	(91,028)	(384,526)
Age of farmer	237	-7,149	325	-7,200
	(1,900)	(6,990)	(1,855)	(6,382)
Gender of farmer	-737	20,4530	1,443	22,6789
	(46,208)	(190,316)	(45,116)	(173,391)
Education of farmer	5,241	-16,516	5,354	-16,138
	(6,870)	(28,625)	(6694)	(26,221)
Land size	28,002**	160,003***	28,657**	157,243***
	(11,620)	(31,029)	(11,361)	(28,846)
Livestock ownership	109,321*	535,311**	105,621*	552,744***
	(62,628)	(231,017)	(61,218)	(208,105)
Off-farm employment	163,508***	-159,133	161,942***	-218,264
	(46,093)	(210,574)	(44,944)	(199,374)
Use of advanced irrigation techniques	91,691*	274,673	91,478*	273,822
	(51,453)	(238,986)	(50,135)	(216,823)
Household size	17,153	18,656	17,947	26,237
	(12,260)	(42,895)	(11,990)	(40,509)
Means of transportation	274,623**	688,958***	270,096**	67,3472***
	(110,194)	(205,075)	(107,525)	(182,812)
Limuru region	-3,727	603,777*	-9,947	501,715
	(59,836)	(358,479)	(58,933)	(321,490)
Kikuyu/Westlands region	-91,029	437,457**	-89,712	388,313**
	(58,100)	(211,757)	(56,622)	(195,206)
Constant	-164,165	-418,159	-158,415	98,987
	(165,734)	(619,694)	(161,646)	(629,472)
First-stage probit: dependent variable HVM_{2008}				
No. of HVM neighbors			0.405***	0.157
			(0.058)	(0.110)
Constant			-1.488***	0.394
			(0.143)	(0.314)
LR test of independent equations (p)			*0.541*	*0.515*
Number of observations	*259*	*77*	*259*	*77*
Adjusted R^2	*0.152*	*0.485*		

Notes: *** p<0.01; ** p<0.05; * p<0.1. HVM, high-value markets. Coefficient estimates are shown with standard errors in parentheses. The dependent variable is annual household income in 2012 measured in Ksh.

4.6.4 Income Divergence or Convergence between Channels

In a next step, we are interested to see whether the income gap between HVM participants and non-participants increases or decreases over time. We estimate:

$$(y_{2012} - y_{2008} | HVM_{2012} = HVM_{2008}) = \alpha + \delta(\boldsymbol{z}_{2012} - \boldsymbol{z}_{2008}) + \gamma_6 HVM_{2008} + e \quad (4.9)$$

This model is confined to farmers that did not change their supply channel between 2008 and 2012, that is, we look at HVM stayers and TM stayers. Hence, γ_6 can be interpreted as the difference in income dynamics between the two channels, controlling for other factors. A positive γ_6 would indicate an increasing income divergence between the two channels, whereas a negative coefficient would imply a converging trend.

Table 4.9 shows the estimation results. The positive and significant coefficient for the HVM dummy indicates that the income difference between the two channels diverges over time. That is, controlling for other factors, HVM stayers have higher income growth than TM stayers, which may be explained by the possibility to build up a larger capital stock from the higher profits in HVM.

Table 4.9.Difference in income between HVM stayers and TM stayers

	OLS	Treatment effect
HVM 2008	137,888**	194,098*
	(69,765)	(104,143)
Change in age of farmer	3,062	2,996
	(3,146)	(3,081)
Change in gender of farmer	-91,695	-94,052
	(65,542)	(64,240)
Change in education of farmer	9,468	9,085
	(9,840)	(9,643)
Change in land size	69,649***	69,728***
	(20,702)	(20,260)
Change in livestock ownership	108,571	104,931
	(72,925)	(71,546)
Change in off-farm employment	112,287**	114,858**
	(47,221)	(46,343)
Change in irrigation techniques	27,966	28,998
	(62,751)	(61,437)
Change in household size	16,362	17,099
	(14,049)	(13,797)
Change in transportation	-112,648	-112,266
	(86,345)	(84,492)
Constant	-25,031	-39,288
	(39,821)	(43,829)
First-stage probit: dependent variable HVM_{2008}		
No. of HVM neighbors		0.508***
		(0.065)
Constant		-1.388***
		(0.130)
LR test of independent equations (p)		*0.474*
Number of observations	*266*	*266*
Adjusted R^2	*0.089*	

Notes: *** p<0.01; ** p<0.05; * p<0.1. HVM, high-value markets. Coefficient estimates are shown with standard errors in parentheses. The dependent variable is change in annual household income measured in Ksh.

4.7 Discussion

Despite the fact that participation in HVM was associated with substantial income gains in 2008 (Rao and Qaim, 2011), almost half of the previous HVM suppliers had dropped out four years later. Our analysis suggests that dropping out of HVM is not a decision based on economic superiority. On the contrary, being in HVM is still associated with higher incomes, while dropping out leads to a significant income loss. When asking the farmers about their reason for dropping out, time constraints were frequently mentioned. This is in line with our econometric result that larger household size increases the probability of staying in HVM, while smaller household size increases the probability of

dropping out. Household size is a proxy for the availability of family labor. Especially cleaning, bundling, and delivering the vegetables to the supermarkets in Nairobi are time-intensive activities that are difficult to outsource to hired labor. Hence, referring back to the diagrams discussed in the conceptual framework, access to household labor seems to be another type of capital that influences farmers' ability to supply HVM.

Strong social networks or assistance through an NGO – as was offered in 2008 – can reduce the need for family labor to a certain extent, because activities can be coordinated and transaction costs reduced. Indeed, we find that farmers with more HVM neighbors and NGO support are more likely to participate themselves in HVM. The NGO also provided specific training for farmers to supply supermarkets successfully. However, when the NGO activities were reduced in subsequent years, many supermarket suppliers switched back to traditional channels, especially those that had relied on NGO support in the past.

Our results also suggest that heterogeneous physical capital endowments, such as piped water, advanced irrigation techniques, transportation, and off-farm income, are important factors in explaining why some farmers join HVM and others do not. Such physical capital components also influence the participation dynamics.

We showed that farmers who dropped out of HVM have a lower income than if they would have stayed in HVM, but do they earn less than if they had stayed in TM? As argued in the conceptual framework, farmers who expected to remain in HVM but, for some reason, are forced to drop out, may find themselves in a situation where they have overinvested in productive assets and equipment. However, in the empirical analysis we did not find that HVM dropouts earn less than TM stayers, suggesting that overinvestment may not be a large problem. This is also confirmed when we look at the value of production equipment across farms. For instance, the 2012 value of irrigation equipment (water pumps, irrigation pipes, and sprinklers) does not differ significantly between HVM dropouts and TM stayers. Another interesting aspect is the role of off-farm income. Compared to the TM stayers, the group of HVM dropouts had lower off-farm incomes in 2008 (when they supplied HVM), but not in 2012. A plausible explanation is that the freed family labor time after the dropout could be used for other income-earning activities, thus reducing the loss from switching back to TM.

Looking at the income dynamics in the HVM channel we found that newcomers have a higher income than if they would have stayed in TM. Moreover, HVM newcomers

realize gains that are similar to those of the HVM stayers, suggesting that earlier market entrants do not have an income advantage through capital accumulation in the earlier period. Indeed, we do not find significant differences when comparing the value of equipment between HVM stayers and newcomers. However, as the number of HVM newcomers in our sample is very small, these results should be interpreted with caution.

Finally, our results suggest that the income growth for farmers who manage to stay in HVM is higher than for farmers in TM, pointing at widening disparities between the two channels. Given the substantial income gains that can be achieved in the supermarket channel, policymakers may be interested in finding ways to increase participation of smallholders. The NGO linkage activities were quite effective as long as they lasted. Yet, a major challenge is to find solutions that are sustainable and do not result in considerable dropout once the support is withdrawn. Recognizing the importance of neighbors supplying HVM, policies that target groups of people should be preferred over policies that target individual farmers.

One limitation of our study is the relatively small sample size, especially when it comes to farmers who newly entered supermarket channels between the first and the second round of the panel survey. Follow-up studies with larger sample sizes and more rounds of data collection would be interesting to verify the results. It should also be stressed that our sample of farmers from Kiambu is not necessarily representative of Kenya as a whole or other regions in Africa. Kiambu is relatively close to Nairobi, where market access is more favorable than in remoter regions. Gains from supplying supermarkets may be lower and participation constraints may be higher in other regions of Africa.

4.8 Conclusion

In this article, we have used panel data from Kenya to study the dynamics of farmer participation in supermarket channels and related impacts on household income. The results confirm that supermarket participation is associated with large income advantages, which is in line with most previous studies that had used cross-section data. However, the estimation results from the first-difference models are mainly driven by a larger number of farmers that dropped out of the supermarket channel – a shift that led to significant reductions in income. The supermarket revolution promises to benefit farmers in Africa,

but it may also contribute to rising income disparities, unless infrastructure improvements and organizational support for smallholders are implemented on a broader scale.

However, taking a broader perspective it should be stressed that rural households can benefit from the supermarket revolution and other supply chain transformations not only as farmers, but also through spillovers to labor markets. While this was not examined here, several studies showed that supermarkets and related high-value supply chains for horticultural crops tend to generate additional rural employment, especially for women (Maertens and Swinnen 2009; Colen et al. 2012; Rao and Qaim 2013). Analyzing such spillovers in more detail is an interesting avenue for future research.

Appendix A4

A4.1 Testing for Endogeneity in Probit Models

In the probit models described in equations (4.1) and (4.2) of the article, two variables may potentially be endogenous, namely the number of farmers supplying HVM among the five nearest neighbors and participation in the NGO project. To test whether endogeneity is an issue that leads to a bias in our estimates, we used an instrumental variable (IV) approach. As instruments, we use neighbor characteristics, aggregated as the sum of the five nearest neighbors' individual values. The number of farmers supplying HVM among the five nearest neighbors is instrumented with the gender (male dummy), education (years of schooling), and household size of these neighbors. As was shown in previous research (e.g., Neven et al., 2009; Reardon et al., 2009), these characteristics influence farmers' supply channel choices. At the same time, neighbor characteristics are not expected to affect the farmer's own participation decision directly. In their study on social networks and technology adoption in India, Matuschke and Qaim (2009) demonstrated that the decisions of neighbors and other network members influenced farmers' own adoption behavior, whereas network members' characteristics did not have a direct effect. This is in line with Santos and Barrett (2010), who used data from Ghana to show that other farmers are important sources of information but that the identity of these other farmers does not play a significant role for own decision-making.

One could argue that better-off farmers, who are more likely to supply HVM, cluster in certain localities, which could lead to correlation between neighbors'

characteristics and the probit model error terms. However, except for certain geographic differences that we control for through regional dummies, the study area is very homogenous in terms of agroecological conditions. Also, regional clustering based on household characteristics is uncommon in rural areas of Kenya, where land is inherited from one generation to the next.

The other potentially endogenous variable, participation in the NGO project, is instrumented with the number of farmers among the five nearest neighbors who participated in the same NGO project and owned a car or van in the previous period. The motivation behind using this instrument is that the NGO promotes collective action among farmers and that the attractiveness of participation increases when neighboring farmers that can provide transportation are also part of this project. At the same time, it is unlikely that this variable is correlated with the error terms in equations (4.1) and (4.2) for the same reasons as explained for the other instruments.

Results from the IV probit, including first-stage results for both potentially endogenous variables, are shown in Table A4.3.1 in the Appendix of this chapter. For comparison the normal probit results are also shown. The significance of the instruments in the first-stage regressions together with the test of overidentifying restrictions suggest that the instruments are valid. Yet a Wald test that we carried out fails to reject the null hypothesis that the two variables – number of HVM neighbors and NGO participation – are exogenous. The models shown in Table A4.3.1 use the total sample of 336 farmers to increase the number of observations and have more degrees of freedom. We carried out the same IV estimations and statistical tests also for the two subsamples of the conditional probit (equations 4.1 and 4.2) with the same general conclusion.

A4.2 Validity of the Instrument in the Impact Models

The models to analyze the impact of HVM participation on household income use differencing techniques that control for time-invariant heterogeneity. However, the treatment variables (HVM or change in HVM) may potentially be correlated with unobserved time-variant effects. If such time-variant effects also influence income, they might lead to biased estimates of the treatment effects. To control for time-variant heterogeneity, we use a treatment-effect estimator, where the treatment variable in each model is instrumented with the number of HVM farmers among the five nearest neighbors. As was shown, this variable is exogenous and correlated with HVM

participation. However, it is theoretically possible that the number of HVM neighbors affects income and income changes also through other channels. For instance, innovative farmers in the neighborhood may contribute to broader knowledge spillovers or gains from collective action beyond the supermarket channel. We carried out several tests to find out whether such alternative effects of the instrument on the outcome variables exist.

In a first test, we follow an approach by Di Falco et al. (2011) and regress the change in household income directly on the number of HVM neighbors, including other controls. Results are shown in Table A4.3.4 further below. In column (1), we use the subsample of TM suppliers to see whether they might also benefit from HVM farmers in their neighborhood. However, we do not find a significant effect. In column (2), we use the subsample of HVM suppliers; their decision to supply HVM is influenced by HVM neighbors, but does the number of HVM neighbors also have a direct effect? In other words, is there a heterogeneous impact on income depending on the number of HVM neighbors (see Bjorklund and Moffitt, 1987)? Again, we do not find a statistically significant effect.

We also correlated the number of HVM neighbors with vegetable revenue. A positive correlation coefficient could indicate that farmers coordinate their supply or jointly negotiate for better prices. But we find a small, insignificant negative coefficient of -0.02. The correlation coefficient between the number of HVM neighbors and total household income is -0.11. We conclude that the number of HVM farmers among the five nearest neighbors is a valid instrument in the impact models.

A4.3 Appendix Tables

Table A4.3.1.Normal probit and IV probit models of HVM participation

	Normal probit (HVM 2012)	IV probit (HVM 2012)	First-stage probit (NHVMN)	First-stage probit (NGO)
No. of HVM neighbors (NHVMN)	0.335*** (0.069)	0.418* (0.253)		
Participation in NGO project (NGO)	0.654* (0.361)	1.164 (2.357)		
Male farmer	-0.051 (0.356)	-0.054 (0.410)	0.290 (0.216)	-0.046 (0.045)
Education of farmer	0.026 (0.030)	0.026 (0.034)	-0.042** (0.019)	0.003 (0.004)
Age of farmer	-0.007 (0.009)	-0.006 (0.009)	-0.015*** (0.005)	0.000 (0.001)
Household size	0.017 (0.054)	0.006 (0.055)	0.053 (0.036)	0.007 (0.008)
Off-farm employment	0.374* (0.192)	0.347* (0.201)	0.254** (0.127)	-0.009 (0.026)
Land size	0.055 (0.062)	0.053 (0.070)	0.029 (0.037)	-0.008 (0.008)
Use of advanced irrigation techniques	0.451 (0.295)	0.424 (0.302)	0.161 (0.164)	0.035 (0.034)
Own livestock	0.219 (0.267)	0.242 (0.285)	-0.346** (0.171)	-0.001 (0.035)
Access to electricity	0.739** (0.292)	0.719** (0.302)	0.295* (0.158)	0.013 (0.033)
Own means of transportation	0.457* (0.268)	0.450 (0.297)	0.302 (0.195)	-0.018 (0.040)
Access to public transportation	0.294 (0.309)	0.247 (0.346)	-0.017 (0.182)	0.042 (0.038)
Access to tarmac road	0.319 (0.216)	0.300 (0.219)	0.149 (0.145)	0.014 (0.030)
Access to piped water	0.246 (0.199)	0.227 (0.211)	0.230 (0.142)	0.008 (0.029)
Limuru region	-0.484 (0.353)	-0.317 (0.451)	-0.653*** (0.229)	-0.082* (0.047)
Kikuyu/Westlands region	0.135(0.269)	0.185 (0.557)	0.405* (0.236)	-0.062 (0.049)
Constant	-3.196*** (0.785)	-3.302*** (0.806)	-1.464** (0.660)	0.061 (0.137)
Male farmers among five nearest neighbors			0.153** (0.063)	-0.017 (0.013)
Education among five nearest neighbors			0.027*** (0.008)	-0.000 (0.002)
Household size among five nearest neighbors			0.038*** (0.013)	0.000 (0.003)
NGO participants and car owners among five nearest neighbors			0.952*** (0.130)	0.137*** (0.027)
Number of observations	*336*	*336*	*336*	*336*

Notes: *** p<0.01; ** p<0.05; * p<0.1. Coefficient estimates are shown with standard errors in parentheses. The test of overidentifying restrictions fails to reject the null hypothesis that the instruments are uncorrelated with the error term (p=0.61). A Wald test fails to reject the null hypothesis that NHMN and NGO are exogenous (p=0.52).

Table A4.3.2.Correlated random effects probit estimates

	HVM participation	
	Coefficients	Std. Error
Male farmer	0.471	(0.379)
Education of farmer	0.0537	(0.0583)
Age of farmer	0.00157	(0.0199)
Household size	-0.207**	(0.0853)
Off-farm employment	-0.0345	(0.284)
Land size	0.0747	(0.124)
Use of advanced irrigation techniques	-0.155	(0.397)
Own livestock	-0.173	(0.454)
Access to electricity	-0.112	(0.489)
Own means of transportation	0.722	(0.449)
Access to public transportation	0.231	(0.314)
Access to tarmac road	-0.399	(0.349)
Access to piped water	-0.0551	(0.314)
No. of HVM neighbors	0.404***	(0.134)
Participation in NGO project	0.916**	(0.445)
Mean of explanatory variables	*yes*	
Number of observations	*672*	

Notes: *** p<0.01; ** p<0.05; * p<0.1. HVM, high-value markets.

Table A4.3.3. Descriptive statistics of difference variables used in impact models

	Mean value	Standard deviation
Change in income	70,124	490,149
Change in HVM	-0.11	0.44
Change in age of farmer	0.99	9.61
Change in gender of farmer	-0.25	0.45
Change in education of farmer	0.23	3.04
Change in land size	0.16	1.65
Change in livestock ownership	0.03	0.39
Change in off-farm employment	0.21	0.60
Change in use of advanced irrigation techniques	-0.01	0.46
Change in household size	0.82	2.07
Change in ownership in means of transportation	-0.05	0.35
Number of observations	*336*	

Note: All changes were calculated as 2012 minus 2008 values.

Table A4.3.4. OLS estimates of change in income depending on the number of HVM neighbors

	(1) Change in income (TM suppliers in 2012)	(2) Change in income (HVM suppliers in 2012)
Age of farmer	344.2	-12584.6*
	(1874.6)	(6836.6)
Gender of farmer	-17375.3	377510.3**
	(45584.6)	(171784.6)
Education of farmer	5229.4	-38537.8
	(6867.0)	(28188.8)
Land size	30357.8***	148954.7***
	(11379.9)	(30059.2)
Livestock ownership	121300.5*	479664.6**
	(62972.8)	(226620.7)
Off-farm employment	161498.6***	-135760.3
	(46089.2)	(212504.3)
Use of advanced irrigation techniques	60501.9	445627.3*
	(49087.7)	(231421.4)
Household size	18200.2	31824.1
	(12237.4)	(42676.2)
Ownership of means of transportation	272894.3**	844515.5***
	(110084.4)	(191767.2)
No. of HVM neighbors	3005.0	-59924.3
	(19165.5)	(46231.2)
Constant	-191739.4	202405.4
	(157469.4)	(629187.8)
Number of observations	*259*	*77*

Notes: *** p<0.01; ** p<0.05; * p<0.1. HVM, high-value markets. TM, traditional markets. Coefficient estimates are shown with standard errors in parentheses. The dependent variable is change in annual household income measured in Ksh.

5 General Conclusion

5.1 Main Findings

Many developing countries are currently experiencing a profound food system transformation, which is associated with a rapid growth of modern retailers such as supermarkets. The growth of modern supply chains has been prominent in developing countries in the past two decades. Recent studies show that supplying emerging high-value markets (HVM) can be beneficial to producers in terms of improved incomes and productivity. However, there is still continued debate on other ways in which producers may benefit and also whether smallholders are able to overcome hurdles associated with supplying the HVM. Supplying HVM necessitates that farmers have the essential capital base to produce the required quantities while meeting the quality requirements. For farmers to supply HVM successfully, they may need information regarding buyer requirements, how to change their production and marketing system to meet those requirements, and benefits that accrue from supplying HVM. Such information may be less required when supplying traditional markets, but lack of access to information may limit smallholders from HVM participation.

In this dissertation, we contribute to the literature by analyzing the role of information networks in disseminating HVM information and hence participation. Additionally, we analyze the impacts of HVM participation on household nutrition and incomes. These aspects have either not been researched before, or they have been insufficiently researched. We have undertaken these analyses in three different but interlinked essays. The first and second essays have primarily used cross-section data collected from smallholder vegetable farmers in rural Kenya in 2012. The third essay has built on panel data from the same smallholder farmers collected over two rounds: 2008 and 2012.

In the first essay, we have analyzed the role of information networks in spreading information regarding HVM participation, an area that has not been analyzed before. Inadequate market information is cited as a main constraint in market participation. In the case of HVM participation, lack of market information may mean that only few farmers participate in these markets. Further developments of the modern markets could therefore

aggravate the difference between small and large farms due to differential access to market information. In this essay, we have analyzed characteristics of farmers that are likely to exchange market information using individual level data and dyadic regressions. We have found that farmers supplying HVM are exchanging market information among themselves, and they are also getting information from those supplying traditional markets (TM). However, we do not find evidence that TM farmers are obtaining market information from HVM farmers. In addition, we have analyzed the impact of having an information link with HVM farmers on participation in HVM. Using probit models, we have shown that having an information link with at least one farmer who previously supplied HVM increases farmers' own probability of participation in HVM by 10 to 19 percentage points. To get a better understanding of these impacts over time, we have analyzed effect of the information networks on HVM participation dynamics using multinomial logit models. We found that having an information link with at least one HVM farmer increases farmer's own probability of participation in HVM over time but it decreases farmer's probability of supplying TM over time.

In the second essay, we have analyzed impacts and impact pathways of HVM participation on household nutrition, an area that has also not been analyzed before. Our analysis has utilized seven-day recall data on household food consumption covering over 180 different food items. To analyze impacts, we have used an instrumental variable approach to control for both observed and unobserved heterogeneity. In a further step, we have used simultaneous equations to explore possible impact pathways. Our results show that participation in HVM has a positive effect on household nutrition. Controlling for other factors, we show that participation in HVM increases calorie, iron and zinc consumption by 15-20% and vitamin A consumption by almost 100%. Further, we have analyzed impact pathways using simultaneous equation models and have shown that HVM participation affects household nutrition through three main pathways: income, crop production choices at the farm level and changes in gender roles within the household. We have shown that the overall positive effect of HVM participation on household nutrition occurs through increases in household income and specialization in vegetable production, but loss in female control over vegetable revenue has a negative effect on household nutrition. This essay contributes to the literature by bringing in a new aspect in the analysis of impacts of HVM participation. It also contributes conceptually to the recent debate on linkages between agriculture and nutrition.

In the third essay, we have analyzed income effects of HVM participation using differencing techniques and instrumental variable approaches. In addition, we have used multinomial logit models to examine dynamics of HVM participation and the effects of the dynamics on household income. We show that participation in HVM is associated with a 59% increase in household income. On the other hand, dropping out of HVM leads to a significant decrease in household income. Finally, we found that the income growth for farmers who stay in HVM is higher than for those staying in TM, hence indicating that the inequality between farmers in the two channels may widen over time. This essay makes important contributions to the literature by reinforcing the positive effects of HVM participation and showing dynamics of HVM participation and their effects on household incomes.

5.2 Policy Recommendations

Overall, our study shows that the food system transformation and the modernization of supply chains in developing countries can contribute to economic development and important welfare benefits to farm households. Policy makers should support measures that allow smallholders to access and remain in HVM. For instance, informal information networks could be used in dissemination of market information, hence increasing HVM participation, but this should be done with care as targeting certain farmers only could lead to further marginalization of poor farmers.

From the first essay, we find that farmers obtain market information from fellow farmers. However, only HVM farmers are likely to obtain information from each other and also from TM farmers. We find no evidence that TM farmers obtain market information from those supplying HVM. As the modern supply chains spread out, the gap between HVM farmers and TM farmers is likely to worsen due to unequal access to market information. To mitigate this risk, policy makers should promote measures that make market information accessible to all farmers irrespective of where they are supplying. Extension officers, for instance, could disseminate such information through small groups of farmers consisting of both HVM and TM supplying farmers.

From the second essay, we have found that participation has a positive effect on household nutrition. This has important implications as smallholder farmers make up a large proportion of all undernourished people worldwide. There is need for policy support to link small farms to emerging supply chains and assist them to overcome constraints

that would otherwise limit them from participation, such as poor infrastructure, lack of physical capital required to participate, and lack of market information among others. Further, the impact pathway analysis shows that a good understanding of agriculture-nutrition linkages is needed to promote desirable outcomes. Our findings show that the role of women needs to be strengthened to further improve nutritional benefits. As modern supply chains expand, programs that work on linking smallholders to these markets should ensure that women are included as the main players in terms of production and marketing of the crops and playing a role in the decision making on the use of revenue that comes from those crops. Addressing challenges of HVM participation in such directions could increase participation by smallholders but also by women smallholders. This could consequently lead to improved dietary quality in the households hence reduction in levels of undernourishment and micronutrient deficiency.

From the third essay, we have found that participation leads to large income gains for farm households. Those who stay in HVM have larger gains than those who stay in TM, indicating possibility of widening inequality between large and small farms. Furthermore, those who drop out of HVM experience a huge income loss. To tap the income benefits arising from HVM participation and avoid the negative consequences of dropping out, policy makers need to address constraints that bar smallholders from supplying HVM, for example poor infrastructure, inadequate physical capital, and missing or insufficient market information. If more smallholders are able to supply and remain in HVM, this could have positive effects on poverty reduction in developing countries.

5.3 Limitation of the Study and Areas for Further Research

Our study shows that obtaining market information from a farmer who has previously supplied HVM increases the farmer's own probability of participation in HVM, which in turn leads to improved household dietary quality and income. However, there are several aspects that limit the scope of our findings.

First, the analysis of effects of information network on HVM participation builds on cross-sectional data, where smallholders self-select into HVM. Even though we test for endogeneity in our analysis, it is still possible that some unobserved factors affect the results. Collecting panel data in combination with behavioral field experiments to capture unobserved endogeneity would be useful.

Second, due to the small number of farmers from different strata that each respondent was matched with, we could only capture the information network as binary variable, hence missing out on the effect of the size of the information network on HVM participation. A future study should increase the number of farmers each respondent is matched with in each stratum so as to increase the probability of knowing farmers in different strata.

Third, the analysis of impacts of HVM participation on household nutrition is also based on cross-section data, which is likely to suffer from farmers self-selecting into HVM. Even though we use a instrumental variable approach and perform validity tests of our instruments, a more rigorous analysis would be possible with panel data. With cross-sectional data, there are several interesting questions that we are not able to analyze. For instance: what happens to household nutrition as the households continue supplying HVM over time? Does the dietary quality of households that drop out of HVM channels deteriorate or not? Does the dietary quality of the households that remain in TM deteriorate with time or not? Since such dynamics cannot be analyzed with cross-sectional data, panel data would be helpful in better controlling for endogeneity and also in analyzing dynamics.

Fourth, our analysis is based on seven-day recall consumption data. Such data can deliver good indicators of dietary quality but not precise measures for nutritional status. To fully understand impacts of HVM participation on nutritional status, better indicators of nutritional status such as anthropometric data need to be collected.

Fifth, the results on impact pathways of HVM participation on household nutrition are specific to the Kenyan context and should not be generalized. Gender effects may differ with culture, and the effects of specialization will differ by the type of crop supplied to HVM. If the crop has no nutritive value, then the impact of the specialization pathway on household nutrition could differ.

Sixth, the interpretability of our results in the third essay on dynamics of HVM participation and their income effects may be limited by the relatively small sample size of farmers that newly joined HVM in the second round. Follow-up study with larger sample sizes and more rounds of survey would be important to verify the results. The results of this essay are also specific to the area of study. Kiambu, the study area is relatively close to Nairobi the capital city, and therefore farmers may have better market access than those in remoter regions. Farmers in remoter regions of Kenya, or in other

parts of Africa, may possibly face more participation constraints or get lower gains from HVM participation. Therefore, there is need for studies to be undertaken in other regions of Kenya and other developing countries in general, so as to make a within-country or cross-country comparison on the impacts and impact dynamics of participation.

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General Appendix

Household Questionnaire

Questionnaire number (HHID) _____

HOUSEHOLD SURVEY 2012

UNIVERSITY OF GÖTTINGEN
FOLLOW UP SURVEY ON ACCESS TO HIGH-VALUE AGRICULTURAL MARKETS AND IMPLICATIONS FOR RURAL DEVELOPMENT: THE CASE OF VEGETABLE PRODUCTION IN CENTRAL KENYA.

"We are students from Gottingen University-Germany, who are studying different aspects of agricultural development. We are currently doing a follow up survey on the study conducted by James Rao in 2008 about vegetable production in Kiambu area. The main purpose of this study is to understand more about farmers' decisions about production and marketing of vegetables. Your participation in answering these questions is very much appreciated. Your responses will be **COMPLETELY CONFIDENTIAL** and will only be used for research purpose. Your responses will be added to those of 402 other households and analyzed together. If you indicate your voluntary consent by participating in this interview, may we begin?

Household No: **HHID**
____

Survey Date: (dd/mm/yyyy) SURDATE

____/____/ 2012

Start time (24 Hrs) **STIME**_____:_____

HH head Name (Full name) _____

Respondent's name (Full name) _____ **RESMEM**_____

Cell phone number _____

(**Enumerator Instruction**: *Record the member number (RESMEM) of the Respondent from the Demography table on page 29 after the survey is completed.)*

Identifying Variables:

Supervisor: _____ **SNUM**_____
Enumerator: _____ **ENUM** _____
District: _____ **DIST** _____
Division: _____ **DIV** _____
Location: _____ LOC _____

Sub-Location: _____ SUBLOC _____
Village: _____ VIL _____
Supplier to HVC in 2008? (0=No;1=Yes directly;2=Indirectly) **HVCSUPLR** _____

GPS Co-ordinates (homestead): GPS No : _____ Waypoint No : _____

(1=North; 2=South) | | | . | | | | | |

EAST=1 | 1 | | | . | | | | | |

ELEVATION (M.A.S.L) | | | | | METRES

Data entry clerk Name: _____ **DECODE**_____

Questionnaire number (HHID) _____

1.0 GENERAL FARMING INFORMATION

1.1 In total, what is the size of the **land holding (area owned)** by this household?

a) Size _____ b) Unit _____ *(1= acres, 2= m^2, 3=Ha, 4=$feet^2$)*

1.2 For how long have you been farming (as an independent household)?

a) Years: _____ b) Months: _____

1.3 What was the size of the farm when you started cultivating it?

a) Size: _____

b) Unit: _____ *(1= acres, 2= m^2, 3=Ha, , 4=$feet^2$)*

1.4 In **the current season (March-August 2012)**, what crops do you grow on your farm and what size of your farm is allocated to each crop grown?

		Total area under crop		Area owned	Area leased in
Crop code	**Crop name**	Area	Unit *(Unit Codes)*[a]	Area *(use the same unit code as for total area under crop)*	Area *(use the unit code for as for total area under crop)*
1	All Vegetables [b]				
2	Potatoes (Irish)				
3	Sweet potatoes				
4	Maize				
5	Beans				
6	Yams				
7	Tea				
8	Coffee				
9	Bananas				
10	Fodder				
11	Other (Specify1_____)				
12	Other (Specify2_____)				
13	Other (Specify3_____)				
14	Other (Specify4_____)				
15	Other (Specify5_____)				
	Total area leased out				

[a] ***UNIT CODE:*** *1= acres, 2= m^2, 3=Ha, , 4=$feet^2$*

[b] *Vegetables refers to all vegetables including tomatoes and onions*

Questionnaire number (HHID) _____

1.5 Do you use irrigation on your farm? _____ *(Yes =1; No =0)* ***(If No, Go to Q1.9)***

1.6 If yes, how long have you been using irrigation? Years: _____ Months: _____

1.7 For the current season **(March-August 2012)**, what size of your total cultivated area is irrigated?

a) Size: _____ b) Unit: _____ *(1= acres, 2= m^2, 3=Ha,, 4=$feet^2$)*

1.8 If you irrigate part/whole of your farm, what special irrigation equipment do you have?

Irrigation equipment/tool	***1=YES; 0=NO***
1) Water pump	
2) Borehole	
3) Well	
4) Dam	
5) Water tank	
6) Drip irrigation system	
7) Special pipes	
8) Sprinkler	
9) Watering can	
10) Other (please specify) _____	

1.9 What is the value of all vegetables sold and consumed from the farm for the **last crop year** (2011/2012)? **(*Please make sure that sales and consumption from the full year is included)***

Rainy season (March-May 2011 and Nov-Dec 2011)				**Dry season** (June-October 2011 and Jan-February 2012)			
Number of months sold	Value sold/month (Ksh)	Number of months consumed	Value consumed from farm/month (Ksh)	Number of months sold	Value sold/month (Ksh)	Number of months consumed	Value consumed from farm/month (Ksh)

Questionnaire number (HHID) _____

1.10 Please give the following production and revenue details for **other** crops grown during both long and short rains seasons **last farming year (2011)** –excluding vegetables

Long rains season (from February- August 2011)									8. Total Annual bonus (tea & coffee) (Kshs)	**Short rains season** (September 2011-January 2012)						
Crop code	**Crop name**	Quantity produced		Quantity sold		5. Average price per unit (Kshs)	6.Highest price received per unit (Kshs)	7.Lowest price received per unit (Kshs)		Quantity produced		Quantity sold		5. Average price per unit (Kshs)	6. Highest price received per unit (Kshs)	7. Lowest price received per unit (Kshs)
		1. Quantity	2.Unit *(Unit code)*[a]	3. Quantity	4.Units *(Unit code)*[a]					1. Quantity	2.Unit *(Unit code)*[a]	3. Quantity	4. Units *(Unit code)*[a]			
2	Potatoes (Irish)															
3	Sweet potatoes															
4	Dry Maize															
11	Green Maize															
5	Beans															
6	Yams															
12	Other (Specify1 _____)															
13	Other (Specify2 _____)															
Last farming year (from February 2011-January 2012)																
7	Tea															
8	Coffee															
9	Bananas															
10	Fodder															
14	Other (Specify3 _____)															

[a]**UNIT CODES**			
1=Kilogram	5=90 kg bag	9=1/4 kg tin	13=Tones
2=5 Kg bag	6=Debe (18 kgs)	10=1/2 kg tin	14=Others(specify)
3=25 Kg bag	7=Number/Unit	11=Kg tin	_____
4=50 kg bag	8=Gorogoro (2.25 kg tin)	12=Bunches(Bananas only)	

Questionnaire number (HHID) _____

1.11For each crop mentioned above please give details of the cost of production for the crop year 2011. ***Details should be for all plots and the two crop seasons mentioned above.***

Crop Code	Crop	1. Land rent cost [a] (Kshs)	Seeds			Fertilizer			Manure			Pesticide			14. Total Machinery Cost in (Kshs) [d]
			2.Quantity	3.Unit *(UNIT CODE)[b]*	4.Total Cost (Ksh)	5.Quantity	6.Unit *(UNIT CODE)[b]*	7.Total Cost (Ksh)	8.Quantity	9.Unit *(UNIT CODE)[b]*	10.Total Cost (Ksh)[c]	11.Quantity	12.Unit *(UNIT CODE)[b]*	13.Total Cost (Ksh)	
1	All Vegetables														
2	Potatoes (Irish)														
3	Sweet potatoes														
4	Maize														
5	Beans														
6	Yams														
7	Tea														
8	Coffee														
9	Bananas														
12	Other (specify1_____)														
13	Other (specify2_____)														
14	Other (specify3_____)														
15	Other (specify4_____)														

[a] Cost of total land rent for the whole year for each of the crop on rented land [c] If farmer used own manure, ask for the local value of the manure [d] If the farmer owns machinery ask for local rates of machinery use;

[b]*UNIT CODE*							
1=Kilogram 2=5 KG. BAG 3=25 KG. BAG	4=50 KG. BAG 5=90 KG. BAG 6=DEBE (18 kg)	7=Number/Unit 8=Gorogoro(2.25tin) 9=1/4 kg tin	10=1/2 kg tin 11=1Kg tin 12=crate (tomatoes)	13=Bunches(Bananas) 14=Liters 15=Milliliters	16=2 kg Packet 17=grams 18=Wheelbarrow	19= Cup (15)	20=Others(specify) _____

Questionnaire number (HHID) _____

1.12How many **permanent farm workers** did you have **last year** (January 2011-December 2011) and what was their monthly salaries *(for both crop & livestock*)?

Worker number	**Monthly salary (in Kshs)**	**Length of employment Jan-Dec 2011** *(In months)*	**Type of work (***1=only crops; 2=only livestock; 3= both)*
1			
2			
3			
4			
5			
6			

1.13Besides permanent workers give the following details on **labor use and cost for causal workers** employed on your farm for crop production on a <u>weekly basis</u> for **last year (January 2011-December 2011).** *(Including both piece rate and daily wage rate)*

Peak season (_____ months) *(To be specified by the respondent)*									
Hired labor					**Family labor**				
Average No. of laborers/week	No. of Male	No. of female	Average No. of working hours per day	Average No. of working days/week	Average No. of laborers/week	No. of Male	No. of female	Average No. of working hours per day	Average No. of working days/week
Off peak season (_____ months) *(To be specified by the respondent)*									
Average No. of laborers/week	No. of Male	No. of female	Average No. of working hours per day	Average No. of working days/week	Average No. of laborers/week	No. of Male	No. of female	Average No. of working hours per day	Average No. of working days/week

1.14 What is the average **daily wage rate** for men and women in this area?
Men _____ Ksh/day Women _____ Ksh/day

1.15 What is the typical number of working hours per day? _____ hours

1.16 Currently, do you have any livestock on your farm? _____ (*1=Yes; 0=No)*

Questionnaire number (HHID) _____

1.17 For the **whole of last year (January 2011-Decemeber 2011)**, please give details of revenue and cost of livestock production?

Please include all animals on the farm last year also those that were later sold or died)

Animal	Number of Livestock owned	Number of Livestock sold	Total revenue (Ksh)	Total Cost of Production (Ksh)			
				Fodder/ feeds	Labor *(temporary labor)*	Veterinary care	Other costs
Cows							
Goat							
Sheep							
Chicken							
Donkeys							
Pigs							
Rabbits							
Ducks							
Other specify1 ____							
Other specify2 ____							
All animals listed above							

Animal product	1.Quantity sold	2.Units *(UNIT CODE)*[a]	3. Price per unit (Ksh)
Milk			
Eggs			
Hide			
Others specify_____			

[a]*UNIT CODE (1=litres, 2=mililitres, 3=Units/numbers, 4=Tray)*

2.0 GENERAL INFORMATION ABOUT VEGETABLES

PLEASE FIND OUT WHO IS IN CHARGE OF VEGETABLE PRODUCTION AND INTERVIEW THIS PERSON.

2.1 Who makes decision about vegetable farming and marketing?

Name of decision maker _____

OPMEM_____

Relationship to household head ____ (1=*Household head; 2=Spouse; 3= Son/Daughter; 4=Relative;*

5=others (specify) _____)

Gender of decision maker _____; *(0 = female; 1 = male)*

Questionnaire number (HHID) _____

(**Enumerator Instruction**: Record the member number (OPMEM) of the decision maker from the Demography table on page 29 after the survey is completed.)

2.2 How long have you been growing vegetables (as an independent household)?

a) Years: _____ b) Months: _____

2.3 Since 2010, how much of the indigenous and exotic vegetables have you been growing? ***(Enumerator, ask the farmer to give the average area for each year, considering all seasons)***

Vegetable type	**Area cultivated in each year for each type (acres)**					
	2012		**2011**		**2010**	
	Area	**Area code[a]**	**Area**	**Area code[a]**	**Area**	**Area code[a]**
1=African indigenous vegetables						
2)= Exotic vegetables						

(African indigenous vegetables are e.g managu, terere, kunde, osuga, pumpkin leaves etc; Exotic vegetables are e.g spinach, sukuma wiki, lettuce, etc)
AREA CODE[a]*: 1= acres, 2= m^2, 3=Ha, 4=$feet^2$*

2.4 How many different vegetable plots did your household have in **2011 main season? _**

2.5 Please tell me the sizes of these different vegetable plots (**for 2011 main season),** and who made the decisions about production, sales and revenue spending for each plot:

IF MORE THAN 3 PLOT: PLEASE RANDOMLY SELECT 3 PLOTS BASED ON THE LAST DIGIT OF THE HHID. Ask the different vegetables in each plot to assist in sampling.

Plots No.	**Size of the plot**	**Unit of measure** *1=acres; 2=m^2; 3=Ha 4=$feet^2$*	**Type of vegetable** *(Vegetable codes below)[a]*	**In total, what was the proportion of output sold from this plot?** *(Proportion of sales codes below)[b]*	**Who made the decisions about the production on this plot? (***I.e. when, where, how much and what type of vegetable to grow)* *(Decision maker codes below)[c]*	**Who made decisions about the output from this plot?** *(I.e. how much to sell, how much to use for home consumption where and when to sell)?* *(Decision maker codes below)[c]*	**Who decided how to use the revenues from sales from this plot?** *(Decision maker codes below)[c]*
Plot1							
Plot2							
Plot3							

Questionnaire number (HHID) _____

[a] *VEGETABLE CODES*		[b] *PROPORTION OF SALES CODE*	[c] *DECISION MAKER CODE*
1=Managu	*7=Spinach*	*1= none at all;*	*1=Husband alone made the decisions,*
2=Sargeti,	*8= Dhania (Corriander),*	*2= less than 25%;*	*2=Husband was the major decision maker*
3=Terere,	*9= Brocolli,*	*3= 25%;*	*after consulting with wife,*
4=Thoroko	*10= Lettuce,*	*4= between 25 – 50%;*	*3=Wife alone made the decisions,*
(cow pea	*11=others,*	*5= 50%;*	*4=Wife was the major decision maker*
leaves),	*specify_____,*	*6=between 50 – 75%;*	*after consulting with husband*
5=Kales	*12=others,*	*7= 75% ;*	*5=Someone else makes decision (specify*
(Sukuma	*specify_____*	*8= between 75-95%*	*who, including gender e.g. daughter,*
wiki),	*13=others,*	*9=95%*	*female relative)*
6=Cabbage,	*specify_____)*	*10=all*	*_____*

2.6 What are the **three ways** in which most of the money from selling vegetables was used? ***(1=largest amount of money spent; 2=2nd largest amount of money spent; 3=3rd largest amount of money spent).***

1. Buy food	2. Furniture	3. Pay hospital bill	4. Pay rent	5. Pay Dowry	6. Leisure	7. Land preparation	8. Buy farm input	9. Pay loans	10. School fees	11. Clothing	12. Others (specify_____

2.7 For the **present season (March-August 2012),** how much of your vegetable area is irrigated?

a) Area: _____ b) Unit: _____ *(1= acres, 2= m^2, 3=Ha, 4=$feet^2$)*

2.8 From where do you get information on production of vegetables such as information on production techniques, new seeds, pest control, input use etc.? ***(<u>Rank three most important sources</u>)****(1=most important source, 2=2nd most important, etc.)*

	Rank (1-3)
1) Government extension (field days etc.)	
2) Agricultural cooperative	
3) NGO (Please specify) _____	
4) Input dealer	
5) Members of my farmers' group	
6) Other farmers (e.g., neighbors, but non-group members)	
7) Public gathering (*barazas*)	
8) Public media (e.g., radio, newspaper, magazines)	
9) Traders	
10) Contracting retailer (supermarket, export companies, etc.)	
11)Agricultural seminars, workshops, group trainings	
12) Own experience	
13) Other (please specify):	

Questionnaire number (HHID) _____

2.9 When it comes to obtaining new information about production of vegetables, would you say that it is very difficult, difficult, easy or very easy for you to obtain such information?

(1 = Very difficult; **2** = Difficult; **3** = Easy; **4** = Very easy) _____

2.10 What kind of production information do you feel you are lacking?

Type of production information lacking	***1=YES; 0=NO***
1. New varieties	
2. Correct pesticide	
3. Production techniques	
4. Credit possibilities	
5. Selection of good seed	
6. Use of inorganic/ organic fertilizer	
7. Others (specify)_____	

3.0 INFORMATION ON MARKETING OF VEGETABLES

3.1 Are you always able to sell all your vegetable that you wish to sell? _____ **(1=YES, 0=NO) (IF YES; SKIP TO QN: 3.3)**

3.2 If no, please give reasons why you are unable to sell.

Reasons	***1=YES; 0=NO***
1. The price is unbearably low	
2. There is no willing buyer (lack of market)	
3. I have no means of transporting	
4. Too much supply on the market (flooded market)	
5. Some of the produce is rejected by the buyer because of quality	
6. Others (Specify1) _____	
7. Others (specify2) _____	

Questionnaire number (HHID) _____

3.3 Whenever you want to sell your vegetables, where do you get information on possible **market opportunities and market prices**? ***(Rank three most important sources)***

(Ranks: 1=most important source; 2=2nd most important source; 3=3rd most important source.)

Source of market information	**Rank (1–3)**
1. From fellow farmers' group members	
2. Other farmers, who are not members of my group	
3. From cooperative society	
4. From agricultural extension staff	
5. From NGO (Specify) _____	
6. From public media (radio, television etc.)	
7. From public gatherings (chief's *baraza* etc.)	
8. Agricultural seminars, workshops, group trainings	
9. From traders	
10. Others (specify)	

3.4 When it comes to obtaining new information about marketing opportunities and prices for vegetables, would you say that it is very difficult, difficult, easy or very easy for you to obtain such information?

(1 = Very difficult; **2** = Difficult; **3** = Easy; **4** = Very easy) _____

3.5 What kind of marketing information do you feel you are lacking?

Type of marketing information lacking	***1=Yes; 0=No***
1. Market opportunities (where to sell)	
2. Prices	
3. Market requirements or standards	
4. Other (please specify)_____	

Questionnaire number (HHID) _____

Please tell me details about marketing of vegetables produced during **2011 crop year (February 2011 to January 2012)**

3.6 During <u>last crop year,</u> to which buyers did you sell your vegetables? *USE THE BUYER CODE* [a]	3.7 ***(If sells to supermarket, companies and institutions-directly)*** During which other years have you been selling to this buyer? ***(Enumerator: If told 2002, 2003, 2004 and 2009 please write 2002-2004, 2009)***	3.8 How did you come in contact with the buyer before you supplied him/her/it for the very first time? [b] *USE CONTACT CODE* [b]	3.9 For the last crop year, to which 3 buyers did you sell most of your vegetables? Please rank them in order of importance *1= buyer that bought the largest share* *2= buyer that bought the second largest share* *3= buyer that bought third largest share*

[a] *BUYER CODE*

To supermarket 1.Uchumi 2. Nakumatt 3. Tuskys 4. Other supermarket(Specify)_____ ***To supermarket via specialized trader/broker*** 5. Trader/broker to Uchumi 6. Trader/broker to Nakumatt 7. Trader/broker to Tuskys 8. Trader/broker to any supermarket(Specify)_____	***Companies and institutions*** 9. City park market 10. Mugoya vegetables 11. Exporting company 12. Hotels 13. Green groceries 14. School 15. Other institutions & companies (Specify) _____ 16. Trader that sells to Companies or Institutions ***Traditional market*** 17. Spot market 18. A specific independent middleman or broker 19. Various independent brokers or middlemen 20. Other (Specify) _____

[b] *CONTACT CODE*

1. Via phone **through other farmers** who supplied the buyer

2. Personally when he was in the village **through other farmers** who supplied the buyer;

3. Personally at the wholesale market **through other farmers** who supplied the buyer;

4. Personally at the wholesale market without knowing the buyer;

5. The buyer contacted the farmer via phone;

6. The buyer contacted the farmer personally when he was in the village

7. Other specify_____

Questionnaire number (HHID) _____

Please tell me more details about your 3 most important buyers (listed in 3.9):

PLEASE LIST THE THREE MOST IMPORTANT BUYERS RANKED IN 3.9		3.10 For the last crop year, when did this buyer mainly pay you for your produce? *1= The same day;* *2=Within 1 week;* *3=Within 2 weeks;* *4=At the end of the month* *5=After more than 1 month*	3.11 Have you ever borrowed money from this buyer? *1= YES* *0= NO*	3.12 Have you ever lent money to this buyer? *1= YES* *0= NO*	3.13 Have you made any specific investments to be able to supply vegetables to this buyer? *1= YES* *0= NO* *IF NO GO TO QUESTION 3.16*	3. 14 If yes, what kind of investments was it? *PLEASE SPECIFY*	3.15 How much did the total investments cost? *IN KSH*
CODE	*NAME*						

Questionnaire number (HHID) _____

3.16 Now we are interested in your reasons for selling to different buyers

PLEASE FILL IN THE NAME OF THE BUYER BASED ON QUESTION 3.9-> *CODES:* *1 = if reason is mentioned* *0= if reason is not mentioned*	*Name:* _____ *Buyer ranked No. 1 in question 3.9*	*Name of supermarket* _____ FILL IN ONLY *IF farmer supplied to any supermarket but not ranked it No.1*	*Name of company or Institution* _____ FILL IN ONLY *IF farmer supplied to any company or institution but not ranked it No. 1*
	Why did you sell vegetables to ------**?**	Why did you sell vegetables to ------**?**	Why did you sell vegetables to ------**?**
1. The buyer offers a high price			
2. The buyer pays a stable price			
3. The buyer does not manipulate price (does not change price arbitrarily)			
4. I can negotiate price with the buyer			
5. The buyer pays promptly			
6. The buyer will always buy the produce (market assurance)			
7. The buyer is not strict on the quality of products, so I can sell all my produce			
8. I do not have to worry about breakages/spoilage after selling			
9. We have a long standing trading relationship			
10. The buyer is well known in the village			
11. We are friends or relatives			
12. Welfare or financial support, e.g. advance			
13. The buyer provide me with knowledge about production methods			
14. I have no other alternative market (buyer)			
15. I cannot supply more to other buyers that I would rather sell to			
16. I have no means of transporting vegetables to other markets			
17. Other reasons (specify)			

Questionnaire number (HHID) _____

IF THE RESPONDENT SOLD AT LEAST SOME VEGETABLES TO SUPERMARKETS DURING THE LAST CROP YEAR: PLEASE GO TO QUESTION 3.21

3.17 Do you know that you can sell vegetables to supermarkets? _____

(1=YES; 0=NO-> go to question 3.22)

3.18 Why did you not supply your vegetables to supermarkets?

Reasons:	*PLEASE FILL IN* *1 = if reason is mentioned* *0= if reason is not mentioned*
1. Do not pay promptly	
2. Cheats on the timing of payment	
3. Too much variation in prices	
4. Cheats on price agreement	
5. Offers low price	
6. Demand too strict standards	
7. Rejects too much of my produce	
8. Cheats on quality agreement	
9. Farmer is unable to supply required quantity	
10. Buys too small quantities	
11. Too much damages/breakages	
12. Cheating on damage/breakages	
13. Difficult to get the initial contract	
14. Require reliable means of transport	
15. Time consuming / labor demanding	
16. Capital intensive	
17. Others (specify 1) _____	
18. Others (specify 2) _____	

3.19 Have you ever supplied to supermarkets? _____ *(1=YES; 0=NO)* ***IF NO SKIP TO 3.21***

3.20If yes, during which years? _____

(*Enumerator*: *Please make sure that all years are included)*

Questionnaire number (HHID) _____

3.21 Have you ever been rejected to supply to supermarkets? _____ *(1=YES; 0=NO)*

3.22 When selling your vegetables to_____ *(buyer ranked one, supermarket or companies and institutions),* when do you agree on…?

PLEASE FILL IN THE NAME OF THE BUYER BASED ON QUESTION 3.9-> *CODES:* *0=no agreement* *1=agreement on spot* *2 = agreement before supply,* *3= agreement before production,* *4= agreement once at the beginning*	*Name:* _____ *Buyer ranked No. 1 in question 3.9*	*Name of supermarket* _____ *FILL IN ONLY* *IF farmer supplied to any supermarket but not ranked it No.1*	*Name of company or institution* _____ *FILL IN ONLY* *IF farmer supplied to any company or institution but not ranked it No. 1*
Agreement on transaction (Transaction attributes)			
1. On type of vegetable			
2. On price			
3. On quantity			
4. To supply continuously (all year round)			
5. To deliver regularly (twice/week etc.)			
6. On production technique			
7. Mode of payment (e.g. cash/cheque/m-pesa)			
8. Specific plot to be used for production			
9. I should have a cell phone for receiving orders			
10. No side-selling			
11. Time of delivery			
12. Time of payment			
13. Other (specify _____			
Agreement of product attributes			
1. Vegetable should be harvested at certain age			
2. Deliver fresh produce (delivered within hours of harvesting)			
3. Vegetable should be cleaned before delivery			
4. Vegetable should be free from pests			
5. Vegetable should be packed in certain quantity and ready for shelf			
6. Minimum pesticide use			
7. Others (specify _____			

3.23 Please give more details of the agreement and rejection rates ***(to be asked for all buyers except Spot market)***

PLEASE FILL IN THE NAME OF THE BUYERS BASED ON QUESTION 3.9 ->	*Name:* _____ *Buyer ranked No. 1 in question 3.9*	*Name of supermarket* _____ *FILL IN ONLY IF farmer supplied to any supermarket but not ranked it No.1*	*Name of company or Institution* _____ *FILL IN ONLY IF farmer supplied to any company or institution but not ranked it No. 1*
1. If there was an agreement, was it oral or written? *1= Oral, 2=Written 3=Partly oral and partly written*			
2. If there was an agreement, what would have happened if you were unable to fulfill the agreement? *USE THE CONSEQUENCE CODE [a] (multiple codes possible)*			
3. If there was an agreement, how many times during last season were you unable to deliver upon request? *IN NUMBER OF TIMES*			
In general….			
4. During last season, how much of your product was rejected? *IN PERCENT*			
5. Did you agree on the rejection? *1= YES; 0=NO*			
6. How often has the buyer been to your farm in the last one year? *(1= Never; 2= Once; 3= More than once)*			

[a] ***CONSEQUENCE CODE***	
1 = Nothing happens	5 = I will have to pay back next season
2 = I will immediately lose the opportunity to supply to the buyer	6 = It will be pressure from the buyer
3 = I will eventually lose the opportunity to supply to the buyer	7 = It will be pressure from other farmers
4 = I will have to pay a fee	8=Other(specify)_____

3.24 Did you receive any other services or assistance from the buyers of your vegetables?

PLEASE FILL IN THE NAME OF THE BUYERS BASED ON QUESTION 3.9 -> *1 = if service/assistance is mentioned* *0= if service/assistance is not mentioned*	*Name:* _____ *Buyer ranked No. 1 in question 3.9*	*Name of supermarket* _____ *FILL IN ONLY* *IF farmer supplied to any supermarket but not ranked it No.1*	*Name of company or Institution* _____ *FILL IN ONLY* *IF farmer supplied to any company or institution but not ranked it No. 1*
I received service or assistance on;			
1. Seeds supply			
2. Pesticide supply			
3. Fertilizer supply			
4. Information on production techniques			
5. Credit on output (welfare support)			
6. Loan guarantee			
7. Advances on crop production			
8. Market information (output)			
9. Market information (input)			
10. Harvest			
11. Transportation to market			
12. Other assistance			

3.25 Please list any problems or complaints/ dissatisfaction that you have about the top ranked buyers of vegetables in question 3.9? **(*Please rank your complaints/problems*).**

PLEASE FILL IN THE NAME OF THE BUYERS ACCORING TO THE RANKING IN QUESTION 3.9 *1 = if reason is mentioned* *0= if reason is not mentioned*	*Name:* _____ *Buyer ranked No. 1 in question 3.9*	*Name of supermarket* _____ *FILL IN ONLY* *IF farmer supplied to any supermarket but not ranked it No.1*	*Name of company or Institution* _____ *FILL IN ONLY* *IF farmer supplied to any company or institution but not ranked it No. 1*
Problem			
1. Cheating on price agreement			
2. Cheating on quality agreement			
3. Cheating on time of buying			
4. Cheating on the timing of payment			
5. Offers low price			
6. Cheating on damage/breakages			
7. Others (specify1)			
8. Others (specify2)			

3.26 **For this season *(March-August 2012)***, where do you sell/plan to sell your vegetables? (Please choose the **three markets where you sell most quantities and rank them** in order of importance)

Market Channels	**RANK** ***1=market where highest quantity is sold/will be sold;*** ***2=market where 2nd highest quantity is sold/will be sold;*** ***3=market where 3rd highest quantity is sold/will be sold;***
1. The supermarkets	
2. Traders/brokers to supermarkets	
3. Companies and institutions	
4. Independent middlemen or traders	
5. Spot market	
6. Others (specify) _____	

4.0 **INPUT AND OUTPUT DATA FOR VEGETABLE PRODUCTION (FOR ONE PLOT)**

*The following questions relate to the **present season (March-August 2012).** 1. Farmers supplying supermarkets (direct or indirect) should give information for the **main vegetable** that they mostly supply to **supermarket**. 2. Farmers supplying to institutions and companies should give information on the main vegetable that they mostly supply to **institutions and companies** (unless they supply to supermarkets). 3. The rest of the farmers should give information about their main vegetable to the **traditional market.***

4.1 Which is the **main vegetable** that you sell/will sell in highest volume to your **most preferred market** chosen in **3.26***(please note: current season March-August 2012)?*

Vegetable	***1=YES; 0=NO***	**Type of vegetable** *1=AFRICAN INDIGENOUS VEGETABLES (AIV) 2= EXOTIC*	**Vegetable**	***1=YES; 0=NO***	**Type of vegetable** *1=AFRICAN INDIGENOUS VEGETABLES (AIV) 2= EXOTIC*
1) Managu			7) Spinach		
2) Sargeti			8) Dhania		
3) Terere			9) Brocolli		
4) Thoroko (cow pea			10)Lettuce _____		
5) Kales (Sukuma wiki)			11)Others_____		
6) Cabbage					

Questionnaire number (HHID) _____

Please identify one plot where the vegetable chosen in 4.1 above is grown and ask the following questions <u>at the site of this plot</u>. *(I f more than one plot, please choose the plot based on the last digit of the HHID)*

4.2 Please give the following information for the chosen plot that contains the main vegetable sold to the most preferred market.

Plot information			Harvest information					Sales		*ONLY if not sale per plot*		*ONLY if sale per plot*
1. Area/size of the plot	2. Units *(Use codes below)*	3. Soil quality *(Use codes below)*	4. Soil type *(Use codes below)*	5. Slope of plot *(Use codes below)*	6. No. of harvesting rounds [a]	7. Quantity produced per harvest	8. Units *1=Bundle; 2=90kg bags 3=kg 4=pieces 5= crates 6=kikapu of dhania*	9. Quantity sold per harvest	10. Units 1=Bundle; 2=90kg bags 3=kg 4=pieces 5= crates 6=kikapu of dhania	11. Highest price per unit (Kshs)	12. Lowest price per unit (Kshs)	13. Sales revenue per plot per harvesting round (Kshs)

[a] *Number of harvesting rounds before the plot is replanted*

<u>Land unit codes:</u>	***<u>Soil quality codes</u>:***	***<u>Soil type codes:</u>***	***<u>Slope codes:</u>***
1= acres, 2= m2, 3=Ha	*1= highly fertile, 2=medium fertile, 3= low fertile.*	*1=black cotton soil, 2=clay soil, 3=loam soil, 4=sandy soil, 5= other specify_____*	*1=steeply sloped plot, 2= gently sloped plot, 3=plot on flat ground.*

4.3 If output is measured in bags, approximately how many bundles can one make from one bag of vegetables? _____ bundles

4.4 How many leaves/stems of this vegetable make one bundle? _____

Questionnaire number (HHID) _____

4.5 For the identified plot of vegetable, please specify all inputs that you use during **the entire crop cycle**, their prices per unit, and the total amount of money spent **on this plot?** ***Please give information for one full plot planted at once.***

Input	**No. of times applied**	**Average amount used each time**		**Purchase cost/unit**		**Total cost (Ksh)**	**Source** ***USE SOURCE CODE*** [b]
		Quantity	**Units** *USE UNIT CODE*[a]	Product price (Ksh)	Unit of purchase *USE UNIT CODE*[a]		
1. Seed							
Organic matter (specify)							
2. Own farm-yard manure							
3. Purchased farm-yard manure							
Pesticides							
4.Insecticide							
5.Fungicide							
6.Herbicide							
7. Electricity							KPLC
8.Fuel for irrigation							
Fertilizers *(Please specify)*							
Other inputs(*Please specify)*							

[a] *UNIT CODE*					[b] **SOURCE CODE**
1=Kilogram 2=5 KG bag 3=25 KG bag	4=50 KG bag 5=90 KG bag 6=DEBE (18 kg)	7=Number/Unit 8=Gorogoro(2.25tin) 9=1/4 kg tin 10=1/2 kg tin 11=1Kg tin	13=Litres 14=Mililitres 15=2 kg Packet	16=grams 17=Wheelbarrow 18=Others (specify) _____	1= input dealer; 2= NGO; 3= trader; 4= fellow farmers; 5 = informal market; 6 = others specify_____.

4.7 **For the identified plot**, please specify how often the following operations were/are carried out for one complete growing cycle. ***Please give information for one full plot planted at once.***

Farm activities	**How many times?**	**Average no. of persons involved each time**		**Average no. of days each time**	**Average No. of hours per day**	**How many of those are usually hired laborers?**	
		Male	**Female**			**Male**	**Female**
1. Land preparation							
2. Planting							
3. Gap filling							
4. Manual weeding							
5. Irrigating							
6. Fertilizer application							
7. Pesticide application							
8. Other chemicals							
9. Harvesting							
10. Cleaning and packing							
11.Other, specify:_____							

4.8 In generally, what method of land preparation (*plowing and harrowing*) do you use? _____ *(0=None, 1 = Tractor 2 = Animal traction 3 = Manual/hand)*

4.9 If you use tractor or animal traction how much do you pay for this service? _____ (Ksh/acre). **(*If the farmer owns tractor or animals, what is the local rate for these services?*)**

4.10 In general, how many times in a year do you grow this vegetable? _____

4.11 In general, how long is one full growing cycle? _____ months _____weeks

Questionnaire number (HHID) _____

5 INFORMATION ON CREDIT ACCESS AND SOCIAL NETWORKS

5.1 Could you obtain credit if you need it for the purpose of operational expenses (e.g. buying fertilizer paying for labor etc.)? _____*1=YES, 0=NO*

5.2 Could you obtain credit if you needed for the purpose of buying production assets (e.g. irrigation infrastructure)? _____*1=YES, 0=NO*

5.3 During the last **12 months**, have you or any other household member received any credit to buy inputs, or received inputs on credit, for **production of vegetables**?_____*1=YES, 0=NO*

5.4 If yes, what were the sources and how much did you receive? (*Include the value of inputs if inputs are provided on credit*)

Source	**Number of times loan received**	**Total amount (Ksh)**
1. Input dealer		
2. NGO.		
3. Bank/cooperative society.		
4. Friends/relatives		
5. Moneylender.		
6. Other (specify)_____		

5.5 Are you or any other household member **currently** a member of any group or association? _____ *(1=YES; 0=NO) (If no please go to question 5.8)*

5.6 If yes what type of group do you/ household members belong to?

Type of group	**1=Yes; 0=No**	How long have you been a member of this group/association? ***(in Months)***
1. Producer group		
2. Farmers' cooperative society		
3. SACCO		
4. Women group		
5. Youth group		
6. Community welfare group		
7. Other (specify) _____		

5.7 What type of benefits/services do you receive from your group(s)?

Benefits/Service	***1=YES; 0=NO***
1. Credit service	
2. Input access	
3. Training on crop production	
4. Training on marketing	
5. Marketing of farm produce	
6. Welfare/social support	
7. Other (specify):	

5.8 Are you currently participating in Farm Concern Internationals marketing activities? *(1=Yes; 0= No)* _____

5.9 In the **last 5 years**, have you participated in "**crop marketing days**" organized by the **district agricultural office**? *(1= Yes; 0= No)* _____

5.10 *(If the head of the household is a woman):* Is the head of the household a member of any women group? *(1= Yes; 0= No)* _____

(If the head of the household is a man): Is the spouse of the head of the household a member of any women group? *(1= Yes; 0= No)* _____

5.11 We are now going to read the names of a number of vegetable farmers from this village and _____village. Please let us know if you know these persons and how you interact with them with respect to agricultural production.

	1. Respondent name	2. Name of head of household	3. HHID number	4. Village code	5. Do you know----? (1=Yes; 0= No)	6. In the past 1 month, how many days have you talked to ----?	7. Do you know to which buyers --- is selling his/her vegetables? (1=Yes; 0= No)	8. Have you ever talked to ---about different marketing channels for vegetables? (1=Yes; 0= No)	9. Could you go to --- if you wanted to find a buyer for vegetables? (1=Yes; 0= No)	10. Have you and --ever been in the same producer or marketing group? *(1=YES; 0=NO)*
Sample 1 (HVC=1 and 2)										
1.										
2.										
3.										
Sample 2 (HVC=0)										
4.										
5.										
Sample 3 (neighboring village; HVC=0, 1 and 2)										
6.										
7.										

The following questions refer to farmers other than those listed in the table above

5.12 Do you know any vegetable farmers who are supplying vegetables to supermarkets? *(1=YES, 0=NO)* _____

(If no go to question 5.20)

5.13 If yes, how many? _____

5.14 Out of these farmers that you know supply to supermarkets, have you ever talked to any of them about marketing of vegetables? _____ *(1=YES, 0=NO)*

(If no go to question 5.20)

5.15If yes, how many? _____

5.16Out of these farmers (who supply to supermarkets and who you talk to about marketing of vegetables?), who do you think was the first farmer to start to supply to supermarket? _____ *(NAME)*

5.17Approximately when do you think that_____ *(NAME FROM 5.16)* started to supply to supermarkets? _____ *(IN NUMBER OF YEARS AGO)*

5.18Did you know _____ *(NAME FROM 5.16)* before he/she started to supply to supermarkets? _____ *(1=YES, 0=NO)*

5.19What is the distance to _____ *(NAME FROM 5.16)* from your homestead? _____ *(IN MINUTES WALKING)*_____*(IN KILOMETERS)*

5.20Have you ever met a buyer/broker/middleman who buys vegetables for supermarkets?

_____ *(1=YES, 0=NO)*

5.21 Do you know any farmers who are supplying to Companies or Institutions? _____ *(1=YES, 0=NO)*

(If no go to question 5.29)

5.22If yes, how many? _____

5.23 Out of the farmers that you know supplies to Companies or Institutions, have you ever talked to any of them about marketing of vegetables? _____ *(1=YES, 0=NO)*

(If no go to question 5.29)

5.24 If yes, how many? _____

5.25 Out of these farmers (who supplies to Companies or Institutions and who you talk to about marketing of vegetables), who do you think was the first farmer to start to supply to Companies or Institutions? _____ *(NAME)*

5.26 Approximately when do you think that_____ *(NAME FROM 5.25)* started to supply to Companies or Institutions? _____ *(IN NUMBER OF YEARS AGO)*

5.27 Did you know _____ *(NAME FROM 5.25)* before he/she started to supply to Companies or Institutions? _____ *(1=YES, 0=NO)*

5.28 What is the distance to _____ *(NAME FROM 5.25)* from your homestead? _____ *(IN MINUTES WALKING)*_____*(IN KILOMETERS)*

5.29 Have you ever met a buyer/broker/middleman from Companies or Institutions?

_____ *(1=YES, 0=NO)*

5.30 In your own opinion do you think farmers **supplying vegetables to supermarket** earn **more, less or the same** amount of income as they would have earned if they supplied to spot market?

(1=more income, 2=less income, 3=same income) _____

Questionnaire number (HHID) _____

6 GENERAL HOUSEHOLD DEMOGRAPHIC INFORMATION

6.1 **Household composition and income details:** Please list all household members (All those who are under the care of household head in terms of food and shelter provision).

1. MEMID	2 Name of the HH member	3 Relationship to HH head (*Use codes [a] below)*	4 Gender *M = 1; F= 2*	5 Age in years	6 Years of formal schooling	7 Marital Status *(Use codes [b] below)*	8 How many days in the last 7 days was this person at home?	9 Main Occupation *(Use codes [c] below)*	10 Number of months in the last 12 months have you been in this occ?	11 Monthly income from occupation (Ksh).	12 Participate in farm work *1=YES; 0=NO*	13. Does this person own a cellphone? *1=YES; 0=NO*
1												
2												
3												
4												
5												
6												
7												
8												
9												
10												
11												
12												

[a] **Relationship with household head**		[c] **Occupation**	[e] **Tribe**
1= Head 2=Spouse 3=Son/daughter 4=Father/mother 5=Sister/brother 6=Grandchildren 7=Grandparents 8=Step children 9=Step parent 10 =Father/mother-in-law	11 =Sister/brother-in-law 12 = House girl 13 =Farm laborers 14 =Other Unrelated 15= Other relative [b] **Marital status** 1= Married 2= Single 3= Divorced/separated 4= Widow/widower	0= None 1= Paid employment (civil servant, working in private company etc) 2= Self-employed outside farm 3= Working on household farm 4= Wage labor (working on other peoples farms) 5= Off-farm employment 6=Student 7= Other (Specify)_____ [d] **Religion** 1=Catholic 2=Protestant 3=Muslim 4=Traditionalist 5=No religion 6=Others (specify) _____	1=Kikuyu 2=Embu 3=Meru 4=Kamba 5=Kalenjin 6=Kisii 7=Luhya 8=Luo 9=Maasai 10=Other (specify) _____

6.2 Kindly tell us the **religion and tribe** of the **household head, spouse of the household head and the respondent** (in case the respondent is not head or spouse to head)

MEMID ***(from demog table***		Tribe ***(Use codes above)*** [e]	Religion ***(Use codes above)*** [d]
	Household head		
	Spouse to household head		
	Respondent ***(Fill only if respondent is not one of the two above)***		

6.3 What was your **household's income** from the following sources during the **past 12 months**? (***include the income of all household members listed in the table on page 29 exclude income already listed in the table on page 29***)

	Income source	**Total Income in past 12 months** ***(Ksh)***
1	Income from hiring out machinery services to other farmers (ploughing etc.)	
2	Income from own **non-agricultural** businesses	
3	Pensions	
4	Remittances from family members/friends who do not live in the household	
5	Revenues from leasing out land	
6	Dividends	
7	Other sources (please specify _____)	

Questionnaire number (HHID) _____

7 HOUSEHOLD ACCESS TO SOCIOECONOMIC INFRASTRUCTURE

7.1 Please indicate whether the following facilities are available in the village and answer whether or not you have access to them.

Social facilities	Available in this village *1=YES; 0=NO*	Does your household have access to it? *1=YES; 0=NO*	Distance to the nearest (km)	Most frequently used means of transportation *(Use codes [a] below)*	Travel time with most frequently used means of transportation (in minutes)	One way cost to travel there (Ksh)
1. Electricity (KPLC)						
2. Piped water system						
3. Bank						
4. Tarmac road						
5. Matatu stage						
6. Public Transport system						
7. Agric. extension agent						
8. Agricultural input market						
9. Agric. product market						
10. Health center						
11. Supermarket retail outlet						
12. Local shopping center						
13. Nearest supermarket that buys fresh fruits and vegetables from farmers?						
14. Nearest place where you can sell vegetables?						
15. Nearest farmer that owns means of transportation for vegetables						

[a] Means of transport Codes

1=Bicycle; 2=Motorbike; 3=Car; 4=Walk; 5=Others (specify)_____

8 HOUSEHOLD ASSETS (Prompt for each item as listed below)

8.1 **At present, how many/much of the following does this household own that are in usable/repairable condition? (*Enumerator**: For value per unit, ask for current value of items as they are in their current condition)*

	Agricultural asset	Quantity	Value per Unit (Ksh)	If Value/Unit not known Ask for Total Value	Year when asset was acquired (*If several assets, write the year of the first*
	ASSET	**QTY**	**UVALUE**	**TOTVAL**	
1	Tractor				
2	Car/Van				
3	pickup)				
4	Trailer				
5	Motorcycle				
6	Bicycle				
7	Television				
8	Radio				
9	Mobile Phone				
10	Refrigerator				
11	Solar panels				
12	Generator				
13	Oxen				
14	Chaf cutter				
15	ploughs for tractor				
16	Animal traction plough				
17	Cart				
18	Vegetable packing shed				
19	Water pump				
20	Borehole				
21	Well				
22	Water tank				
23	Drip irrigation system				
24	Irrigation pipes				
25	Sprinkler				

9 SHOCKS

9.1 Over the past **four years**, was your household negatively affected by any of the following events or developments? ***Please rank the 3 most severe problems experienced.***

	PLEASE ANSWER THE FOLLOWING QUESTIONS ACCORDINGLY	The household was […] affected by […]		
		Severely	Slightly	Not at all
		(1=Yes; 0=No)	***(1=Yes; 0=No)***	***(1=Yes; 0=No)***
1	Drought			
2	Too much rain or flood			
3	Erosion and gully formation			
4	Frosts or hailstorm			
5	Pests or diseases that affected crops before they were harvested			
6	Pests or diseases that led to storage losses			
7	Theft of crops			
8	Loss of livestock (death, theft, illness)			
9	Fire			
10	Death of male household head			
11	Death of female household head			
12	Death of other person			
13	Illness of male household head			
14	Illness of female household head			
15	Illness of other person			

Questionnaire number (HHID) _____

10 CHARACTERISTICS OF MAIN HOUSE

(ENUMERATOR: PLEASE OBSERVE AND ASK ABOUT THE FOLLOWING)

10.1 What is the **roofing** material of the **main house**? **ROOF _____**

(1=grass /makuti 2=iron sheet 3=tiles 4=other, specify_____)

10.2 What is the wall material of the main house? **WALL _____**

(1=mud 2=bricks/stones 3=iron sheet 4=wood 5=plastered 6=other, specify_____)

10.3 What is the floor material of the main house? **FLOOR _____**

(1= earth 2=cement 3=wood 4=tiles 5=other, specify_____)

10.4 What is the mode of ownership of the main house? **HSEOWN _____**

(1= owned 2= rented 3= owned by relative 4=other, specify_____)

10.5 What type of toilet do you use? **TOILET _____**

(1= pit latrine 2= bush 3= flush toilet 4= other, specify_____)

10.6 What is the main source of water for domestic use during the **wet-season**?

MAINWET _____

Distance (minutes walking) _____

(1=Pond 2=dam /sanddam 3=lake 4=stream/river 5=unprotected spring 6=protected spring =well 8=borehole 9=piped into compound 10=piped outside compound 11=water tankers 12=roof catchments 13=waterhawkers-cart /bodaboda 14= other, specify_____)

10.7 What is the **main** source of water for domestic use during the **dry-season**?

MAINDRY _____

Distance (minutes walking) _____

(1=Pond 2=dam /sanddam 3=lake 4=stream/river 5=unprotected spring 6=protected spring 7=well 8=borehole 9=piped into compound 10=piped outside compound 11=water tankers 12=roof catchments 13=waterhawkers-cart /bodaboda 14= other, specify_____)

10.8 What is your **main cooking fuel**? **COOKFUEL _____**

(1=electricity 2=paraffin 3=firewood 4=gas 5=charcoal 6=solar power 7=other, specify_____)

10.9 What is your **main type of lighting**? **LITFUEL_____**

(1=electricity 2=pressure lamp 3=tin lamp 4=fuel wood 5=lantern 6=solar power 7=other, specify_____)

Questionnaire number (HHID) _____

11. HOUSEHOLD NUTRITION KNOWLEDGE AND AWARENESS

11.1 Has any member of this household ever been trained /received any information on the nutritive benefits of consuming different type foods? (1=Yes; 0=No) **NTRAIN_____**

11.2 If yes, what were they trained on/ got information on?

TRAIN1 _____

TRAIN2_____

TRAIN3_____

TRAIN4_____

11.3 What was the source of the training/information?

1= From a radio program *4= Local leader* *7= From a neighbor* *9=From supermarket representative*

2= From a TV program *5=School* *8= From my group members* *10=Others (specify)_____*

3=Church *6=From Hospital*

TSOURCE1_____ TSOURCE2_____ TSOURCE3_____ TSOURCE4___

11.4 Amongst the following foods, please tell me which foods provide Carbohydrates, Protein and Vitamins?

1= Beans, 2= Rice, 3=Sukumawiki (kales), 4= Ugali, 5= Chicken, 6=Mangoes

(Enumerator: Please write down whatever the respondent says, whether correct or wrong. Write 99 for don't know)

1=Carbohydrate1	2=Carbohydrate2	3=Carbohydrate3	4=Carbohydrate4	5=Carbohydrate5	6=Carbohydrate6
7=Protein1	8=Protein2	9=Protein3	10=Protein4	11=Protein5	12=Protein6
13=Vitamin1	14=Vitamin2	15=Vitamin3	16=Vitamin4	17=Vitamin5	18=Vitamin6

12. HOUSEHOLD FOOD CONSUMPTION IN THE LAST 7 DAYS *(Enumerators: Please ask the following questions to the person who is mainly responsible for preparing food)*

12.1 In the past seven days indicate how much of the following food items your household consumed and the prices in Kshs ***(This is for all food consumed in the household, including own-produced, bought, gifts and from food aid program, by all the people listed on demographic table on page 29 before. INCLUDE food prepared at home but eaten outside. EXCLUDE meals prepared outside the home)***

Questionnaire number (HHID) _____

	Food Items consumed in the past 7 DAYS	How much in total did your household consume during the last 1 week?	Unit of quantities consumed *(Use codes below)*	Total value of consumption in Kshs		Food Items consumed in the past 7 DAYS	How much in total did your household consume during the last 1 week?	Unit of quantities consumed *(Use codes below)*	Total value of consumption in Kshs
	Staple foods					**Vegetables**			
1	Cassava Tuber				30	Okra			
2	Cassava flour				31	Tomato			
3	Cassava chips				32	Pepper			
4	Yam Tuber				33	Onion			
5	Yam flour				34	Carrot			
6	Yam chips				35	Egg plant (biringanya)			
7	Orangefleshed sweet potato				36	Cabbage			
8	Other sweetpotato				37	Cucumber			
9	Sweet potato chips				38	Pumpkin			
10	Irish potato				39	Butternut			
11	Irish potato chips				40	Spinach			
12	Arrowroots				41	Kales (Sukuma wiki)			
13	Maize green				42	Amarantha leaves (terere)			
14	Maize grain				43	Pumpkin leaves			
15	Maize flour				44	Sweet potato leaves			
16	Sorghum grain				45	Black night shade			
17	Sorghum Flour				46	Cow pea leaves			
18	Millet grain				47	Stinging netle (thabai)			
19	Millet flour					**Other vegetables (specify)**			
20	Brown rice				48				
21	White rice				49				
22	Wheat grain				50				
23	Wheat flour brown					**Nuts and Pulses**			
24	Wheat flour white				51	Beans dry			
25	Cooking banana				52	Beans fresh			
	Other staple foods				53	Black beans (Njahi)			
26					54	Green grams (Ndengu)			
27					55	Soybean			
28					56	Peas (incl cowpea, pigeon			
29					57	Lentils			
					58	Groundnut			
					59	Cashew nut (korosho)			

Questionnaire number (HHID) _____

	Food Items consumed in the past 7 DAYS	**How much in total did your household consume during the last 1 week?**	**Unit of quantities consumed *(Use codes below)***	**Total value of consumption in Kshs**		**Food Items consumed in the past 7 DAYS**	**How much in total did your household consume during the last 1 week?**	**Unit of quantities consumed *(Use codes below)***	**Total value of consumption in Kshs**
60	Soya meat (e.g. Sossi)				89	Pork Sausage			
61	Soybean flour				90	Eggs (pieces) with yolk			
	Other pulses and nuts				91	Eggs without yolk			
62					92	Liver (from any animal)			
63					93	Offals (matumbo)			
	Fruits					**Other meats**			
64	Orange				94				
65	Ripe mango				95				
66	Ripe pawpaw				96				
67	Pineapple				97				
68	Apple					**Dairy products**			
69	Coconut				98	Milk (cow/goat milk)			
70	Guava				99	Powdered milk			
71	Ripe bananas				100	Sour milk (mala)			
72	Melon				101	Cheese			
73	Sugar cane				102	Yoghurt			
74	Avocado				103	Ice cream			
	Other fruits					**Other dairy product**			
75					104				
76					105				
77					106				
	Meat and animal Products					**Beverages**			
78	Cow meat				107	Cocoa powder			
79	Goat/ Sheep meat				108	Tea (leaves)			
80	Pork				109	Coffee (powder)			
81	Chicken				110	Milo powder			
82	Bush meat (Game meat)				111	Soya powder			
83	Turkey (bata mzinga)				112	Drinking chocolate			
84	Fish					**Other beverages**			
85	Snail				113				
86	Crabs				114				
87	Chicken sausage				115				
88	Beef sausage				116				

Questionnaire number (HHID) _____

	Food Items consumed in the past 7 DAYS	How much in total did your household consume during the last 1 week?	Unit of quantities consumed *(Use codes below)*	Total value of consumption in Kshs		Food Items consumed in the past 7 DAYS	How much in total did your household consume during the last 1 week?	Unit of quantities consumed *(Use codes below)*	Total value of consumption in Kshs
	Drinks				145	Butter			
117	Soft drinks (coke/fanta/etc)				146	Margarine			
118	Orange juice				147	Sunflower oil			
119	Apple juice				148	Cooking fat			
120	Pineapple juice				149	**Other oil(specify)_____**			
121	Other juice (concentrates)				150				
122	Local beer				151				
123	Bottled beer				152				
124	Other beer				153				
125	Wine					**Snacks**			
	Other drinks				154	Bread			
126					155	Biscuit/cookies			
127					156	Popcorn			
128					157	Cakes			
	Condiments and spices					**Other snacks**			
129	Salt				158				
130	Curry				159				
131	Ginger (tangawizi)				160				
132	Ketchup, Tomato sauce								
	Other spices _____								
133									
134									
135									
136									
	Sugar and sweets								
138	Sugar								
139	Chocolate								
140	Other sweet								
	Fat and Oil								
141	Red palm oil								
142	Groundnut oil								
143	Coconut oil								
144	Sheer butter oil								

UNIT CODES							
1= LITER	3= KGS	5= 5 KG. BAG	7= 50 KG. BAG	9= DEBE	11= PIECE/NUMBER	13= 1/4 KG TIN	15= 1 KG TIN 16= BUNDLES
2= MILILITER	4= GRAMS	6= 25 KG. BAG	8= 90 KG. BAG	10= BUNCH (Bananas)	12= GOROGORO	14= 1/2 KG TIN	17= Cup (15) 18=Others Specify_____

12.2 **Food consumed by household members away from home in the last 7 days (eg in schools, in restaurants, during ceremony etc), Household members are the people listed in page 29.**

Mem ID	Type of food eaten	No. of times	Components of the food				Total value in Kshs
			Component 1	Component 2	Component 3	Component 4	

Thank you for your time and patience!

END TIME: _____:_____