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Abstract

This dissertation consists of three essays that contribute to both applied and theoretical microeconomics. The first two essays provide a theoretical framework, empirical evidence, and an empirical strategy for a better understanding of the seasonality of food insecurity in developing countries, with a special focus on seasonal price changes of staple foods. More specifically, the first essay constructs a theoretical model to analyze how seasonal price changes of a staple food affect farmers' seasonal consumption in developing countries, where storage of the staple food can be used to smooth consumption. Crucially, sharp increases in the price of the staple food just before harvest can be viewed as a high return to savings, and this has important implications for interpreting the consumption and savings behavior of poor rural households. Then, the second essay addresses whether and how farmers smooth their consumption within a crop year, using three years of weekly household panel data from rural Zambia. Given seasonal price changes of the staple food, maize, some farmers buy it when prices are low and store it for consumption during the hunger season, while others run out of the staple food before the next harvest, and so buy it when prices are high. Results indicate that the former group successfully smooths its consumption, while the latter group reduces consumption during the hunger season in response to a negative harvest at the end of the previous crop year, and the effect of these negative harvest shocks produces an inverse U consumption pattern during the crop year, especially for farmers with few assets. These farmers reduce their consumption of non-staple foods and thus reduce their food diversity to maintain consumption of the staple food in the hunger season in spite of its price hike in that season. The third essay proposes an empirical strategy (the network approach) to analyze complex interactions among several agents, and illustrates how this approach works by applying it to the analysis of soccer games. By using a longitudinal data set of all soccer players in the top German league (the Bundesliga) over the course of ten seasons (2000/01-2009/10), causal peer effects during soccer games are identified. This unique identification strategy is applicable for other studies to analyze complex interactions without simplifying the structure of those interactions.

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Chapter 1

Introduction

This dissertation consists of three essays that contribute to both applied and theoretical microeconomics. The first two essays provide a theoretical framework, empirical evidence, and an empirical strategy for a better understanding of the seasonality of food insecurity in developing countries, with a special focus on seasonal price changes of staple foods. The third essay proposes an empirical strategy (the network approach) to analyze complex interactions among several agents, and illustrates how this approach works by applying it to the analysis of soccer games.

Seasonality is an important aspect of food security for subsistence farmers in developing countries. Farmers receive agricultural income only at the harvest season, and that income is uncertain. Their previous year's harvest stocks gradually dwindle, and some farmers run out of food before the next harvest. Such farmers need to buy food with cash, but food prices are usually high right before the harvest season. Those farmers who run out of food and buy food when prices are high often cannot buy an adequate amount of food. Most malnutrition and deaths of young children occur in those periods (e.g. Devereux et al, 2012), and so do famines (e.g. Sen, 1981). Those periods are often referred to as the hunger season (e.g. Devereux et al., 2012, Vaitla et al., 2009, and Khandker and Mahmud., 2012).

Despite the importance of the topic, little is known about the seasonal consumption patterns of rural farmers in developing countries, and the seasonal aspect of food insecurity has received insufficient attention in global efforts to combat rural poverty. The main reason for this is data limitations. Most household level statistics are collected at one point in time, usually during a slack season on the farm, which is not the "hunger season". Those statistics are not suitable for tracing seasonal consumption patterns or for analyzing seasonal hunger, which discourages researchers from working on this topic. This dissertation provides a theoretical framework, empirical evidence, and an empirical strategy to better understand the seasonality of food insecurity in developing countries, with the ultimate goal of recommending policies for tackling seasonal poverty in developing countries. This dissertation pays special attention to seasonal price changes of staple foods, which are lowest immediately after the harvest, gradually increase over time, and are extremely high in the hunger season which occurs right before the next harvest season.

Chapter 2 provides a theoretical framework for the analysis of farmers' seasonal consumption under common seasonal price patterns of staple foods. In rural areas of developing countries, a staple food is often used to achieve consumption smoothing. However, the theoretical frameworks used in previous analyses of seasonal consumption smoothing have paid little attention to the use of stocks of staple food to smooth consumption. In Chapter 2, I discuss how seasonal price changes of a staple food affect farmers' seasonal consumption in developing countries, where stocks of staple foods are used as a means of consumption smoothing and the price of the staple food increases sharply just before the next harvest. High prices of the staple food just before the harvest can be viewed as a high return to savings that take the form of physical stocks of the staple food, and this is of significant importance for interpreting the consumption and savings behavior of poor rural households. I emphasize that models of farmers' savings should include saving in the form of stocks of agricultural output. In addition, the findings of the model are used to re-consider the so-called "sell low, buy high" puzzle in rural areas of developing countries.

Chapter 3 discusses farmers' heterogenous abilities to smooth consumption. Examining seasonality of food insecurity as a consequence of farmers' inabilities to smooth consumption, my co-author and I address whether and how farmers smooth their consumption during a crop year. We use three years of detailed weekly household panel data from rural Zambia. Given seasonal price changes of the staple food, maize, some farmers buy it when prices are low and store it for the hunger season, while others run out of the staple food before the next harvest, and thus buy it when prices are high. Results indicate that the former group successfully smooths its consumption, while the latter group is unable to smooth consumption within the crop year, and in particular, reduces consumption during the hunger season. These heterogenous results are important for understanding the impacts of pro-poor programs that offer credit, because they are related to farmers' heterogenous motivations for using credit programs: the former group likely wants long-term credit for investment purposes, while the latter group wants short-term credit for consumption smoothing purposes. This result suggests that optimal schemes and timing of credit should be designed separately to suit the purpose of each type of farmer. In addition, we find that the latter group reduces consumption of vegetables and meats to smooth consumption of the staple food when facing high prices during the hunger season, which likely leads to micronutrient deficiency problems. This result suggests that micronutrient deficiencies should be part of any discussion of the problem of seasonal price changes of staple foods.

At first glance, Chapter 4 is very different from Chapter 2 and 3. However, they are related to some extent. Increases of the price of the staple food in the hunger season decrease the welfare of net buyers of the staple food in that season. Such farmers are more likely to be poorer farmers, and thus mitigating seasonal price changes should be an important policy goal. One possible solution can be market integration, because it can offset the price variations across different markets. This requires knowledge of the interaction of food prices across different markets. However, analogous to the identification problem of peer effects (Manski, 1993), identifying the impact on food prices of one market from the pricing in other markets is difficult. Due to these difficulties, there are no empirical studies to analyze the interactions of prices among several markets.

One potential way to overcome these difficulties is the network approach. In order to illustrate how this approach works, my coauthor and I apply it to the analysis of soccer games. Chapter 4 identifies intricately woven peer effects in soccer games, using a longitudinal data set of all soccer players in the top German league (the Bundesliga) during ten seasons (2000/01-2009/10). As Manski (1993) points out, identifying peer effects is not an easy task. Similar players' performances can be due to similar but unobserved characteristics of the team members (i.e., correlated effects) or to peer effects. It is also hard to pinpoint whether one player's performance is affecting other players, or vice versa (i.e., simultaneity effects). Furthermore, it is difficult to estimate endogenous peer effects separately from exogenous peer effects. To control for these problems, we impose the network structure on the players in the game, and apply the spatial econometric methodology suggested by Lee and Yu (2014), which is the network approach. This unique identification strategy can be applied to analyze other types of complex interactions in teams without simplifying the structure of those interactions.

Together, these three essays shed light on seasonality of food insecurities in developing countries, with a special focus on seasonal price changes of staple foods. All three essays provide insight into a theoretical framework, empirical evidence, and an empirical strategy for a better understanding of the seasonality of food insecurity in developing countries. The arguments, methodologies, and findings here will be of interest not only to development economists, but also to policy-makers that are tackling rural poverty.

Chapter 2

A Note on the Theoretical Framework for Seasonal Consumption Patterns in Developing Countries

2.1 Introduction

Seasonal hunger is an acute problem in developing countries, especially in rain-fed agricultural areas. Many farmers store their harvests for their own consumption until the next harvest, but sometimes their stocks run out before the next harvest. Such farmers need to buy food in the last one or two months before the next harvest, but food prices are usually high at that time. The season just before the harvest is often called the hunger season, when malnutrition is most common and most child deaths occur (Devereux et al., 2012). Thus, the impact of seasonal price patterns on seasonal consumption is an important policy concern. This paper makes two contributions to the theory of consumption smoothing in developing countries. First, it models household behavior when saving physical agricultural goods is more profitable than saving money. Second, it shows that higher prices in the hunger season may not affect, or may even increase, consumption in that season for households that save physical amounts of agricultural goods. Third, it re-considers the so-called "sell low, buy high" paradox, which is discussed in Stephens and Barrett (2011).

2.2 Theoretical Framework

2.2.1 Infinite-period Model

Paxson (1993) initiated modern research on consumption smoothing in developing countries. Her infinite-period model was subsequently adopted by Dercon and Krishnan (2000), Chaudhuri and Paxson (2002), and Khandker (2012). Her model assumes that there are two seasons per year, and considers the following farmer utility maximization problem:

$$\max_{\{c_{1t},c_{2t}\}_{t=1}^{\infty}} \sum_{t=1}^{\infty} \beta^{2t}[u(c_{1t}) + \beta u(c_{2t})] \tag{2.1}$$

$$\text{subject to} \quad \sum_{t=1}^{\infty}(1+r)^{-2t}\left(p_1 c_{1t} + p_2 \frac{c_{2t}}{1+r}\right) = W + \sum_{t=1}^{\infty}(1+r)^{-2t}\left(y_1 + \frac{y_2}{1+r}\right) \tag{2.2}$$

where c_{jt} is consumption in season j in year t, y_j is income in season j in all years (does not vary over years), p_j represents the price of consumption in season j in all years, W is initial financial wealth, β is a per season discount rate with $\beta \leq 1$, and, r is a constant per season interest rate. Assume that the farmer's utility function is continuous, strictly increasing, strictly concave, twice differentiable in all its arguments, and $u'(0) = \infty$. For simplicity and in order to focus on consumption smoothing within one year, credit constraints, income uncertainty, and price uncertainty are ignored. The assumption no no credit constraints will be relaxed in subsection 2.2.2. The first order conditions for this problem yield the following expression for each year t:

$$\frac{u'(c_{1t})}{u'(c_{2t})} = \beta(1+r)\frac{p_1}{p_2} \tag{2.3}$$

Paxson (1993) assumes a constant relative risk averion (CRRA) utility function, with a risk aversion parameter of σ ($\sigma > 0, \sigma \neq 1$):

$$u(c_{jt}) = \frac{c_{jt}^{1-\sigma} - 1}{1-\sigma} \tag{2.4}$$

Combining equations (2.3) and (2.4) yields the change in consumption across the two seasons:

$$\Delta \log c_t = -\frac{1}{\sigma}\Delta \log p + \frac{1}{\sigma}\log k \tag{2.5}$$

where $\Delta \log c_t = \log c_{2t} - \log c_{1t}$, $\Delta \log p = \log p_2 - \log p_1$, and $k = \beta(1+r)$. Equation (2.5) shows that a higher relative price of the consumption good in season 2 reduces $\Delta \log c_t$, shifting consumption from season 2 to season 1. This is essentially a substitution effect. In this model, the farmer borrows and saves in the form of money, but not in the form of consumption goods. Thus, this model implicitly assumes that either the consumption good cannot be stored over time, or that the return to saving money is equal to or greater than the return to saving the consumption good. This assumption could be inaccurate and potentially misleading in situations where farmers save quantities of the consumption good to smooth consumption (e.g. Kazianga and Udry, 2006, Stephens and Barrett, 2011, Basu and Wong, 2012). The following subsection assumes that consumption goods can be stored over seasons, and that saving the physical consumption good is more profitable than saving money. As will be seen below, this can change the predictions of the model.

2.2.2 Two-period Model

This section presents a theoretical model that allows for savings in the form of the consumption good. Since it is difficult to solve the infinite-period model with varying saving rates across seasons, a simpler two-period model is considered.

Two-period Model with One Good

Consider a farmer's utility maximization decision, written as:

$$\max_{c_1,c_2,B,S} u(c_1) + \beta u(c_2) \tag{2.6}$$

$$\text{subject to} \qquad p_1 c_1 + p_1 S = y_1 + B \tag{2.7}$$

$$p_2 c_2 + (1+r)B = p_2(1-\nu)S + y_2 \tag{2.8}$$

$$B \leq \bar{B} \tag{2.9}$$

where *S* is the amount of the staple food stored in season 1, y_1 is income, including the value of the staple food produced, *B* is borrowing in the form of money, with an upper limit $\bar{B}$, ν is the depreciation rate of storage of the consumption good, and other notation is the same as in the infinite-period model. Equations (2.7) and (2.8) are the budget constraints in seasons 1 and 2, respectively. Assume that $p_2 > p_1$ and that p_2 is sufficiently high to satisfy:

$$\frac{p_2}{p_1}(1-\nu) > 1 + r \tag{2.10}$$

This condition implies that saving money is never optimal, because saving by storing the consumption good is more profitable. Under this condition, the farmer borrows money up until the upper limit, i.e. until equation (2.9) binds (assuming that storage capacity does not bind). This binding monetary borrowing constraint does not sharply constrain reallocation of resources across seasons, because the farmer can reallocate his or her resources across seasons by storing the consumption good.[1] The first order conditions for this utility maximization problem imply that:

$$\frac{u'(c_1)}{u'(c_2)} = \beta(1-\nu) \tag{2.11}$$

Assuming a CRRA utility function, equation (2.11) yields the optimal change in consumption over the two seasons,

$$\Delta \log c = \frac{1}{\sigma} \log k' \tag{2.12}$$

where $\Delta \log c = \log c_2 - \log c_1$, and $k' = \beta(1-\nu)$. Note that higher prices in season 2 do *not* affect seasonal consumption patterns. Intuitively, this is because high prices in season 2 affects farmers in two ways: through the high consumption good price in season 2, and through the higher return to savings in season 2. Seasonal price hikes in season 2 do not affect seasonal consumption patterns, because the negative effect of a higher price on consumption in season 2 is offset by the positive effect of higher returns to savings and the consumption good must be consumed in season 2.[2]

Two-period Model with Two Goods

Next consider an increase in the price of the consumption good during the hunger season, relative to the price of another, non-produced consumption good; the theoretical framework above can be extended to two goods. This is basically the model of Stephens and Barrett

[1] A higher $\bar{B}$ can be interpreted as a greater share of life cycle income received in season 1.

[2] When $p_2(1-\nu)/p_1 \leq 1+r$ holds, (and the assumption of $S \geq 0$ replaces equation (2.9)), this Euler equation with a CRRA utility function becomes equation (2.5).

(2011) and Basu and Wong (2012) but, unlike those models, it imposes equation (2.10).[3] The farmer's utility maximization problem is;

$$\max_{c_1,x_1,c_2,x_2,B,S} u(c_1,x_1) + \beta u(c_2,x_2) \tag{2.13}$$

$$\text{subject to} \qquad p_1c_1 + x_1 + p_1S = y_1 + B \tag{2.14}$$

$$p_2c_2 + x_2 + (1+r)B = p_2(1-\nu)S + y_2 \tag{2.15}$$

$$B \leq \bar{B} \tag{2.16}$$

where x_j is a non-produced consumption good in season j with a time invariant price, normalized to one, and all other notation is the same as before. The first order conditions for this problem yield the following:

- $$\frac{u'(c_1)}{u'(c_2)} = \beta(1-\nu) \tag{2.17}$$
- $$\frac{u'(x_1)}{u'(x_2)} = \frac{p_2}{p_1}\beta(1-\nu) \tag{2.18}$$

Assuming the following CRRA utility function

$$u(c_j,x_j) = \frac{c_j^{1-\sigma}-1}{1-\sigma} + \frac{x_j^{1-\sigma}-1}{1-\sigma} \tag{2.19}$$

[3] Basu and Wong (2012) considered three possibilities to transfer assets across seasons - saving in kind, saving cash, or borrowing. If equation (2.10) holds, farmers will want to borrow money to purchase and save as much of the staple good as possible, so unlike Basu and Wong (2012), saving in kind and borrowing can happen simultaneously. If equality holds for equation (2.10), saving cash and borrowing are redundant. These differences show that the sign in equation (2.10) is the key to induce different implications.

equations (2.17) and (2.18) yield the following (optimal) changes in consumption over time,

$$\Delta \log c = \frac{1}{\sigma} \Delta \log k' \tag{2.20}$$

$$\Delta \log x = \frac{1}{\sigma} \Delta \log p + \frac{1}{\sigma} \log k' \tag{2.21}$$

where $\Delta \log c = \log c_2 - \log c_1$, $\Delta \log x = \log x_2 - \log x_1$, $\Delta \log p = \log p_2 - \log p_1$, and $k' = \beta(1 - \nu)$. Note that equation (2.20) is identical to equation (2.12): the effect of high prices in season 2 is offset by the high returns to savings. In contrast, equation (2.21) implies that an increase in the relative price of the consumption good in season 2 *increases* the relative consumption of the non-produced good in season 2. This occurs because the price of x_2 is time invariant while the returns to savings, due to the higher price of c_2, are high. This implication is the *opposite* of that for Paxson's infinite-period model in which farmers save using money; in Paxson's model, a higher relative price of the consumption in season 2 reduces $\Delta \log c$.

2.2.3 Adding Borrowing Constraints of Produced Consumption Goods to the Model

Thus far, the model has allowed the possibility that $S < 0$. That is, a farmer could borrow the staple food for consumption in season 1, and repay it in season 2. Now, consider the case where such borrowing is impossible. This constraint is

$$S \geq 0 \tag{2.22}$$

Consider adding equation (2.22) to the two-period model with two goods in the previous section. If the strict inequality of (2.22) holds, the implications of the previous section are unchanged. However, once equation (2.22) binds, that is, once the farmer exhausts his or her stocks in season 1, he or she cannot reallocate consumption across from season 2 to season 1 any more, and cash in hand in either season is used only for consumption in that season. In this case, a higher price for the produced staple good in season 2 would decrease its consumption in season 2 through income and substitution effects. Thus, income and substitution effects decrease consumption in season 2 only if the farmer would like to, but cannot, borrow physical amounts of the staple good in season 1.

2.3 Re-considering the "Sell Low, Buy High" Puzzle

This section explains how the two-period model with two goods in the previous section can be used to explain the "sell low, buy high" puzzle, in which some farmers sell staple foods (the consumption good) when prices are low, and in the same year, such farmers buy them when prices are high. The first subsection discusses why the so-called "sell low, buy high" puzzle happens, explicitly assuming equation (2.10).[4] I then conduct welfare analysis to see who gains or loses welfare due to seasonal price increases in the hunger season. The second subsection provides a diagramatic representation to provide an intuitive explanation for "sell low, buy high" puzzle.

[4] Stephens and Barrett (2011) provide on explanation for the "sell low, buy high" puzzle, but do not explicitly discuss the assumption of equation (2.10). When the inequality in equation (2.10) holds, every farmer borrows up until upper limit, that is, every farmer hits the binding credit constraint regardless of his or her trade patterns ("sell low, buy high", or not) of staple foods. Nevertheless, they compare a farmer with a binding credit constraint with a farmer without a binding credit constraint, though the latter farmer should not exist in theory. When the inequality in equation (2.10) is replaced by an equality, "sell low, buy high" behavior is no longer a paradox, because the savings in the form of money and the savings in the form of staple foods are equivalent, that is, "sell low, buy high" for staple foods is equivalent to "buy low, sell high" for money.

2.3.1 "Sell low, buy high" puzzle

To understand the "sell low, buy high" puzzle, it is useful to distinguish income in kind from cash income. Let $y_1 = p_1 y + wL_1$ and $y_2 = wL_2$ where y is the amount harvested at the beginning of season 1 and wL_j is an exogenous cash income wL_j at the beginning of each season j due to labor market work. Combining equations (2.14) and (2.15), and setting $B = \bar{B}$, the farmer's utility maximization problem can be written as:

$$\max_{c_1, x_1, c_2, x_2, B, S} u(c_1, x_1) + \beta u(c_2, x_2) \tag{2.23}$$

$$\text{subject to} \qquad p^*_{c_1} c_1 + p^*_{x_1} x_1 + p^*_{c_2} c_2 + p^*_{x_2} x_2 = M \tag{2.24}$$

where $p^*_{c_1}, p^*_{x_1}, p^*_{c_2}$, and $p^*_{x_2}$ are $p_1, 1, \frac{p_1}{1-\nu}$, and $\frac{p_1}{p_2(1-\nu)}$, respectively, and

$$M \equiv p_1 y + wL_1 + \frac{p_1}{p_2(1-\nu)} wL_2 + \left\{ 1 - \frac{p_1(1+r)}{p_2(1-\nu)} \right\} \bar{B} \tag{2.25}$$

Note that $p^*_{c_1}, p^*_{x_1}, p^*_{c_2}$, and $p^*_{x_2}$ can be interpreted as shadow prices of c_1, x_1, c_2, and x_2, and that M is the full income of the farmer for the whole year. Since the return to savings (in the form of physical stocks of the staple good) is $\frac{p_2}{p_1}(1-\nu)$,[5] the farmer's full income can be decomposed into three parts: income in season 1 ($p_1 y + wL_1 + \bar{B}$), the discounted value of income in season 2 ($\frac{p_1}{p_2(1-\nu)} wL_2$), and the discounted value of the repayment in season 2 ($\frac{p_1(1+r)}{p_2(1-\nu)} \bar{B}$). Let P be a vector of shadow prices, then c_j and x_j ($j = 1, 2$) can be written as a function of P and M.

Let q_j be the amount of the staple good a farmer buys in season j. First, "sell low" behavior ($q_1 < 0$) is discussed. The amount of the staple good the farmer sells in season 1

[5] Due to equation (2.10), the farmer saves in the form of the staple good. One unit of money in season 1 is worth $\frac{1}{p_1}$ units of the staple good, which is depreciated to $\frac{1}{p_1}(1-\nu)$ units of the staple good. This staple good is worth $\frac{p_2}{p_1}(1-\nu)$ in monetary terms.

$(-q_1)$ can be expressed as:

$$
\begin{aligned}
-q_1 &= y - S - c_1 \\
&= \frac{1}{p_1}\left\{x_1(P,M) - (\bar{B} + wL_1)\right\} \\
&= \frac{1}{p_1}\left\{x_1(P,M) - \frac{\bar{B} + wL_1}{M}M\right\}
\end{aligned}
\tag{2.26}
$$

Equation (2.26) implies that "Sell low" behavior happens if the proportion of cash income in season 1 ($\bar{B} + wL_1$) to full income (M) is too low to satisfy consumption of the *other* good in season 1 ($x_1(P,M)$).

Next, "buy high" behavior ($q_2 > 0$) is discussed. The amount of the staple good that the farmer sells in season 2 (q_2) can be expressed as:

$$
q_2 = c_2(P,M) - (1-\nu)S \tag{2.27}
$$

and S can be represented as:

$$
\begin{aligned}
S &= \frac{p_1 y + wL_1 + \bar{B} - x_1(P,M)}{p_1} - c_1(P,M) \\
&= \frac{1}{p_1}\left\{\frac{p_1 y + wL_1 + \bar{B}}{M}M - C_1(P,M)\right\}
\end{aligned}
\tag{2.28}
$$

where $C_1(P,M) \equiv x_1(P,M) + p_1 c_1(P,M)$, that is, total consumption in season 1 in monetary terms. Equations (2.27) and (2.28) imply that, if the proportion of income in season 1 ($p_1 y + wL_1 + \bar{B}$) to full income (M) is so low that the farmer cannot store enough of the staple good to satisfy the demand of consumption of the staple good in season 2 ($c_2(P,M)$), then he or she will buy the staple good in season 2.

In sum, the timing of the trade of the staple good depends on the timing of income, whether it is in kind or not, and the financial capacity to borrow money. One thing to note is that, regardless of the timing of the trading of the staple good - whether the farmer buys the staple good at high prices or not, the shadow prices are identical across farmers because they all have the same return to savings in the form of the staple good, which is $\frac{p_2}{p_1}(1-\nu)$.[6] In other words, every farmer takes advantage of the highly profitable inter-temporal price arbitrage of the staple good. This leads to a new question: Is the price increase of the staple good in the hunger season really bad for farmers? To address this issue, welfare analysis is conducted. Define the indirect utility function induced from the utility maximization problem of this section as $V(P,W)$, and define $\lambda(>0)$ as the Lagrange multiplier corresponding to equation (2.24), then the the following equation is derived by applying the envelope theorem;

$$\begin{aligned}\frac{\partial V(P,M)}{\partial p_2} &= \left\{-\frac{p_1}{p_2^2(1-\nu)}wL_2 + \frac{p_1(1+r)}{p_2^2(1-\nu)}\bar{B} + \frac{p_1}{p_2^2(1-\nu)}x_2^*\right\}\lambda \\ &= \{x_2^* + (1+r)\bar{B} - wL_2\}\frac{p_1\lambda}{p_2^2(1-\nu)} \\ &= -p_2q_2\frac{p_1\lambda}{p_2^2(1-\nu)} \\ &= -q_2\frac{p_1\lambda}{p_2(1-\nu)} \end{aligned} \tag{2.29}$$

where $x_2^* \equiv x_2(P,M)$, given fixed (P,M). Since λ, p_1, p_2 and $1-\nu$ are strictly positive, and q_2 is the amount of the staple good a farmer buys in season 2, equation (2.29) indicates that net buyers of the staple good in season 2 decrease their welfare by the increase of the price of the staple good in season 2, while net sellers of the staple good in season 2 increase their welfare by the increase of the staple good prices in season 2. This result emphasizes the importance of policies to mitigate seasonal price changes, because poorer farmers are less

[6] If transaction costs are added to the model, the return to savings and shadow prices could be heterogenous, depending on the trade patterns. See Appendix A for a further discussion.

likely to have access to financial resources, and are more likely to purchase the staple good in season 2. Mitigating seasonal price changes could reduce the gap between poor farmers and rich farmers.

2.3.2 Diagramatic Representation

A diagram provides an intuitive explanation for "sell low, buy high" puzzle. To simplify notation, define $u(c_1, x_1)$ and $\beta u(c_2, x_2)$ as $u_1(c_1, x_1)$ and $u_2(c_2, x_2)$, respectively. Since preferences over time are assumed to be additive, the farmer's utility maximization problem can be divided into two stages; at the first stage, expenditure is allocated to either season 1 or season 2, and at the second stage, expenditure in each season is allocated to the staple good and other goods.[7] Solving this maximization problem by backward induction, the farmer's demand at the second stage can be represented as $c_j(P, M_j)$ and $x_j(P, M_j)$ ($j = 1, 2$), where P is a vector of p_1 and p_2, and M_j is the expenditure in season j. Then, given fixed P, the farmer's utility to be maximized at the first stage can be written as;

$$\begin{aligned} u_1(c_1, x_1) + u_2(c_2, x_2) &= u_1(c_1(P, M_1), x_1(P, M_1)) + u_2(c_2(P, M_2), x_2(P, M_2)) \\ &= U(M_1, M_2 \mid P) \end{aligned} \tag{2.30}$$

Figure 2.1 illustrates the utility maximization problem of the farmer. The first quadrant represents the decision making at the first stage, that is, total expenditure is allocated to either season 1 or season 2. Its horizontal axis is for the expenditure in season 1 (M_1), and the vertical axis for the expenditure in season 2 (M_2). OA, AB, BC, and OD represent wL_1, $\bar{B}$, $p_1 y$, and wL_2, respectively. This farmer borrows $\bar{B}$ in season 1 and repays $(1 + r)\bar{B}$ in season 2, which is represented by DE in the diagram. OC represents the total money the farmer can spend in season 1 without savings of the staple good, and OE represents

[7] See Chapter 5 in Deaton and Muellbauer (1980) for more details.

the total money that the farmer can spend in season 2 without savings of the staple good. Since this farmer can save the staple good from season 1 to season 2 with the return rate of $\frac{p_2}{p_1}(1-\nu)$, GH represents the inter-seasonal budget constraint for this farmer with the slope of $\frac{p_2}{p_1}(1-\nu)$. This farmer maximizes his or her utility $U(M_1, M_2 \mid P)$, given this budget constraint. Note that the change of P changes the functional form of $U(M_1, M_2 \mid P)$, which makes it difficult to conduct comparative statistics with respect to P on this diagram. As a result of utility maximization, OJ represents total expenditure in season 1, and OI represents total expenditure in season 2. Note that JC represents the amount of savings of the staple good in monetary terms, that is, $p_1 S$. At the second stage of the utility maximization problem, these total expenditures OJ and OI are allocated to the staple good and other goods in each season. The fourth quadrant represents the decision making on the second stage for season 1. The horizontal axis represents the amount of other goods consumed in season 1 (x_1), and the vertical axis represents the amount of the staple good consumes in season 1 (c_1). Since one unit of maize is worth p_1 units of money, the slope of the budget constraint (JK) is p_1. The optimal amounts of c_1 and x_1 are determined to maximize a contemporaneous utility function $u_1(c_1, x_1)$ given this budget constraint JK. As a result of this utility maximization, OM represents the amount of the staple good consumed in season 1 (c_1^*) and OB represents the amount of other goods consumed in season 1 (x_1^*). LB represents the value of the staple good sold in season 1, that is, $-p_1 q_1$ (so in fact, $p_1 q_1$ is the amount of the staple good bought in season 1). If OL is bigger than OB, in other words, if x_1^* is bigger than $wL_1 + \bar{B}$, the farmer sells the staple good in season 1.That is, if total cash in hand other than the value of the staple food harvested, $wL_1 + \bar{B}$ is less than the demand for the other good in season 1 (x_1), the farmer must sell some of the staple good to purchase that other good. If OL is smaller than OB, the farmer buys the staple food in season 1. And if OL=OB, the farmer neither buys nor sells the staple good. The second quadrant represents the decision making on the second stage for season 2. The vertical axis represents the amount of other goods consumed in season 2 (x_2), and the horizontal axis represents the amount of the staple good consumed in season 2 (c_2). Since one unit of the staple good is worth p_2 units of money, the slope of budget constraint (IN) is p_2. The optimal amounts of c_2 and x_2 are chosen to maximize a contemporaneous utility function $u_2(c_2, x_2)$ given the budget constraint IN. As a result of this utility maximization, OP represents the amount of the staple good consumed in season 2 (c_2^*) and OQ represents the amount of the other good consumed in season 2 (x_2^*). EQ represents the value of the staple good bought in season 2, that is, $p_2 q_2$. If OQ is smaller than OE, the farmer sells the staple good in season 2, and if OQ is bigger than OE, the farmer buys the staple good in season 2 (so, it is the amount of the staple food bought in season 2). Figure 2.2 represents the utility maximization problem of a farmer whose full income (GH) is identical to the farmer represented in Figure 2.1, but whose timing of income is different: the amount of the staple food harvested at the beginning of season 1 (y_1) is greater, and cash income in season 2 (wL_2) is less. In this setting, the farmer buys the staple food in season 2 (OQ is bigger than OE), but the amounts of the goods consumed in each season (c_1, x_1, c_2 and x_2) are identical to those of the farmer in Figure 2.1. Obviously, whether the farmer sells or buys the staple good at higher prices or lower prices (the sign of $q_t(t = 1, 2)$) does not change the slope of the diagram, that is, any farmer faces the same return to savings and the same shadow prices. The determinants of the timing of trading the staple food are the timing of income, whether it is in kind or not, the financial capacity to borrow money, and the farmer's preferences.

2.4 Concluding Remarks

In settings where produced staple foods are used to smooth consumption of the staple good, seasonal price changes could affect seasonal consumption patterns not only through income and substitution effects, but also through changing the return to savings. In this situation, the reduced consumption in the hunger season in response to high prices at that time should not be interpreted only as simple income and substitution effects. Rather, it could signal an inability to reallocate resources across seasons. This implies that models of farmers' savings should include saving in the form of stocks of agricultural output.

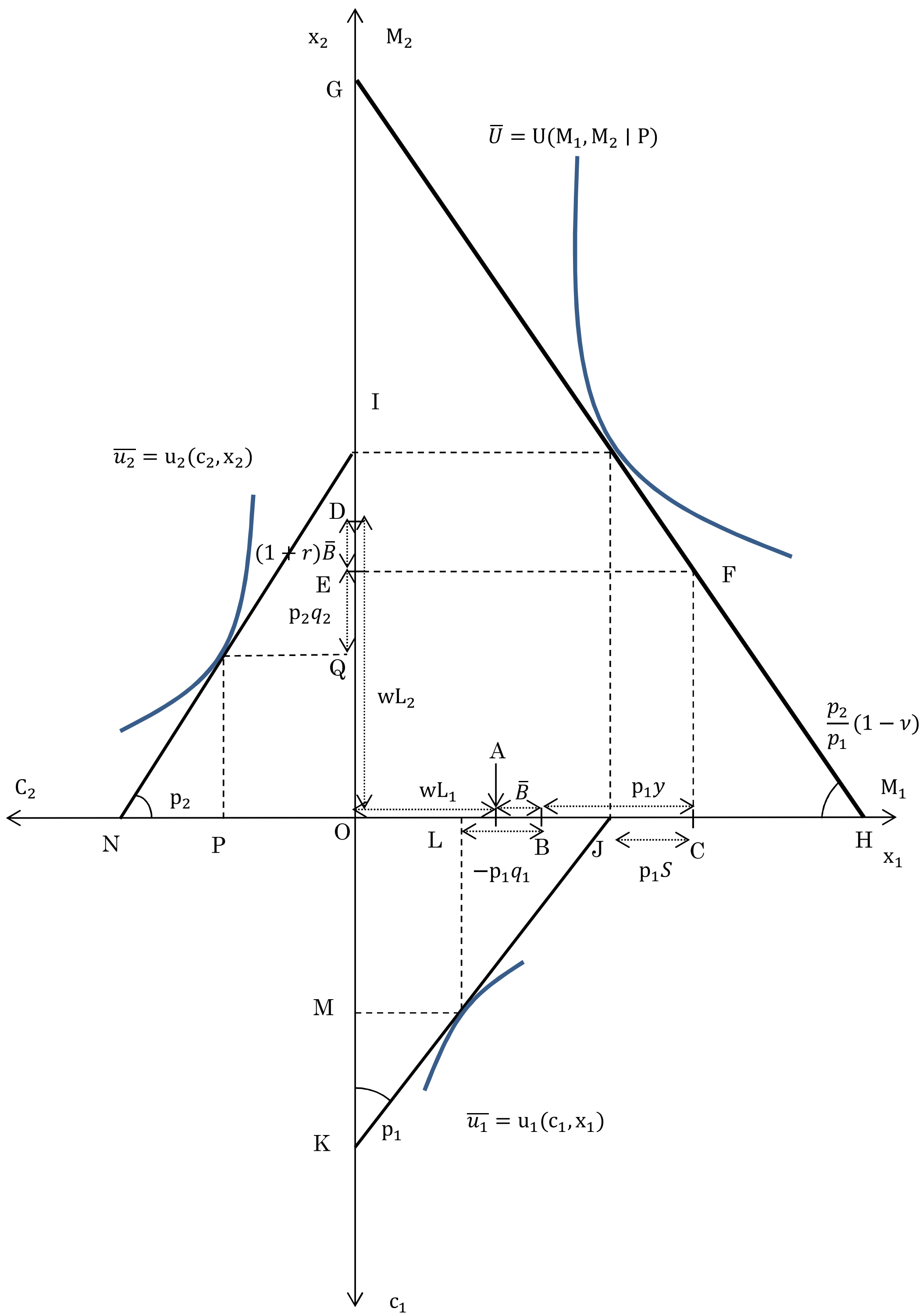


Figure 2.1: Diagram for the Utility Maximization Problem: "Buy High"

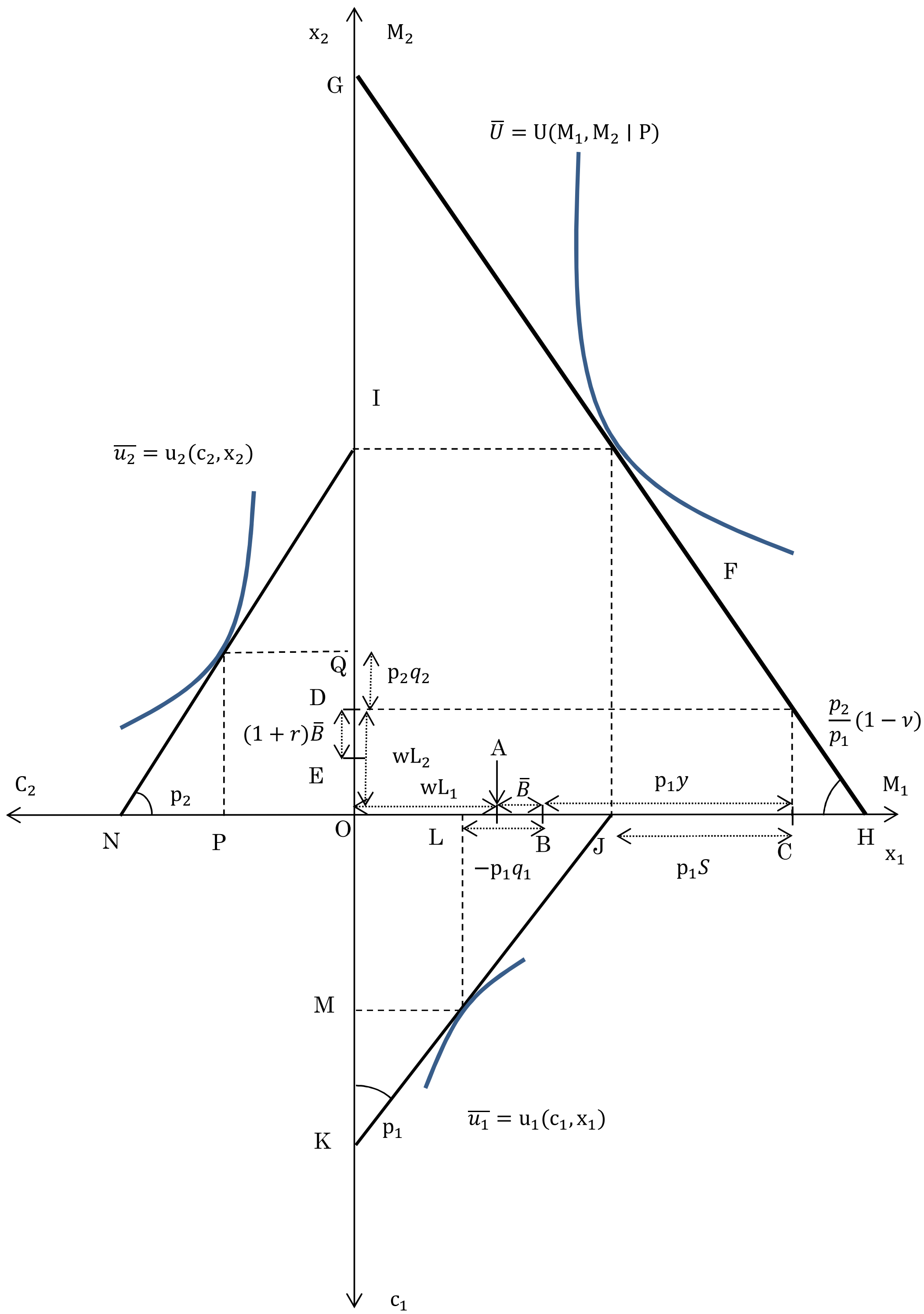


Figure 2.2: Diagram for the Utility Maximization Problem: “Sell High”

Chapter 3

The Seasonality of Food Insecurity in Rural Zambia[1]

3.1 Introduction

Seasonality is an important aspect of food security for subsistence farmers in developing countries. Farmers receive agricultural income only at the harvest season, and it is uncertain. Their previous year's harvest stocks gradually dwindle, and some farmers run out of their food before the next harvest. Such farmers need to buy their food with cash, but food prices are usually high right before the next harvest. Those farmers who run out of food and buy their food when prices are high cannot buy an adequate amount of food. Most malnutrition and deaths of young children occur in those periods (e.g. Devereux et al, 2012), and so do famines (e.g. Sen, 1981). Those periods are often referred to as the hunger season (e.g. Devereux et al., 2012, Vaitla et al., 2009, and Khandker and Mahmud., 2012).

To cope with income seasonality and instability due to the agricultural cycle, farmers

[1]This chapter is co-authored with Takeshi Sakurai.

smooth their consumption by relying on borrowing or savings (e.g. Paxson, 1992), or by entering into informal risk sharing arrangements (e.g. Townsend, 1994). However, when such mechanisms do not function well (e.g. incomplete credit markets, insufficient risk sharing networks, and so on), farmers are unable to achieve perfect consumption smoothing, and may reduce their food consumption during the time just before they receive their harvest income.[2] Thus, seasonality of food insecurity can be seen as a consequence of farmers' inability to smooth food consumption in that season. This paper addresses whether, and how, farmers in rural Zambia smooth their consumption within a crop year.

Several previous studies have addressed this issue by testing whether seasonal consumption tracks seasonal income patterns, but their results are somewhat mixed. Paxson (1993) and Chaudhuri and Paxon (2002) found no evidence that seasonal consumption tracks seasonal income patterns in Thailand and India, respectively, while Dercon and Krishnan (2000) and Khandker (2012) showed that seasonal income affects seasonal consumption in Ethiopia and Bangladesh, respectively. These studies implicitly assume that each farmer's ability to smooth consumption is identical. However, as Jalan and Ravallion (1999) showed, poorer farmers are more likely to fail consumption smoothing, which casts doubt on the validity of this assumption. This paper focuses on heterogeneity in the ability to smooth consumption.

This paper also contributes to two additional threads of the consumption smoothing literature. One is related to the more conventional consumption smoothing literature, which uses annual household consumption data to test whether, and to what extent, farmers smooth their consumption (e.g. Paxson, 1992; Townsend, 1994; Ravallion and Chaudhuri, 1997; Fafchamps and Lund, 2003, and Kurosaki, 2001, 2006). They examine the impact

[2] Fafchamps (2003) and Dercon (2005) provide comprehensive surveys of this literature.

of income shocks on consumption, usually measured as annual average consumption or average consumption during the time just before the survey was conducted. However, the impact could be relatively large or small during certain seasons of the year. Therefore, this paper traces how the impact of agricultural harvest shocks on consumption varies over time *during the year*. The other thread is a growing literature which evaluates the impact of seasonal credit programs that aim to counter seasonal price increases of staple foods during the hunger season. These studies have addressed the impacts of such programs not only on total consumption but also on consumption of staple foods, non-food expenditure, and a health index (Basu and Wong, 2015), local prices of staple foods (Burke, 2014), and the allocation of household labor and local farming wages (Fink, Jack and Maiye, 2014). But food diversity is also important for food security, because lack of food diversity could result in micronutrient deficiencies. In Zambia, the prevalence of vitamin A deficiency in 2003 was 53.3% for children and 13.4% for women of child-bearing age (National Food Nutrition Committee of Zambia, 2011), and this increases the risk of disease and death from severe infections. Thus, this paper pays special attention to how farmers adjust their consumption of non-staple foods in response to harvest shocks.[3]

Using three years of weekly household panel data collected in the southern part of Zambia, and two retrospective household surveys that collected data on the trading patterns of maize and crop harvests of the sampled households in each year, this paper estimates demand functions to examine whether, and to what extent, harvest shocks affect consumption and, if so, how the impacts persist over time. The estimation method pays careful attention to heterogenous timing of purchases of the staple food, maize. The farmers in the study area grow maize for self-consumption. If their maize yields are not enough for their annual

[3]The farmers' consumption of non-staple foods includes a variety of local foods for which nutrient tables are not available. Thus, we could not calculate their intakes of specific micronutrients to test whether consumption of them is smoothed during the hunger season.

consumption, they must buy maize. Given seasonal price changes of maize, some farmers buy maize when prices are low and store it for the hunger season; these farmers will henceforth be called NBH (not buy high) farmers. In contrast, other farmers run out of maize and so engage in off-farm work to obtain cash to buy maize when prices are high; these farmers will be called BH (buy high) farmers. These differences indicate heterogeneity across farmers in their ability to smooth consumption. To investigate this phenomena, demand functions are estimated separately for both types of farmers. To see how farmers adjust their composition of consumption, this paper uses as dependent variables of these demand functions not only total consumption but also consumption of the staple food, of other foods, and of non-food items.

Regression results suggest that NBH farmers successfully smooth their consumption. In contrast, BH farmers reduce total consumption after the harvest in response to harvest shocks, and the shocks produce an inverse U consumption pattern during the crop year, especially for farmers with little assets. One reason that they do not recover from harvest shocks is that they have difficulties smoothing their consumption through off-farm labor; since maize prices increase while they work, their incomes in real terms decrease as maize prices increase. Looking into how BH farmers adjust the composition of their consumption, they almost smooth consumption of staple foods despite the seasonal hike in maize prices. However, they decrease consumption of non-staple food items, such as vegetables and meats. This result suggests that the policies to improve food diversity should be included in discussions of policies to help farmers cope with seasonal price changes of the staple food.

The remainder of this chapter is organized as follows. Section 2 describes the data from the household survey. Section 3 discusses the estimation strategies, and Section 4 provides the estimation results. Section 5 discusses policy implications and concludes.

3.2 Data and Descriptive Statistics

3.2.1 Survey Outline

The household survey data used in this paper were collected as part of the Resilience Project - Vulnerability and Resilience of Social-Ecological Systems, administered as part of a collaboration among the Research Institute for Humanity and Nature (RIHN), the Inter-University Research Institute Corporation, and the National Institutes for the Humanities, all of which are in Japan. The study area is located in Choma and Sinazongwe Districts, in the Southern Province of Zambia, and data were collected from three ecological zones: Site A (the lower flat land zone near Lake Kariba), Site B (the middle slope zone), and Site C (the upper land zone on the plateau). These three sites are located within a radius of 15 kilometers, but cover a wide diversity of agricultural ecosystems. Annual rainfall and natural vegetation are different due to the variation in altitude, but the ethnicity and culture of the local populations are the same across the survey sites. From each site, 16 households were chosen randomly, so the total sample size is 47.[4] More information on the survey is found in Sakurai (2008).

The household survey was conducted from November 2007 to December 2011, and it consists of an annual household survey, a monthly household survey, and a weekly household survey. The weekly household survey collected detailed data on consumption. This chapter uses data for three crop years.[5] Moreover, in September 2010, additional retrospec-

[4]One household was dropped because it moved away.

[5]The data used are from May, 2008 to April, 2011. We define the crop year 08/09 as the 12 months from May, 2008 to April, 2009, the crop year 09/10 from May 2009 to April 2010, and the crop year 10/11 from May 2010 to April 2011. The data from November 2007 to April 2008 are not used because there are no data

tive data were collected on the crop yields in the harvest seasons (April or May) of 2008, 2009 and 2010. For each plot, for each year, farmers were also asked about planted crops, and asked to rate their crop yields using three categories - above average, average, and below average. To evaluate the farmers' relative value of each plot, they were asked each plot's rental cost. In addition, in March 2011, farmers were interviewed to collect data on their maize purchases from the beginning of the research period, and those who purchased maize were asked when, how often, and the amounts they purchased at each time.

3.2.2 Seasonal Patterns of Income and Consumption

In the study area, almost all the villagers are subsistence farmers whose main income source is agricultural production. All the sampled households are farmers who grow their staple food, maize, for self-consumption and, if their harvests exceed their annual consumption, for sale. If their maize production is insufficient for their annual consumption, farmers buy maize with cash. Farmers plant seeds once it starts raining, typically in November, and harvest from March to May. This period of time is the rainy season. After the harvest, the dry season starts and there is almost no rain. Throughout the year, but mainly during the dry season, farmers engage in various types of on-farm or off-farm work. Farmers who have fields near the river cultivate a second crop during the dry season, typically from June to November. Table 3.1 shows the number of households who grow maize in the dry season. In the study area, 22 households (6 in Site A, 4 in Site B, and 12 in Site C) have fields near the river. In addition, the sample households can engage in a variety of off-farm work activities to obtain cash. The major way to obtain cash in Site A is to work at a fisheries company at Lake Kariba. In Site B, production and trade of lumber is a major work activity, and in Site C, growing food crops for trade, such as double cropping maize and vegetables,

on crop harvest for that year. The data from May 2011 to December 2011 are not used because there are no data regarding maize trading patterns in those periods.

is important. Other types of piece work, such as the selling handicraft products by a female household member, are also a major source of cash in all three sites. In this way, every household engages in some kind of wage or self-employment work during the dry season.

The typical meal of a farmer's family consists of Nsima (a very thick porridge made from maize flour) and one or two side dishes. Side dishes are usually seasonal vegetables (e.g. cabbage, tomato, onion, okra, pumpkin leaves, mushroom, and so on) sauteed in oil and salt, which is an important source of micronutrients, such as vitamin A and zinc. Their main source of protein is kapenta (dried small fish), which is sometimes added to the sauteed vegetables. Only on very special days, meats are added to the side dish. For example, many households celebrate Christmas, and eat chicken or goat on that day. Figure 3.1 shows the average composition of values of consumption per week per adult-equivalent[6] over the three years of data collection, calculated based on the weekly household survey data. Food consumption accounts for 83% of their total consumption, almost half of which is for staple foods, which is primarily maize. The other half of food consumption is for vegetables and fruits, animal products, and processed food products, which is mainly for side dishes.[7] Of course, agricultural inputs such as fertilizers or seeds are excluded from these estimates of household consumption. Figure 3.2 shows seasonal patterns of average total (food and non-food) consumption per week per adult-equivalent, and Figure 3.3 presents seasonal patterns of average consumption for staple foods, other foods, and non-food items. The spike of consumption of non-staple foods in December is due to Christmas. Although non-food items account for only 17% of the value of these households' total consumption,

[6]Adult-equivalent scales are adopted from the Living Conditions Monitoring Survey reports published by the Central Statistics Office, Zambia. For each household, the number of adult equivalents is defined as: (Number of adult males) + (Number of adult females) + (Number of children (10-12 years)) * 0.76 + (Number of children (7-9 years)) * 0.78+ (Number of children (4-6 years)) * 0.62 + (Number of children (0-3 years)) * 0.36. Adults are defined as above 12 years old.

[7]Cooking oil and salt are categorized as processed food products.

their consumption is relatively concentrated just after harvest, that is, in May, June and July. The main reason for this trend is that these are purchases of household goods such as clothes and kitchen utensils, and these households tend to purchase these household goods just after the harvest.

3.2.3 Seasonal Price Changes and the Way Farmers Buy Maize

Figure 3.4 shows average maize prices per bucket[8] over the three crop years, and Figure 3.5 shows average maize prices per bucket for each crop year. In each crop year, maize prices are cheapest after the harvest season, and gradually increase until next harvest season. Compared with the lowest prices in each crop year, peak prices increased by 86%, 69%, and 29% in crop years 08/09, 09/10, and 10/11, respectively.[9] Given these seasonal price changes, it is profitable for households to buy maize when maize prices are low and sell when maize prices are higher. However, only a few villagers sell maize in the hunger season, when maize prices are high, and thereby practice an inter-seasonal price arbitrage.[10] Possible reasons for not doing this would be high transaction costs for selling maize in the hunger season, and incomplete credit markets. One particularly important source of transaction costs for selling maize during the hunger season is social pressure. In the study villages, it is a common custom that farmers with surplus maize in the hunger season give some of their maize to neighboring farmers in bad situations. Thus, in order to practice an inter-seasonal price arbitrage of maize, farmers first need to secure enough maize to distribute to other, poorer farmers. Another source of transaction costs for selling maize in

[8] In the study area, a bucket is a standard unit in the market. One bucket of maize is a bucket filled with maize (about 15.5kg), and the bucket size is standardized in the study area.

[9] Note that this number is in real terms, that is, deflated by the GDP deflater, which is about 12% during the year. Peak prices highly depend on crop situations around the study area in each year.

[10] As far as we know, in our study area, only one villager, who obviously had a large amount of capital, practiced such inter-temporal price arbitrage, and he was not one of our sample households. There are some outside inter-village traders, called briefcase businessman, who practice such inter-temporal price arbitrage.

the hunger season is fixed costs for storage. Since farmers do not have additional storage capacity for inter-temporal price arbitrage, they need to invest in additional storage capacity. Finally, there is the opportunity cost of trading maize during the hunger season, which can be considered to be a transaction cost because this time of year is the agricultural busy season and thus the marginal cost of labor is high. In combination, these transaction costs appear to prevent farmers from selling maize in the hunger season.

On the maize purchasing side, Table 3.2 presents data on households by their purchase patterns for maize. Over three crop years, slightly less than half (68) of the 141 household year observation had purchases of maize, and there are two distinct patterns for these maize purchases. One is purchases of maize from May to December, and almost all of these observations consist of only one or two purchases. These are situations where households bought maize relatively soon after the harvest, when maize prices are low, and stored them for the hunger season. The other group of observations is of households who purchased maize from January to April (many also purchased maize before January), and almost all of them bought maize more than three times. They bought maize frequently, because they repeated a cycle in which they worked until they had enough money to buy some units of maize (for example, one bucket of maize), and then purchased the maize, and repeated this several times. This is likely to be a cycle of every week, every 15 days, or every month. The three possible reasons for why some farmers bought maize at high prices include incomplete credit markets, impatience or lack of storage. However, lack of storage seems not to be the case in the study area, because every household has enough storage for annual consumption (direct observation by the author). Impatience also seems unlikely to explain this behavior, because the increase in the price of maize from the lowest season to the highest season is very high, ranging from 29% to 86% after deflating using Zambia's GDP deflater, which is much higher than any plausible discount rate for future utility. Thus, incomplete credit markets appear to be the most likely reason that households buy maize when prices are high.

3.3 Empirical Framework

3.3.1 The Consumption Equation

The theoretical model in Appendix A shows that incomplete credit markets and high transaction costs of maize selling in the hunger season, combined with seasonal price changes of maize, will affect seasonal consumption differently for those farmers who did not buy maize at higher prices during the crop year (NBH farmers) relative to those farmers who bought maize at higher prices (BH farmers). This is because high prices of the staple food just before harvest can be viewed as a (potentially) high return to savings for BH farmers, or more accurately, a high opportunity cost of not saving, but not for NBH farmers.[11] In particular, the ability of farmers to smooth consumption is likely to be different for BH and NBH farmers, because BH farmers buy maize at higher prices than NBH farmers by using cash income from off-farm labor. Thus, this paper estimates seasonal consumption separately for NBH and BH farmers. See Appendix A for a more detailed discussion.

To examine whether, and to what extent, harvest shocks affect consumption, and how these effects persist over time, the following demand function is estimated separately for

[11] High prices of the staple food just before harvest cannot be viewed as a high return to savings for NBH farmers, because they save enough maize for self-consumption and need to pay high transaction costs if they want to sell maize at high prices. This is explained in detail in Appendix A, which explains that NBH farmers are not influenced by p_2 (the price during the hunger season)

BH and NBH farmers:

$$C^j_{imyw} = \sum_{y=1}^{3}\sum_{m=1}^{12}\alpha^j_{my}\cdot D_{my} + \sum_{m=1}^{12}\beta^j_m TI_{iy}\cdot D_m + \gamma^j X_{imy} + \xi^j_{vy} + \upsilon^j_i + u^j_{iymw}$$

$$\text{for } j = NBH, BH \tag{3.1}$$

where C^j_{iymw} is consumption of household i in village v in (crop) year y in month m in week w, and superscript j is BH or NBH. D_{my} is a dummy variable that equals one if the month is m and the year is y, and 0 otherwise, and the term α^j_{my} captures average seasonal consumption patterns in each year. Note that the sequence of maize prices in each year affects seasonal consumption patterns in that year. These seasonal price effects are captured by (α^j_{my} for $m = 1, \cdots, 12$).[12] D_m is a dummy variable that equals one if the month is m, and 0 otherwise, and TI_{iy} is the harvest shock that household i suffered at the beginning of the crop year y.[13] X_{imy} is a vector of time-varying household variables, ξ^j_{vy} is unobserved year varying village fixed effects, υ^j_i is household fixed effects, and u^j_{iymw} is an error term that has an expected value of zero.

The coefficients β^j_m capture the impact of harvest shocks on consumption in each month, and are the parameters of interest. If the farmer successfully smooths consumption both across years and within a crop year, all the β^j_m coefficients should be zero. If the farmer cannot smooth consumption across years, but can smooth consumption within

[12]Since the study villages are located within a radius of 15 kilometers, maize prices are assumed to be identical for all the sample households. In addition, as discussed in the previous section, there are two distinctive groups with different crop patterns in the study area: one group whose members have their own fields near the river and so can grow maize in the off-farm season, and the other group whose members do not. To allow for different seasonal consumption patterns by different cropping patterns, seasonal consumption patterns are allowed to differ for different cropping patterns.

[13]Income shocks in the middle of the year are not included in equation (3.1). This is discussed in the following subsection.

years, then the β_m^j coefficients will be negative but will be equal across months. However, if this failure to smooth consumption across years is due to village level income shocks, year varying village fixed effects will control for this and all β_j^m coefficients will equal zero. In this case, inability to smooth consumption within a crop year will results in some β_m^j coefficients being negative. If the farmer fails to smooth consumption, β_m^j coefficients should be negative for at least one month, and how farmers adjust their consumption during the year is discussed.

3.3.2 Identification

OLS estimation for equation (3.1) is likely to lead to biased estimates of β_m^j because, in general, there will be sample selection bias due to correlation between u_{iymw}^j and I_{iy}^j, that is,

$$E[u_{iymw}^j \mid \alpha_m^j, TI_{iy}, D_m, X_{imy}, I_{iy}^j] \neq 0 \qquad \text{for } j = NBH, BH \tag{3.2}$$

where I_{iy}^{BH} (I_{iy}^{NBH}) is a dummy variable that equals one if household i was a BH farmer in year y (or a NBH farmer in year y). Whether a farmer becomes a BH farmer or a NBH farmer in each year (I_{iy}^j) depends on assets and on borrowing abilities, which allow the farmer to buy maize when maize prices are low. Yet, these factors could also affect consumption (C_{iymw}^j) through the error term (u_{iymw}^j). These factors can be considered as household specific characteristics, so household fixed effects are added to equation (3.1). In addition, to control for any village level shocks, year varying village fixed effects are also added. Error terms are clustered at the household level which are robust to heteroscedasticity of unknown form. To see how this identification strategy is plausible for identifying the causal impact of harvest shocks on seasonal consumption, consider three sources of statistical endogeneity in turn: unobserved heterogeneity, reverse causality, and measurement error. Special attention is given to unobserved heterogeneity caused by sample selection that leads some farmers to be NBH farmers and others to be BH farmers.

Unobserved heterogeneity refers to the problem of omitted variables that are correlated with both seasonal consumption and any of the regressors in equation (3.1). Fortunately, household fixed effects control for this bias as long as the unobservable factors which determine both I_{iy}^{j} and C_{iymw}^{j} are invariant across years within the same household. However, if such determinants vary across years, household fixed effects are not enough to avoid bias. This could happen if households' ability to raise funds, such as asset holdings, varies over time. In that case, year-variant household fixed effects are required. However, one drawback of the year-variant household fixed effects estimation is that year variant household fixed effects make it impossible to estimate β_{m}^{j} for all m, because the cross-terms $TI_{iy} \cdot D_{m}$ ($m = 1, \cdots, 12$) and year variant household fixed effects are linearly dependent. Thus, one of those cross-terms for some base month should be dropped from the model (in this paper, May), and all that one can estimate are the differences of coefficient from May, that is, ($\beta_{m}^{j} - \beta_{5}^{j}$). In this paper, estimation results without year variant household fixed effects are used to interpret the results, and as robustness checks, the results are compared to estimation results with year variant household fixed effects to see the extent to which these two estimators are different. But still, if some unobservables which are not captured even by year variant household fixed effects are correlated with both I_{iy}^{j} and C_{iymw}, estimation results will be biased. One possible source of this bias is large income shocks in the middle of the year. If a household that was going to purchase maize in the middle of the year, prices were relatively low suffered income shocks, and put off purchases of maize, this income shock can cause bias. Or, if a double cropping household who was not supposed to purchase maize when maize prices are high had a failure of dry season maize and purchased maize, this harvest shock causes bias. Since there are no data on such income shocks, this possibility cannot be ruled out. However, this is unlikely to be a serious problem, because off-farm work in the study area is relatively stable compared to the rain-fed harvest in May. Fishery companies at Lake Kariba provide many stable employment opportunities in site A, and a high demand of lumber to build ships for them provides a stable supply market for the producers and traders of lumber in site B. The harvest of dry season maize in site C is also relatively stable, because this harvest does not depend on rainfall, but on water coming from the river near their fields.

Another regressor that should receive careful attention is the TI_{iy} variable, which represents harvest shocks. For this variable, the survey data collected in September 2010, which include retrospective data on income shocks, are used. For each plot in each year, households were asked whether each plot was fallow in that year. If not fallow, a general indicator crop yield of each plot was asked, using a simple scale of “above average”, “average” or “below average”. The reasons for being “below average” are categorized into: 1. heavy rain: 2. lack of seed; 3. lack of fertilizer: or 4. other reasons. In addition, for each plot, rental costs were asked to evaluate the relative value of each plot. Note that since the land market is incomplete, rental costs are subjective.[14] By using these data, the fraction of the value of plots that are below average due to other reasons divided by the total value of the land is calculated for each household in each year, and used as a proxy for harvest shocks. For example, if the farmer has three plots with rental costs of 300ZMK, 500ZMK, and 200ZMK, and whose crop situations are below average due to insects (which would be included as “other reasons” in the data), average, and below average due to the lack of fertilizer, respectively, the proxy is $0.3 = 300/(300 + 500 + 200)$. The fraction of “below average due to lack of seed, or lack of fertilizer” is excluded from the proxy, because these phenomena could reflect the farmer’s farm management decisions in the previous year,

[14]But as long as relative rental costs are not affected by subjectivity, then this is not a problem.

which could be correlated with farmers' other decisions in the previous year that affect consumption of the following year (e.g. off-farm labor supply). The fraction of "below average due to heavy rain" is not included, because the impact of heavy rain is absorbed in year variant village fixed effects.[15]

Reverse causality refers to the statistical endogeneity problem that arises from the fact that the dependent variable might have causal impact on the explanatory variable of interest. This problem could arise if seasonal consumption affects harvest shocks. In fact, consumption decisions after the harvest cannot affect harvest shocks, because these harvest shocks happen at the beginning of the crop year, and consumption is decided after that.

A final endogeneity problem arises from measurement error. The variable indicating whether the farmer bought maize at higher prices or not (I^j_{iy}) is highly unlikely to be a problem in our application given that this should be easy to remember and there is no obvious advantage or disadvantage to misreporting it. In addition, respondents were not only asked the timing of their maize trade, but also asked some other associated questions, such as the frequency of trade and its volume, which would remind respondents of the situation at that time and would minimize their errors. To allow for the possibility that the adult equivalence scales use may cause measurement errors in consumption, demand functions are also estimated without equivalence scales to check for robustness (see Appendix B).

[15]Two noteworthy income shocks that occurred during the study period are heavy rains in December 2007 and in February 2010. These heavy rains ruined or even washed away maize fields, and decreased households' transitory income in crop years 08/09 and 10/11. The impact of these heavy rains varied according to geographical conditions. Since differences of geographical condition almost correspond to village classification, year variant village fixed effects capture village level income shocks caused by heavy rains. Note that, in this village classification, Site B is divided into two areas, because the geomorphological feature and soil conditions of these two areas are different. Heterogenous impacts of heavy rain among households are captured by year variant household fixed effects, which are included in some robustness check estimations.

In sum, although it is definitely possible that there remain some sources of bias that can undo the proposed identification of a causal effect, this identification strategy has ruled out a number of sources of bias, and it minimizes bias from other sources as much as possible given the available data. Especially, compared to the conventional strategies which fix the sample selection bias by specifying a selection equation (e.g. Heckman, 1976, Wooldridge, 1995, and Kyriazidou, 1997), the identification strategy using household fixed effects used in this paper has the strength that it does not need to find variables which appear with a non-zero coefficient in a selection equation but do not appear in the equation of interest. In addition, the strategy does not require any assumption on the functional form of the error term.

3.3.3 Definitions of Variables

The main dependent variable is the value of total consumption per week per adult-equivalent, normalized by its simple sample average over three years, which is $c_{iwmy} - \bar{c}$ where $\bar{c}$ represents a simple arithmetic average of c_{iwmy}. Also of interest are micronutrient deficiencies, especially for infants, young children aged 6-24 months and women of child-bearing age, since such deficiencies are an acute problem in Zambia. To account for micronutrient deficiencies, total consumption is divided into staple foods, other foods (almost always corresponding to side dishes of their diet) and non-food items, and demand functions for each set of goods are estimated. This is done to focus on the demand for other foods, because those foods are the most important source of many micronutrients. Farmers who buy maize at higher prices are defined as the farmers who bought maize after December, because distinctive patterns for their maize purchases can be seen for them, as shown in Table 3.2. Summary statistics of the variables used to estimate the demand functions are reported in Table 3.3.

3.4 Estimation Results

3.4.1 Main Results

Tables 3.4 and 3.5 report the estimated parameters β_m^j in equation (3.1), in which the dependent variable is total consumption (Table 3.4), and its components, that is staple food, other food, and non-food (Table 3.5).[16] Recall that, if the farmer successfully smooths consumption within a crop year, all the β_m^j coefficients should be zero. If the farmer fails to smooth consumption, β_m^j coefficients should be negative at least for one month. If deviations from consumption smoothing are found, how farmers adjust their consumption during the year is discussed. Recall as well that most households harvest in April and May, and that the value of total consumption per week per adult-equivalent is normalized by its sample average over three years. The coefficients can be interpreted as the changes in the value of consumption per week per adult equivalent (compared to sample average over three years) when all of their plots are "below average".[17] In addition, to see how sensitivity to income shocks differs depending on asset holdings, interaction terms of harvest shocks and number of cattle are added in each month. In this case, coefficients of the intersection terms of harvest shocks and month dummy are interpreted as income sensitivities for the farmers with no cattle, and coefficients on the intersection terms for harvest shocks, month dummy, and the number of cattle are interpreted as the marginal impact of one cattle on income sensitivities. Test results for the null hypothesis that (i) all the β coefficients of intersection terms of the income shock and the month dummies are zero; and that (ii) all the coefficients of intersection terms of the income shock, the month dummies, and the number of cattle are zero; are reported at the bottom of the Tables 3.4 and 3.5. Figure 3.6 reports confidence

[16] The estimated results including all other control variables are reported in Appendix B.

[17] For example, consider the BH group in May. The coefficient for total consumption is -0.363. This implies that, if 10$\%$ of the plot of the BH farmer is below average, the total consumption per week per adult equivalent decreases 3.63$\%$ of total consumption of sample average.

intervals at 95% level for the coefficients of the intersection terms of the income shock and month dummies.

The first column of Table 3.4 shows the results using all sample households together. The null hypothesis that all of the coefficients on the interaction terms of income shock and month dummy are zero cannot be rejected. To see how such income sensitivities differ for NBH farmers and BH farmers, all other columns in Tables 3.4 and 3.5 report the results of separate estimations for NBH farmers and BH farmers. Of the 47 farmers in the sample, 26 were NBH farmers in all three years, 3 were BH farmers in all three years, 18 were NBH farmers in one or two years, and BH farmers in the other years. For this last group of farmers, the seasons when they were BH are included in the BH group and the seasons when they were NBH are included in the NBH group.

NBH farmers: The Farmer Who Does Not Buy Maize at Higher Prices

The second column of Table 3.4 presents results for the seasons when farmers did not "buy high" (NBH farmers). None of the coefficients is significant, and neither are they jointly significant. In addition, looking at the fourth column of Table 3.4, even NBH farmers with no cattle do not decrease their consumption in response to harvest shocks.[18] These results indicate that farmers who do not buy maize at higher prices successfully smooth their consumption during a crop year, regardless of their wealth status. Furthermore, there is no evidence that they smooth total consumption by adjusting the composition of their consumption. This is seen by looking at Table 3.5 (a); no coefficients of the interaction terms between the income shock and the month dummy variable are significant.

[18]The coefficients of intersection terms of the income shock, the month dummies, and the number of cattle are jointly significant, but almost all the coefficients are insignificant, and they are not very large.

BH farmers: The Farmer Who Buys Maize at Higher Prices

The third column of Table 3.4 shows that BH farmers reduce total consumption throughout the crop year in response to income shocks, especially just after the harvest and during the "hunger season" just before the next harvest. In addition, the fifth column of Table 3.4 exhibits some role of household assets to smooth consumption; the coefficients of interaction terms of the income shock, the month dummies, and the number of cattle are significant in February and in March. These results indicate that farmers who buy maize at higher prices are unable to achieve perfect consumption smoothing, regardless of their wealth status, but that they can mitigate the impacts of negative harvest shocks in the hunger season, as household assets increase. Note also that the size of the impact of harvest shocks is not negligible. For example, the coefficient of harvest shocks in March is -0.418, which is significant at the 1 % level. This means that, if 10% of these farmers' land suffers from a below average harvest, they decrease their consumption by 4.2% of the sample average of total consumption.

Although the farmers in the BH group decrease their total consumption in response to harvest shocks, they almost smooth their consumption of staple foods, in spite of the seasonal price hike for maize. This is seen by looking at the first column of Table 3.5(b); only the coefficient in February is significant.[19] In addition, the fourth column of Table 3.5(b) shows that the negative coefficient in February is mitigated as household assets increase. In contrast, these farmers reduce consumption of *other food* at a non-negligible level throughout the year. For example, the coefficient of harvest shocks in March is -0.683, which is significant at the 1 % level. This means that, if 10% of these farmers' land suffers from

[19] The coefficients of intersection terms of the income shock and the month dummies are jointly significant. In addition, the coefficients in March and in April are negative with relatively small standard errors, although these are insignificant. These results indicate that BH farmers may also slightly decrease their consumption of staple foods throughout the hunger season.

a below average harvest, they decrease their consumption of other food by 6.83$\%$ of the sample average. The fifth column of Table 3.5(b) shows that, for BH farmers with more assets, these shocks are mitigated mainly during the latter half of the crop year. Note that these other foods generally correspond to the side dishes of their diet, which are important sources of their micronutrients. Even if the farmers in this group suffer income shocks, they sustain their consumption of staple foods by purchasing maize at higher prices. To do so, they decrease their consumption of other foods. Thus, one dimension of income shocks, that is often overlooked, is food diversity, which could change over time with a crop year due to seasonal price changes of the staple food.

Lastly, consider the non-food items. BH households significantly decrease their consumption in June, July, and August, but do not decrease after August. These results are reasonable, considering that households in the study area tend to purchase non-food household goods such as clothes and kitchen utensils just after the harvest, and that most of these other goods consist of daily necessities that can be stored over the crop year, such as candles or soap.

3.4.2 Robustness Checks

As discussed in the subsection on identification, adding household fixed effects may not be sufficient to control for selection bias, and year-varying household fixed effects may be required. However, since year-varying household fixed effects prevent identification of one of β_m^j parameters, it is useful to compare estimation results with and without year varying household fixed effects are to see whether the within-year consumption patterns are comparable. If they are comparable, then the restriction that household fixed effects do not vary over years is not driving the within-year consumption patterns. Table 3.6 reports both estimation results, where "HH" indicates household fixed effects that do not vary over years, and "YHH" indicates year-varying household fixed effects, and "dif" is the within crop-year difference, which represents the differences of each coefficient from the May coefficient, that is, $(\beta_m^j - \beta_5^j)$.[20] Thus, columns "dif" and "YHH" are compared. These differences indicate that most estimates are similar and comove, so that there is no reason to doubt the patterns found in the results that use household fixed effects that do not change over years.

Another robustness check considers the possibility that use of the adult equivalent scales may cause measurement errors in consumption. To check the robustness of these results, demand functions are estimated without equivalent scales (each household member has a weight equal to 1). The estimation results are reported in Appendix Table C.2. It shows that no coefficients of the interaction terms of the income shock and the month dummies are significant for NBH farmers. In contrast, the farmers in the BH group decrease their total consumption in response to harvest shocks, and in particular, they reduce consumption of other food. These results are consistent with the results in Tables 3.4 and 3.5 which use the adult equivalent scales, and thus they indicate that the estimation results are robust to different types of scaling.

3.4.3 Limitations

Despite their robustness, it is worth noting a limitation of this study's external validity. Although the sample households were chosen by using a well-organized two-stage cluster sampling scheme (Sakurai, 2008), external validity is limited because the sample consists of only in three villages, due to budget limitations. A related point is that these small

[20]The estimated results including all other control variables are reported in Appendix Table C.1.

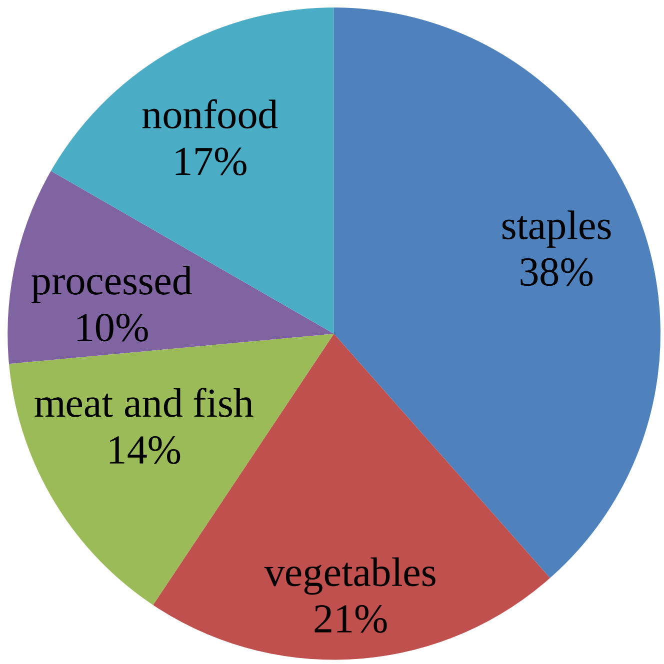
variations across households (due to their similarities within villages and across the three villages) allow one to utilize variations only within each group of farmers (NBH farmers and BH farmers), and it is not possible to take advantage of variations across each group of farmers, which prevents an analysis of why some farmers buy maize at higher prices in some years while other farmers do not. Thus, future collection of seasonal household data should be collected on a larger scale.

3.5 Concluding Remarks

Using three years of weekly household panel data collected in rural Zambia, this paper has analyzed seasonality of food insecurity in rural Zambia by examining whether, and to what extent, harvest shocks affect consumption patterns during the crop year. When faced with seasonal price changes of the staple food, some farmers buy it when prices are low and store enough for consumption during the hunger season (NBH farmers), while others do not store enough and so run out of the staple food, and so they buy it when prices are high (BH farmers). Results indicate that NBH farmers successfully smooth their consumption over the 12 months of the crop year. In contrast, BH farmers reduce total consumption in response to harvest shocks, and the shocks produce an inverse U consumption pattern during the year, especially for farmers with few assets. Looking into the composition of their consumption, BH farmers almost smooth tjeor consumption of staple foods, in spite of the seasonal price hike of maize. Instead, they decrease consumption of non-staple food items, such as vegetables and meats.

Heterogenous results between BH farmers and NBH farmers have important implications for poverty programs that offer short-term credit, because it relates to farmers' heterogenous motivations for using credit programs. BH farmers are those who were unable to purchase sufficient amounts of maize when prices were low, and the results in this chapter indicate that they are unable to smooth their consumption within any given year. Considering the extremely high maize prices in the hunger season, the impacts of the availability of the credit for consumption smoothing to mitigate the impact of price increases during the hunger season should be large, and BH farmers would want to have access to such short-term credit rather than, or in addition to, credit for investment. On the other hand, NBH farmers are those who are able to cope with the negative impacts of such price increases in the hunger season by purchasing sufficient maize when maize prices are low, and these results indicate that they successfully smooth consumption. Such farmers likely still want access to credit, not for consumption smoothing, but for other purposes such as long-term investments. Optimal schemes, repayment terms, and the timing of offers of credit programs should differ depending on different motivations for using such programs, and different credit programs should be designed to suit the purposes of each group of farmers.

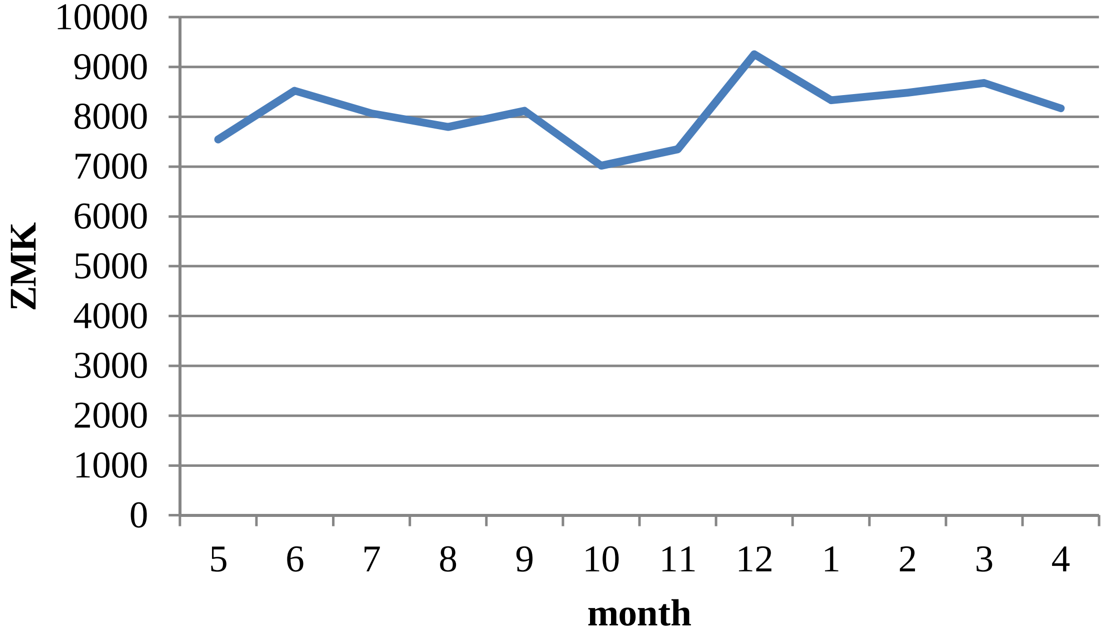
The results in this chapter are also important because of the link between high prices of staple foods in the hunger season and mirconutrient deficiencies, which have been deemed a high priority by policy makers (e.g. National Food Nutrition Committee of Zambia, 2011, FAO, 2016). For BH farmers, price increases of staple foods in the hunger season decrease their welfare by decreasing their full income. However, in spite of this, consumption of staple foods is generally insensitive to harvest shocks. Instead, they reduce consumption only of non-staple food items, such as vegetables and meats. These results indicate that such farmers reduce food diversity to smooth consumption of staple foods. Thus, mirconutrient deficiency problems should be part of any discussion of the problem of seasonal price changes of staple foods.



(Source) Household Survey Data. Resilience Project.

* Percentages are based on average total consumption per week per adult-equivalent, which are in ZMK deflated by a monthly price index (=1 for November 2007)

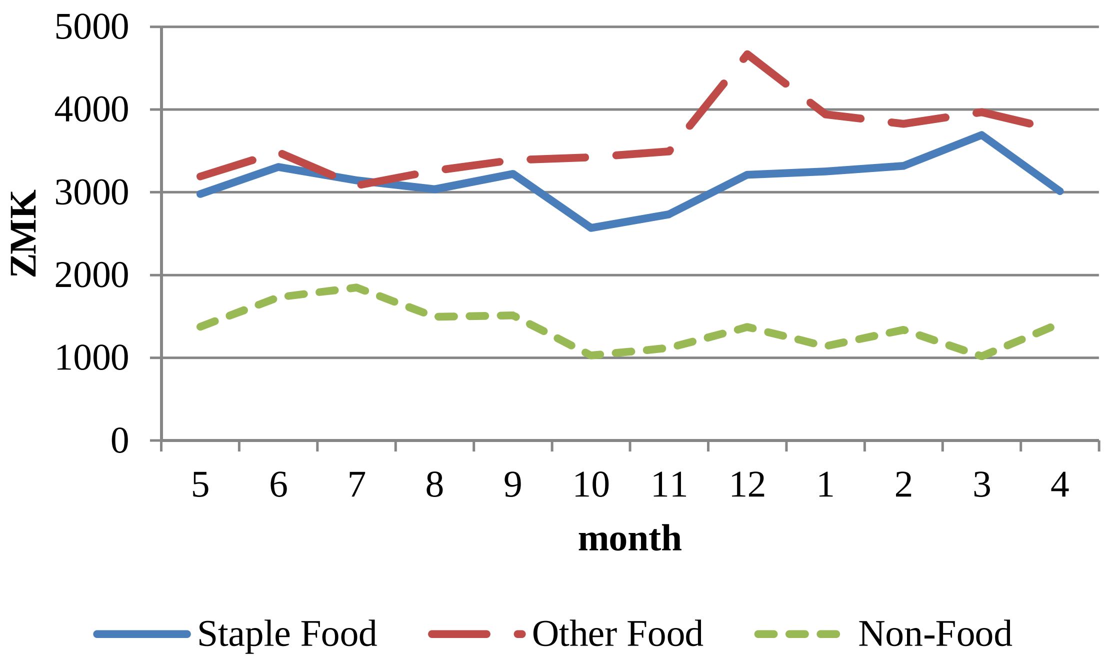
Figure 3.1: Average Composition of Consumption Values of Consumption over 3 Years (real terms)



(Source) Household Survey Data. Resilience Project.

* Average total (food and non-food) consumption per week per adult-equivalent. Numbers are in ZMK deflated by a monthly price index (=1 for November 2007)

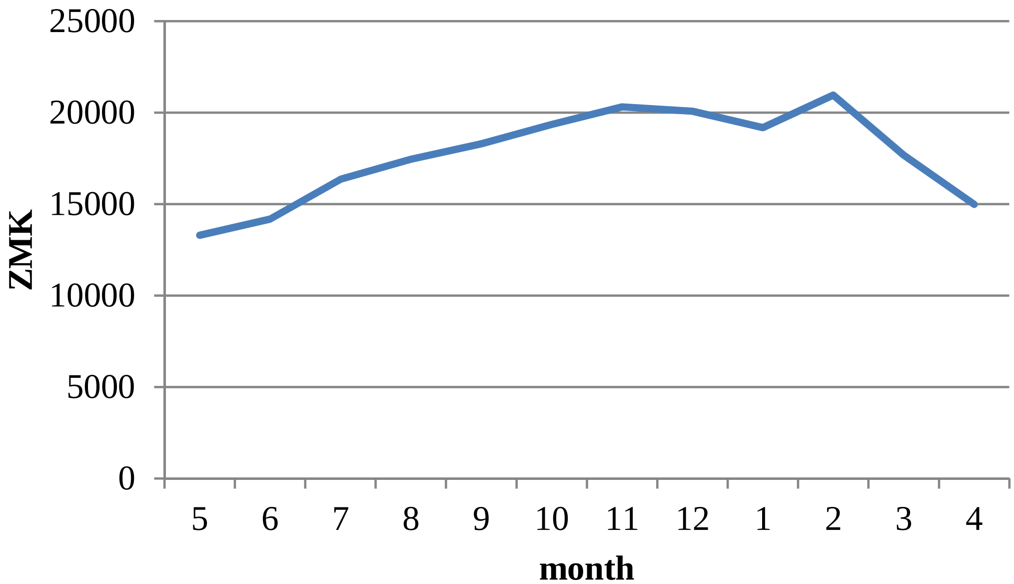
Figure 3.2: Seasonal Patterns of Average Consumption over 3 years



(Source) Household Survey Data. Resilience Project.

* Average total consumption per week per adult-equivalent. Numbers are in ZMK deflated by a monthly price index (=1 as November 2007)

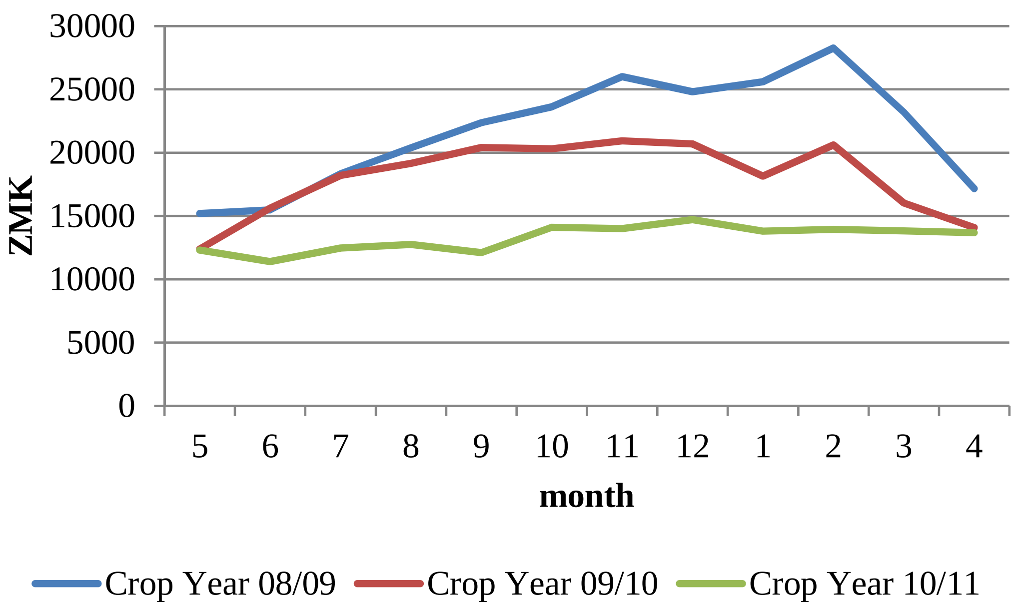
Figure 3.3: Seasonal Patterns of Average Consumption over 3 years



(Source) Household Survey Data. Resilience Project.

* Numbers are in ZMK deflated by a monthly price index (=1 for November 2007)

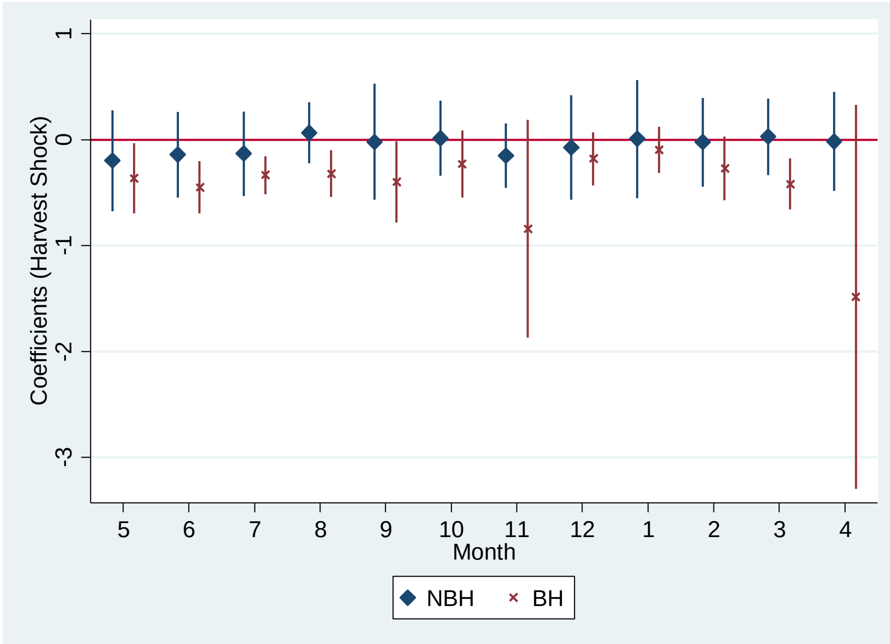
Figure 3.4: Seasonal Patterns of Average Maize Price Per Bucket, over 3 years



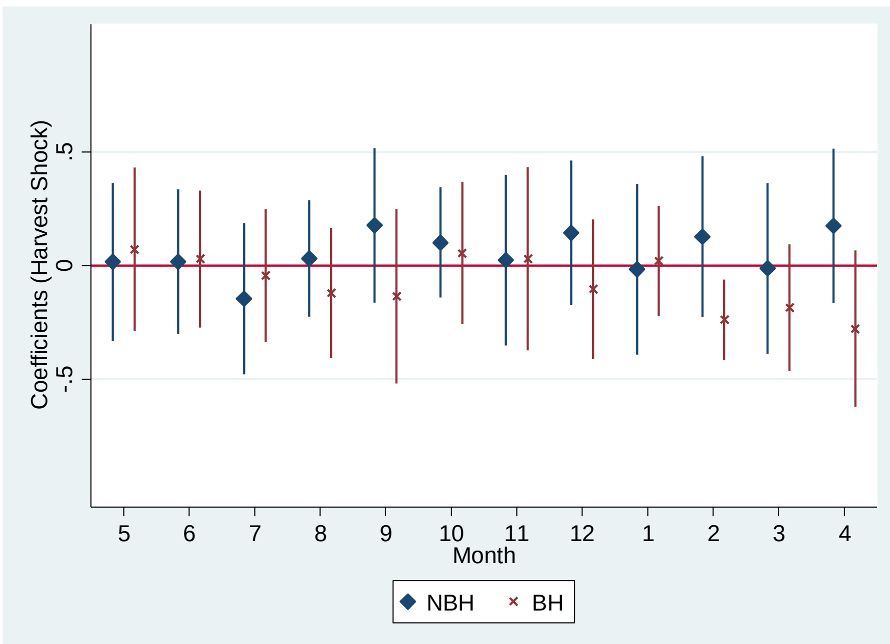
(Source) Household Survey Data. Resilience Project.

* Numbers are in ZMK deflated by a monthly price index (=1 for November 2007)

Figure 3.5: Seasonal Patterns of Average Maize Price Per Bucket by crop year

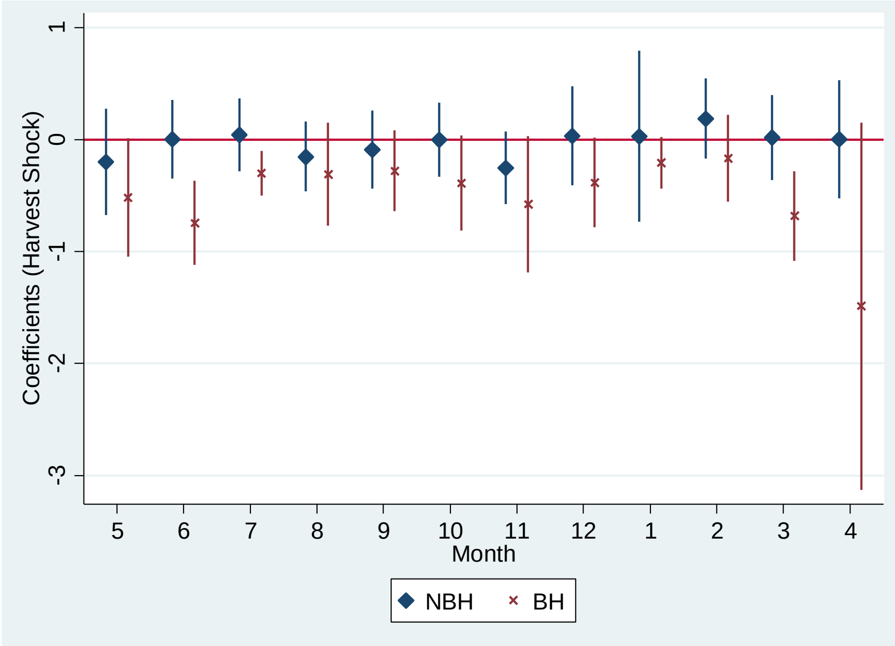


(a) Total Consumption

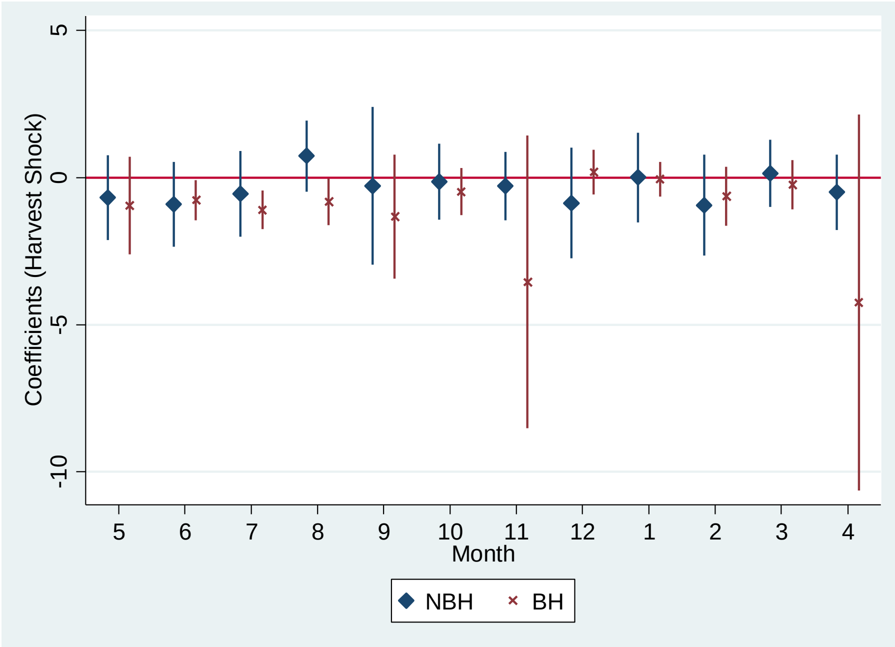


(b) Staple Food

Figure 3.6: Coefficients of Harvest shock



(c) Other Food



(d) Non Food

Figure 3.6. Coefficients of Harvest shock: Continued

Table 3.1: Number of Households That Have Fields near the River

	Number of households that have fields near the river	Number of households that do not have fields near the river	Total
Site A	6	9	15
Site B	4	12	16
Site C	12	4	16
Total	22	25	47

(Source) Household Survey Data. Resilience Project.

Table 3.2: Number of Household Years by Maize Purchase Patterns

			Over 3 years		Crop Year 08/09		Crop Year 09/10		Crop Year 10/11	
			Number	%	Number	%	Number	%	Number	%
Purchase			68	48%	27	57%	25	53%	16	34%
	Purchase only until December ("buy low")	One or two times	30	21%	15	32%	8	17%	7	15%
		More than two times	2	1%	0	0%	0	0%	2	4%
	Purchase some after December ("buy high")	One or two times	1	1%	0	0%	0	0%	1	2%
		More than two times	35	25%	12	26%	17	36%	6	13%
Does not purchase			73	52%	20	43%	22	47%	31	66%
Total			141	100%	47	100%	47	100%	47	100%

(Source) Household Survey Data. Resilience Project.

Table 3.3: Summary Statistics

	NBH		BH		
		Mean		Mean	
VARIABLES	N	(SD)	N	(SD)	Diff.
Weekly Variant Variables					
Total Consumption (*1)					
May	392	7,752	127	6,898	-854
		(6032)		(4381)	(579)
June	396	8,704	117	7,898	-806
		(7840)		(3818)	(750)
July	418	8,271	129	7,424	-847
		(10065)		(3599)	(904)
August	405	7,925	133	7,402	-523
		(5964)		(3951)	(553)
September	442	8,372	149	7,371	-1,001
		(10715)		(4300)	(902)
October	413	6,986	159	7,108	122
		(4375)		(3601)	(390)
November	431	7,236	145	7,684	448
		(4968)		(7046)	(534)
December	482	9,682	170	8,037	-1,645**
		(9744)		(4486)	(775)
January	412	8,594	142	7,563	-1,031
		(7383)		(3682)	(646)
February	413	8,666	141	7,940	-726
		(6535)		(4651)	(596)
March	485	8,832	166	8,236	-596
		(5293)		(4703)	(463)
April	443	8,103	156	8,360	258
		(5291)		(13908)	(784)
Staple Food (*1)					
May	392	3,007	127	2,896	-111
		(1566)		(1640)	(162)
June	396	3,326	117	3,234	-92
		(1716)		(1209)	(170)
July	418	3,153	129	3,113	-41
		(2524)		(1306)	(231)
August	405	3,015	133	3,108	93
		(1801)		(1507)	(173)
September	442	3,225	149	3,203	-22
		(4316)		(1769)	(364)
October	413	2,408	159	2,987	578***
		(1409)		(2170)	(155)
November	431	2,679	145	2,897	218
		(1573)		(1314)	(145)
December	482	3,208	170	3,223	14
		(1987)		(1599)	(169)
January	412	3,293	142	3,135	-159
		(1922)		(1396)	(175)
February	413	3,348	141	3,232	-116
		(1897)		(1764)	(182)
March	485	3,736	166	3,567	-170
		(2560)		(2009)	(219)
April	443	2,941	156	3,212	271
		(2141)		(1739)	(190)

Table 3.3 Summary Statistics: Continued

VARIABLES	NBH N	NBH Mean (SD)	BH N	BH Mean (SD)	Diff.
Non Staple Food (*1)					
May	392	3,302	127	2,841	-461
		(3049)		(2018)	(289)
June	396	3,504	117	3,412	-92
		(2777)		(2140)	(278)
July	418	3,062	129	3,136	74
		(2892)		(1681)	(268)
August	405	3,247	133	3,312	66
		(2349)		(2144)	(230)
September	442	3,468	149	3,153	-314
		(2668)		(1813)	(235)
October	413	3,462	159	3,321	-141
		(2406)		(1973)	(214)
November	431	3,549	145	3,335	-214
		(3116)		(2274)	(281)
December	482	4,864	170	4,118	-746*
		(4612)		(3418)	(387)
January	412	4,067	142	3,570	-497
		(4828)		(2608)	(425)
February	413	3,848	141	3,757	-91
		(3048)		(2494)	(285)
March	485	4,007	166	3,857	-151
		(3425)		(3613)	(312)
April	443	3,792	156	3,601	-191
		(2844)		(5890)	(361)
Non Food Item (*1)					
May	392	1,443	127	1,161	-282
		(4385)		(3278)	(423)
June	396	1,874	117	1,252	-622
		(6023)		(2087)	(567)
July	418	2,056	129	1,175	-881
		(8446)		(2394)	(753)
August	405	1,664	133	982.0	-682*
		(4201)		(1978)	(377)
September	442	1,679	149	1,014	-665
		(8735)		(3015)	(730)
October	413	1,115	159	800.2	-315
		(2402)		(1556)	(205)
November	431	1,008	145	1,453	444
		(2534)		(5925)	(354)
December	482	1,610	170	697.0	-913*
		(6395)		(1407)	(495)
January	412	1,234	142	858.8	-375
		(3995)		(1365)	(342)
February	413	1,469	141	950.6	-519
		(4734)		(2960)	(425)
March	485	1,088	166	813.2	-275
		(2432)		(1312)	(198)
April	443	1,370	156	1,547	177
		(3355)		(8281)	(476)

Table 3.3 Summary Statistics: Continued

	NBH		BH		
VARIABLES	N	Mean (SD)	N	Mean (SD)	Diff.
Monthly Variant variables					
Number of Adult males	1219	1.70	416	1.62	-0.08
		(1.12)		(1.17)	(0.06)
Number of Adult females	1219	1.96	416	1.64	-0.33***
		(1.33)		(0.61)	(0.07)
Number of Children (10-12 years)	1219	1.19	416	1.29	0.10*
		(1.03)		(1.00)	(0.06)
Number of Children (7-9 years)	1219	0.98	416	1.10	0.12**
		(0.81)		(0.87)	(0.05)
Number of Children (4-6 years)	1219	0.67	416	0.55	-0.12***
		(0.76)		(0.70)	(0.04)
Number of Children (0-3 years)	1219	0.79	416	0.60	-0.19***
		(0.92)		(0.73)	(0.05)
Year Variant Variables					
Number of Cattle	105	3.47	36	1.69	-1.77**
		(4.30)		(2.42)	(0.76)
Proportion of rental values of land whose crop situation is "below average, because of reasons other than heavy rain, no fertilizer, no seeds" to total rental values of land	105	0.17	35	0.19	0.02
		(0.25)		(0.30)	(0.05)
Year In-Variant Variables					
Dummy variable=1 if households have dry season maize field	35	0.51	12	0.33	-0.18
		(0.51)		(0.49)	(0.17)

(Source) Household Survey Data. Resilience Project

*1. Average consumption is per week per adult-equivalent. Numbers are in ZMK deflated by a monthly price index (=1 as November 2007)

Table 3.4: Estimation Results (Total Consumption) with HH Fixed Effects

	Total Consumption				
VARIABLES	Full Sample	NBH	BH	NBH	BH
(i) Income Shock * Month Dummy					
May	-0.275	-0.198	-0.363**	-0.237	-0.361**
	(0.185)	(0.236)	(0.160)	(0.350)	(0.158)
June	-0.193	-0.142	-0.450***	-0.022	-0.459***
	(0.139)	(0.200)	(0.118)	(0.254)	(0.119)
July	-0.193	-0.130	-0.334***	-0.001	-0.340***
	(0.152)	(0.198)	(0.087)	(0.209)	(0.072)
August	-0.037	0.066	-0.321***	0.104	-0.333***
	(0.134)	-0.142	(0.106)	(0.181)	(0.097)
September	-0.143	-0.020	-0.399**	-0.184	-0.404**
	(0.185)	(0.272)	(0.183)	(0.313)	(0.172)
Octobor	-0.062	0.016	-0.232	0.035	-0.237
	(0.131)	(0.176)	(0.151)	(0.244)	(0.159)
November	-0.277*	-0.152	-0.840	-0.142	-0.806*
	(0.153)	(0.150)	(0.492)	(0.202)	(0.459)
December	-0.189	-0.072	-0.180	-0.172	-0.200
	(0.179)	(0.245)	(0.121)	(0.283)	(0.126)
January	-0.046	0.008	-0.096	0.074	-0.100
	(0.174)	(0.277)	(0.105)	(0.345)	(0.113)
February	-0.071	-0.023	-0.271*	-0.134	-0.393***
	(0.144)	(0.207)	(0.144)	(0.281)	(0.093)
March	-0.056	0.028	-0.418***	0.057	-0.529***
	(0.119)	(0.180)	(0.116)	(0.243)	(0.145)
April	-0.272	-0.016	-1.483	-0.149	-1.367*
	(0.182)	(0.233)	(0.869)	(0.303)	(0.793)
(ii) Income Shock * Month Dummy * Cattle					
May				0.010	0.004
				(0.034)	(0.105)
June				-0.035	0.035
				(0.027)	(0.165)
July				-0.032*	-0.051
				(0.018)	(0.171)
August				-0.010	0.098
				(0.023)	(0.156)
September				0.043	0.050
				(0.027)	(0.121)
Octobor				-0.006	0.050
				(0.023)	(0.135)
November				-0.003	-0.011
				(0.023)	(0.153)
December				0.027	0.093
				(0.022)	(0.098)
January				-0.019	0.053
				(0.030)	(0.112)
February				0.030	0.277***
				(0.026)	(0.096)
March				-0.009	0.242**
				(0.025)	(0.107)
April				0.033	-0.131
				(0.025)	(0.189)
Fixed Effect					
Period * Village	Yes	Yes	Yes	Yes	Yes
Household	Yes	Yes	Yes	Yes	Yes
Period * household	No	No	No	No	No
(i) F-statistics	F(12,46)	F(12,43)	F(12,20)	F(12,43)	F(12,20)
(Income Shock * Month Dummy)	0.84	0.84	21.42	0.54	17.45
p-value	0.6079	0.6092	0.0000	0.8746	0.0000
(ii) F-statistics				F(12,43)	F(12,20)
(Income Shock * Month Dummy * Cattle)				3.58	19.53
p-value				0.0010	0.0000
Observations	6,813	5,132	1,681	5,132	1,681
R-squared	0.178	0.203	0.182	0.204	0.187

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3.5: Estimation Results (Staple Food, Other Food, Non Food) with HH Fixed Effects

(a) NBH farmers

	NBH					
VARIABLES	Staple Food	Other Food	Non Food	Staple Food	Other Food	Non Food
(i) Income Shock * Month Dummy						
May	0.016	-0.200	-0.689	-0.130	-0.117	-0.807
	(0.173)	(0.235)	(0.714)	(0.242)	(0.342)	(1.042)
June	0.017	0.003	-0.901	0.118	0.098	-0.670
	(0.158)	(0.173)	(0.715)	(0.211)	(0.220)	(0.980)
July	-0.147	0.041	-0.553	-0.013	0.135	-0.341
	(0.165)	(0.162)	(0.721)	(0.227)	(0.191)	(0.770)
August	0.031	-0.152	0.734	0.043	-0.119	0.847
	(0.127)	(0.154)	(0.599)	(0.186)	(0.167)	(0.697)
September	0.176	-0.090	-0.283	0.071	-0.096	-1.009
	(0.169)	(0.173)	(1.332)	(0.190)	(0.218)	(1.344)
Octobor	0.101	-0.002	-0.132	0.100	0.051	-0.155
	(0.121)	(0.163)	(0.639)	(0.155)	(0.211)	(0.831)
November	0.024	-0.253	-0.288	0.094	-0.228	-0.455
	(0.187)	(0.160)	(0.571)	(0.212)	(0.205)	(0.736)
December	0.144	0.035	-0.859	0.224	-0.188	-1.040
	(0.157)	(0.220)	(0.936)	(0.207)	(0.192)	(1.163)
January	-0.017	0.030	0.006	0.013	0.235	-0.220
	(0.186)	(0.378)	(0.755)	(0.225)	(0.469)	(0.886)
February	0.126	0.187	-0.935	0.058	0.094	-1.191
	(0.175)	(0.178)	(0.849)	(0.227)	(0.216)	(1.048)
March	-0.011	0.019	0.143	0.066	0.056	0.039
	(0.186)	(0.188)	(0.567)	(0.231)	(0.227)	(0.725)
April	0.174	0.003	-0.503	0.027	-0.041	-0.845
	(0.169)	(0.262)	(0.632)	(0.209)	(0.307)	(0.855)
(ii) Income Shock * Month Dummy * Cattle						
May				0.038	-0.020	0.025
				(0.027)	(0.037)	(0.093)
June				-0.029	-0.026	-0.075
				(0.027)	(0.025)	(0.139)
July				-0.032	-0.022	-0.055
				(0.026)	(0.022)	(0.050)
August				-0.003	-0.008	-0.034
				(0.020)	(0.021)	(0.108)
September				0.028	0.003	0.186
				(0.028)	(0.027)	(0.163)
Octobor				0.001	-0.014	-0.001
				(0.021)	(0.024)	(0.063)
November				-0.018	-0.006	0.037
				(0.027)	(0.033)	(0.057)
December				-0.022	0.062*	0.043
				(0.021)	(0.032)	(0.072)
January				-0.008	-0.055	0.054
				(0.025)	(0.046)	(0.078)
February				0.019	0.027	0.062
				(0.027)	(0.025)	(0.077)
March				-0.022	-0.009	0.022
				(0.031)	(0.026)	(0.060)
April				0.037*	0.012	0.080
				(0.021)	(0.026)	(0.071)
Fixed Effect						
Period * Village	Yes	Yes	Yes	Yes	Yes	Yes
Household	Yes	Yes	Yes	Yes	Yes	Yes
Period * household	No	No	No	No	No	No
(i) F-statistics	F(12,43)					
(Income Shock * Month Dummy)	0.80	0.83	1.14	0.59	0.64	1.01
p-value	0.6454	0.6209	0.3545	0.8340	0.8003	0.4573
(ii) F-statistics	F(12,43)					
(Income Shock * Month Dummy * Cattle)				4.24	3.21	0.77
p-value				0.0002	0.0024	0.6744
Observations	5,132	5,132	5,132	5,132	5,132	5,132
R-squared	0.189	0.246	0.086	0.191	0.248	0.086

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(b) BH farmers

VARIABLES	Staple Food	Other Food	Non Food	Staple Food	Other Food	Non Food
	BH					
(i) Income Shock * Month Dummy						
May	0.070	-0.516*	-0.951	0.034	-0.536*	-0.803
	(0.173)	(0.252)	(0.795)	(0.186)	(0.259)	(0.771)
June	0.030	-0.744***	-0.765**	0.022	-0.785***	-0.696**
	(0.145)	(0.180)	(0.331)	(0.128)	(0.196)	(0.327)
July	-0.044	-0.301***	-1.094***	-0.055	-0.323***	-1.043***
	(0.141)	(0.096)	(0.316)	(0.117)	(0.091)	(0.313)
August	-0.121	-0.309	-0.817**	-0.135	-0.307	-0.861**
	(0.137)	(0.221)	(0.380)	(0.133)	(0.209)	(0.390)
September	-0.136	-0.280	-1.325	-0.212	-0.281	-1.175
	(0.184)	(0.173)	(1.007)	(0.194)	(0.179)	(0.904)
Octobor	0.055	-0.388*	-0.476	-0.005	-0.377	-0.394
	(0.151)	(0.204)	(0.385)	(0.149)	(0.228)	(0.370)
November	0.030	-0.578*	-3.547	-0.044	-0.579*	-3.172
	(0.194)	(0.292)	(2.384)	(0.165)	(0.316)	(2.128)
December	-0.104	-0.383*	0.194	-0.087	-0.416*	0.122
	(0.147)	(0.193)	(0.365)	(0.145)	(0.201)	(0.331)
January	0.020	-0.209*	-0.058	0.056	-0.216*	-0.146
	(0.117)	(0.110)	(0.281)	(0.126)	(0.119)	(0.274)
February	-0.238**	-0.167	-0.631	-0.375***	-0.280*	-0.738
	(0.084)	(0.185)	(0.479)	(0.126)	(0.153)	(0.444)
March	-0.185	-0.683***	-0.241	-0.218	-0.840***	-0.409
	(0.133)	(0.192)	(0.403)	(0.143)	(0.276)	(0.357)
April	-0.278	-1.489*	-4.245	-0.172	-1.456*	-3.882
	(0.165)	(0.786)	(3.059)	(0.122)	(0.744)	(2.787)
(ii) Income Shock * Month Dummy * Cattle						
May				0.100	0.140	-0.583*
				(0.087)	(0.131)	(0.295)
June				-0.052	0.268*	-0.390
				(0.204)	(0.131)	(0.398)
July				-0.032	0.045	-0.354
				(0.198)	(0.186)	(0.401)
August				0.090	0.111	0.080
				(0.106)	(0.198)	(0.396)
September				0.217**	0.150	-0.603
				(0.098)	(0.150)	(0.392)
Octobor				0.141*	0.146	-0.417
				(0.081)	(0.175)	(0.298)
November				0.160*	0.166	-0.882
				(0.089)	(0.149)	(0.525)
December				0.001	0.247**	-0.105
				(0.125)	(0.113)	(0.333)
January				-0.015	0.178	-0.128
				(0.080)	(0.116)	(0.350)
February				0.303***	0.383***	-0.067
				(0.079)	(0.112)	(0.355)
March				0.097	0.442***	0.036
				(0.077)	(0.137)	(0.340)
April				-0.115	0.119	-0.836
				(0.103)	(0.210)	(0.661)
Fixed Effect						
Period * Village	Yes	Yes	Yes	Yes	Yes	Yes
Household	Yes	Yes	Yes	Yes	Yes	Yes
Period * household	No	No	No	No	No	No
(i) F-statistics			F(12,20)			
(Income Shock * Month Dummy)	5.68	7.08	14.57	5.61	13.13	16.29
p-value	0.0003	0.0001	0.0000	0.0004	0.0000	0.0000
(ii) F-statistics			F(12,20)			
(Income Shock * Month Dummy * Cattle)				32.58	7.58	2.84
p-value				0.0000	0.0000	0.0190
Observations	1,681	1,681	1,681	1,681	1,681	1,681
R-squared	0.314	0.229	0.097	0.324	0.234	0.100

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3.6: Estimation Results (HH Fixed Effects vs Year Variant HH Fixed Effects)

	NBH									BH								
	Staple Food			Other Food			Non Food			Staple Food			Other Food			Non Food		
	HH	dif	YHH	HH	dif	YHH	HH	dif	YHH	HH	dif	YHH	HH	dif	YHH	HH	dif	YHH
Income Shock * Month Dummy																		
May	-0.130			-0.117			-0.807			0.034			-0.536*			-0.803		
	(0.242)			(0.342)			(1.042)			(0.186)			(0.259)			(0.771)		
June	0.118	0.248	0.243	0.098	0.215	0.227	-0.670	0.137	0.139	0.022	-0.012	-0.018	-0.785***	-0.249	-0.225	-0.696**	0.107	0.243
	(0.211)		(0.167)	(0.220)		(0.349)	(0.980)		(0.937)	(0.128)		(0.144)	(0.196)		(0.183)	(0.327)		(0.766)
July	-0.013	0.117	0.100	0.135	0.252	0.272	-0.341	0.466	0.408	-0.055	-0.089	-0.110	-0.323***	0.213	0.235	-1.043***	-0.240	0.068
	(0.227)		(0.236)	(0.191)		(0.363)	(0.770)		(0.825)	(0.117)		(0.236)	(0.091)		(0.225)	(0.313)		(0.728)
August	0.043	0.173	0.180	-0.119	-0.002	0.015	0.847	1.654	1.739*	-0.135	-0.169	-0.184	-0.307	0.229	0.201	-0.861**	-0.058	0.000
	(0.186)		(0.233)	(0.167)		(0.346)	(0.697)		(0.911)	(0.133)		(0.237)	(0.209)		(0.352)	(0.390)		(0.963)
September	0.071	0.201	0.185	-0.096	0.021	0.004	-1.009	-0.202	-0.205	-0.212	-0.246	-0.252	-0.281	0.255	0.186	-1.175	-0.372	-0.585
	(0.190)		(0.256)	(0.218)		(0.304)	(1.344)		(0.831)	(0.194)		(0.180)	(0.179)		(0.246)	(0.904)		(1.067)
Octobor	0.100	0.230	0.191	0.051	0.168	0.120	-0.155	0.652	0.714	-0.005	-0.039	-0.050	-0.377	0.159	0.143	-0.394	0.409	0.324
	(0.155)		(0.227)	(0.211)		(0.335)	(0.831)		(0.769)	(0.149)		(0.216)	(0.228)		(0.155)	(0.370)		(0.805)
November	0.094	0.224	0.218	-0.228	-0.111	-0.150	-0.455	0.352	0.432	-0.044	-0.078	-0.074	-0.579*	-0.043	-0.069	-3.172	-2.369	-2.549
	(0.212)		(0.341)	(0.205)		(0.266)	(0.736)		(0.635)	(0.165)		(0.241)	(0.316)		(0.213)	(2.128)		(2.198)
December	0.224	0.354	0.301	-0.188	-0.071	-0.115	-1.040	-0.233	-0.137	-0.087	-0.121	-0.118	-0.416*	0.120	0.104	0.122	0.925	0.924
	(0.207)		(0.302)	(0.192)		(0.367)	(1.163)		(0.825)	(0.145)		(0.143)	(0.201)		(0.335)	(0.331)		(0.850)
January	0.013	0.143	0.148	0.235	0.352	0.294	-0.220	0.587	0.714	0.056	0.022	0.034	-0.216*	0.320	0.318	-0.146	0.657	0.692
	(0.225)		(0.278)	(0.469)		(0.513)	(0.886)		(0.800)	(0.126)		(0.221)	(0.119)		(0.326)	(0.274)		(0.700)
February	0.058	0.188	0.192	0.094	0.211	0.133	-1.191	-0.384	-0.289	-0.375***	-0.409	-0.405**	-0.280*	0.256	0.246	-0.738	0.065	0.066
	(0.227)		(0.264)	(0.216)		(0.327)	(1.048)		(0.786)	(0.126)		(0.183)	(0.153)		(0.273)	(0.444)		(0.993)
March	0.066	0.196	0.150	0.056	0.173	0.088	0.039	0.846	0.911	-0.218	-0.252	-0.244	-0.840***	-0.304	-0.319	-0.409	0.394	0.394
	(0.231)		(0.289)	(0.227)		(0.291)	(0.725)		(0.767)	(0.143)		(0.165)	(0.276)		(0.294)	(0.357)		(0.879)
April	0.027	0.157	0.154	-0.041	0.076	-0.007	-0.845	-0.038	0.200	-0.172	-0.206	-0.200	-1.456*	-0.920	-0.923	-3.882	-3.079	-3.051
	(0.209)		(0.189)	(0.307)		(0.253)	(0.855)		(0.557)	(0.122)		(0.171)	(0.744)		(0.646)	(2.787)		(2.770)

Table 3.6 Estimation Results (HH Fixed Effects vs Year Variant HH Fixed Effects): Continued

	NBH									BH								
	Staple Food			Other Food			Non Food			Staple Food			Other Food			Non Food		
	HH	dif	YHH	HH	dif	YHH	HH	dif	YHH	HH	dif	YHH	HH	dif	YHH	HH	dif	YHH
Income Shock * Month Dummy * Cattle																		
May	0.038			-0.020			0.025			0.100			0.140			-0.583*		
	(0.027)			(0.037)			(0.093)			(0.087)			(0.131)			(0.295)		
June	-0.029	-0.067	-0.068***	-0.026	-0.006	-0.009	-0.075	-0.100	-0.110	-0.052	-0.152	-0.184	0.268*	0.128	0.136***	-0.390	0.193	0.265
	(0.027)		(0.022)	(0.025)		(0.036)	(0.139)		(0.142)	(0.204)		(0.164)	(0.131)		(0.047)	(0.398)		(0.199)
July	-0.032	-0.070	-0.065***	-0.022	-0.002	-0.003	-0.055	-0.080	-0.079	-0.032	-0.132	-0.198	0.045	-0.095	-0.085	-0.354	0.229	0.418
	(0.026)		(0.019)	(0.022)		(0.035)	(0.050)		(0.094)	(0.198)		(0.192)	(0.186)		(0.116)	(0.401)		(0.256)
August	-0.003	-0.041	-0.039	-0.008	0.012	0.011	-0.034	-0.059	-0.067	0.090	-0.010	-0.057	0.111	-0.029	-0.061	0.080	0.663	0.617**
	(0.020)		(0.026)	(0.021)		(0.031)	(0.108)		(0.126)	(0.106)		(0.072)	(0.198)		(0.130)	(0.396)		(0.264)
September	0.028	-0.010	-0.007	0.003	0.023	0.024	0.186	0.161	0.152	0.217**	0.117	0.117	0.150	0.010	-0.023	-0.603	-0.020	-0.140
	(0.028)		(0.034)	(0.027)		(0.028)	(0.163)		(0.131)	(0.098)		(0.073)	(0.150)		(0.106)	(0.392)		(0.336)
Octobor	0.001	-0.037	-0.034	-0.014	0.006	0.009	-0.001	-0.026	-0.034	0.141*	0.041	0.062	0.146	0.006	-0.035	-0.417	0.166	-0.021
	(0.021)		(0.024)	(0.024)		(0.032)	(0.063)		(0.068)	(0.081)		(0.091)	(0.175)		(0.095)	(0.298)		(0.242)
November	-0.018	-0.056	-0.055	-0.006	0.014	0.016	0.037	0.012	-0.000	0.160*	0.060	0.079	0.166	0.026	-0.005	-0.882	-0.299	-0.421
	(0.027)		(0.034)	(0.033)		(0.025)	(0.057)		(0.063)	(0.089)		(0.085)	(0.149)		(0.096)	(0.525)		(0.466)
December	-0.022	-0.060	-0.054*	0.062*	0.082	0.081*	0.043	0.018	0.004	0.001	-0.099	-0.103	0.247**	0.107	0.072	-0.105	0.478	0.346
	(0.021)		(0.030)	(0.032)		(0.045)	(0.072)		(0.066)	(0.125)		(0.103)	(0.113)		(0.121)	(0.333)		(0.222)
January	-0.008	-0.046	-0.045*	-0.055	-0.035	-0.027	0.054	0.029	0.009	-0.015	-0.115	-0.093	0.178	0.038	0.014	-0.128	0.455	0.314
	(0.025)		(0.027)	(0.046)		(0.049)	(0.078)		(0.079)	(0.080)		(0.080)	(0.116)		(0.098)	(0.350)		(0.254)
February	0.019	-0.019	-0.018	0.027	0.047	0.056	0.062	0.037	0.019	0.303***	0.203	0.220***	0.383***	0.243	0.218	-0.067	0.516	0.386
	(0.027)		(0.028)	(0.025)		(0.036)	(0.077)		(0.067)	(0.079)		(0.072)	(0.112)		(0.128)	(0.355)		(0.275)
March	-0.022	-0.060	-0.056	-0.009	0.011	0.021	0.022	-0.003	-0.018	0.097	-0.003	0.018	0.442***	0.302	0.282*	0.036	0.619	0.498**
	(0.031)		(0.034)	(0.026)		(0.032)	(0.060)		(0.075)	(0.077)		(0.060)	(0.137)		(0.157)	(0.340)		(0.238)
April	0.037*	-0.001	0.001	0.012	0.032	0.039	0.080	0.055	0.025	-0.115	-0.215	-0.183	0.119	-0.021	-0.054	-0.836	-0.253	-0.473
	(0.021)		(0.016)	(0.026)		(0.025)	(0.071)		(0.062)	(0.103)		(0.113)	(0.210)		(0.149)	(0.661)		(0.622)

Chapter 4

Identifying Intricately Woven Peer Effects in a Specialized Team[1]

4.1 Introduction

Teamwork plays an important role in workplaces globally. People divide work among members of a team who are assigned particular tasks (e.g. cleaners of a huge building, mail sorting clerks, and so on). In many cases, different tasks are allocated to each worker (e.g. factory workers in an assembly line), and in many cases, each task requires highly specialized skills (e.g. a team in a consulting firm). There is considerable interdependence among workers and, consequently, there are many cross-worker interactions and influences. To improve teamwork in such workplaces, knowledge of how people in teams influence each other - what is called “peer effects” - is essential.

Although teamwork could produce more than the sum of individual production through synergy effects, it could also produce less due to the free ride problem; a member of the

[1]This chapter is co-authored with Avner Ben-Ner.

team may provide less than optimal effort for the team, and the extent to which this happens could depend on the output of other members of the group (e.g. Kandel and Lazear, 1992). Thus, much empirical literature has addressed whether, and to what extent, the productivity of a worker depends on the productivity of coworkers (e.g. Falk and Ichino, 2006, and Bandiera, Barankay and Rasul, 2005), and most of them focus on peer effects in the division of work among low-skilled workers. For example, Mas and Moretti (2009) examined checkout cashiers for a large grocery chain, and Lazear, Shaw, and Stanton (2015) looked at sales clerks, movie theater concession stand employees, and so on. Other studies have examined high-skilled laborers, but most of them have focused on knowledge spillovers (e.g. Jackson and Brugmann, 2009, Waldinger, 2010, Lindquist, Sauermann, and Zenou, 2015, and Ichniowski and Preston, 2013). However, these studies do not address a common aspect of team production: each member of the team is allocated different specialized tasks, and the interactions between each member are quite complex. The aim of this paper is to shed light on such intricately woven peer effects in a specialized team.

Gould and Winter (2009) is the only previous study that has addressed this aspect of peer effects. Using a panel data set of professional baseball players from 1970 to 2003, they examined peer effects from pitching performance and batting performance of other players. They showed that a player's batting average significantly increases with the batting performance of other players on his team, but decreases with the quality of the team's pitching. They also showed that a pitcher's performance increases with the pitching quality of the other pitchers on the same team, but is unaffected by the batting output of the pitcher's team. These heterogenous impacts are well explained by the different production technologies in players' tasks. However, one drawback of their analysis is that they simplified the complex interactions in games to make their identification feasible.[2] More

[2] See Manski (1993) for a general discussion regarding the difficulties of econometrically identifying peer

specifically, they ignored peer effects from opponent players. They also assumed that there are no exogenous peer effects, which are the peer effects transmitted through other players' fixed characteristics (e.g. age, tenure). These simplifications may overlook important aspects of peer effects.

Our paper contributes to the literature on peer effects among high-skilled laborers in a team. We suggest a unique framework to analyze peer effects in a specialized team without simplifying the complex interactions in the team. To illustrate the framework, we use a longitudinal data set of all soccer players in the top German league (the Bundesliga) during ten seasons (2000/01-2009/10), and identify intricately woven peer effects in soccer games. We impose the network structure on the players in the games, and estimate a structural model of networks by applying the spatial econometric methodology suggested by Lee and Yu (2014). Then, we address the following questions: (1) Does the short-term performance of one worker affect the performance of other workers on the same team? If so, does the effect of peers depend on the nature of tasks? (2) Does the performance of competitors affect workers' performance? and (3) What individual and team attributes affect workers' performance?

Our estimation results show: (1) There are positive endogenous peer effects from teammates, but the extent of the impacts varies depending on the nature of the task (the goal keeper differs from all other positions); (2) In contrast, there are negative endogenous peer effects from opponent players onto defense players, mid-fielders, and forward players, while they are slightly positive for the goal keeper; (3) There are negative impacts of ethnic diversity among offensive players (mid-fielders and forward players), but they are mitigated over time.

effects.

The rest of this chapter is organized as follows. Section 2 explains the difficulties of identification of peer effects, and discusses how the network approach solves these problems. Section 3 describes the data we use, Section 4 presents estimation strategies, and Section 5 provides estimation results. Concluding remarks are provided in Section 6.

4.2 The Estimation Problem and the Network Approach

4.2.1 Difficulties of Identifying Peer Effects: The Reflection Problem

To identify peer effects, a linear-in-means model is often used, which is given by:

$$y_{ir} = \alpha + \beta E[y_{ir} \mid r] + \gamma E[x_{ir} \mid r] + \delta x_{ir} + u_{ir} \tag{4.1}$$

where y_{ir} is the performance of player i in group r (e.g. team) with exogenous characteristics x_{ir} (e.g. player's age), and u_{ir} is an error term with $u_{ir} = u_r + \epsilon_{ir}$ and $E[u_{ir} \mid r] = u_r$. The expectations are averages of y_{ir}, x_{ir} and u_{ir} for group r. In this model, β represents the impact of endogenous effects and γ represents the impact of exogenous effects. Identifying endogenous peer effects separately from exogenous peer effects is important, because endogenous peer effects generate social multiplier effects, while exogenous peer effects do not. For example, if endogenous peer effects exist, introducing a high productivity worker to a team improves performances of his or her co-workers, which in turn will improve the performance of the high productivity worker, and so on. Taking the conditional expectation on r and rearranging terms, equation (4.1) becomes

$$E[y_{ir} \mid r] = \frac{\alpha}{1-\beta} + \frac{\gamma + \delta}{1-\beta} E[x_{ir} \mid r] + \frac{1}{1-\beta} u_r \tag{4.2}$$

Substitute equation (4.2) into (4.1), then

$$y_{ir} = \frac{\alpha}{1-\beta} + \frac{\gamma + \delta\beta}{1-\beta} E[x_{ir} \mid r] + \delta x_{ir} + \frac{\beta}{1-\beta} u_r + u_{ir} \tag{4.3}$$

Manski (1993) shows that β and γ cannot be identified separately (the reflection problem). Thus, most studies implicitly assume that either endogenous peer effects (β) or exogenous peer effects (γ) are zero.[3] Moreover, even if we assume no exogenous peer effects, that is,

$$y_{ir} = \alpha + \beta E[y_{ir} \mid r] + \delta x_{ir} + u_{ir} \tag{4.4}$$

identifying endogenous effects (β) is still not an easy task. One problem is simultaneous effects, in which an individual's behavior in a group and the behavior of other members of the group simultaneously affect each other. Another problem is unobservable correlated effects. One example of unobservable correlated effects in the soccer context is the funding ability of a team, that is, a team with strong funding ability can hire players with high ability, and hence, the average team ability will also be high. In this case, endogenous peer effects will be overestimated. Common solutions for these two problems are using instrumental variables, fixed effects, lag variables, and randomized experiments. More details are discussed in Mouw (2006).

4.2.2 Network Approach

Basic Idea

This subsection summarizes how the network approach (e.g., Bramoule et al, 2009, Calvo-Armengol et al, 2009, Lin, 2010, Liu et al, 2011, Patacchini et al, 2017) solves the identifi-

[3] The latter assumption ($\gamma = 0$) implies that average age or average tenure in the game does not affect player's performance. The former assumption ($\beta = 0$) is that there are no endogenous effects.

cation problems of peer effects, including the reflection problem, simultaneous effects and unobservable correlated effects. The reflection problem arises because the reference group completely overlaps among players. To break the reflection problem, the network approach generates individual-level variation within the reference group by imposing network structures among players. Figure 4.1 illustrates the example of network structure among players in a soccer game. The direction of each arrow represents the direction of impact. Note that the reference group varies by the position of the players. For example, in this setting, the reference group of a goal keeper is the defense players, while the reference group of a defense player is a goal keeper, other defense players and mid-fielders. These variations of reference group overcome the reflection problem.

The network structure of players can also be used to solve the identification problem caused by simultaneous effects and unobservable correlated effects by providing a mechanism for constructing valid instrumental variable for these effects. To see how the network structure can be used to construct instruments, consider the simple network represented in Figure 4.2. The performance of player A (y_a) is influenced by the performance of player B (y_b), and the performance of player B is influenced by the performance of player C. Player C has an impact on player A only through player B. In this case, exogenous characteristics of player C (x_c) can be valid instruments for y_b.

Specification

The network structure can be formulated by defining an adjacency matrix. Let $N = \{1, \cdots, n\}$ be a finite set of players, and define the adjacency matrix as $W = w_{ij}$ where $w_{ij} = 1$ if player i is directly influenced by player j, and $w_{ij} = 0$ otherwise. Figure 4.3 illustrates one example where n equals three, say, players A, B, and C with exogenous variable x_a, x_b, and x_c, respectively. (For simplicity, x_a, x_b, and x_c are assumed to be scalars.)

Assume that players' performances (y_a, y_b, and y_c) are determined by the sum of reference players' performance (the direction of the arrow represents the direction of impact) as well as their own exogenous variable,[4] then players' performance on this network can be represented as

$$Y = \alpha WY + \beta X + \epsilon \tag{4.5}$$

where $Y = (y_a, y_b, y_c)', X = (x_a, x_b, x_c)', \epsilon = (\epsilon_a, \epsilon_b, \epsilon_c)'$ and the $\epsilon_i's (i \in \{a, b, c\})$ are i.i.d random variables, and the adjacency matrix is given by

$$W = \begin{bmatrix} 0 & 1 & 1 \\ 1 & 0 & 1 \\ 0 & 0 & 0 \end{bmatrix} \tag{4.6}$$

Note that

$$WY = \begin{bmatrix} 0 & 1 & 1 \\ 1 & 0 & 1 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} y_a \\ y_b \\ y_c \end{bmatrix} = \begin{bmatrix} y_b + y_c \\ y_a + y_c \\ 0 \end{bmatrix} \tag{4.7}$$

If W is row-normalized to one, WY represents the average of performances of adjacent players.

Constructing Instruments

Since Y and WY are determined simultaneously in equation (4.5), instrumental variables for WY are necessary to identify endogenous peer effects α. Continuing with the example

[4]To simplify the explanation, players' performances are assumed neither to be influenced by other players' exogenous variables nor by performances in the previous game. These assumptions are relaxed in the following section.

in Figure 4.3, WX provides valid instruments for WY,

$$WX = \begin{bmatrix} 0 & 1 & 1 \\ 1 & 0 & 1 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} x_a \\ x_b \\ x_c \end{bmatrix} = \begin{bmatrix} x_b + x_c \\ x_a + x_c \\ 0 \end{bmatrix} \tag{4.8}$$

because $x_b + x_c$ influences player A only through the performances of players B and C (y_b and y_c), $x_a + x_c$ influences player B only through the performances of players A and C (y_a and y_c), and neither x_a nor x_b influence player C. Note that, if W is row-normalized to one, WX represents the average of the exogenous variables of adjacent players.

One advantage of this approach is that, in theory, we can construct multiple (or infinite) numbers of instruments from one exogenous variable under some plausible conditions. To see how this works, consider Figure 4.3. There are two "two arrow" impacts on player A. The first is from player C to player B, and then to player A. The second is from player A to player B, and then back player A. The W matrix can be used to show this. The "2 arrow" effects on all three players can be shown by the matrix W^2 where

$$W^2 = \begin{bmatrix} 0 & 1 & 1 \\ 1 & 0 & 1 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} 0 & 1 & 1 \\ 1 & 0 & 1 \\ 0 & 0 & 0 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 1 \\ 0 & 1 & 1 \\ 0 & 0 & 0 \end{bmatrix} \tag{4.9}$$

As is in the case of $p = 1$, W^2X can be instruments for each player where

$$W^2X = \begin{bmatrix} 1 & 0 & 1 \\ 0 & 1 & 1 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} x_a \\ x_b \\ x_c \end{bmatrix} = \begin{bmatrix} x_a + x_c \\ x_b + x_c \\ 0 \end{bmatrix} \tag{4.10}$$

The first row of W^2X $(= x_a + x_c)$ captures the impact of player A himself and player C through player B on player A, both of which pass through two arrows. More generally, all "p arrow" impacts are given by W^p.[5] Likewise, $W^3X, W^4X, \cdots$ can be the instruments for each player as long as the matrices $X, WX, W^2X, W^3X, W^4X, \cdots$ are linearly independent.[6]

Introducing Heterogeneity

The peer effect of one player (e.g. a goal keeper) on another player (e.g. a defense player) could be different from the peer effect of a different type of player (e.g. a forward player) on another player (e.g. a mid-fielder). Another noteworthy feature of this network approach is that we can analyze heterogenous peer effects by overlaying adjacency matrices. To see how this works, consider a futsal[7] example represented in Figure 4.4. Assuming that the impacts of peer effects are different depending on their positions, we can define the adjacency matrix as

$$W_{FW} = \begin{bmatrix} 0 & 1 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix} W_{MF} = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 1 & 1 & 0 \\ 1 & 1 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix} W_{DF} = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 1 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

[5]See pp.23-24 in Jackson (2008) for more formal discussions.
[6]In the case of Figure 4.3, W^3X is not a new set of valid instruments, because $WX = W^3X$.
[7]The indoor soccer game which is played between two teams of five players each.

$$W_{GK} = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \end{bmatrix} \tag{4.11}$$

where player i corresponds to the i th row, and players' performances can be formulated as:

$$Y = \sum_k \alpha_k W_k Y + \beta X + \epsilon \tag{4.12}$$

where $Y = (y_1, y_2, y_3, y_4, y_5)', X = (x_1, x_2, x_3, x_4, x_5)', \epsilon = (\epsilon_1, \epsilon_2, \epsilon_3 \epsilon_4, \epsilon_5)'$, ϵ_i's $(i = 1, \cdots, 5)$ are i.i.d, $k \in \{FW, MF, DF, GK\}$, and α_k's represent the heterogenous peer effects, depending on the position k. This feature enables us to analyze diverse aspects of peer effects in a soccer game in a flexible manner.

4.3 Data

Bundesliga is a professional football league in Germany, which consists of 18 teams. Seasons run from August to May, and a system of promotion and relegation with the 2nd Bundesliga (lower division) is adopted: in each season, the top three teams of the 2nd Bundesliga in the final standing are promoted to the Bundesliga and the bottom three teams of the Bundesliga are relegated to 2nd Bundesliga. Our data set was provided by IMPIRE AG, and covers 10 seasons between 2000/2001 and 2009/2010. The data set consists of: (1) Team data by season; (2) Team data by game; and (3) Player data by game. Player data by game includes name, nationality, age, team, position, and player performance in the game. Table 4.1 shows summary statistics for the variables used in estimation. Player performance is rated on a 0 (worst) to 10 (best) scale, which is a weighted average of several objective indicators such as the number of tackles won, tackles lost, and aerial challenges won, on the basis of the player's position. Since the weights on objective indicators are determined by the rating company so that the aggregated index represents each player's performance in each game, this index represents subjective player performance. Figure 4.5 shows the distribution of the players' performance. Age is player's age in years, and team tenure is the number of years since the players' first game with their current team. To represent the diversity of each team in each season, we construct a diversity index defined as $1 - \sum_{k=1}^{K}(p_k)^2$, where p_k is the proportion of players' ethnicity on the team, and thus $\sum_{k=1}^{K}(p_k)^2$ is a Herfindahl index. To define ethnicity, we use Levinson (1998)'s classification based on language and geographical/cultural markers. A player on a team in a season is defined as a player who played at least one game during the season. In addition to this team diversity index among all players, we also define team diversity separately for defensive players and of offensive players, which are calculated as the diversity index among defensive players (a goal keeper, defense players, and mid-fielders), and offensive players (defense players, mid-fielders, and forward players). More details regarding these indices are discussed in Ben-Ner, Licht and Park (2017).

4.4 Estimation Strategies

Based on the network approach, we use the spatial dynamic panel data (SDPD) econometric models with fixed effects developed by Lee and Yu (2014). The general specification for player n in game g in season s is:

$$Y_{ngs} = \sum_{j=1}^{J} \alpha_j W_j Y_{ngs} + \beta Y_{ngs-1} + \sum_{j=1}^{J} \gamma_j W_j X_{ngs} + X_{ngs}\delta + C_n + V_{ngs} \tag{4.13}$$

where $Y_{ngs} = (y_{1gs}, \cdots, y_{Ngs})'$ and $V_{ngs} = (v_{1gs}, \cdots, v_{Ngs})'$ are N×1 column vectors, and the error terms v_{igs} are i.i.d. across n, g, and s with zero mean and variance σ_0^2. Subscript $n \in \{1, \cdots, N\}$ represents a player (N is the number of players in the league.), $g \in G = \{1, \cdots, 34\}$ represents the game index which is arranged in time series in each season, and $s \in S = \{2000, \cdots, 2010\}$ represents seasons. The dependent variable y_{ngs} is player n's performance in game g within season s. The N×1 column vectors $Y_{ngs-1} = (y_{1gs-1}, \cdots, y_{Ngs-1})'$ are lagged player's performance, and thus β captures spells of good or bad performance over seasonal games. The N×k matrix $X_{ngs} = (x_{1gs}, \cdots, x_{Ngs})'$ are exogenous variables, such as age and tenure. $C_n = (c_1, \cdots, c_N)$ is an N×1 column vector of individual fixed effects. W_j is an N×N adjacency matrix where $j \in \{1, \cdots, J\}$.[8] As for the interpretation of coefficients, α_j represents endogenous effects, and γ_j represents exogenous peer effects.

Roodman (2006) explains that, under the dynamic panel setting, there are two common ways to eliminate individual fixed effects in estimating (4.13) - first difference (FD) transformation and forward orthogonal difference (FOD) transformation. The FD transformation eliminates individual fixed effects by subtracting the previous observation from the contemporaneous one, and the FOD transformation substracts the average of all future available observations of a variable. There are two advantages of the FOD transformation over the FD transformation. First, while the resulting disturbances after the FD transformation have serial correlation, the disturbances after the FOD transformation remain i.i.d if they are originally i.i.d. Second, the FD transformation magnifies gaps in an unbalanced panel, that is, if one variable, say y_{it}, is missing, then both Δy_{it} and Δy_{it+1} are missing in the transformed data. Thus, in this paper, we apply the FOD transformation to equation

[8]We can interpret W_j as a spatial weights matrix in the spatial econometrics literature.

(4.13), which yields equation (4.14) :

$$Y^*_{ngs} = \sum_{j=1}^{J} \alpha_j W_j Y^*_{ngs} + \beta Y^*_{ngs-1} + \sum_{j=1}^{J} \gamma_j W_j X^*_{ngs} + X^*_{ngs}\delta + V^*_{ngs} \tag{4.14}$$

where $Y^*_{ngs} = (y^*_{1gs}, \cdots, y^*_{Ngs})'$, $X^*_{ngs} = (x^*_{1gs}, \cdots, x^*_{Ngs})'$ and $V^*_{ngs} = (v^*_{1gs}, \cdots, v^*_{Ngs})'$, defining $\Psi_i(g,s) = \{(g',s') \in G \times S \mid (s' = s \text{ and } g' > g) \text{ or } s' > s\}$ for player i, and

$$y^*_{igs} = c_{igs}\left(y_{igs} - \frac{1}{T_{igs}} \sum_{(g',s') \in \Psi_i(g,s)} y_{ig's'}\right) \tag{4.15}$$

$$x^*_{igs} = c_{igs}\left(x_{igs} - \frac{1}{T_{igs}} \sum_{(g',s') \in \Psi_i(g,s)} x_{ig's'}\right) \tag{4.16}$$

$$v^*_{igs} = c_{igs}\left(v_{igs} - \frac{1}{T_{igs}} \sum_{(g',s') \in \Psi_i(g,s)} v_{ig's'}\right) \tag{4.17}$$

where T_{igs} is the number of elements of $\Psi_i(g,s)$, and the scale factor is $c_{igs} = \sqrt{T_{igs}/(T_{igs}+1)}$. Note that the choice of c_{igs} assures the i.i.d property of disturbance terms.

The network structure imposed on players in each game is represented in Figure 4.6. Among teammates, the performance of the goal keeper is affected by the defense players, the performance of a defense player is affected by the goal keeper, the other defense players and mid-fielders, the performance of a mid-fielder is affected by the defense players, the other mid-fielders and the forward players, and the performance of a forward player is affected by the mid-fielders and the other forward players. The performance of the players in an opponent team is also taken into consideration. The performance of a goal keeper is affected by the opponents' forward players and mid-fielders, the performance of a defense player is also affected by opponents' forward players and mid-fielders, the performance of a mid-fielder is affected by the opponents' forward players, mid-fielders, and defense players, and performance of a forward player is affected by opponent mid-fielders, defense players, and goal keeper. Each player's performance is also assumed to depend on his performance in the previous game. Note that any peer effects which are not captured in this network structure (e.g. peer effects from mid-fielders to a goal keeper) are in the error terms of equation (4.13).

The degrees of the impacts of peer effects, which are both from teammates and opponent players, are assumed to be different by position. The exogenous characteristics of players' age, age squared value, and team tenure are added, and their impacts are captured by δ. The exogenous peer effects from adjacent players' age, its squared value, and team tenure are captured by $\gamma_j's$. In addition, the average age and average team tenure of teammates in each game are taken into consideration. Team diversity among all players is also added to the estimation equation: if team diversity disturbs communication among players, its impact could be negative, and if team diversity enhances the creativity of team production, it could be positive. Since such an impact could differ depending on the nature of team production, the impact of ethnic diversity is allowed to differ by position. Moreover, the impact of ethnic diversity may change over time. For example, a diverse team may perform poorly at first due to poor communication, but this problem may be resolved over time. Thus, cross terms of ethnic diversity and game index, which are arranged in time series in each season, are added. To take into account the endogenous network formation arising from different recruiting policies, season specific team fixed effects, as well as individual fixed effects, are added. Error terms are clustered by players.

As instrumental variables for $W_j Y^*_{nsg}$ and Y^*_{nsg-1}, we use the previous game's teammates and opponent players' exogenous characteristics, performance, and team environment (average age, average tenure, and home dummy), as well as the previous game's opponent players' previous game's performance, which would affect players' performance through their performance in previous game. As additional instruments, we use previous game's performance of opponent players, which would affect players' performance through performance of current performance of opponent players.

4.5 Estimation Results

Equation (4.14) was estimated by both OLS and two-stage least squares (2SLS), and the estimation results are reported in Table 4.2 . The first and second columns of Table 2 show the OLS and 2SLS estimators, respectively. The Kleibergen-Paap rk Wald F statistics for the test of weak instruments is 10.379, which states that instruments have reasonable explanatory power for the endogenous variables. In addition, the p-value of Hansen's J statistics for the over-identification tests is 0.777 ($\chi^2(26) = 20.313$), so we cannot reject the null-hypothesis that the instruments are exogenous. Thus, the 2SLS estimation results can now be used to address three questions regarding peer effects in a specialized team: (1) Does the short-term performance of one worker affect the performance of other workers on the same team? If so, does the effect of peers vary by the nature of the tasks? (2) Does the performance of competitors affect worker performance? (3) What individual and team attributes affect workers' performance?

For the first question, which is about endogenous peer effects among teammates, OLS results indicate that, for any player, good performances of adjacent teammates improve his performance. For example, a defense player's performance improves by 0.572 points when the average performance of his adjacent teammates (a goal keeper, other defense players, and mid-fielders) increases by one point. In addition, the extents of these impacts are similar regardless of a player's position (0.470, 0.572, 0.503, 0.444 for a goal keeper, a defense player, a mid-fielder, and a forward player). But recall that OLS estimators do not control the simultaneous effects, in which players' performances in the game are determined on the complex network represented in Figure 6. It is also worth noting that OLS cannot detect asymmetric impacts of endogenous peer effects between two players, because endogenous peer effects estimated by OLS are just a conditional correlation between the two players. This may produce estimates with similar impacts among different positions. Moreover, unobservable factors which are not captured by fixed effects cause bias in OLS estimation. For example, peer effects which are not captured in the network structure in Figure 4.6 are in the error term. The 2SLS estimators reported in the second column of Table 4.2 control these potential problems. The 2SLS estimaters (0.764, 1.412, 1.177, 1.444 for a goal keeper, a defense player, a mid-fielder, and a forward player, respectively) are larger than the OLS estimators, indicating that endogenous peer effects from teammates estimated by OLS are under-estimated. Looking at the extent of endogenous peer effects from teammates, it is relatively small for a goal keeper, compared to other players of different positions. This may reflect the fact that a goal keeper's interactions are fewer compared to those of defense players, mid-fielders, and forward players.

For the second question, which is about endogenous peer effects from opponent players, the OLS results exhibit significantly negative coefficients for all of the positions, that is, good performances of opponent players decrease a player's performance. Looking at the results of 2SLS, this implication is true for defense players, mid-fielders, and forward players, although OLS estimators are over-estimated. One interesting asymmetric result is that the coefficient for a goal keeper is no longer significantly negative. Rather, it is positive with a relatively small standard errors (The p-value is 0.140), meaning that high performances of forward players and mid-fielders on the opposing team could improve a goal keepers' performance. These results of endogenous peer effects from opponent players imply that severe environmental factors or hard tasks could decline, have no effect, or even improve players' productivities, depending on the nature of the task in a team.

For the third question, which is about exogenous peer effects and other control variables, both the average age and the average squared age of adjacent teammates in the game affect a player's performance,[9] while the coefficients of an average team tenure of adjacent teammates have no significant effort for any position. As for the exogenous peer effects from adjacent opponent players in the game, the impacts of the average age and the average squared age are large for the goal keeper, and the average team tenure has significantly negative effects on defense players and on forward players. Note that the impact of team diversity on a player's performance cannot be estimated, because the diversity index, which represents the team ethnic diversity among all players who played at least one game during the season in the team, is captured by the season specific team fixed effects in the second column of Table 2. Thus, we also estimate equation (4.14) by controlling for team fixed effects and season fixed effects separately.

The third column of Table 4.2 shows the 2SLS results with both types of fixed effects. The Kleibergen-Paap rk Wald F statistics for the test of weak instruments is 11.789, and the p-value of Hansen's J statistics for the over-identification tests is 0.830 ($\chi^2(26) = 19.163$). In addition, the estimation results are similar to those with season-specific team

[9]The coefficients for the goal keeper and the defense players are not significant, even though they have relatively low standard errors.

fixed effects. Thus, the 2SLS estimators reported in the third column of Table 2 can be used to measure the impacts of a team diversity. Note that the impact of the diversity index is allowed to be different by each player's position, that is, the cross terms of the diversity index and players' position dummy variables are added to the equation. To see how these impacts change over time, the cross-terms of these indices and the game index, which are arranged in time series in each season, are also added. Looking at the coefficients of the diversity index, which represent the impacts of the team diversity on a player's performance in the first game in the season, there is no strong evidence that a team's diversity affects a player's performance, although all coefficients are negative. However, the coefficient of the cross term of the diversity index and the game index is significantly positive and equal to 0.007 for a mid-fielder.[10] This means that a 0.1 point increase in the diversity index will improve a mid-fielder's performance per 0.0007 by one game. Since each team plays 34 games in one season, 0.1 points of the increase of the diversity index will result in a 0.0238 ($= 0.0007 * 34$) point increase in a mid-fielder's performance by the last game.

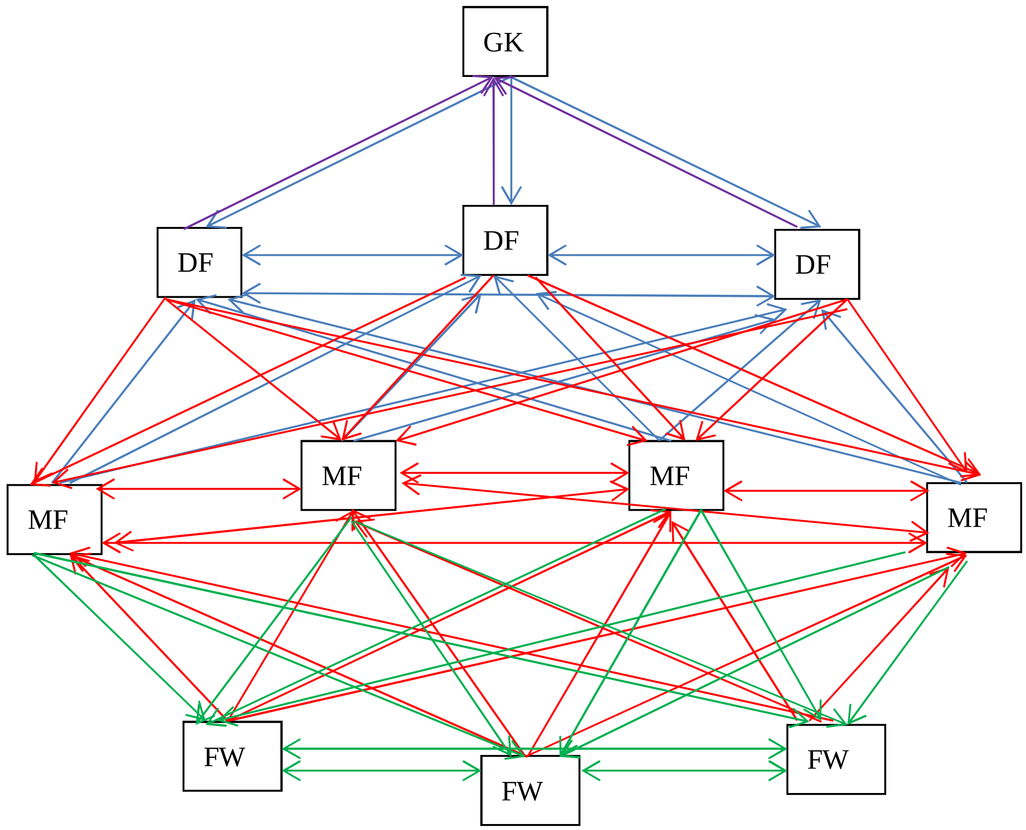
Instead of using the diversity index among all players, if the index is defined as the diversity among players with a similar mission, we can see the impacts of the diversity more clearly. Following Ben-Ner, Licht, and Park (2017), the diversity index among defensive players (a goal keeper, defense players, and mid-fielders), and offensive players (defense players, mid-fielders, and forward players) are constructed. The cross terms of each diversity index and its position dummy variable (defensive player dummy and offensive player dummy) are added to equation (4.14). The cross terms of these indices and the game index are also added. The fourth column of Table 4.2 shows the 2SLS results with these diversity indices. The results show that defensive players' diversity does not affect a de-

[10]The F-statistics for the null hypothesis that all the four cross terms are zero is 10.56 (p-value is 0.0320). Thus, the null hypothesis is rejected.

fensive player's performance. On the other hand, the offensive players' diversity decreases a offensive player's performance at the beginning of the season, but this negative effect is mitigated over time, although it takes 54 ($\approx 0.326/0.006$) games to offset this negative impact. This indicates that we should evaluate the impact of diversity on a team performance not only in the short run, but also in the long run, and it would take a long time to bring about any benefit of diversity to a team.

4.6 Conclusion

This paper has examined the features of peer effects for a team where each member of the team is allocated a different specialized task, and the interactions between each member are quite complex. We use a longitudinal data set of all soccer players in the top German league (the Bundesliga) over the course of ten seasons (2000/01-2009/10), and identify various aspects of peer effects among players on a team in a game. We draw three major conclusions: (1) There are positive endogenous peer effects from teammates, but the extent of the impacts varies depending on the nature of the task (the impact for the goal keeper differs from the impacts for all other positions); (2) In contrast, there are negative endogenous peer effects from opponent players onto defense players, mid-fielders, and forward players, although te effect is slightly positive for a goal keeper; (3) There are negative impacts ethnic diversity among offensive players (mid-fielders and forward players), but they are mitigated over time. Our unique application of the network approach enables us to identify intricately woven peer effects. This approach is applicable to other workplaces with specialized teams, such as consulting teams. Further studies should be conducted to analyze these relations within other types of specialized teams.



GK : Goal Keeper — DF : Defense Player

MF : Mid-fielder — FW : Forward Player

Figure 4.1: Example of Network Structure in a Soccer Game

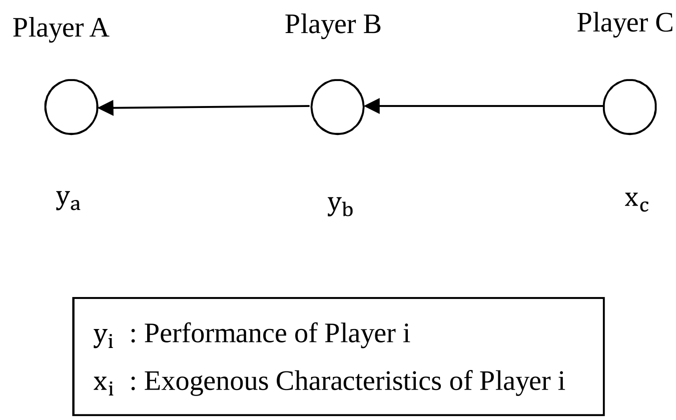


Figure 4.2: Identification by Network Structure

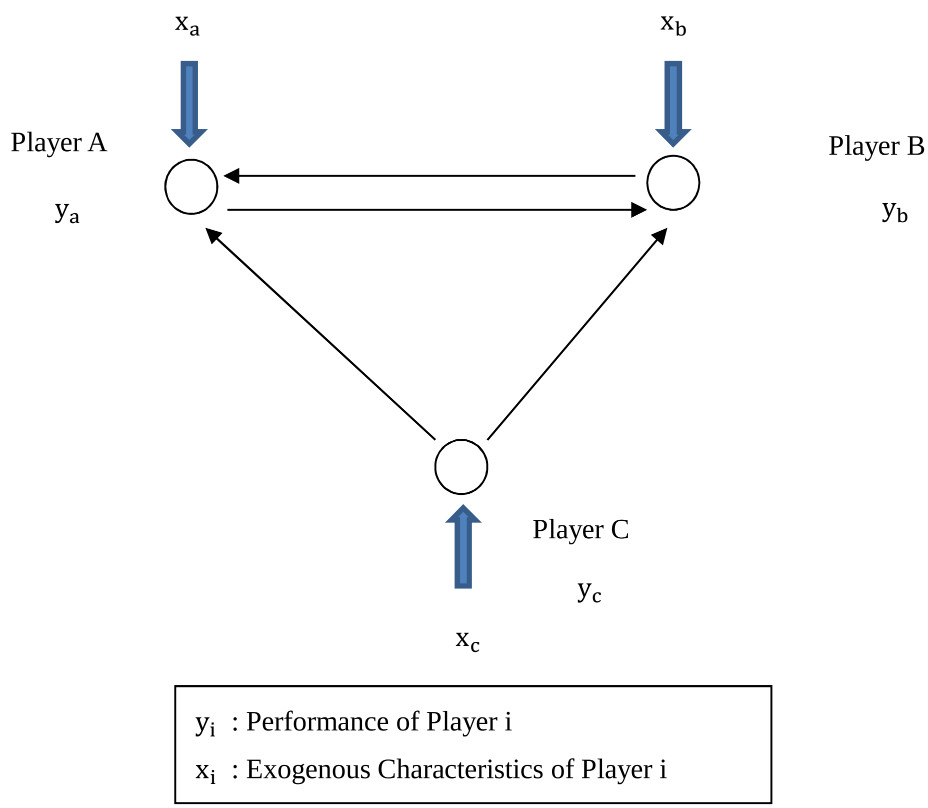


Figure 4.3: Example of Network Structure (n=3)

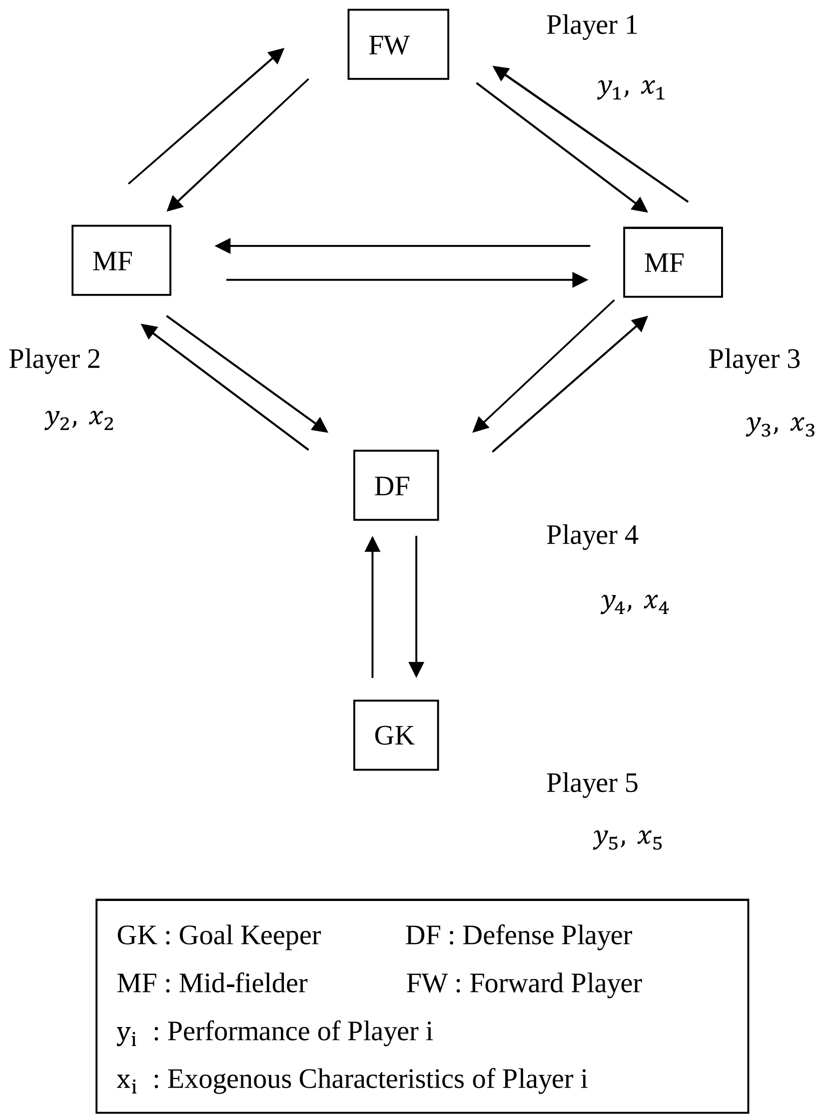


Figure 4.4: Heterogeneity in a Simplified Game: Example of Futsal

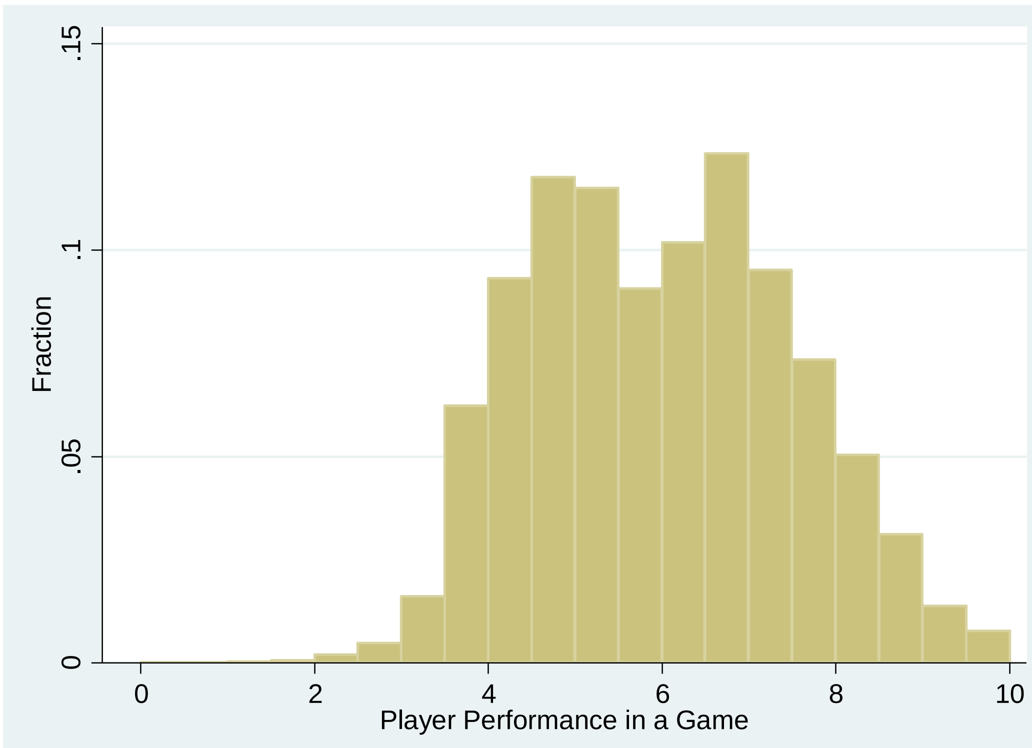


Figure 4.5: Histogram of Player Performance: All Players (N=83,345)

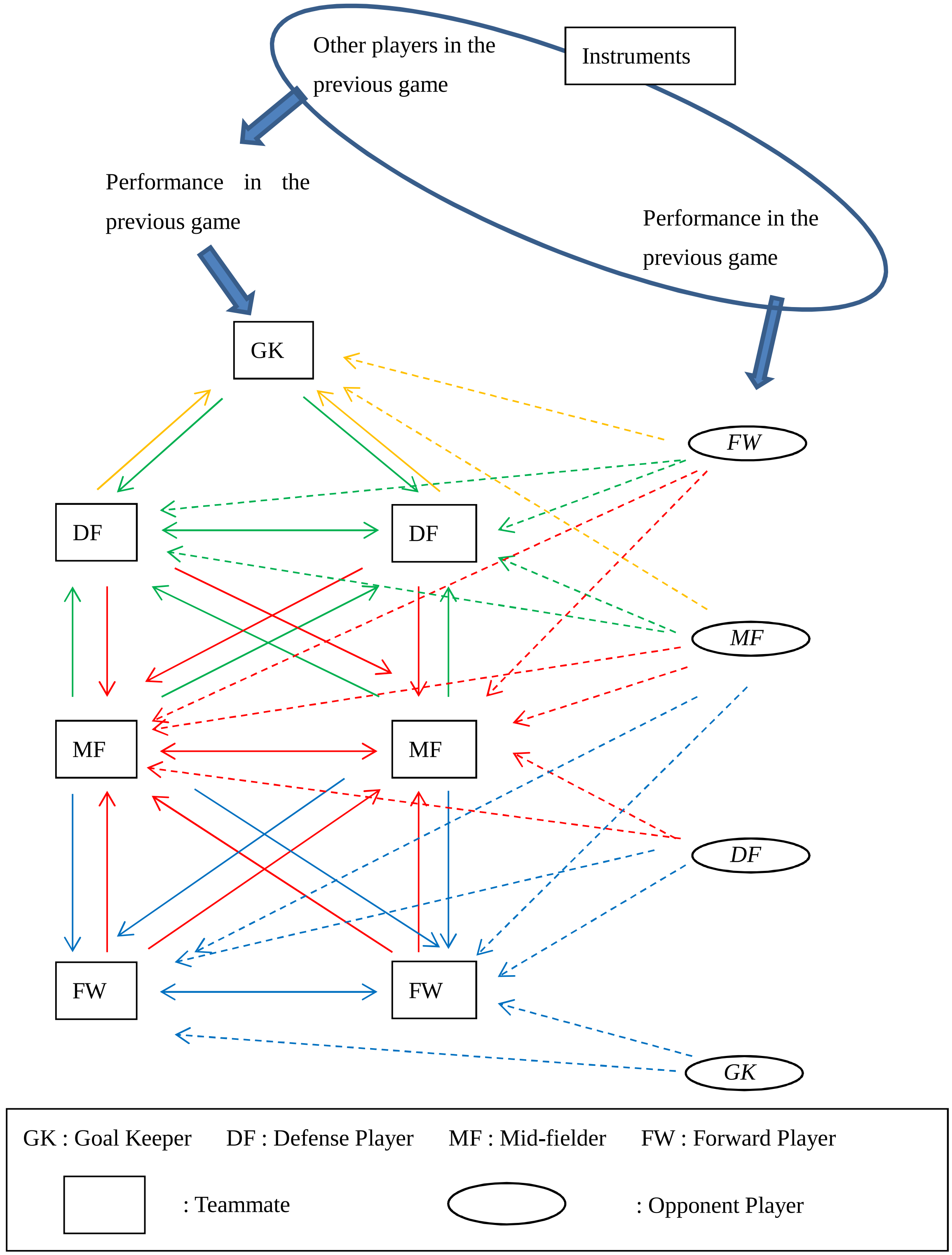


Figure 4.6: Estimated Network Structure in a Game

Table 4.1: Summary Statistics

	Observations	Mean	S.D.	Min	Max
Player performance	83,345	5.957	1.505	0	10
Player performance by position					
Goal Keeper	6,218	6.502	1.511	1.100	10
Defense Player	28,546	5.843	1.475	0.500	10
Mid-fielder	28,612	5.944	1.509	0	10
Forward Player	19,969	5.970	1.504	1.300	10
Age	83,345	27.08	4.040	16.92	40.54
Age by position					
Goal Keeper	6,218	29.59	4.662	18.64	40.54
Defense Player	28,546	26.94	3.750	17.70	39.55
Mid-fielder	28,612	26.98	4.184	16.92	38.51
Forward Player	19,969	26.62	3.738	17.71	37.45
Team Tenure	83,345	2.201	2.360	0	21.21
Team Tenure by position					
Goal Keeper	6,218	2.811	2.911	0	21.21
Defense Player	28,546	2.216	2.220	0	15.98
Mid-fielder	28,612	2.285	2.500	0	17.85
Forward Player	19,969	1.869	2.092	0	13.94
Team Diversity					
All Players	180	0.692	0.093	0.361	0.854
Defensive Players	180	0.644	0.118	0.185	0.852
Offensive Players	180	0.708	0.100	0.367	0.878

(Source) IMPIRE AG

Table 4.2: Estimation Results: Equation (4.14)

VARIABLES	OLS (1)	2SLS (2)	2SLS (3)	2SLS (4)
I. Endogenous Effects (α)				
From Teammates				
Goal Keeper	0.470***	0.764***	0.732***	0.741***
	(0.023)	(0.124)	(0.122)	(0.121)
Defense Player	0.572***	1.412***	1.389***	1.388***
	(0.016)	(0.107)	(0.103)	(0.105)
Mid-fielder	0.503***	1.177***	1.170***	1.170***
	(0.019)	(0.090)	(0.088)	(0.088)
Forward Player	0.444***	1.444***	1.453***	1.459***
	(0.019)	(0.117)	(0.115)	(0.116)
From Opponent Players				
Goal Keeper	-0.521***	0.211	0.177	0.177
	(0.029)	(0.143)	(0.144)	(0.144)
Defense Player	-0.361***	-0.189**	-0.209***	-0.212***
	(0.015)	(0.074)	(0.067)	(0.067)
Mid-fielder	-0.455***	-0.141*	-0.149**	-0.147**
	(0.020)	(0.074)	(0.074)	(0.074)
Forward Player	-0.343***	-0.093*	-0.106**	-0.105**
	(0.019)	(0.055)	(0.053)	(0.053)
II. Lag Variable (β)				
Player's performance in the previous game	0.061***	0.037***	0.029**	0.030**
	(0.004)	(0.014)	(0.013)	(0.013)
III. Exogenous Effects (γ)				
(A) From adjacent teammates in the game				
Goal Keeper				
Average Age	-0.709***	-0.416	-0.543*	-0.542*
	(0.253)	(0.273)	(0.279)	(0.280)
Average Age Squared	0.012***	0.008	0.010**	0.010**
	(0.005)	(0.005)	(0.005)	(0.005)
Average Team Tenure	0.079**	-0.006	-0.003	-0.004
	(0.040)	(0.039)	(0.040)	(0.041)
Defense Player				
Average Age	-0.373**	-0.263	-0.305	-0.310
	(0.174)	(0.195)	(0.190)	(0.189)
Average Age Squared	0.003	0.004	0.005	0.005
	(0.003)	(0.004)	(0.003)	(0.003)
Average Team Tenure	0.055**	0.048	0.031	0.032
	(0.027)	(0.032)	(0.029)	(0.029)
Mid-fielder				
Average Age	-0.553***	-0.795***	-0.725***	-0.710***
	(0.207)	(0.224)	(0.211)	(0.208)
Average Age Squared	0.007*	0.014***	0.013***	0.013***
	(0.004)	(0.004)	(0.004)	(0.004)
Average Team Tenure	0.038	0.013	-0.002	0.000
	(0.032)	(0.035)	(0.032)	(0.032)

Table 4.2 Estimation Results: Equation (4.14): Continued

VARIABLES	OLS (1)	2SLS (2)	2SLS (3)	2SLS (4)
Forward Player				
Average Age	0.071	-0.442**	-0.343	-0.367*
	(0.191)	(0.224)	(0.221)	(0.221)
Average Age Squared	-0.005	0.008*	0.007	0.007
	(0.004)	(0.004)	(0.004)	(0.004)
Average Team Tenure	0.029	-0.007	-0.014	-0.014
	(0.033)	(0.037)	(0.039)	(0.039)
(B) From adjacent opponent players in the game				
Goal Keeper				
Average Age	-0.648***	-1.137***	-1.143***	-1.142***
	(0.202)	(0.259)	(0.260)	(0.265)
Average Age Squared	0.011***	0.020***	0.021***	0.021***
	(0.004)	(0.005)	(0.005)	(0.005)
Average Team Tenure	0.066*	0.006	0.013	0.010
	(0.037)	(0.047)	(0.046)	(0.046)
Defense Player				
Average Age	0.317***	0.192	0.199	0.202
	(0.122)	(0.152)	(0.149)	(0.149)
Average Age Squared	-0.005**	-0.004	-0.004	-0.004
	(0.002)	(0.003)	(0.003)	(0.003)
Average Team Tenure	0.081***	-0.076***	-0.070***	-0.069***
	(0.018)	(0.027)	(0.026)	(0.027)
Mid-fielder				
Average Age	0.294*	0.228	0.215	0.213
	(0.162)	(0.172)	(0.173)	(0.173)
Average Age Squared	-0.005*	-0.005	-0.005	-0.005
	(0.003)	(0.003)	(0.003)	(0.003)
Average Team Tenure	0.099***	-0.039	-0.035	-0.034
	(0.024)	(0.030)	(0.029)	(0.029)
Forward Player				
Average Age	-0.703***	-0.296*	-0.325**	-0.319**
	(0.139)	(0.152)	(0.154)	(0.156)
Average Age Squared	0.013***	0.004	0.005	0.004
	(0.003)	(0.003)	(0.003)	(0.003)
Average Team Tenure	0.034	-0.095***	-0.098***	-0.100***
	(0.024)	(0.032)	(0.032)	(0.032)
IV. Player's own characteristics (δ)				
Age	-0.038	0.239*	0.250*	0.215**
	(0.118)	(0.133)	(0.128)	(0.084)
Age Squared	-0.005***	-0.005***	-0.005***	-0.005***
	(0.001)	(0.001)	(0.001)	(0.001)
Team Tenure	0.026***	0.025***	0.022**	0.021**
	(0.008)	(0.009)	(0.009)	(0.009)

Table 4.2 Estimation Results: Equation (4.14): Continued

VARIABLES	OLS (1)	2SLS (2)	2SLS (3)	2SLS (4)
V. Other Variables				
(A) Diversity Index				
Team Diversity				
Goal Keeper			-0.139	
			(0.420)	
Defense Player			-0.110	
			(0.216)	
Mid-fielder			-0.164	
			(0.258)	
Forward Player			-0.551	
			(0.370)	
Team Diversity * game				
Goal Keeper	0.008*	0.001	0.000	
	(0.005)	(0.005)	(0.005)	
Defense Player	0.009**	0.002	0.001	
	(0.004)	(0.005)	(0.004)	
Mid-fielder	0.012***	0.007*	0.007*	
	(0.004)	(0.005)	(0.004)	
Forward Player	0.011***	0.004	0.004	
	(0.004)	(0.005)	(0.005)	
Team Position Diversity				
Defensive Players				0.012
				(0.138)
Offensive Players				-0.326*
				(0.187)
Team Position Diversity * game				
Defensive Players				0.003
				(0.002)
Offensive Players				0.006***
				(0.002)
(B) Additional Control Variables				
Average Age of teammate in the game	0.003	-0.009	-0.015	-0.015
	(0.011)	(0.012)	(0.011)	(0.012)
Average Tenure of teammate in the game	-0.001	-0.003	0.005	0.006
	(0.017)	(0.019)	(0.016)	(0.016)
Home Dummy	0.056***	-0.143***	-0.148***	-0.148***
	(0.013)	(0.041)	(0.042)	(0.042)
Fixed Effects				
Individual	Yes	Yes	Yes	Yes
Team	-	-	Yes	Yes
Season	-	-	Yes	Yes
Team*Season	Yes	Yes	No	No
Weak Identification Test	**Kleibergen-Paap rk Wald F statistics**			
	-	10.379	11.789	11.485
Overidentification Test	**Hansen's J statistics**			
Hansen's J statistics	-	20.313	19.163	19.091
P-value	-	Chi(26)	Chi(26)	Chi(26)
	-	0.777	0.830	0.833
Observations	66,398	63,084	63,084	63,084

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Chapter 5

Conclusion

This dissertation has provided a theoretical framework, empirical evidence, and an empirical strategy for a better understanding of the seasonality of food insecurity in developing countries, with a special attention to seasonal price changes of staple foods. Despite the importance of the topic, little is known about the seasonal consumption patterns of rural farmers in developing countries, and the seasonal aspect of food insecurity has received insufficient attention in global efforts to combat rural poverty. This dissertation provides one of the first comprehensive analyses aimed at understanding seasonal poverty in developing countries. This thesis also estimates peer effects for a specific type of team where team members' interactions are complex: professional soccer teams.

Chapter 2 constructs a theoretical model to analyze how seasonal price changes of a staple food affect farmers' seasonal consumption in developing countries, where storage of the staple food can be used to smooth consumption. In this situation, sharp increases in the price of the staple food just before harvest can be viewed as a high return to savings, and this has important implications for interpreting the consumption and savings behavior of poor rural households. It is particularly worth noting that the reduced consumption in the hunger season in response to high prices at that time should not be interpreted only as simple income and substitution effects. Rather, it could signal an inability to reallocate resources across seasons. In addition, the findings of the model are also used to re-consider the so-called “sell low, buy high” puzzle in rural areas of developing countries.

Chapter 3 empirically illustrates farmers’ heterogenous abilities to smooth consumption during a crop year, by using three years of detailed weekly household panel data from rural Zambia. Given seasonal price changes of the staple food, maize, some farmers buy it when prices are low and store it for consumption during the hunger season, while others run out of the staple food before the next harvest, and thus buy it when prices are high. Results indicate that the former group successfully smooths its consumption, while the latter group reduces consumption during the hunger season in response to a negative harvest at the end of the previous crop year, and the effect of these negative harvest shocks produces an inverse U consumption pattern during the crop year, especially for farmers with few assets. These farmers reduce their food diversity to maintain consumption of the staple food in the hunger season in spite of its price hike in that season.

Chapter 4 demonstrates how the network approach can be used to analyze complex interactions among several agents. By using a longitudinal data set of all soccer players in the top German league (the Bundesliga) over the course of ten seasons (2000/01-2009/10), causal peer effects during soccer games are identified by applying the econometric technique of spatial dynamic panel data estimation with fixed effects (the network approach). Three major conclusions are drawn: (1) There are positive endogenous peer effects from teammates, but the extent of the impacts varies depending on the nature of the task (the impacts for goal keepers differs from the impacts for all other positions); (2) In contrast, there are negative endogenous peer effects from opponent players onto defense players, mid-fielders, and forward players, although slightly positive effects for goal keepers; (3) There are negative impacts of ethnic diversity among offensive players (mid-fielders and forward players) that are mitigated over time, but no such effects for defensive players.

The conclusions in each chapter of this dissertation provide many insights into policies to reduce, and future studies of, seasonal poverty in developing countries. The essay in Chapter 2 emphasizes that, in settings where produced consumption goods are used to smooth consumption, theoretical models of farmers' savings should include saving in the form of stocks of agricultural output. The essay in Chapter 3 has important implications for poverty reduction programs that offer short-term credit to farmers, because farmers' heterogenous abilities to smooth consumption are related to their heterogenous motivations in using credit programs: consumption vs. investment. Optimal schemes, repayment terms, and the timing of offers of credit programs should differ depending on different motivations for using such programs, and different credit programs should be designed to suit the purposes of both farmers who are able to smooth consumption over the crop year and farmers that are unable to smooth their consumption. The essay in Chapter 3 also suggests that mirconutrient deficiency problems in developing countries should be part of any discussion of the problem of seasonal price changes of staple foods. Finally, the essay in Chapter 4 suggests a potential approach for the analysis of the interactions among several markets in developing countries, which is the analysis of efficiency of the interactions among markets, relating to seasonal price changes. Although the identification of such interactions is not an easy task, the network approach could solve the potential identification problem. To date, the literature in this area is sparse, but the contribution of this dissertation will be valuable if future work builds on it.

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Appendix A

Theoretical Framework

A.1 The Basic Two-period (two-season) Model

A.1.1 The Basic Two-period (two-season) Model

Start with the the two-period model with two goods discussed in Chapter 2 with an additional constraint of equation (A.5), [1] so that the model becomes:

$$\max_{c_1,x_1,c_2,x_2,B,S} U(c_1, x_1, c_2, x_2) \tag{A.1}$$

$$\text{subject to} \qquad p_1c_1 + x_1 + p_1S = y_1 + B \tag{A.2}$$

$$p_2c_2 + x_2 + (1 + r)B = p_2(1 - \nu)S + y_2 \tag{A.3}$$

$$B \leq \bar{B} \tag{A.4}$$

$$q_2 = c_2 - (1 - \nu)S \geq 0 \tag{A.5}$$

where c_j is a produced consumption good (maize) in season j with price p_j, x_j is a non-produced consumption good in season j with a time invariant price, normalized to one, S

[1] To simplify notation, $u(c_1, x_1 \mid \theta_1) + \beta u(c_2, x_2 \mid \theta_2)$ is replaced by $U(c_1, x_1, c_2, x_2)$.

is the physical amount of the staple food stored in season 1, B is borrowing in the form of money, with an upper limit $\bar{B}$, y_j is income at the beginning of each season j, including the value of the staple food produced, q_2 is the amount of maize the farmer buys in season 2, r is a constant per season interest rate, and ν is the physical depreciation rate of maize storage. Equation (A.5) represents the situation in which transaction costs of maize selling in the hunger season (season 2) are so large that there is no maize selling during the season. Assume that $p_2 > p_1$ and p_2 is sufficiently high to satisfy:

$$\frac{p_2}{p_1}(1-\nu) > 1+r \tag{A.6}$$

This modification of the model leads to the different consumption patterns between BH farmers and NBH farmers.

A.1.2 Solution of the Utility Maximization Problem

The utility maximization problem for the farmer is to maximize (A.1) subject to (A.2)-(A.5). The solution of the problem can be divided into two cases: (1) $q_2 > 0$, representing the farmer who buys maize at higher prices (BH); (2) $q_2 = 0$, representing the farmer who does not buy maize at higher prices (NBH).

The Farmer Who Buys Maize at Higher Prices (BH: $q_2 > 0$)

Combining (A.2) and (A.3) by substituting out S, the following intertemporal budget constraint equation is derived:

$$\begin{aligned}&\frac{p_2}{p_1}(1-\nu)[p_1c_1+x_1]+p_2c_2+x_2\\&\qquad=\frac{p_2}{p_1}(1-\nu)[y_1+B]+y_2-(1+r)B\end{aligned} \tag{A.7}$$

This farmer maximizes equation (A.1) subject to (A.7) and (A.4). Given equation (A.7), maximized utility can be achieved by borrowing money up to the limit, that is, equation (A.4) binds.

$$B = \bar{B} \tag{A.8}$$

This farmer borrows as much money as the borrowing constraint allows, because he or she can save money by borrowing as much as possible at interest rate r to purchase as much maize as possible in season 1. Substituting (A.8) into (A.7), the inter-temporal budget constraint becomes:

$$\begin{aligned} &\frac{p_2}{p_1}(1-\nu)[p_1 c_1 + x_1] + p_2 c_2 + x_2 \\ &\quad = \frac{p_2}{p_1}(1-\nu)[y_1 + \bar{B}] + y_2 - (1+r)\bar{B} \end{aligned} \tag{A.9}$$

The right hand side of equation (A.9) represents the full income of the farmer for the whole year. Note that the cash in hand in season 1, $y_1 + \bar{B}$, is weighted by $\frac{p_2}{p_1}(1-\nu)$, while cash in hand in season 2, y_2, is not. This means that high prices of maize in season 2, $\frac{p_2}{p_1}(1-\nu)$, can be viewed as a high return to savings, and thus, cash in hand in season 1 is more valuable than cash in hand in season 2. For BH farmers, the loss of cash in hand in season 1 requires a larger increase of cash in hand in season 2 to maintain the same inter-temporal budget constraint, and thus, consumption smoothing through the rainy season labor supply will be difficult.

The utility maximization problem for the farmer is reduced to maximizing (A.1) subject to (A.9). Define $\lambda \geq 0$ as the Lagrange multipliers which correspond to equations (A.9).

Then the first order conditions for this problem are:

- w.r.t c_1 $$\frac{\partial U}{\partial c_1} = p_2(1-\nu)\lambda \tag{A.10}$$
- w.r.t x_1 $$\frac{\partial U}{\partial x_1} = \frac{p_2}{p_1}(1-\nu)\lambda \tag{A.11}$$
- w.r.t c_2 $$\frac{\partial U}{\partial c_2} = p_2\lambda \tag{A.12}$$
- w.r.t x_2 $$\frac{\partial U}{\partial x_2} = \lambda \tag{A.13}$$

where $\lambda > 0$. Note that $p_2(1-\nu), \frac{p_2}{p_1}(1-\nu), p_2$, and 1 can be interpreted as shadow prices of c_1, x_1, c_2, x_2 in the sense that marginal rate of substitution between any two goods is equalized to the ratio of their shadow prices.

The Farmer Who Does Not Buy Maize at Higher Prices (NBH: $q_2 = 0$)

This farmer saves enough maize for self-consumption, which provides for all of his or her consumption during season 2 ($c_2 = (1-\nu)S$). For additional savings to purchase non-staple food or non-food items, he or she saves in the form of money (even though saving maize has a high return) due to the prohibitively high transaction costs of maize selling during season 2.[2] First, consider the case where equation (A.4) is not binding (i.e. $B < \bar{B}$). Combining equations (A.2), (A.3) and (A.5) with equality by substituting out B, the inter-temporal budget constraint becomes:

$$p_1c_1 + x_1 + \frac{p_1}{1-\nu}c_2 + \frac{1}{1+r}x_2 = y_1 + \frac{y_2}{1+r} \tag{A.14}$$

The right hand side of equation (A.14) represents the full income of the farmer. Note that the cash in hand in season 1, $y_1 + \bar{B}$, is no more weighted by $\frac{p_2}{p_1}(1-\nu)$, because high prices of maize in season 2, $\frac{p_2}{p_1}(1-\nu)$, can no longer be viewed as a high return to savings.

[2]This saving implies that $B < 0$.

The utility maximization problem for this type of farmer is reduced to maximizing (A.1) subject to (A.14) and (A.4). Define $\lambda \geq 0$ as the Lagrange multiplier which corresponds to equation (A.14), then the first order conditions for this problem are:

- w.r.t c_1 $$\frac{\partial U}{\partial c_1} = p_1 \lambda \tag{A.15}$$
- w.r.t x_1 $$\frac{\partial U}{\partial x_1} = \lambda \tag{A.16}$$
- w.r.t c_2 $$\frac{\partial U}{\partial c_2} = \frac{p_1}{1-\nu}\lambda \tag{A.17}$$
- w.r.t x_2 $$\frac{\partial U}{\partial x_2} = \frac{1}{1+r}\lambda \tag{A.18}$$

where $\lambda > 0$, and $p_1, 1, \frac{p_1}{1-\nu}$, and $\frac{1}{1-r}$ can be interpreted as shadow prices of c_1, x_1, c_2, x_2. Demand functions $c_t^{NBH}, x_t^{NBH}(t = 1, 2)$ are determined by equations (A.14) and (A.15)-(A.18). Since p_2 plays no role in these shadow prices, the corresponding indirect utility function does not change in response to any change in p_2. The intuition here is that this type of farmer does not buy maize in period 2, so the price of maize in that period has no effect on his or her welfare. Note that these shadow prices for a NBH farmer are different from those for a BH farmer. This implies that seasonal price changes of maize would affect seasonal consumption differently for a BH farmer than for a NBH farmer.

In the case where equation (A.4) is binding (i.e. $B = \bar{B}$), the first order conditions for this problem are:

- w.r.t c_1 $$\frac{\partial U}{\partial c_1} = \left(p_1 + \frac{p_1 \phi}{\lambda}\right)\lambda \tag{A.19}$$
- w.r.t x_1 $$\frac{\partial U}{\partial x_1} = \left(1 + \frac{\phi}{\lambda}\right)\lambda \tag{A.20}$$
- w.r.t c_2 $$\frac{\partial U}{\partial c_2} = \left\{\frac{p_1}{1-\nu} + \frac{p_1}{1-\nu}\frac{\phi}{\lambda}\right\}\lambda \tag{A.21}$$
- w.r.t x_2 $$\frac{\partial U}{\partial x_2} = \frac{1}{1+r}\lambda \tag{A.22}$$

where ϕ is defined as the Lagrange multiplier which corresponds to equation (A.4), $\lambda > 0$, and $\phi > 0$. The shadow prices of goods consumed or purchased in season 1 (shadow prices of c_1, x_1 and c_2) increase, and the utility maximization problem of the farmer with a binding borrowing constraint, $B = \bar{B}$, can be re-written as follows:

$$\max_{c_1, x_1, c_2, x_2} U(c_1, x_1, c_2, x_2) \tag{A.23}$$

$$\text{subject to} \qquad x_1 + p_1(c_1 + c_2) = y_1 + \bar{B} \tag{A.24}$$

$$x_2 + (1+r)\bar{B} = y_2 \tag{A.25}$$

The implication of a binding credit constraint ($B = \bar{B}$) is that a NBH farmer with a binding credit constraint wants to consume c_1, x_1 and c_2 more, but not x_2. In the empirical part of this paper, a binding credit constraint of a NBH farmer is not taken into consideration, due to data limitations. However, note that the focus of this paper is the high prices of staple foods in the hunger season, and that such high prices do not affect a NBH farmer, regardless of whether credit constraint is binding.

Appendix B

Estimation results (Full version)

Table B.1 reports all the coefficients of Table 3.4 , and Table B.2 reports all the coefficients of Table 3.5 .

Table B.1: Estimation Results (Total Consumption) with HH Fixed Effects

	Total Consumption				
VARIABLES	Full Sample	NBH	BH	NBH	BH
(i) Income Shock * Month Dummy					
May	-0.275	-0.198	-0.363**	-0.237	-0.361**
	(0.185)	(0.236)	(0.160)	(0.350)	(0.158)
June	-0.193	-0.142	-0.450***	-0.022	-0.459***
	(0.139)	(0.200)	(0.118)	(0.254)	(0.119)
July	-0.193	-0.130	-0.334***	-0.001	-0.340***
	(0.152)	(0.198)	(0.087)	(0.209)	(0.072)
August	-0.037	0.066	-0.321***	0.104	-0.333***
	(0.134)	-0.142	(0.106)	(0.181)	(0.097)
September	-0.143	-0.020	-0.399**	-0.184	-0.404**
	(0.185)	(0.272)	(0.183)	(0.313)	(0.172)
Octobor	-0.062	0.016	-0.232	0.035	-0.237
	(0.131)	(0.176)	(0.151)	(0.244)	(0.159)
November	-0.277*	-0.152	-0.840	-0.142	-0.806*
	(0.153)	(0.150)	(0.492)	(0.202)	(0.459)
December	-0.189	-0.072	-0.180	-0.172	-0.200
	(0.179)	(0.245)	(0.121)	(0.283)	(0.126)
January	-0.046	0.008	-0.096	0.074	-0.100
	(0.174)	(0.277)	(0.105)	(0.345)	(0.113)
February	-0.071	-0.023	-0.271*	-0.134	-0.393***
	(0.144)	(0.207)	(0.144)	(0.281)	(0.093)
March	-0.056	0.028	-0.418***	0.057	-0.529***
	(0.119)	(0.180)	(0.116)	(0.243)	(0.145)
April	-0.272	-0.016	-1.483	-0.149	-1.367*
	(0.182)	(0.233)	(0.869)	(0.303)	(0.793)
(ii) Income Shock * Month Dummy * Cattle					
May				0.010	0.004
				(0.034)	(0.105)
June				-0.035	0.035
				(0.027)	(0.165)
July				-0.032*	-0.051
				(0.018)	(0.171)
August				-0.010	0.098
				(0.023)	(0.156)
September				0.043	0.050
				(0.027)	(0.121)
Octobor				-0.006	0.050
				(0.023)	(0.135)
November				-0.003	-0.011
				(0.023)	(0.153)
December				0.027	0.093
				(0.022)	(0.098)
January				-0.019	0.053
				(0.030)	(0.112)
February				0.030	0.277***
				(0.026)	(0.096)
March				-0.009	0.242**
				(0.025)	(0.107)
April				0.033	-0.131
				(0.025)	(0.189)
Month Dummy (08/09 Crop Year)					
(Compared with May)					
June	-0.103	-0.057	-0.168	-0.057	-0.171
	(0.081)	(0.103)	(0.113)	(0.103)	(0.112)
July	0.093	0.224	-0.189	0.225	-0.188
	(0.196)	(0.270)	(0.142)	(0.269)	(0.144)
August	-0.084	-0.026	-0.168	-0.026	-0.174
	(0.098)	(0.125)	(0.159)	(0.125)	(0.160)
September	0.044	0.139	-0.184	0.138	-0.192
	(0.154)	(0.207)	(0.170)	(0.206)	(0.171)
Octobor	-0.223***	-0.250**	-0.181	-0.251**	-0.188
	(0.078)	(0.100)	(0.148)	(0.100)	(0.149)
November	-0.164*	-0.209**	0.000	-0.211**	-0.007
	(0.089)	(0.103)	(0.214)	(0.103)	(0.217)
December	-0.115	-0.098	-0.196	-0.098	-0.204
	(0.087)	(0.111)	(0.143)	(0.111)	(0.141)
January	-0.096	-0.030	-0.308**	-0.032	-0.316**
	(0.086)	(0.115)	(0.119)	(0.114)	(0.118)

Table B.1 Estimation Results (Total Consumption) with HH Fixed Effects: Continued

	Total Consumption				
VARIABLES	Full Sample	NBH	BH	NBH	BH
February	-0.084	-0.068	-0.126	-0.066	-0.138
	(0.109)	(0.139)	(0.195)	(0.139)	(0.192)
March	0.044	0.075	-0.013	0.074	-0.025
	(0.090)	(0.099)	(0.208)	(0.099)	(0.207)
April	-0.163*	-0.138	-0.070	-0.137	-0.076
	(0.081)	(0.097)	(0.184)	(0.097)	(0.189)
Month Dummy (09/10 Crop Year)					
(Compared with May)					
June	0.254**	0.299*	0.208***	0.305*	0.212***
	(0.099)	(0.160)	(0.071)	(0.162)	(0.072)
July	0.074	0.062	0.101	0.065	0.102
	(0.104)	(0.163)	(0.071)	(0.163)	(0.074)
August	0.019	0.038	-0.046	0.038	-0.041
	(0.090)	(0.131)	(0.100)	(0.132)	(0.102)
September	0.017	0.009	0.029	0.014	0.033
	(0.103)	(0.172)	(0.079)	(0.171)	(0.081)
Octobor	-0.114*	-0.143	-0.062	-0.144	-0.059
	(0.060)	(0.088)	(0.081)	(0.089)	(0.083)
November	-0.119*	-0.151	-0.061	-0.152	-0.068
	(0.071)	(0.091)	(0.142)	(0.092)	(0.147)
December	0.124	0.145	-0.004	0.147	0.003
	(0.106)	(0.151)	(0.145)	(0.151)	(0.150)
January	0.085	0.101	0.069	0.097	0.073
	(0.110)	(0.167)	(0.136)	(0.169)	(0.141)
February	0.101	0.125	0.090	0.127	0.125
	(0.083)	(0.122)	(0.148)	(0.121)	(0.142)
March	0.105	0.137	0.069	0.135	0.102
	(0.071)	(0.096)	(0.116)	(0.096)	(0.123)
April	-0.025	-0.072	0.046	-0.068	0.019
	(0.069)	(0.093)	(0.105)	(0.092)	(0.106)
Month Dummy (10/11 Crop Year)					
(Compared with May)					
June	-0.108	-0.130	0.210*	-0.133	0.205*
	(0.078)	(0.089)	(0.110)	(0.089)	(0.104)
July	-0.028	-0.024	0.174	-0.028	0.201
	(0.133)	(0.163)	(0.153)	(0.163)	(0.134)
August	-0.085	-0.085	0.150	-0.088	0.129
	(0.077)	(0.090)	(0.157)	(0.091)	(0.161)
September	-0.001	-0.014	0.224	-0.010	0.208
	(0.112)	(0.131)	(0.221)	(0.132)	(0.225)
Octobor	-0.124	-0.142	0.010	-0.144	-0.008
	(0.106)	(0.120)	(0.211)	(0.120)	(0.211)
November	-0.109	-0.168**	0.457	-0.169**	0.432
	(0.079)	(0.081)	(0.503)	(0.081)	(0.500)
December	0.434**	0.477**	0.099	0.479**	0.079
	(0.202)	(0.229)	(0.181)	(0.229)	(0.179)
January	-0.098	-0.092	-0.128	-0.095	-0.146
	(0.097)	(0.115)	(0.152)	(0.114)	(0.150)
February	0.018	-0.001	0.169	0.001	0.164
	(0.113)	(0.132)	(0.182)	(0.133)	(0.148)
March	-0.014	-0.034	0.237	-0.036	0.237
	(0.108)	(0.121)	(0.185)	(0.121)	(0.180)
April	0.122	0.023	1.316	0.026	1.273
	(0.128)	(0.097)	(1.017)	(0.098)	(1.004)

Table B.1 Estimation Results (Total Consumption) with HH Fixed Effects: Continued

			Total Consumption		
VARIABLES	Full Sample	NBH	BH	NBH	BH
Month Dummy* Dummy=1 if growing maize in dry season					
June	0.190**	0.185*	0.133	0.186*	0.120
	(0.087)	(0.106)	(0.083)	(0.105)	(0.093)
July	0.026	-0.026	0.103	-0.028	0.109
	(0.133)	(0.180)	(0.102)	(0.179)	(0.118)
August	0.106	0.052	0.284**	0.053	0.256*
	(0.082)	(0.095)	(0.129)	(0.096)	(0.134)
September	0.050	0.017	0.144	0.015	0.133
	(0.108)	(0.144)	(0.125)	(0.144)	(0.142)
Octobor	0.098	0.092	0.184*	0.094	0.173
	(0.080)	(0.100)	(0.103)	(0.100)	(0.115)
November	0.173**	0.169**	0.264	0.171**	0.282
	(0.077)	(0.081)	(0.165)	(0.082)	(0.191)
December	0.051	-0.001	0.300**	-0.002	0.273*
	(0.120)	(0.153)	(0.137)	(0.153)	(0.151)
January	0.128	0.109	0.197	0.113	0.185
	(0.089)	(0.114)	(0.115)	(0.113)	(0.132)
February	0.058	0.052	0.100	0.050	-0.009
	(0.086)	(0.118)	(0.156)	(0.118)	(0.153)
March	0.027	0.003	0.110	0.006	0.011
	(0.073)	(0.093)	(0.134)	(0.093)	(0.152)
April	0.148	0.071	0.352	0.070	0.425*
	(0.089)	(0.081)	(0.206)	(0.081)	(0.244)
Year-variant control variables					
Number of cattle	0.021**	0.023***	-0.110***	0.022**	-0.112***
	(0.009)	(0.008)	(0.028)	(0.009)	(0.027)
Month-variant control variables					
Number of male HH member	-0.145***	-0.159**	-0.044	-0.159**	-0.047
	(0.045)	(0.059)	(0.056)	(0.060)	(0.058)
Number of female HH member	-0.219***	-0.216***	-0.270**	-0.216***	-0.256**
	(0.051)	(0.050)	(0.101)	(0.051)	(0.105)
Number of child HH member (0-3 years)	-0.134***	-0.109***	-0.063	-0.110***	-0.063
	(0.041)	(0.040)	(0.084)	(0.040)	(0.086)
Number of child HH member (4-6 years)	-0.187***	-0.231***	-0.220*	-0.230***	-0.232*
	(0.051)	(0.058)	(0.110)	(0.057)	(0.115)
Number of child HH member (7-9 years)	-0.134**	-0.217***	-0.328***	-0.212***	-0.358***
	(0.053)	(0.047)	(0.072)	(0.049)	(0.105)
Number of child HH member (10-12 years)	-0.106***	-0.109**	-0.351***	-0.106**	-0.364***
	(0.036)	(0.041)	(0.074)	(0.041)	(0.082)
Fixed Effect					
Period * Village	Yes	Yes	Yes	Yes	Yes
Household	Yes	Yes	Yes	Yes	Yes
Period * household	No	No	No	No	No
(i) F-statistics	F(12,46)	F(12,43)	F(12,20)	F(12,43)	F(12,20)
(Income Shock * Month Dummy)	0.84	0.84	21.42	0.54	17.45
p-value	0.6079	0.6092	0.0000	0.8746	0.0000
(ii) F-statistics				F(12,43)	F(12,20)
(Income Shock * Month Dummy * Cattle)				3.58	19.53
p-value				0.0010	0.0000
Observations	6,813	5,132	1,681	5,132	1,681
R-squared	0.178	0.203	0.182	0.204	0.187

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table B.2: Estimation Results (Staple Food, Other Food, Non Food) with HH Fixed Effects

	NBH						BH					
VARIABLES	Staple Food	Other Food	Non Food	Staple Food	Other Food	Non Food	Staple Food	Other Food	Non Food	Staple Food	Other Food	Non Food
(i) Income Shock * Month Dummy												
May	0.016	-0.200	-0.689	-0.130	-0.117	-0.807	0.070	-0.516*	-0.951	0.034	-0.536*	-0.803
	(0.173)	(0.235)	(0.714)	(0.242)	(0.342)	(1.042)	(0.173)	(0.252)	(0.795)	(0.186)	(0.259)	(0.771)
June	0.017	0.003	-0.901	0.118	0.098	-0.670	0.030	-0.744***	-0.765**	0.022	-0.785***	-0.696**
	(0.158)	(0.173)	(0.715)	(0.211)	(0.220)	(0.980)	(0.145)	(0.180)	(0.331)	(0.128)	(0.196)	(0.327)
July	-0.147	0.041	-0.553	-0.013	0.135	-0.341	-0.044	-0.301***	-1.094***	-0.055	-0.323***	-1.043***
	(0.165)	(0.162)	(0.721)	(0.227)	(0.191)	(0.770)	(0.141)	(0.096)	(0.316)	(0.117)	(0.091)	(0.313)
August	0.031	-0.152	0.734	0.043	-0.119	0.847	-0.121	-0.309	-0.817**	-0.135	-0.307	-0.861**
	(0.127)	(0.154)	(0.599)	(0.186)	(0.167)	(0.697)	(0.137)	(0.221)	(0.380)	(0.133)	(0.209)	(0.390)
September	0.176	-0.090	-0.283	0.071	-0.096	-1.009	-0.136	-0.280	-1.325	-0.212	-0.281	-1.175
	(0.169)	(0.173)	(1.332)	(0.190)	(0.218)	(1.344)	(0.184)	(0.173)	(1.007)	(0.194)	(0.179)	(0.904)
Octobor	0.101	-0.002	-0.132	0.100	0.051	-0.155	0.055	-0.388*	-0.476	-0.005	-0.377	-0.394
	(0.121)	(0.163)	(0.639)	(0.155)	(0.211)	(0.831)	(0.151)	(0.204)	(0.385)	(0.149)	(0.228)	(0.370)
November	0.024	-0.253	-0.288	0.094	-0.228	-0.455	0.030	-0.578*	-3.547	-0.044	-0.579*	-3.172
	(0.187)	(0.160)	(0.571)	(0.212)	(0.205)	(0.736)	(0.194)	(0.292)	(2.384)	(0.165)	(0.316)	(2.128)
December	0.144	0.035	-0.859	0.224	-0.188	-1.040	-0.104	-0.383*	0.194	-0.087	-0.416*	0.122
	(0.157)	(0.220)	(0.936)	(0.207)	(0.192)	(1.163)	(0.147)	(0.193)	(0.365)	(0.145)	(0.201)	(0.331)
January	-0.017	0.030	0.006	0.013	0.235	-0.220	0.020	-0.209*	-0.058	0.056	-0.216*	-0.146
	(0.186)	(0.378)	(0.755)	(0.225)	(0.469)	(0.886)	(0.117)	(0.110)	(0.281)	(0.126)	(0.119)	(0.274)
February	0.126	0.187	-0.935	0.058	0.094	-1.191	-0.238**	-0.167	-0.631	-0.375***	-0.280*	-0.738
	(0.175)	(0.178)	(0.849)	(0.227)	(0.216)	(1.048)	(0.084)	(0.185)	(0.479)	(0.126)	(0.153)	(0.444)
March	-0.011	0.019	0.143	0.066	0.056	0.039	-0.185	-0.683***	-0.241	-0.218	-0.840***	-0.409
	(0.186)	(0.188)	(0.567)	(0.231)	(0.227)	(0.725)	(0.133)	(0.192)	(0.403)	(0.143)	(0.276)	(0.357)
April	0.174	0.003	-0.503	0.027	-0.041	-0.845	-0.278	-1.489*	-4.245	-0.172	-1.456*	-3.882
	(0.169)	(0.262)	(0.632)	(0.209)	(0.307)	(0.855)	(0.165)	(0.786)	(3.059)	(0.122)	(0.744)	(2.787)
(ii) Income Shock * Month Dummy * Cattle												
May				0.038	-0.020	0.025				0.100	0.140	-0.583*
				(0.027)	(0.037)	(0.093)				(0.087)	(0.131)	(0.295)
June				-0.029	-0.026	-0.075				-0.052	0.268*	-0.390
				(0.027)	(0.025)	(0.139)				(0.204)	(0.131)	(0.398)
July				-0.032	-0.022	-0.055				-0.032	0.045	-0.354
				(0.026)	(0.022)	(0.050)				(0.198)	(0.186)	(0.401)
August				-0.003	-0.008	-0.034				0.090	0.111	0.080
				(0.020)	(0.021)	(0.108)				(0.106)	(0.198)	(0.396)
September				0.028	0.003	0.186				0.217**	0.150	-0.603
				(0.028)	(0.027)	(0.163)				(0.098)	(0.150)	(0.392)
Octobor				0.001	-0.014	-0.001				0.141*	0.146	-0.417
				(0.021)	(0.024)	(0.063)				(0.081)	(0.175)	(0.298)
November				-0.018	-0.006	0.037				0.160*	0.166	-0.882
				(0.027)	(0.033)	(0.057)				(0.089)	(0.149)	(0.525)
December				-0.022	0.062*	0.043				0.001	0.247**	-0.105
				(0.021)	(0.032)	(0.072)				(0.125)	(0.113)	(0.333)
January				-0.008	-0.055	0.054				-0.015	0.178	-0.128
				(0.025)	(0.046)	(0.078)				(0.080)	(0.116)	(0.350)
February				0.019	0.027	0.062				0.303***	0.383***	-0.067
				(0.027)	(0.025)	(0.077)				(0.079)	(0.112)	(0.355)
March				-0.022	-0.009	0.022				0.097	0.442***	0.036
				(0.031)	(0.026)	(0.060)				(0.077)	(0.137)	(0.340)
April				0.037*	0.012	0.080				-0.115	0.119	-0.836
				(0.021)	(0.026)	(0.071)				(0.103)	(0.210)	(0.661)
Month Dummy (08/09 Crop Year)												
(Compared with May)												
June	0.045	-0.062	-0.280	0.043	-0.061	-0.276	0.068	-0.150	-0.758	0.074	-0.164	-0.757
	(0.086)	(0.149)	(0.470)	(0.082)	(0.150)	(0.467)	(0.086)	(0.160)	(0.921)	(0.091)	(0.157)	(0.935)
July	0.214	-0.086	1.081	0.212	-0.084	1.083	0.075	-0.301**	-0.496	0.080	-0.302**	-0.497
	(0.184)	(0.208)	(1.215)	(0.184)	(0.209)	(1.215)	(0.116)	(0.121)	(0.805)	(0.120)	(0.122)	(0.816)
August	0.209	-0.165	-0.193	0.206	-0.164	-0.191	0.212	-0.216	-0.916	0.210	-0.228	-0.917
	(0.128)	(0.192)	(0.593)	(0.128)	(0.192)	(0.596)	(0.178)	(0.135)	(1.089)	(0.180)	(0.134)	(1.098)
September	0.053	-0.099	0.975	0.050	-0.098	0.974	0.200	-0.249*	-0.896	0.192	-0.265*	-0.880
	(0.110)	(0.166)	(1.048)	(0.110)	(0.166)	(1.046)	(0.166)	(0.135)	(0.905)	(0.170)	(0.133)	(0.922)
Octobor	-0.126	-0.199	-0.674**	-0.129	-0.198	-0.676**	0.125	-0.176**	-0.898	0.119	-0.194**	-0.881
	(0.088)	(0.173)	(0.327)	(0.087)	(0.173)	(0.328)	(0.143)	(0.084)	(0.999)	(0.147)	(0.077)	(1.014)
November	-0.046	-0.180	-0.666*	-0.050	-0.179	-0.665*	0.151	-0.226	0.261	0.146	-0.246	0.286
	(0.104)	(0.177)	(0.390)	(0.101)	(0.177)	(0.391)	(0.120)	(0.173)	(1.165)	(0.122)	(0.170)	(1.186)
December	0.044	-0.085	-0.463	0.041	-0.083	-0.460	0.255	-0.215	-1.186	0.254	-0.236*	-1.177
	(0.085)	(0.159)	(0.469)	(0.083)	(0.156)	(0.471)	(0.148)	(0.132)	(1.070)	(0.151)	(0.123)	(1.084)
January	0.253***	-0.109	-0.469	0.250***	-0.112	-0.468	0.207*	-0.468**	-1.065	0.206*	-0.490**	-1.052
	(0.082)	(0.173)	(0.421)	(0.080)	(0.170)	(0.423)	(0.106)	(0.187)	(0.920)	(0.106)	(0.181)	(0.935)
February	0.200**	-0.207	-0.312	0.200**	-0.204	-0.310	0.210*	-0.142	-0.855	0.202	-0.167	-0.845
	(0.086)	(0.155)	(0.655)	(0.086)	(0.155)	(0.655)	(0.121)	(0.176)	(1.161)	(0.121)	(0.166)	(1.175)
March	0.418***	0.032	-0.599	0.415***	0.032	-0.600	0.385**	0.018	-1.012	0.383**	-0.010	-1.005
	(0.134)	(0.178)	(0.405)	(0.131)	(0.178)	(0.406)	(0.161)	(0.229)	(1.087)	(0.164)	(0.219)	(1.106)
April	0.143	-0.148	-0.757**	0.142	-0.146	-0.754**	0.178*	-0.107	-0.540	0.177*	-0.130	-0.516
	(0.088)	(0.158)	(0.331)	(0.087)	(0.158)	(0.332)	(0.101)	(0.175)	(1.049)	(0.101)	(0.178)	(1.075)

Table B.2 Estimation Results (Staple Food, Other Food, Non Food) with HH Fixed Effects: Continued

	NBH						BH					
VARIABLES	Staple Food	Other Food	Non Food	Staple Food	Other Food	Non Food	Staple Food	Other Food	Non Food	Staple Food	Other Food	Non Food
Month Dummy (09/10 Crop Year)												
(Compared with May)												
June	0.033	0.061	1.547**	0.040	0.063	1.562**	0.225	0.220	0.134	0.210	0.232	0.166
	(0.108)	(0.150)	(0.753)	(0.107)	(0.151)	(0.764)	(0.132)	(0.136)	(0.206)	(0.130)	(0.138)	(0.197)
July	0.045	-0.093	0.518	0.050	-0.094	0.525	0.110	0.035	0.257	0.100	0.032	0.295
	(0.148)	(0.157)	(0.531)	(0.147)	(0.157)	(0.530)	(0.077)	(0.057)	(0.340)	(0.076)	(0.059)	(0.338)
August	-0.053	0.018	0.303	-0.050	0.015	0.303	0.001	-0.062	-0.111	-0.007	-0.065	-0.054
	(0.126)	(0.185)	(0.527)	(0.128)	(0.185)	(0.527)	(0.161)	(0.105)	(0.405)	(0.163)	(0.110)	(0.392)
September	-0.211	0.085	0.312	-0.205	0.083	0.332	-0.058	0.098	0.047	-0.047	0.096	0.052
	(0.130)	(0.160)	(0.673)	(0.130)	(0.159)	(0.670)	(0.127)	(0.087)	(0.270)	(0.128)	(0.094)	(0.282)
Octobor	-0.280***	0.047	-0.334	-0.278***	0.043	-0.339	-0.143	0.059	-0.199	-0.138	0.048	-0.163
	(0.098)	(0.116)	(0.282)	(0.100)	(0.116)	(0.283)	(0.083)	(0.119)	(0.356)	(0.081)	(0.123)	(0.349)
November	-0.237**	-0.017	-0.315	-0.236**	-0.020	-0.314	-0.194*	0.058	-0.075	-0.186	0.051	-0.113
	(0.113)	(0.152)	(0.245)	(0.114)	(0.151)	(0.249)	(0.113)	(0.223)	(0.373)	(0.116)	(0.228)	(0.382)
December	-0.140	0.350**	0.252	-0.140	0.355**	0.252	-0.012	0.086	-0.229	-0.025	0.087	-0.157
	(0.132)	(0.165)	(0.479)	(0.135)	(0.161)	(0.485)	(0.122)	(0.216)	(0.375)	(0.125)	(0.221)	(0.376)
January	0.137	0.314	-0.554	0.138	0.304	-0.553	0.013	0.167	-0.063	-0.007	0.163	0.016
	(0.149)	(0.249)	(0.360)	(0.150)	(0.252)	(0.358)	(0.101)	(0.199)	(0.312)	(0.102)	(0.203)	(0.311)
February	0.040	0.116	0.346	0.044	0.115	0.346	0.016	0.018	0.454	0.043	0.043	0.536
	(0.126)	(0.164)	(0.426)	(0.127)	(0.161)	(0.428)	(0.108)	(0.205)	(0.645)	(0.107)	(0.205)	(0.662)
March	0.232	0.238**	-0.350	0.232	0.235**	-0.354	0.042	0.166	-0.132	0.041	0.204	-0.030
	(0.150)	(0.112)	(0.346)	(0.152)	(0.111)	(0.346)	(0.100)	(0.232)	(0.320)	(0.107)	(0.245)	(0.321)
April	-0.065	0.046	-0.403*	-0.056	0.046	-0.398*	-0.083	0.144	0.078	-0.119	0.131	0.035
	(0.101)	(0.133)	(0.226)	(0.101)	(0.130)	(0.227)	(0.121)	(0.207)	(0.264)	(0.120)	(0.211)	(0.296)
Month Dummy (10/11 Crop Year)												
(Compared with May)												
June	0.078	-0.191**	-0.444	0.072	-0.191**	-0.451	0.051	0.272	0.407	0.070	0.247	0.406
	(0.078)	(0.090)	(0.429)	(0.075)	(0.092)	(0.432)	(0.156)	(0.160)	(0.657)	(0.139)	(0.150)	(0.653)
July	0.003	-0.174	0.319	-0.005	-0.174	0.312	0.109	0.022	0.735	0.134	0.058	0.739
	(0.093)	(0.117)	(0.780)	(0.093)	(0.118)	(0.777)	(0.297)	(0.149)	(0.684)	(0.279)	(0.159)	(0.710)
August	-0.010	-0.101	-0.217	-0.015	-0.100	-0.225	0.212	0.108	0.118	0.193	0.106	0.044
	(0.075)	(0.124)	(0.407)	(0.074)	(0.124)	(0.407)	(0.274)	(0.287)	(0.953)	(0.282)	(0.315)	(0.913)
September	0.149	-0.004	-0.416	0.148	-0.001	-0.396	0.426**	-0.133	0.713	0.405**	-0.158	0.738
	(0.114)	(0.104)	(0.540)	(0.115)	(0.104)	(0.543)	(0.176)	(0.239)	(0.925)	(0.173)	(0.242)	(0.937)
Octobor	-0.203***	0.054	-0.527	-0.208***	0.054	-0.531	0.259	0.027	-0.612	0.250	-0.014	-0.583
	(0.067)	(0.099)	(0.511)	(0.065)	(0.098)	(0.513)	(0.412)	(0.211)	(0.728)	(0.399)	(0.214)	(0.728)
November	-0.128*	-0.007	-0.689**	-0.135*	-0.006	-0.687**	-0.237	0.165	2.842	-0.241	0.124	2.810
	(0.073)	(0.112)	(0.269)	(0.070)	(0.113)	(0.270)	(0.329)	(0.187)	(2.447)	(0.318)	(0.185)	(2.419)
December	0.045	0.709***	0.850	0.037	0.719***	0.854	-0.096	0.590	-0.770	-0.112	0.547	-0.738
	(0.100)	(0.158)	(0.974)	(0.097)	(0.157)	(0.978)	(0.177)	(0.384)	(0.826)	(0.174)	(0.382)	(0.797)
January	-0.095	0.149	-0.727	-0.101	0.143	-0.723	-0.283	0.145	-0.502	-0.311	0.106	-0.444
	(0.072)	(0.115)	(0.484)	(0.070)	(0.113)	(0.484)	(0.278)	(0.240)	(0.721)	(0.283)	(0.247)	(0.707)
February	-0.038	0.079	-0.133	-0.040	0.084	-0.127	0.179	0.093	0.349	0.176	0.066	0.398
	(0.079)	(0.122)	(0.587)	(0.079)	(0.122)	(0.590)	(0.167)	(0.226)	(0.946)	(0.168)	(0.200)	(0.940)
March	-0.033	0.161	-0.559	-0.039	0.161	-0.560	0.008	0.510	0.034	-0.003	0.497	0.096
	(0.088)	(0.132)	(0.459)	(0.087)	(0.132)	(0.459)	(0.164)	(0.328)	(0.792)	(0.164)	(0.336)	(0.775)
April	-0.075	0.093	0.065	-0.075	0.096	0.072	-0.067	1.479	4.067	-0.108	1.432	4.030
	(0.083)	(0.113)	(0.328)	(0.083)	(0.114)	(0.328)	(0.175)	(0.893)	(3.474)	(0.183)	(0.888)	(3.444)
Month Dummy* Dummy=1 if growing maize in dry season												
June	0.091	0.173*	0.433	0.093	0.173*	0.436	-0.037	0.282*	0.126	0.012	0.241	0.043
	(0.083)	(0.096)	(0.478)	(0.079)	(0.097)	(0.478)	(0.130)	(0.155)	(0.436)	(0.140)	(0.164)	(0.424)
July	0.019	0.047	-0.327	0.019	0.046	-0.332	-0.020	0.330***	-0.223	0.017	0.348***	-0.322
	(0.129)	(0.130)	(0.793)	(0.126)	(0.130)	(0.793)	(0.145)	(0.098)	(0.514)	(0.175)	(0.116)	(0.525)
August	-0.054	0.162	0.003	-0.052	0.162	0.006	-0.094	0.504***	0.565	-0.082	0.520***	0.326
	(0.099)	(0.139)	(0.422)	(0.098)	(0.139)	(0.421)	(0.158)	(0.125)	(0.613)	(0.174)	(0.139)	(0.596)
September	0.061	0.068	-0.219	0.060	0.067	-0.227	-0.122	0.277**	0.403	-0.164	0.288**	0.401
	(0.167)	(0.116)	(0.565)	(0.167)	(0.115)	(0.566)	(0.138)	(0.110)	(0.536)	(0.146)	(0.135)	(0.598)
Octobor	0.006	0.078	0.329	0.007	0.079	0.334	-0.095	0.268**	0.602	-0.108	0.287**	0.513
	(0.082)	(0.116)	(0.350)	(0.083)	(0.116)	(0.350)	(0.155)	(0.096)	(0.568)	(0.162)	(0.116)	(0.601)
November	0.022	0.231**	0.341	0.026	0.231**	0.341	0.013	0.330*	0.665	-0.010	0.342	0.794
	(0.091)	(0.113)	(0.300)	(0.089)	(0.113)	(0.299)	(0.133)	(0.173)	(0.749)	(0.158)	(0.198)	(0.838)
December	0.074	0.040	-0.283	0.077	0.035	-0.283	-0.038	0.528***	0.465	0.007	0.508**	0.255
	(0.097)	(0.163)	(0.555)	(0.094)	(0.164)	(0.556)	(0.167)	(0.176)	(0.585)	(0.195)	(0.190)	(0.583)
January	-0.027	0.033	0.626	-0.024	0.039	0.626	-0.067	0.353**	0.388	-0.007	0.357*	0.169
	(0.095)	(0.150)	(0.393)	(0.093)	(0.147)	(0.391)	(0.128)	(0.163)	(0.494)	(0.159)	(0.182)	(0.510)
February	-0.004	0.062	0.156	-0.005	0.057	0.156	-0.056	0.347*	-0.203	-0.138	0.262	-0.440
	(0.091)	(0.131)	(0.495)	(0.091)	(0.130)	(0.494)	(0.139)	(0.193)	(0.697)	(0.136)	(0.215)	(0.736)
March	0.057	-0.088	0.122	0.061	-0.088	0.128	0.046	0.158	0.128	0.053	0.040	-0.163
	(0.097)	(0.130)	(0.355)	(0.097)	(0.130)	(0.353)	(0.106)	(0.220)	(0.527)	(0.119)	(0.266)	(0.531)
April	-0.155*	0.095	0.527*	-0.155*	0.093	0.530*	0.138	0.203	1.244	0.244	0.235	1.356
	(0.078)	(0.114)	(0.282)	(0.078)	(0.114)	(0.282)	(0.167)	(0.223)	(0.740)	(0.206)	(0.258)	(0.870)

Table B.2 Estimation Results (Staple Food, Other Food, Non Food) with HH Fixed Effects: Continued

	NBH						BH					
VARIABLES	Staple Food	Other Food	Non Food	Staple Food	Other Food	Non Food	Staple Food	Other Food	Non Food	Staple Food	Other Food	Non Food
Year-variant control variables												
Number of cattle	0.011	0.033**	0.021	0.011	0.034**	0.014	-0.018	-0.116***	-0.307**	-0.020	-0.121***	-0.303**
	(0.007)	(0.013)	(0.028)	(0.008)	(0.015)	(0.028)	(0.018)	(0.034)	(0.109)	(0.018)	(0.032)	(0.112)
Month-variant control variables												
Number of male HH member	-0.048	-0.214***	-0.265	-0.048	-0.216***	-0.260	-0.106**	-0.103	0.258	-0.116**	-0.104	0.264
	(0.035)	(0.071)	(0.205)	(0.035)	(0.072)	(0.208)	(0.050)	(0.071)	(0.182)	(0.052)	(0.076)	(0.187)
Number of female HH member	-0.189***	-0.260***	-0.157	-0.188***	-0.262***	-0.157	-0.333***	-0.424***	0.289	-0.313***	-0.404***	0.277
	(0.041)	(0.072)	(0.201)	(0.041)	(0.074)	(0.202)	(0.087)	(0.103)	(0.450)	(0.083)	(0.119)	(0.437)
Number of child HH member (0-3 years)	-0.087**	-0.094**	-0.202	-0.087**	-0.096**	-0.203	0.049	-0.040	-0.380	0.046	-0.037	-0.385
	(0.040)	(0.045)	(0.139)	(0.041)	(0.045)	(0.140)	(0.065)	(0.086)	(0.335)	(0.064)	(0.083)	(0.342)
Number of child HH member (4-6 years)	-0.211***	-0.195***	-0.373**	-0.210***	-0.196***	-0.366**	-0.066	-0.281*	-0.410	-0.069	-0.326*	-0.352
	(0.054)	(0.070)	(0.175)	(0.054)	(0.068)	(0.175)	(0.109)	(0.157)	(0.294)	(0.110)	(0.165)	(0.277)
Number of child HH member (7-9 years)	-0.159***	-0.221***	-0.343***	-0.158***	-0.221***	-0.311**	-0.168*	-0.424***	-0.436**	-0.205**	-0.525***	-0.265
	(0.050)	(0.067)	(0.110)	(0.055)	(0.067)	(0.126)	(0.085)	(0.090)	(0.194)	(0.096)	(0.123)	(0.294)
Number of child HH member (10-12 years)	-0.118**	-0.082*	-0.161	-0.117**	-0.084*	-0.141	-0.183***	-0.473***	-0.413*	-0.199***	-0.515***	-0.340
	(0.050)	(0.043)	(0.156)	(0.051)	(0.047)	(0.151)	(0.050)	(0.118)	(0.206)	(0.048)	(0.124)	(0.201)
Fixed Effect												
Period * Village	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Period * household	No	No	No	No	No	No	No	No	No	No	No	No
(i) F-statstics	F(12,43)						F(12,20)					
(Income Shock * Month Dummy)	0.80	0.83	1.14	0.59	0.64	1.01	5.68	7.08	14.57	5.61	13.13	16.29
p-value	0.6454	0.6209	0.3545	0.8340	0.8003	0.4573	0.0003	0.0001	0.0000	0.0004	0.0000	0.0000
(ii) F-statistics	F(12,43)						F(12,20)					
(Income Shock * Month Dummy * Cattle)				4.24	3.21	0.77				32.58	7.58	2.84
p-value				0.0002	0.0024	0.6744				0.0000	0.0000	0.0190
Observations	5,132	5,132	5,132	5,132	5,132	5,132	1,681	1,681	1,681	1,681	1,681	1,681
R-squared	0.189	0.246	0.086	0.191	0.248	0.086	0.314	0.229	0.097	0.324	0.234	0.100

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix C

Estimation results (Robustness Checks)

Table C.1 reports all the coefficients of Table 3.6, and Table C.2 reports estimation results without adjusting adult equivalent scale.

Table C.1: Estimation Results (HH Fixed Effects vs Year Variant HH Fixed Effects)

	NBH									BH								
	Staple Food			Other Food			Non Food			Staple Food			Other Food			Non Food		
	HH	dif	YHH	HH	dif	YHH	HH	dif	YHH	HH	dif	YHH	HH	dif	YHH	HH	dif	YHH
Income Shock * Month Dummy																		
May	-0.130			-0.117			-0.807			0.034			-0.536*			-0.803		
	(0.242)			(0.342)			(1.042)			(0.186)			(0.259)			(0.771)		
June	0.118	0.248	0.243	0.098	0.215	0.227	-0.670	0.137	0.139	0.022	-0.012	-0.018	-0.785***	-0.249	-0.225	-0.696**	0.107	0.243
	(0.211)		(0.167)	(0.220)		(0.349)	(0.980)		(0.937)	(0.128)		(0.144)	(0.196)		(0.183)	(0.327)		(0.766)
July	-0.013	0.117	0.100	0.135	0.252	0.272	-0.341	0.466	0.408	-0.055	-0.089	-0.110	-0.323***	0.213	0.235	-1.043***	-0.240	0.068
	(0.227)		(0.236)	(0.191)		(0.363)	(0.770)		(0.825)	(0.117)		(0.236)	(0.091)		(0.225)	(0.313)		(0.728)
August	0.043	0.173	0.180	-0.119	-0.002	0.015	0.847	1.654	1.739*	-0.135	-0.169	-0.184	-0.307	0.229	0.201	-0.861**	-0.058	0.000
	(0.186)		(0.233)	(0.167)		(0.346)	(0.697)		(0.911)	(0.133)		(0.237)	(0.209)		(0.352)	(0.390)		(0.963)
September	0.071	0.201	0.185	-0.096	0.021	0.004	-1.009	-0.202	-0.205	-0.212	-0.246	-0.252	-0.281	0.255	0.186	-1.175	-0.372	-0.585
	(0.190)		(0.256)	(0.218)		(0.304)	(1.344)		(0.831)	(0.194)		(0.180)	(0.179)		(0.246)	(0.904)		(1.067)
Octobor	0.100	0.230	0.191	0.051	0.168	0.120	-0.155	0.652	0.714	-0.005	-0.039	-0.050	-0.377	0.159	0.143	-0.394	0.409	0.324
	(0.155)		(0.227)	(0.211)		(0.335)	(0.831)		(0.769)	(0.149)		(0.216)	(0.228)		(0.155)	(0.370)		(0.805)
November	0.094	0.224	0.218	-0.228	-0.111	-0.150	-0.455	0.352	0.432	-0.044	-0.078	-0.074	-0.579*	-0.043	-0.069	-3.172	-2.369	-2.549
	(0.212)		(0.341)	(0.205)		(0.266)	(0.736)		(0.635)	(0.165)		(0.241)	(0.316)		(0.213)	(2.128)		(2.198)
December	0.224	0.354	0.301	-0.188	-0.071	-0.115	-1.040	-0.233	-0.137	-0.087	-0.121	-0.118	-0.416*	0.120	0.104	0.122	0.925	0.924
	(0.207)		(0.302)	(0.192)		(0.367)	(1.163)		(0.825)	(0.145)		(0.143)	(0.201)		(0.335)	(0.331)		(0.850)
January	0.013	0.143	0.148	0.235	0.352	0.294	-0.220	0.587	0.714	0.056	0.022	0.034	-0.216*	0.320	0.318	-0.146	0.657	0.692
	(0.225)		(0.278)	(0.469)		(0.513)	(0.886)		(0.800)	(0.126)		(0.221)	(0.119)		(0.326)	(0.274)		(0.700)
February	0.058	0.188	0.192	0.094	0.211	0.133	-1.191	-0.384	-0.289	-0.375***	-0.409	-0.405**	-0.280*	0.256	0.246	-0.738	0.065	0.066
	(0.227)		(0.264)	(0.216)		(0.327)	(1.048)		(0.786)	(0.126)		(0.183)	(0.153)		(0.273)	(0.444)		(0.993)
March	0.066	0.196	0.150	0.056	0.173	0.088	0.039	0.846	0.911	-0.218	-0.252	-0.244	-0.840***	-0.304	-0.319	-0.409	0.394	0.394
	(0.231)		(0.289)	(0.227)		(0.291)	(0.725)		(0.767)	(0.143)		(0.165)	(0.276)		(0.294)	(0.357)		(0.879)
April	0.027	0.157	0.154	-0.041	0.076	-0.007	-0.845	-0.038	0.200	-0.172	-0.206	-0.200	-1.456*	-0.920	-0.923	-3.882	-3.079	-3.051
	(0.209)		(0.189)	(0.307)		(0.253)	(0.855)		(0.557)	(0.122)		(0.171)	(0.744)		(0.646)	(2.787)		(2.770)
Income Shock * Month Dummy * Cattle																		
May	0.038			-0.020			0.025			0.100			0.140			-0.583*		
	(0.027)			(0.037)			(0.093)			(0.087)			(0.131)			(0.295)		
June	-0.029	-0.067	-0.068***	-0.026	-0.006	-0.009	-0.075	-0.100	-0.110	-0.052	-0.152	-0.184	0.268*	0.128	0.136***	-0.390	0.193	0.265
	(0.027)		(0.022)	(0.025)		(0.036)	(0.139)		(0.142)	(0.204)		(0.164)	(0.131)		(0.047)	(0.398)		(0.199)
July	-0.032	-0.070	-0.065***	-0.022	-0.002	-0.003	-0.055	-0.080	-0.079	-0.032	-0.132	-0.198	0.045	-0.095	-0.085	-0.354	0.229	0.418
	(0.026)		(0.019)	(0.022)		(0.035)	(0.050)		(0.094)	(0.198)		(0.192)	(0.186)		(0.116)	(0.401)		(0.256)
August	-0.003	-0.041	-0.039	-0.008	0.012	0.011	-0.034	-0.059	-0.067	0.090	-0.010	-0.057	0.111	-0.029	-0.061	0.080	0.663	0.617**
	(0.020)		(0.026)	(0.021)		(0.031)	(0.108)		(0.126)	(0.106)		(0.072)	(0.198)		(0.130)	(0.396)		(0.264)
September	0.028	-0.010	-0.007	0.003	0.023	0.024	0.186	0.161	0.152	0.217**	0.117	0.117	0.150	0.010	-0.023	-0.603	-0.020	-0.140
	(0.028)		(0.034)	(0.027)		(0.028)	(0.163)		(0.131)	(0.098)		(0.073)	(0.150)		(0.106)	(0.392)		(0.336)
Octobor	0.001	-0.037	-0.034	-0.014	0.006	0.009	-0.001	-0.026	-0.034	0.141*	0.041	0.062	0.146	0.006	-0.035	-0.417	0.166	-0.021
	(0.021)		(0.024)	(0.024)		(0.032)	(0.063)		(0.068)	(0.081)		(0.091)	(0.175)		(0.095)	(0.298)		(0.242)
November	-0.018	-0.056	-0.055	-0.006	0.014	0.016	0.037	0.012	-0.000	0.160*	0.060	0.079	0.166	0.026	-0.005	-0.882	-0.299	-0.421
	(0.027)		(0.034)	(0.033)		(0.025)	(0.057)		(0.063)	(0.089)		(0.085)	(0.149)		(0.096)	(0.525)		(0.466)
December	-0.022	-0.060	-0.054*	0.062*	0.082	0.081*	0.043	0.018	0.004	0.001	-0.099	-0.103	0.247**	0.107	0.072	-0.105	0.478	0.346
	(0.021)		(0.030)	(0.032)		(0.045)	(0.072)		(0.066)	(0.125)		(0.103)	(0.113)		(0.121)	(0.333)		(0.222)
January	-0.008	-0.046	-0.045*	-0.055	-0.035	-0.027	0.054	0.029	0.009	-0.015	-0.115	-0.093	0.178	0.038	0.014	-0.128	0.455	0.314
	(0.025)		(0.027)	(0.046)		(0.049)	(0.078)		(0.079)	(0.080)		(0.080)	(0.116)		(0.098)	(0.350)		(0.254)
February	0.019	-0.019	-0.018	0.027	0.047	0.056	0.062	0.037	0.019	0.303***	0.203	0.220***	0.383***	0.243	0.218	-0.067	0.516	0.386
	(0.027)		(0.028)	(0.025)		(0.036)	(0.077)		(0.067)	(0.079)		(0.072)	(0.112)		(0.128)	(0.355)		(0.275)
March	-0.022	-0.060	-0.056	-0.009	0.011	0.021	0.022	-0.003	-0.018	0.097	-0.003	0.018	0.442***	0.302	0.282*	0.036	0.619	0.498**
	(0.031)		(0.034)	(0.026)		(0.032)	(0.060)		(0.075)	(0.077)		(0.060)	(0.137)		(0.157)	(0.340)		(0.238)
April	0.037*	-0.001	0.001	0.012	0.032	0.039	0.080	0.055	0.025	-0.115	-0.215	-0.183	0.119	-0.021	-0.054	-0.836	-0.253	-0.473
	(0.021)		(0.016)	(0.026)		(0.025)	(0.071)		(0.062)	(0.103)		(0.113)	(0.210)		(0.149)	(0.661)		(0.622)

Table C.1 Estimation Results (HH Fixed Effects vs Year Variant HH Fixed Effects): Continued

	NBH									BH								
	Staple Food			Other Food			Non Food			Staple Food			Other Food			Non Food		
	HH	dif	YHH	HH	dif	YHH	HH	dif	YHH	HH	dif	YHH	HH	dif	YHH	HH	dif	YHH
Month Dummy (08/09 Crop Year)																		
(Compared with May)																		
June	0.043		0.036	-0.061		-0.030	-0.276		-0.284	0.074		0.058	-0.164		-0.174	-0.757		-0.777
	(0.082)		(0.081)	(0.150)		(0.155)	(0.467)		(0.473)	(0.091)		(0.093)	(0.157)		(0.160)	(0.935)		(0.939)
July	0.212		0.209	-0.084		-0.080	1.083		1.116	0.080		0.063	-0.302**		-0.304**	-0.497		-0.475
	(0.184)		(0.189)	(0.209)		(0.211)	(1.215)		(1.247)	(0.120)		(0.121)	(0.122)		(0.123)	(0.816)		(0.822)
August	0.206		0.166	-0.164		-0.185	-0.191		-0.199	0.210		0.195	-0.228		-0.213	-0.917		-0.817
	(0.128)		(0.130)	(0.192)		(0.196)	(0.596)		(0.609)	(0.180)		(0.182)	(0.134)		(0.133)	(1.098)		(1.106)
September	0.050		-0.000	-0.098		-0.138	0.974		0.997	0.192		0.155	-0.265*		-0.234	-0.880		-0.722
	(0.110)		(0.112)	(0.166)		(0.170)	(1.046)		(1.061)	(0.170)		(0.173)	(0.133)		(0.139)	(0.922)		(0.958)
October	-0.129		-0.165*	-0.198		-0.204	-0.676**		-0.668**	0.119		0.090	-0.194**		-0.186**	-0.881		-0.866
	(0.087)		(0.087)	(0.173)		(0.178)	(0.328)		(0.325)	(0.147)		(0.146)	(0.077)		(0.088)	(1.014)		(1.009)
November	-0.050		-0.060	-0.179		-0.165	-0.665*		-0.651	0.146		0.117	-0.246		-0.243	0.286		0.258
	(0.101)		(0.104)	(0.177)		(0.184)	(0.391)		(0.390)	(0.122)		(0.114)	(0.170)		(0.184)	(1.186)		(1.194)
December	0.041		0.021	-0.083		-0.057	-0.460		-0.503	0.254		0.229	-0.236*		-0.241*	-1.177		-1.193
	(0.083)		(0.086)	(0.156)		(0.160)	(0.471)		(0.464)	(0.151)		(0.148)	(0.123)		(0.129)	(1.084)		(1.076)
January	0.250***		0.233***	-0.112		-0.095	-0.468		-0.521	0.206*		0.173	-0.490**		-0.500**	-1.052		-1.080
	(0.080)		(0.084)	(0.170)		(0.174)	(0.423)		(0.440)	(0.106)		(0.103)	(0.181)		(0.194)	(0.935)		(0.929)
February	0.200**		0.189**	-0.204		-0.177	-0.310		-0.372	0.202		0.172	-0.167		-0.175	-0.845		-0.878
	(0.086)		(0.086)	(0.155)		(0.158)	(0.655)		(0.682)	(0.121)		(0.119)	(0.166)		(0.165)	(1.175)		(1.165)
March	0.415***		0.381***	0.032		0.049	-0.600		-0.679	0.383**		0.350**	-0.010		-0.016	-1.005		-1.046
	(0.131)		(0.126)	(0.178)		(0.185)	(0.406)		(0.420)	(0.164)		(0.158)	(0.219)		(0.219)	(1.106)		(1.097)
April	0.142		0.100	-0.146		-0.113	-0.754**		-0.886**	0.177*		0.143	-0.130		-0.138	-0.516		-0.565
	(0.087)		(0.085)	(0.158)		(0.165)	(0.332)		(0.386)	(0.101)		(0.107)	(0.178)		(0.184)	(1.075)		(1.047)
Month Dummy (09/10 Crop Year)																		
(Compared with May)																		
June	0.040		0.050	0.063		0.092	1.562**		1.567**	0.210		0.201	0.232		0.218	0.166		0.157
	(0.107)		(0.103)	(0.151)		(0.152)	(0.764)		(0.761)	(0.130)		(0.131)	(0.138)		(0.139)	(0.197)		(0.209)
July	0.050		0.036	-0.094		-0.095	0.525		0.572	0.100		0.109	0.032		0.040	0.295		0.261
	(0.147)		(0.148)	(0.157)		(0.156)	(0.530)		(0.535)	(0.076)		(0.075)	(0.059)		(0.057)	(0.338)		(0.342)
August	-0.050		-0.070	0.015		0.022	0.303		0.285	-0.007		-0.015	-0.065		-0.100	-0.054		-0.161
	(0.128)		(0.124)	(0.185)		(0.188)	(0.527)		(0.528)	(0.163)		(0.170)	(0.110)		(0.125)	(0.392)		(0.403)
September	-0.205		-0.218*	0.083		0.074	0.332		0.331	-0.047		-0.093	0.096		0.033	0.052		-0.027
	(0.130)		(0.128)	(0.159)		(0.159)	(0.670)		(0.673)	(0.128)		(0.134)	(0.094)		(0.099)	(0.282)		(0.302)
October	-0.278***		-0.290***	0.043		0.057	-0.339		-0.324	-0.138		-0.190**	0.048		-0.077	-0.163		-0.439
	(0.100)		(0.095)	(0.116)		(0.125)	(0.283)		(0.289)	(0.081)		(0.091)	(0.123)		(0.136)	(0.349)		(0.294)
November	-0.236**		-0.249**	-0.020		0.017	-0.314		-0.277	-0.186		-0.236*	0.051		-0.078	-0.113		-0.442
	(0.114)		(0.109)	(0.151)		(0.155)	(0.249)		(0.247)	(0.116)		(0.115)	(0.228)		(0.243)	(0.382)		(0.360)
December	-0.140		-0.139	0.355**		0.399**	0.252		0.268	-0.025		-0.074	0.087		-0.036	-0.157		-0.484
	(0.135)		(0.127)	(0.161)		(0.161)	(0.485)		(0.489)	(0.125)		(0.119)	(0.221)		(0.229)	(0.376)		(0.335)
January	0.138		0.138	0.304		0.359	-0.553		-0.562	-0.007		-0.055	0.163		0.039	0.016		-0.314
	(0.150)		(0.144)	(0.252)		(0.235)	(0.358)		(0.365)	(0.102)		(0.096)	(0.203)		(0.227)	(0.311)		(0.258)
February	0.044		0.039	0.115		0.166	0.346		0.318	0.043		0.003	0.043		-0.077	0.536		0.175
	(0.127)		(0.117)	(0.161)		(0.157)	(0.428)		(0.417)	(0.107)		(0.117)	(0.205)		(0.219)	(0.662)		(0.616)
March	0.232		0.248*	0.235**		0.288**	-0.354		-0.361	0.041		0.002	0.204		0.084	-0.030		-0.392
	(0.152)		(0.144)	(0.111)		(0.114)	(0.346)		(0.354)	(0.107)		(0.120)	(0.245)		(0.253)	(0.321)		(0.266)
April	-0.056		-0.055	0.046		0.124	-0.398*		-0.400	-0.119		-0.159	0.131		0.003	0.035		-0.409
	(0.101)		(0.090)	(0.130)		(0.120)	(0.227)		(0.248)	(0.120)		(0.109)	(0.211)		(0.236)	(0.296)		(0.319)

Table C.1 Estimation Results (HH Fixed Effects vs Year Variant HH Fixed Effects): Continued

	NBH									BH								
	Staple Food			Other Food			Non Food			Staple Food			Other Food			Non Food		
	HH	dif	YHH	HH	dif	YHH	HH	dif	YHH	HH	dif	YHH	HH	dif	YHH	HH	dif	YHH
Month Dummy (10/11 Crop Year)																		
(Compared with May)																		
June	0.072		0.068	-0.191**		-0.181**	-0.451		-0.479	0.070		0.072	0.247		0.217	0.406		0.283
	(0.075)		(0.075)	(0.092)		(0.089)	(0.432)		(0.425)	(0.139)		(0.136)	(0.150)		(0.156)	(0.653)		(0.608)
July	-0.005		-0.008	-0.174		-0.184	0.312		0.334	0.134		0.161	0.058		0.049	0.739		0.499
	(0.093)		(0.097)	(0.118)		(0.116)	(0.777)		(0.777)	(0.279)		(0.246)	(0.159)		(0.165)	(0.710)		(0.671)
August	-0.015		-0.029	-0.100		-0.106	-0.225		-0.273	0.193		0.234	0.106		0.163	0.044		-0.102
	(0.074)		(0.075)	(0.124)		(0.124)	(0.407)		(0.405)	(0.282)		(0.269)	(0.315)		(0.303)	(0.913)		(0.947)
September	0.148		0.133	-0.001		-0.009	-0.396		-0.423	0.405**		0.363*	-0.158		-0.021	0.738		1.101
	(0.115)		(0.114)	(0.104)		(0.101)	(0.543)		(0.536)	(0.173)		(0.188)	(0.242)		(0.253)	(0.937)		(1.138)
Octobor	-0.208***		-0.228***	0.054		0.046	-0.531		-0.566	0.250		0.186	-0.014		0.037	-0.583		-0.369
	(0.065)		(0.067)	(0.098)		(0.095)	(0.513)		(0.506)	(0.399)		(0.381)	(0.214)		(0.236)	(0.728)		(0.705)
November	-0.135*		-0.147**	-0.006		-0.003	-0.687**		-0.711**	-0.241		-0.318	0.124		0.182	2.810		3.101
	(0.070)		(0.071)	(0.113)		(0.108)	(0.270)		(0.267)	(0.318)		(0.320)	(0.185)		(0.198)	(2.419)		(2.590)
December	0.037		0.020	0.719***		0.708***	0.854		0.851	-0.112		-0.175	0.547		0.602	-0.738		-0.552
	(0.097)		(0.097)	(0.157)		(0.155)	(0.978)		(0.971)	(0.174)		(0.165)	(0.382)		(0.379)	(0.797)		(0.757)
January	-0.101		-0.121	0.143		0.143	-0.723		-0.750	-0.311		-0.389	0.106		0.152	-0.444		-0.282
	(0.070)		(0.074)	(0.113)		(0.104)	(0.484)		(0.481)	(0.283)		(0.289)	(0.247)		(0.249)	(0.707)		(0.624)
February	-0.040		-0.052	0.084		0.104	-0.127		-0.135	0.176		0.109	0.066		0.122	0.398		0.625
	(0.079)		(0.079)	(0.122)		(0.112)	(0.590)		(0.582)	(0.168)		(0.178)	(0.200)		(0.197)	(0.940)		(0.997)
March	-0.039		-0.064	0.161		0.176	-0.560		-0.605	-0.003		-0.074	0.497		0.554*	0.096		0.322
	(0.087)		(0.084)	(0.132)		(0.127)	(0.459)		(0.456)	(0.164)		(0.163)	(0.336)		(0.318)	(0.775)		(0.819)
April	-0.075		-0.121	0.096		0.139	0.072		-0.048	-0.108		-0.178	1.432		1.479	4.030		4.195
	(0.083)		(0.081)	(0.114)		(0.110)	(0.328)		(0.326)	(0.183)		(0.191)	(0.888)		(0.875)	(3.444)		(3.561)
Month Dummy* Dummy=1 if growing maize in dry season																		
June	0.093		0.095	0.173*		0.164	0.436		0.484	0.012		0.017	0.241		0.241	0.043		0.021
	(0.079)		(0.078)	(0.097)		(0.100)	(0.478)		(0.479)	(0.140)		(0.140)	(0.164)		(0.163)	(0.424)		(0.423)
July	0.019		0.023	0.046		0.061	-0.332		-0.374	0.017		0.014	0.348***		0.326***	-0.322		-0.390
	(0.126)		(0.126)	(0.130)		(0.132)	(0.793)		(0.804)	(0.175)		(0.173)	(0.116)		(0.114)	(0.525)		(0.502)
August	-0.052		-0.034	0.162		0.173	0.006		0.004	-0.082		-0.073	0.520***		0.481***	0.326		0.226
	(0.098)		(0.093)	(0.139)		(0.140)	(0.421)		(0.427)	(0.174)		(0.177)	(0.139)		(0.128)	(0.596)		(0.579)
September	0.060		0.082	0.067		0.108	-0.227		-0.240	-0.164		-0.124	0.288**		0.255*	0.401		0.183
	(0.167)		(0.166)	(0.115)		(0.117)	(0.566)		(0.565)	(0.146)		(0.153)	(0.135)		(0.137)	(0.598)		(0.572)
Octobor	0.007		0.026	0.079		0.109	0.334		0.325	-0.108		-0.066	0.287**		0.313**	0.513		0.494
	(0.083)		(0.078)	(0.116)		(0.120)	(0.350)		(0.355)	(0.162)		(0.161)	(0.116)		(0.127)	(0.601)		(0.555)
November	0.026		0.031	0.231**		0.243**	0.341		0.303	-0.010		0.040	0.342		0.362*	0.794		0.692
	(0.089)		(0.085)	(0.113)		(0.113)	(0.299)		(0.306)	(0.158)		(0.161)	(0.198)		(0.206)	(0.838)		(0.819)
December	0.077		0.086	0.035		0.056	-0.283		-0.296	0.007		0.059	0.508**		0.518**	0.255		0.132
	(0.094)		(0.090)	(0.164)		(0.164)	(0.556)		(0.557)	(0.195)		(0.198)	(0.190)		(0.188)	(0.583)		(0.595)
January	-0.024		-0.026	0.039		0.050	0.626		0.609	-0.007		0.038	0.357*		0.365*	0.169		0.088
	(0.093)		(0.093)	(0.147)		(0.145)	(0.391)		(0.397)	(0.159)		(0.160)	(0.182)		(0.189)	(0.510)		(0.528)
February	-0.005		-0.022	0.057		0.075	0.156		0.124	-0.138		-0.098	0.262		0.268	-0.440		-0.485
	(0.091)		(0.086)	(0.130)		(0.129)	(0.494)		(0.501)	(0.136)		(0.139)	(0.215)		(0.212)	(0.736)		(0.753)
March	0.061		0.066	-0.088		-0.060	0.128		0.129	0.053		0.093	0.040		0.045	-0.163		-0.213
	(0.097)		(0.089)	(0.130)		(0.129)	(0.353)		(0.371)	(0.119)		(0.121)	(0.266)		(0.257)	(0.531)		(0.549)
April	-0.155*		-0.137*	0.093		0.093	0.530*		0.560*	0.244		0.274	0.235		0.259	1.356		1.484*
	(0.078)		(0.072)	(0.114)		(0.114)	(0.282)		(0.322)	(0.206)		(0.203)	(0.258)		(0.268)	(0.870)		(0.854)

Table C.1 Estimation Results (HH Fixed Effects vs Year Variant HH Fixed Effects): Continued

	NBH									BH								
	Staple Food			Other Food			Non Food			Staple Food			Other Food			Non Food		
	HH	dif	YHH	HH	dif	YHH	HH	dif	YHH	HH	dif	YHH	HH	dif	YHH	HH	dif	YHH
Year-variant control variables																		
Number of cattle	0.011			0.034**			0.014			-0.020			-0.121***			-0.303**		
	(0.008)			(0.015)			(0.028)			(0.018)			(0.032)			(0.112)		
Month-variant control variables																		
Number of male HH member	-0.048		-0.175**	-0.216***		-0.189***	-0.260		-0.248	-0.116**		-0.129**	-0.104		-0.136	0.264		-0.153
	(0.035)		(0.070)	(0.072)		(0.068)	(0.208)		(0.336)	(0.052)		(0.059)	(0.076)		(0.096)	(0.187)		(0.211)
Number of female HH member	-0.188***		-0.156***	-0.262***		-0.118**	-0.157		-0.296	-0.313***		-0.243*	-0.404***		-0.380**	0.277		0.051
	(0.041)		(0.038)	(0.074)		(0.053)	(0.202)		(0.215)	(0.083)		(0.127)	(0.119)		(0.150)	(0.437)		(0.263)
Number of child HH member (0-3 years)	-0.087**		0.003	-0.096**		-0.015	-0.203		0.153	0.046		-0.010	-0.037		0.073	-0.385		0.519**
	(0.041)		(0.048)	(0.045)		(0.071)	(0.140)		(0.133)	(0.064)		(0.091)	(0.083)		(0.109)	(0.342)		(0.186)
Number of child HH member (4-6 years)	-0.210***		-0.348**	-0.196***		-0.440*	-0.366**		-0.097	-0.069		-0.170	-0.326*		-0.600***	-0.352		-0.926***
	(0.054)		(0.133)	(0.068)		(0.238)	(0.175)		(0.219)	(0.110)		(0.113)	(0.165)		(0.164)	(0.277)		(0.209)
Number of child HH member (7-9 years)	-0.158***		-0.041	-0.221***		-0.011	-0.311**		0.061	-0.205**		-0.514***	-0.525***		-0.403***	-0.265		0.727
	(0.055)		(0.070)	(0.067)		(0.134)	(0.126)		(0.141)	(0.096)		(0.119)	(0.123)		(0.137)	(0.294)		(0.489)
Number of child HH member (10-12 years)	-0.117**		-0.077	-0.084*		0.051	-0.141		-0.226	-0.199***		0.053	-0.515***		-0.038	-0.340		0.196
	(0.051)		(0.068)	(0.047)		(0.091)	(0.151)		(0.382)	(0.048)		(0.049)	(0.124)		(0.123)	(0.201)		(0.210)
Fixed Effect																		
Period * Village	Yes		-	Yes		-	Yes		-	Yes		-	Yes		-	Yes		-
Household	Yes		-	Yes		-	Yes		-	Yes		-	Yes		-	Yes		-
Period * Household	No		Yes	No		Yes	No		Yes	No		Yes	No		Yes	No		Yes
Observations	5,132		5,132	5,132		5,132	5,132		5,132	1,681		1,681	1,681		1,681	1,681		1,681
R-squared	0.191		0.226	0.248		0.288	0.086		0.100	0.324		0.333	0.234		0.244	0.100		0.114

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table C.2: Estimation Results (No Adjustment of Adult Equivalent)

	NBH				BH			
VARIABLES	Total	Staple	Other Food	Non Food	Total	Staple	Other Food	Non Food
Income Shock * Month Dummy								
May	-0.259	-0.183	-0.148	-0.742	-0.432**	0.004	-0.635*	-0.902
	(0.366)	(0.276)	(0.377)	(0.992)	(0.168)	(0.220)	(0.310)	(0.673)
June	-0.025	0.076	0.060	-0.497	-0.547***	0.008	-0.869***	-0.971**
	(0.262)	(0.233)	(0.251)	(0.991)	(0.147)	(0.163)	(0.239)	(0.357)
July	-0.009	-0.024	0.123	-0.337	-0.413***	-0.093	-0.404***	-1.191***
	(0.227)	(0.254)	(0.229)	(0.745)	(0.073)	(0.111)	(0.109)	(0.330)
August	0.102	0.039	-0.109	0.833	-0.417***	-0.156	-0.397*	-1.084**
	(0.205)	(0.193)	(0.183)	(0.702)	(0.088)	(0.117)	(0.203)	(0.383)
September	-0.199	0.043	-0.109	-1.011	-0.514**	-0.255	-0.337	-1.610
	(0.325)	(0.201)	(0.259)	(1.323)	(0.192)	(0.251)	(0.200)	(1.099)
Octobor	0.119	0.147	0.121	0.048	-0.346*	-0.041	-0.480*	-0.692
	(0.254)	(0.161)	(0.251)	(0.805)	(0.183)	(0.161)	(0.276)	(0.402)
November	-0.094	0.142	-0.203	-0.350	-1.026*	-0.100	-0.726*	-4.027
	(0.201)	(0.226)	(0.229)	(0.710)	(0.544)	(0.152)	(0.368)	(2.650)
December	-0.106	0.250	-0.164	-0.787	-0.298**	-0.118	-0.535**	-0.072
	(0.281)	(0.223)	(0.208)	(1.099)	(0.136)	(0.157)	(0.231)	(0.342)
January	0.107	0.015	0.278	-0.145	-0.177*	0.053	-0.306**	-0.365
	(0.332)	(0.226)	(0.469)	(0.849)	(0.097)	(0.109)	(0.111)	(0.302)
February	-0.105	0.057	0.109	-1.074	-0.456***	-0.415**	-0.312*	-0.948**
	(0.274)	(0.228)	(0.223)	(1.012)	(0.080)	(0.164)	(0.165)	(0.430)
March	0.085	0.055	0.072	0.192	-0.610***	-0.219	-0.939***	-0.632
	(0.242)	(0.220)	(0.247)	(0.695)	(0.182)	(0.158)	(0.330)	(0.367)
April	-0.114	-0.000	-0.000	-0.695	-1.665*	-0.222	-1.698*	-4.975
	(0.291)	(0.206)	(0.307)	(0.817)	(0.958)	(0.130)	(0.878)	(3.503)
Income Shock * Month Dummy * Cattle								
May	0.014	0.048	-0.017	0.021	0.018	0.147	0.151	-0.650*
	(0.035)	(0.030)	(0.039)	(0.089)	(0.126)	(0.102)	(0.152)	(0.356)
June	-0.034	-0.021	-0.022	-0.094	0.049	-0.049	0.324*	-0.477
	(0.030)	(0.029)	(0.029)	(0.157)	(0.195)	(0.222)	(0.158)	(0.472)
July	-0.029	-0.029	-0.022	-0.047	-0.047	-0.027	0.062	-0.394
	(0.021)	(0.028)	(0.026)	(0.048)	(0.206)	(0.217)	(0.225)	(0.465)
August	-0.008	0.003	-0.008	-0.035	0.136	0.142	0.142	0.106
	(0.025)	(0.021)	(0.024)	(0.103)	(0.181)	(0.113)	(0.230)	(0.463)
September	0.046	0.038	0.006	0.170	0.075	0.310***	0.171	-0.739
	(0.027)	(0.031)	(0.031)	(0.154)	(0.145)	(0.104)	(0.181)	(0.455)
Octobor	-0.015	-0.004	-0.023	-0.018	0.083	0.207**	0.170	-0.447
	(0.024)	(0.021)	(0.028)	(0.061)	(0.158)	(0.074)	(0.207)	(0.354)
November	-0.006	-0.021	-0.006	0.031	-0.005	0.223**	0.191	-1.076
	(0.024)	(0.027)	(0.035)	(0.055)	(0.182)	(0.088)	(0.177)	(0.637)
December	0.024	-0.023	0.062*	0.029	0.153	0.043	0.343**	-0.108
	(0.024)	(0.023)	(0.031)	(0.069)	(0.118)	(0.131)	(0.137)	(0.385)
January	-0.019	-0.007	-0.056	0.050	0.086	0.030	0.227	-0.169
	(0.030)	(0.024)	(0.046)	(0.077)	(0.135)	(0.091)	(0.142)	(0.405)
February	0.031	0.027	0.028	0.051	0.348***	0.391***	0.473***	-0.094
	(0.025)	(0.028)	(0.026)	(0.072)	(0.112)	(0.083)	(0.131)	(0.410)
March	-0.011	-0.016	-0.014	0.009	0.309**	0.183**	0.522***	0.025
	(0.026)	(0.031)	(0.029)	(0.057)	(0.123)	(0.082)	(0.149)	(0.390)
April	0.032	0.047**	0.007	0.066	-0.142	-0.060	0.104	-1.010
	(0.024)	(0.022)	(0.027)	(0.068)	(0.231)	(0.102)	(0.248)	(0.787)

Table C.2 Estimation Results (No Adjustment of Adult Equivalent): Continued

	NBH				BH			
VARIABLES	Total	Staple	Other Food	Non Food	Total	Staple	Other Food	Non Food
Month Dummy (08/09 Crop Year)								
(Compared with May)								
June	-0.067	0.029	-0.034	-0.382	-0.155	0.067	-0.206	-0.537
	(0.103)	(0.081)	(0.141)	(0.478)	(0.095)	(0.083)	(0.152)	(0.725)
July	0.207	0.188	-0.043	0.938	-0.166	0.075	-0.310**	-0.335
	(0.247)	(0.182)	(0.191)	(1.087)	(0.122)	(0.111)	(0.118)	(0.637)
August	-0.033	0.185	-0.143	-0.241	-0.154	0.187	-0.247*	-0.704
	(0.125)	(0.125)	(0.174)	(0.585)	(0.130)	(0.160)	(0.141)	(0.854)
September	0.132	0.034	-0.077	0.938	-0.164	0.160	-0.269**	-0.639
	(0.199)	(0.111)	(0.148)	(1.048)	(0.138)	(0.153)	(0.124)	(0.714)
Octobor	-0.232**	-0.124	-0.159	-0.687**	-0.153	0.104	-0.203**	-0.619
	(0.097)	(0.089)	(0.157)	(0.337)	(0.114)	(0.137)	(0.075)	(0.793)
November	-0.205**	-0.066	-0.147	-0.690*	0.045	0.143	-0.234	0.580
	(0.096)	(0.100)	(0.161)	(0.389)	(0.207)	(0.119)	(0.153)	(1.076)
December	-0.112	0.021	-0.078	-0.517	-0.192*	0.218	-0.291**	-0.889
	(0.111)	(0.084)	(0.146)	(0.469)	(0.110)	(0.137)	(0.127)	(0.840)
January	-0.044	0.236***	-0.111	-0.521	-0.297***	0.167*	-0.515***	-0.795
	(0.114)	(0.078)	(0.168)	(0.419)	(0.098)	(0.090)	(0.177)	(0.731)
February	-0.036	0.180**	-0.167	-0.187	-0.119	0.162	-0.196	-0.566
	(0.149)	(0.088)	(0.143)	(0.759)	(0.155)	(0.110)	(0.172)	(0.921)
March	0.087	0.392***	0.085	-0.626	-0.029	0.305*	-0.062	-0.723
	(0.101)	(0.132)	(0.175)	(0.404)	(0.169)	(0.150)	(0.202)	(0.857)
April	-0.124	0.128	-0.101	-0.783**	-0.028	0.157	-0.135	-0.170
	(0.100)	(0.094)	(0.154)	(0.340)	(0.192)	(0.096)	(0.191)	(0.957)
Month Dummy (09/10 Crop Year)								
(Compared with May)								
June	0.299*	0.030	0.072	1.555*	0.192***	0.202*	0.181	0.199
	(0.171)	(0.101)	(0.150)	(0.803)	(0.061)	(0.113)	(0.126)	(0.170)
July	0.043	0.019	-0.104	0.499	0.090	0.090	0.020	0.280
	(0.163)	(0.138)	(0.173)	(0.505)	(0.070)	(0.072)	(0.057)	(0.314)
August	0.013	-0.067	-0.006	0.250	-0.053	-0.014	-0.076	-0.082
	(0.131)	(0.123)	(0.182)	(0.504)	(0.098)	(0.143)	(0.113)	(0.357)
September	0.018	-0.203	0.071	0.393	0.030	-0.033	0.084	0.029
	(0.180)	(0.131)	(0.172)	(0.722)	(0.080)	(0.116)	(0.095)	(0.288)
Octobor	-0.139	-0.269**	0.049	-0.353	-0.053	-0.132*	0.044	-0.131
	(0.089)	(0.104)	(0.112)	(0.290)	(0.085)	(0.074)	(0.131)	(0.329)
November	-0.159	-0.243**	-0.027	-0.325	-0.070	-0.161	0.023	-0.109
	(0.101)	(0.117)	(0.160)	(0.261)	(0.153)	(0.110)	(0.231)	(0.418)
December	0.117	-0.151	0.326*	0.175	-0.001	-0.014	0.052	-0.118
	(0.152)	(0.135)	(0.165)	(0.469)	(0.161)	(0.111)	(0.239)	(0.354)
January	0.085	0.134	0.279	-0.561	0.072	0.006	0.140	0.040
	(0.179)	(0.154)	(0.272)	(0.355)	(0.138)	(0.091)	(0.195)	(0.309)
February	0.108	0.030	0.098	0.316	0.097	0.035	-0.020	0.567
	(0.121)	(0.126)	(0.162)	(0.444)	(0.150)	(0.083)	(0.220)	(0.637)
March	0.134	0.222	0.237*	-0.359	0.081	0.025	0.154	0.011
	(0.107)	(0.152)	(0.124)	(0.355)	(0.131)	(0.083)	(0.254)	(0.324)
April	-0.066	-0.052	0.056	-0.435*	-0.001	-0.078	0.065	-0.002
	(0.107)	(0.108)	(0.151)	(0.239)	(0.127)	(0.123)	(0.222)	(0.371)

Table C.2 Estimation Results (No Adjustment of Adult Equivalent): Continued

	NBH				BH			
VARIABLES	Total	Staple	Other Food	Non Food	Total	Staple	Other Food	Non Food
Month Dummy (10/11 Crop Year)								
(Compared with May)								
June	-0.145	0.058	-0.175*	-0.540	0.236**	0.059	0.262*	0.581
	(0.092)	(0.072)	(0.087)	(0.453)	(0.097)	(0.136)	(0.143)	(0.555)
July	-0.054	-0.032	-0.169	0.210	0.231*	0.143	0.102	0.791
	(0.157)	(0.090)	(0.113)	(0.747)	(0.129)	(0.313)	(0.167)	(0.667)
August	-0.100	-0.033	-0.099	-0.258	0.182	0.201	0.185	0.129
	(0.091)	(0.072)	(0.120)	(0.410)	(0.155)	(0.306)	(0.327)	(0.851)
September	-0.019	0.137	-0.002	-0.434	0.261	0.420**	-0.164	1.051
	(0.132)	(0.114)	(0.099)	(0.559)	(0.242)	(0.161)	(0.255)	(1.012)
Octobor	-0.131	-0.196***	0.078	-0.554	0.021	0.226	0.008	-0.425
	(0.126)	(0.069)	(0.104)	(0.531)	(0.211)	(0.413)	(0.226)	(0.609)
November	-0.172**	-0.136*	0.000	-0.726**	0.593	-0.263	0.202	3.679
	(0.084)	(0.078)	(0.107)	(0.284)	(0.600)	(0.374)	(0.190)	(2.931)
December	0.474**	0.043	0.747***	0.738	0.139	-0.145	0.671	-0.652
	(0.221)	(0.100)	(0.169)	(0.931)	(0.194)	(0.183)	(0.440)	(0.679)
January	-0.083	-0.094	0.173	-0.762	-0.112	-0.373	0.187	-0.316
	(0.122)	(0.076)	(0.129)	(0.496)	(0.153)	(0.335)	(0.260)	(0.683)
February	0.020	-0.032	0.113	-0.117	0.190	0.176	0.094	0.484
	(0.142)	(0.092)	(0.133)	(0.604)	(0.136)	(0.164)	(0.223)	(0.871)
March	-0.021	-0.037	0.202	-0.596	0.279	-0.050	0.580	0.227
	(0.137)	(0.096)	(0.156)	(0.476)	(0.201)	(0.158)	(0.394)	(0.712)
April	0.053	-0.057	0.138	0.082	1.623	-0.089	1.741	5.330
	(0.117)	(0.108)	(0.127)	(0.345)	(1.235)	(0.210)	(1.094)	(4.265)
Month Dummy* Dummy=1 if growing maize in dry season								
June	0.209*	0.118	0.158*	0.565	0.114	0.009	0.261	-0.042
	(0.110)	(0.076)	(0.092)	(0.516)	(0.086)	(0.131)	(0.152)	(0.356)
July	-0.006	0.050	0.027	-0.227	0.101	0.031	0.336***	-0.379
	(0.168)	(0.122)	(0.125)	(0.727)	(0.110)	(0.180)	(0.107)	(0.468)
August	0.066	-0.034	0.157	0.048	0.257*	-0.067	0.522***	0.297
	(0.096)	(0.096)	(0.132)	(0.407)	(0.126)	(0.167)	(0.136)	(0.517)
September	0.024	0.068	0.060	-0.179	0.139	-0.179	0.296**	0.459
	(0.142)	(0.167)	(0.112)	(0.573)	(0.137)	(0.142)	(0.130)	(0.583)
Octobor	0.065	-0.011	0.039	0.317	0.152	-0.098	0.277**	0.398
	(0.103)	(0.087)	(0.116)	(0.363)	(0.106)	(0.162)	(0.112)	(0.518)
November	0.166*	0.026	0.218**	0.354	0.300	-0.015	0.342*	0.924
	(0.084)	(0.094)	(0.108)	(0.304)	(0.204)	(0.159)	(0.193)	(0.928)
December	0.018	0.092	0.039	-0.215	0.263*	0.006	0.523**	0.156
	(0.156)	(0.098)	(0.176)	(0.538)	(0.147)	(0.187)	(0.205)	(0.486)
January	0.113	-0.012	0.029	0.642	0.170	-0.004	0.344*	0.101
	(0.119)	(0.099)	(0.160)	(0.391)	(0.124)	(0.159)	(0.168)	(0.435)
February	0.042	0.011	0.045	0.107	-0.028	-0.127	0.240	-0.530
	(0.124)	(0.100)	(0.132)	(0.530)	(0.140)	(0.124)	(0.209)	(0.644)
March	0.001	0.076	-0.111	0.131	-0.007	0.060	0.023	-0.249
	(0.105)	(0.103)	(0.139)	(0.357)	(0.137)	(0.100)	(0.248)	(0.448)
April	0.060	-0.164*	0.069	0.565*	0.459	0.204	0.288	1.529
	(0.090)	(0.088)	(0.119)	(0.289)	(0.298)	(0.197)	(0.298)	(1.047)

Table C.2 Estimation Results (No Adjustment of Adult Equivalent): Continued

	NBH				BH			
VARIABLES	Total	Staple	Other Food	Non Food	Total	Staple	Other Food	Non Food
Year-variant control variables								
Number of cattle	0.022**	0.011	0.035**	0.015	-0.100***	0.003	-0.109***	-0.318**
	(0.010)	(0.008)	(0.016)	(0.028)	(0.030)	(0.019)	(0.037)	(0.127)
Month-variant control variables	-0.163**	-0.039	-0.231***	-0.270	-0.030	-0.098	-0.067	0.230
Number of male HH member	(0.065)	(0.040)	(0.082)	(0.220)	(0.063)	(0.057)	(0.090)	(0.198)
	-0.216***	-0.173***	-0.269***	-0.169	-0.272**	-0.333***	-0.485***	0.453
Number of female HH member	(0.066)	(0.044)	(0.092)	(0.216)	(0.122)	(0.064)	(0.147)	(0.525)
Number of child HH member (0-3 years)	-0.186***	-0.156***	-0.178***	-0.280*	-0.145	-0.027	-0.103	-0.536
	(0.050)	(0.048)	(0.053)	(0.150)	(0.095)	(0.059)	(0.094)	(0.390)
Number of child HH member (4-6 years)	-0.293***	-0.258***	-0.276***	-0.420**	-0.170	-0.051	-0.239	-0.264
	(0.071)	(0.062)	(0.087)	(0.182)	(0.124)	(0.091)	(0.172)	(0.329)
Number of child HH member (7-9 years)	-0.241***	-0.170***	-0.261***	-0.351**	-0.341***	-0.215**	-0.509***	-0.176
	(0.055)	(0.059)	(0.077)	(0.131)	(0.114)	(0.090)	(0.135)	(0.340)
Number of child HH member (10-12 years)	-0.127***	-0.141**	-0.106*	-0.150	-0.427***	-0.253***	-0.567***	-0.456*
	(0.046)	(0.057)	(0.055)	(0.156)	(0.094)	(0.051)	(0.138)	(0.243)
Fixed Effect								
Period * Village	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Period * household	No	No	No	No	No	No	No	No
(i) F-statistics		F(12,43)				F(12,20)		
(Income Shock * Month Dummy)	0.59	0.64	0.57	1.01	30.86	6.44	12.92	2.35
p-value	0.8387	0.7920	0.8540	0.4536	0.0000	0.0001	0.0000	0.0000
(ii) F-statistics		F(12,43)				F(12,20)		
(Income Shock * Month Dummy * Cattle)	3.23	44.65	2.94	0.84	22.76	41.07	8.55	3.53
p-value	0.0023	0.0001	0.0046	0.6132	0.0000	0.0000	0.0000	0.0062
Observations	5,132	5,132	5,132	5,132	1,681	1,681	1,681	1,681
R-squared	0.218	0.228	0.265	0.083	0.221	0.413	0.274	0.102

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1