Evaluation of Food Assistance Programs and Implications of Patients' Health Information Seeking

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Abstract

The first part of this dissertation evaluates the effectiveness of food assistance by gathering evidence from developing countries and the United States. The first essay applies a multi-market model to three developing countries and simulate recent spikes in staple prices and food aid impacts. Results indicate that higher food prices would result in reduction in household real income and deterioration of household welfare. Food aid in the form of cash transfers targeted at low-income groups could improve household real income of the target group after world price shocks and, partially or completely, offset the negative impacts of higher food prices. The impact of cash transfer on untargeted groups is ambiguous. It is likely to be positive for households that are net producers of the commodities that have increased production and prices under cash transfer and the production surplus is sufficiently large. The second essay focuses on the Food Stamp Program (FSP), a cornerstone of food assistance safety net efforts in the U.S. to reduce household food insecurity, particularly among children. The essay examines the dynamic relationship between FSP participation and child food security using monthly measures. Empirical estimates using the Panel Study of Income Dynamics demonstrate that child food security declines in the months immediately prior to FSP entrance, but then partially recovers following program

entrance. These dynamic FSP effects are masked when annual measures are employed.

The third paper of this dissertation studies the potential impacts of patient's widespread use of online health information. In particular, the essay employs a principal agent model and focuses on the quality of online health information. The model shows that when the quality of health information improves, since medical consultations become more efficient and less costly, a higher effort will be induced or contracted from the physician. Diagnosis becomes more accurate, because physicians will try exert more effort in diagnosing patients and patients will suffer less loss from their illnesses.

DEDICATION

I dedicate this dissertation to my parents.
To my mother,
who stands right next to me every step of my life with
unconditional love.
To my father,
who has nurtured my life with his firm belief in dreams and
powerful words of encouragement.

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CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1

INTRODUCTION

In spite of advanced technological development and an aggregate surplus of food, currently throughout the world, many households still struggle to obtain enough food for a nutritious diet. Concerns about food security have been heightened by unprecedented spikes in world food prices and the global economic crisis. In response to needy households' vulnerability to food uncertainties, governments and international organizations worldwide maintain food assistance programs that serve as an important social safety net to low-income families with food difficulties.

Food challenges unfold in different ways for households living in developing and developed countries. In developing countries and in particular, low-income countries highly dependent on food imports, households are especially vulnerable to volatile and, as seen in recent years, skyrocketing international food prices. In developed countries, however, food prices are of less importance, but economic shocks such as unemployment brought by the recent economic downturn render many households food insecure. In addition, food assistance programs play an important role in the welfare system as a consistent safeguard for vulnerable families. But factors such as mental distress and social stigma may prevent needy households from seeking help from food assistance programs.

In the literature the interrelationship of food sufficiency (or food security), food prices and food assistance programs has been studied extensively, but a few facets still need further exploration. In developing countries several papers have focused on the impacts of recent food price increases on household welfare. Previous papers have extensively studied the efficacy of international food aid. But the impacts of both food assistance and international staple price increases are likely to differ by the structure of food economy and the types of households within the economy. Also a more synthesized analysis is needed to provide a broader view of the impacts of food price increases in the international markets, not only on the well-being of households but also on the agricultural sectors for developing countries. Meanwhile, it is important to understand the effects of food aid provided in the face of rising food prices, not only in terms of the efficacy of food assistance for targeted groups but also the spillover effects on untargeted groups and the agricultural sector.

Domestically, most papers examine household food security and the Food Stamp Program (FSP). A vast body of literature is devoted to studying the effects of the FSP on household food security using annual measures but counter-intuitively only a handful of papers have found a positive impact of the FSP on food security. The lack of evidence of empirical impact may be, in part, due to the relative short time-frame within which households self-select into the program. Empirical data suggests that changes in food security occur over a time frame far shorter than a year and there is a need to employ intra-annual measures to more accurately assess the link between food security and the FSP. However, because most of the surveys to date have collected food security information on an annual, rather than monthly basis, intra-annual measures have rarely been employed in previous studies.

The first part of this dissertation is devoted to providing a broader picture for the landscape of food security and food assistance programs by gathering evidence from both low-income developing countries and the United States in the first two essays. The first essay, entitled "The Impact of International Food Price Spikes and Food Aid: Evidence from Multimarket Applications" documents the effects of recent spikes in food prices and the impacts of food aid in the face of high food prices by focusing on three low-income developing countries. From April 2007 to June 2008, average world food price surged by 76 percent, leading to the 2007-2008 global food crisis. The price index trended down in 2009 and early 2010, but rose sharply again from June 2010 to February 2011, by about 50 percent. Volatile food prices can be extremely challenging to the livelihood of vulnerable households in developing countries, who spend a significant proportion of disposable income on food. Food aid, often provided by international organizations such as the World Food Programme, has been in place for decades to safeguard vulnerable households' well-being.

Not surprisingly, previous studies find higher food prices to increase poverty (both headcount and gap). In fact the poor are likely to be the most adversely affected as their net food purchases constitute a larger expenditure share compared to their counterparts (Simler 2010, Wodon et al. 2008 and Ivanic and Martin 2008). There is evidence that the adverse impact of high food prices can be mitigated by households' substitution of more expensive food items with cheaper ones and the majority of gainers from high food prices live in rural areas (Ulimwengu and Ramadan 2009). On the other hand, food aid can play an important role in improving short-term food security, when adequate attention is given to targeting at vulnerable households and to mitigation of adverse price effects on producers (delNinno, Dorosh and Subbarao, 2007). Previous studies focus on either high food prices or food aid, rather than examine the two in an integrated framework. Given recent spikes in food prices and prevalence of food aid during food crisis, there is a need to study the effects of high food prices and food aid simultaneously.

The first essay uses a multimarket framework to simulate both price hikes in major agricultural commodities and food aid in response to price hikes. Three countries are under investigation: East Timor (an island economy), Kenya (an open trade economy) and Niger (a landlocked and closed economy). Households are categorized into four groups: rural food insecure, urban food insecure, rural food secure and urban food secure. Synthesis of simulation results yield several important points. First, higher food prices decrease households' real income and result in compromised household welfare in most cases. The severity of welfare deterioration depends to a large extent on the discrepancy between revenue and expenditure shares of the commodities exposed to price shocks. Second, higher international prices of commodities encourage the domestic production of both commodities at shock and substitutes for commodities at shock, for which price levels also increase. Third, cash transfer targeted to the low-income groups (rural food insecure) all, partially or completely, effectively offset the negative impacts of higher food prices. In some cases, cash transfer outweighs the negative impact of high food prices resulting in higher real income than pre-price shocks while other times the negative impact of high food prices is dominant but real income decreases by a much smaller magnitude. The impact of cash transfer on untargeted populations, however, is ambiguous.

The second essay, entitled “Child Food Security and the Food Stamp Program: What a Difference a Month Makes”, investigates in the U.S. how household participation in the Food Stamp Program affects food security among children in the household. In 2011, approximately 3.9 million households (10 percent of households with children) had food insecurity among children who did not have consistent access to adequate and safe foods. (Coleman-Jensen, McFall and Nord 2013). Food insecurity can lead to a variety of undesirable outcomes in children’s health and development: a less healthy food consumption pattern (Casey et al., 2001; Kaiser et al. 2002), higher risks of being overweight (e.g.Casey et al., 2006; Jyoti et al., 2005), adverse physical health outcomes among young children (Cook et al., 2004, Cook et al., 2006, and Skalicky et al., 2006), as well as comprised mental health, social skills and academic performance (Dunifon and Kowaleski-Jones, 2003; Howard, 2011; Alaimo, Olson and Frongillo, 2001).

The largest component of the USDA’s nutrition programs, the FSP took up 73 percent ($75.3 billion) of all federal food and nutrition spending in FY 2011. With highly undesirable outcomes of food insecurity among children and so much of the nation’s food assistance resources devoted to the FSP, it is important to document the effectiveness of the FSP in providing basic protection to food insecure populations, and to food insecure children in particular.

The effect of FSP participation on food security has been studied extensively in the literature using annual measures of both FSP participation and food security because food security information has normally been collected on a yearly basis. But empirical data suggest significant within year variations in both FSP participation and food security. Households (and children in the households) often move in and out of food security and participate in the FSP at sub-intervals within a year. The second essay uses 1999, 2001 and 2003 waves of the Panel Study of Income Dynamics, where information on food security among children and household FSP participation is available on a monthly basis. By focusing on households that become FSP participants at some point in 1998, 2000 or 2002, the paper examines how child food insecurity changes before and after a household enters the FSP. Results from a fixed effect model that controls for unobserved household heterogeneity indicate that child food insecurity first increases in months immediately before a household enters the program, and then starts decreasing once a household is in the program. This provides evidence that the FSP is effective, at least partially, in mitigating declining food security among children.

The third paper of the dissertation is devoted to studying how patients' behavior of health information seeking on the internet may affect the dynamics between patients, physicians and insurers. Information outlets online have become a significant source of health information in the U.S. Eighty percent internet users (or 59 percent adults) in the U.S. have looked online about health information on a specific disease or treatment (Fox 2011). The extensive body of literature on internet health information have surveyed the types of information sought for by patients, the timing and reasons of information search, quality of internet information, physicians' reception of health information brought to consultations by their patients and so on (e.g. Diaz et al. 2002, McMullan 2006, Powell, Darvell and Gray 2003, Sommerhalder et al. 2009, Murray et al. 2003, Lawrentschuk et al. 2012). Inquiry on the impacts of health information on healthcare outcomes, however, is quite limited in that physicians are asked to state whether they think healthcare outcomes are improved by internet information (Murray et al. 2003). On the other hand, patients' possession of extra health information has a potential to partially bridge the information gap between patients and physicians and change the dynamics of healthcare market, which is plagued by agency problems resulting from information asymmetry and unaligned incentives. Meanwhile, there are both governmental and clinic efforts that aim at improving the general public's health knowledge and providing guidelines for online health information search. Hence, it is both an interesting research question and an important policy inquiry to study how internet health information may affect clinical encounters.

The third essay entitled "A Closer Look at Patient-Physician Relationship at 'Internet Age': From a Principal-Agent Perspective" uses a principal-agent framework and considers three parties (patients, physicians and a public insurer) in the game. The public insurer is the principal who acts entirely in patients' interest and designs optimal physician payment contracts that maximizes patients' utility given a fixed amount of budget to spend per patient.

The probability of physician correctly diagnosing the patient is increasing in physician's effort. Patients' health information affects physicians' effort cost, which is decreasing in information quality. That is, when the patient has more accurate health information, the physician's communication with the patient becomes more efficient and diagnosis becomes less costly. Our model shows that no matter effort is contractible or not, when the quality of information improves, the insurer is able to either contract or induce higher effort (or input) from the physician and diagnosis becomes more accurate. As a result, the patient will bear less health loss. Meanwhile, the physician's expected compensation will increase as well since the expected treatment costs are reduced due to more accurate diagnosis. The physician's net earnings under contractible effort is always zero because no information rent can be earned with symmetric information. When effort is non-contractible, the physician's net earnings may increase or decrease depending on how physician payment and effort cost change.

CHAPTER 2

THE IMPACT OF INTERNATIONAL FOOD PRICE SPIKES AND FOOD AID: EVIDENCE FROM MULTIMARKET APPLICATIONS

2.1 Introduction

Soaring food prices have become a worldwide concern in recent years. From April 2007 to June 2008, average world food price surged by 76 percent, leading to the 2007-2008 global food crisis. The price index trended down in 2009 and early 2010, but rose sharply again from June 2010 to February 2011, by about 50 percent. Maize prices more than doubled between April 2010 and April 2011, reaching a record high of $320 per metric ton. Wheat prices also more than doubled between June 2010 and May 2011, rising from $158 to $355 per metric ton. Rice prices on international markets surged from $459 to $616 per metric ton (about 34 percent) between June 2010 and

September 2011. High food prices posit big challenges to the livelihood of poor populations in low-income countries, especially in economies that are highly dependent on food imports.

Food aid, both for short-term emergency relief and as program food aid, has served for decades as an important source of food for vulnerable households in low-income countries. Food aid by World Food Programme, for instance, provides food to more than 90 million people on average each year. In the face of sudden and unexpected food price spikes, food aid plays an especially important role in helping low-income households fight against hunger.

It is important to understand the impacts of global food price spikes, both on the welfare of households and on the agricultural sector for developing countries. Meanwhile, there is a need to assess the effects of food aid on both targeted and untargeted groups as well as the agricultural sector especially when international food prices surge to record high levels. This paper uses a multimarket framework to model the agricultural sector for three developing countries, simulating both international food price increases and international food aid targeted at poor populations to generate cross-country evidence.

2.2 Literature Review

Several recent papers have studied the implications of high food prices on poverty in developing countries and found that poor households, in many cases net buyers of food, are likely to be hurt in the face of high food prices. Simler (2010) uses the net benefit ratio (NBR) to analyze the short-term impact of observed food price increases between 2007 and 2008 for Uganda. The NBR analysis shows that in both rural and urban areas net food purchases constitute a larger expenditure share for the poor, who are consequently more vulnerable to increases in food prices. Higher food prices are estimated to increase poverty headcount ratio by 2.6 percentage points at national level, and the increase is greater for urban areas (3.6 percentage points) than rural areas (2.4 percentage points). On the contrary, poverty gap increases more for rural areas than urban areas. Regionally, the poorest region (the Northern region) is also hit hardest by high food prices, both by poverty headcount and poverty gap. Similarly, Wodon et al. (2008) simulate the impacts of hypothetical price increases on poverty for 12 West and Central African countries, adding a severity measure to poverty (squared poverty gap). Their results suggest that higher food prices lead to more poverty in all sample countries, but the magnitudes can differ a lot across individual countries. Ivanic and Martin (2008) also uses a first-order approximation of the effects of price changes on real income but incorporates the possible impacts of agricultural wage rate changes arising from food price increases. They simulate the impacts of both hypothetical and observed higher food prices (between 2005 and 2007) on real income and poverty for nine low-income countries in Asia, Africa and Latin America. Their results indicate that increases in food prices lead to increased poverty, both headcount and gap, and more for urban areas than rural areas because of concentration of net sellers in rural areas. The inclusion of wage impacts does not change the sign of price impacts on poverty, but reduces poverty rate modestly for some and sharply for others when all food prices rise. Meanwhile when individual commodity price increase is simulated, inclusion of wage impacts may even change the sign of poverty impacts. Haq, Nazli and Meilke (2008) use the almost ideal demand system to calculate for Pakistan price and expenditure elasticities, which are in turn used to compute changes in food demand and expenditures. The estimated poverty increase arising from 2007/2008 higher domestic prices is 34.8% on average, 44.6% for urban households and 32.5% for rural households.

A cross-country study by Zezza et al. (2009) goes beyond estimating the potential impacts of rising food prices on the poor, and further identifies the subgroups of the poor that are most likely to be adversely affected. They find that larger, female-headed poor households with no or low landholdings, less use of fertilizers and pesticides suffer extreme losses in the face of higher food prices in most cases. Moderate and extreme losers from price increases are prevalent in rural areas. In urban areas wealthier households are consistently less adversely affected by increases in food prices. Households that specialize in agriculture with more than 75 percent of income derived from farming actually stand to gain most from price increases.

Dessus, Herrera and de Hoyos (2008) estimates the monetary cost of food inflation using a sample of 72 developing countries by calculating the change in poverty deficit due to higher food prices. They find that for most countries, the cost represents less than 0.2% of GDP and in all countries the change in cost is mostly due to the negative real income effect of those already poor households before the price shock, rather than the newly added poor households after the price shock.

On the other hand, there has been a rich amount of literature that studies various facets of food aid. Food assistance can, if effectively disbursed, mitigate household vulnerability to food deficits. In-kind and cash transfers are likely to converge in emergency situations when food needs are high and when the transaction costs associated with selling food aid are low (Faminow, 1995). Food aid can play an important role in improving short term food security, when adequate attention is given to targeting to vulnerable households and to mitigation of adverse price effects on producers. Other mechanisms may more effectively address longer term food insecurity, including cash transfers (delNinno, Dorosh, and Subbarao, 2007).

The model developed in this paper will only examine the effects of cash transfer and will assume that market and cash-equivalent values of food assistance are equal. The near equivalence of values of in-kind food assistance and cash transfers is also supported by Webb et al. (1992), who find a high share of food aid was consumed by the Ethiopian households. Further, most respondents stated they preferred in-kind food to cash payments. Similarly, Moffitt (1989) finds that for Puerto Rico offering cash instead of food stamps has no impact on household food expenditures, most likely due to an active market for in-kind goods.

A second important concern with food aid is potential disincentives generated for agricultural production. However, the magnitude of disincentives is an open empirical question. Maxwell and Singer (1979) document labor market disincentives when wages under food-for-work programs are above prevailing market wage rates. Barrett and Maxwell (2005) note evidence of depressed food prices associated with in-kind food assistance. But Abulai, Barrett, and Hoddinott (2005) find no evidence of disincentives for food production from food aid using household level or macro-level data, suggesting effects may be small within the overall economy.

This paper employs a multimarket model to examine the impacts of both recent high food prices and food aid in response to food price spikes. Multi-market model is a powerful tool to study different aspects of the impacts of high food prices on an economy. The complex interactions of food markets, household assets, and social safety nets are, arguably, best captured through multi-agent, multi-market economic models.

Ulimwengu and Ramadan (2009) are among the few papers that employ a multimarket framework to examine the impacts of higher food prices. Using the integrated Ugandan National Household Survey 2005/2006 they estimate a measure of net consumption impact that includes both price and profit effects. Their results suggest that the adverse impact of high food prices may be mitigated by households' substitution of more expensive food items with cheaper ones and the majority of gainers from high food prices live in rural areas.

There are several multi-market applications examining the impacts of food assistance on various household groups. Dorosh, delNinno, and Sahn (1995) examine impacts on poverty of yellow maize imports in Maputo Mozambique using an Almost Ideal Demand System and multi-market. A caloric poverty line is also employed that allows household changes in consumption to translate into changes in poverty. The study finds yellow maize to be a good assistance mechanism in that it is self-targeting, has a low cross-price elasticity with local staples, and generates negligible disincentives for domestic production. Dorosh and Haggblade (1997) develop a multi-market that explicitly captures seasonality in agricultural markets in Bangladesh. As in Dorosh, delNinno, and Sahn (1995), welfare impacts are mainly captured through changes in caloric consumption. Model simulation results suggest that a switch from food-for-work programs with in-kind delivery of wheat to cash-for-work assistance programs would unambiguously improve the welfare of the poor. Arndt and Tarp (2001) employ a more complex computable General Equilibrium model to examine the economy-wide impacts of monetization of food aid and alternative distribution schemes, including endogenous foreign exchange rate adjustment.

This paper fills in a gap in the literature by examining both the effects of recent food price spikes and the impacts of food aid in the face of high food prices. The multimarket framework employed provides a more comprehensive picture than single-market analysis or income analysis and makes it possible to study potential changes in the agricultural sector and compare the impacts of food aid on both targeted and untargeted populations.

The countries examined in the study are:

- East Timor (an island economy)
- Kenya (an open trade with a strong history of cash cropping, but a recent history of political unrest)
- Niger (a landlocked and closed economy)

2.3 Multimarket Framework

Multimarket models of major commodity groups in the food sector are generated in all four countries. This section lays out the basic components of a parsimonious food-sector multimarket model. The multimarket model simulates the aggregate impacts of the actions of four types of households:

- Rural food insecure (RFI)
- Urban food insecure (UFI)
- Rural food secure (RFS)
- Urban food secure (UFS)

Each household undertakes economic activities as both a consumer of food commodities and producer of food commodities. As in most multimarket models, the consumption and production decisions are assumed to be made separately by the household. The model focuses on rates of change in quantities, prices, and incomes. These changes are used to simulate changes in household well-being; as indicated by changes in the ability to access food. The impacts of external shocks to international food prices on household well-being of th e four household types are explored. The effectiveness of cash transfers in ameliorating international shocks to food insecure populations are also simulated across country types. The model presented below is divided into five components: consumer demand, producer supply, market clearing conditions, income effects, and model solutions.

2.3.1 Consumer demand

Demand for specific goods is determined separately for each household type. For example, demand for good i by household type h is a function of a vector of own good and other good prices, p, the real income, Y_R , of household type h, and other shifters in demand, z_h^d.

$$q_{ih}^d = q_{ih}^d(p, Y_h^R, z_h^d) \tag{2.1}$$

Assuming that the initial demand functions are approximately log-linear and transforming each demand equation into rates of change, yields the rate of change in demand for good i as a function of price changes $\dot{p}$, own and cross-elasticities ε_{ijh}^d, income elasticities ε_h^y, and exogenous rates of change in demand $\dot{z}_h^d$.

$$\dot{q}_{ih}^d = \sum_j \varepsilon_{ijh}^d \dot{p}_j + \varepsilon_h^y \dot{Y}_h^R + \dot{z}_h^d \tag{2.2}$$

Aggregate demand is a simple function of the household specific demands for good i.

$$q_i^d = \sum_h N_h q_{ih}^d(p, y_h, z_h^d) \tag{2.3}$$

where N_h is the number of households of type h.

Rewriting equation (2.3) in terms of rates of changes,

$$\dot{q}_i^d = \sum_h \lambda_{ih} \dot{q}_{ih}^d \tag{2.4}$$

where λ_{ih} is the share of commodity i consumed by household type h.

The rate of change equations (2.2) and (2.4) are the equations employed in the multimarket simulation.

2.3.2 Producer supply

In order to simplify the model, we focus only on the supply responses in the agricultural sector and ignore associated changes in agricultural input demands that may be expected. This simplification is reasonable in the current application, as relatively few inputs (including labor) are purchased in the market. Information on differential supply responses of food insecure and food secure household types are also not available, so aggregate commodity supply responses are employed. However, impacts from commodity production changes on household revenues are later allocated to household types based on the importance of the commodity in household revenues. The supply function for commodity i is:

$$q_i^s = q_i^s(p_i, z_i^s) \tag{2.5}$$

where q_i^s is the quantity supplied of product i, p_i is the price, and z_i^s represents exogenous shifts in supply such as drought. Again, log-linearizing the equation to focus on associated rates of change yields used in the multimarket simulation:

$$\dot{q}_i^s = \varepsilon_i^s \dot{p}_i + \dot{z}_i^s \tag{2.6}$$

2.3.3 Market clearing conditions

Food markets clear by equating supply and imports with quantity demanded

$$q_i^s + M_i = q_i^d \tag{2.7}$$

where M_i is the level of imports in market i. The associated rate of change equation is:

$$\frac{q_i^s}{M_i}\dot{q}_i^s + \dot{M}_i = \frac{q_i^d}{M_i}\dot{q}_i^d \tag{2.8}$$

Each market may be specified as either tradable, in which case price is exogenously fixed based on the world market $p_i = \bar{p}_i$ and M_i is endogenously determined in the model, or non-tradable, in which case M_i is fixed and commodity price p_i is endogenously determined in the model.

2.3.4 Household class income

Nominal income for the class h household is:

$$Y_h^N = \sum_i p_i q_{ih}^s + \bar{R}_h \tag{2.9}$$

where $\bar{R}_h$ is income for sources other than production in the nine food commodity groups by the type h household. The corresponding change in incomes in terms of rates of change in prices and household h output of commodities is:

$$\dot{Y}_h^N = \sum_i \gamma_{hi}\dot{p}_i + \sum_i \gamma_{hi}\dot{q}_{hi}^s + \dot{\bar{R}}_h \tag{2.10}$$

where γ_{hi} is the share of house type h's income from production of commodity group i. The household type change in real income is the change in nominal income minus the household type specific consumer price index.

$$\dot{Y}_h^R = \dot{Y}_h^N - \sum_i \omega_{hi}\dot{p}_i \tag{2.11}$$

where ω_{hi} is the share of household type h expenditure on commodity group i. This is the measure of changes in household economic well-being used in model simulations.

2.3.5 Solving the multimarket

Equations 2.2, 2.4, 2.6, 2.8, 2.10, and 2.11 form a system of linear equations with the same number of endogenous variables. The relationships between endogenous variable and exogenous variable rates of change can be written in matrix form as:

$$A\dot{x} = B\dot{z} \tag{2.12}$$

where A is the matrix of endogenous variable coefficients, B is the matrix of exogenous variable coefficients, $\dot{x}$ is the vector of endogenous variables, and $\dot{z}$ is the vector of exogenous variables. Solving for the endogenous variables by inverting the endogenous variable parameter matrix yields:

$$\dot{x} = A^{-1}B\dot{z} \tag{2.13}$$

The impacts of simulated exogenous rate of change shocks enter as non-zero elements of the $\dot{z}$ vector in equation (2.13).

2.4 Model Parameterization

Parameterization of the model is discussed in this section.

2.4.1 Data

Most model parameters are generated from the analysis of nationally representative household datasets for East Timor, Kenya, and Niger. More details on the survey used in each country are provided in Box 1.

Box 1: Details on Households Surveys

- The 2001 Timor-Leste Living Standards Measurement Survey (World Bank, 2005) is used for East Timor and the survey has a sample size of 1,800 households.
- For Kenya, the Kenya Integrated Household Budget Survey (KIHBS) 2004/05 is used to obtain most model parameters. The survey has a sample size of 13,430 observations.
- For Niger, the 2005 Questionnaire des Indicateurs de Base du Bienetre (QUIBB) is used to obtain most of the model parameters and the survey has a sample size of 6,690 households.

The analysis of household consumption patterns from these datasets is combined with FAO production and trade statistics to identify the major food commodities that are included in the model. Similarly, FAO Food Balance Sheets are employed to characterize food commodities as tradable or non-tradable. Table 2.1 provides supply/import and demand/import ratios for the major commodities in each country. In East Timor imported rice is a major tradable commodity by definition. While, local rice, corn, fish fruit, legumes, meat, tubers, and vegetables are identified as major non-tradable food commodities. In Kenya rice and wheat are identified as tradable commodities (again based on low supply/import ratios) and corn, fish/meat, fruits/tubers, legumes, other cereals, and vegetables are non- tradable commodities. For Niger, corn and wheat are tradable commodities with low supply/import ratios and sorghum-millet, root crops, beans, fruits, vegetables, and animal products are non-tradable commodities. As noted in the model specification, commodity price is exogenous for tradable commodities, while net import levels are exogenous for non-tradable commodities.

Crucial for the analysis is the generation of information on consumption and production behavior of typical food insecure rural and urban households. In all four countries rural and urban households are identified as food insecure if their expenditure levels do not exceed the level needed to purchase a nutritionally adequate diet. As might be expected, there is considerable variation in how this food insecurity threshold is implemented with the four different surveys. Box 2 provides details on the food security definition employed for rural and urban areas.

Box 2: Food Security Thresholds in the Four Countries

In all of the countries the food security threshold is based on the expenditure level necessary for an adequate diet.

East Timor: The food security threshold is based on the expenditures necessary to reach the basic nutritional requirement of 2,100 calories per person per day using the 2001 Timor-Leste Living Standards Measurement Survey. The resulting food security cutoff is US $10.81 (or 108101.8 RUPIAH) per month per person.

Kenya: The food security threshold is 987.99 KSHS per month per person. This threshold is provided in the KIHBS and represents the expenditures needed to obtain a nutritionally adequate diet.

Niger: The food security threshold is based on the expenditure amount necessary for each household member to receive 2,100 calories per day using the 2005 Questionnaire des Indicateurs de Base du Bien-etre (QUIBB) data. The resulting food security cutoff is FCFA 144,750 for an urban area and FCFA 105,827 for a rural area.

The shares of households identified as rural food insecure (RFI), rural food secure (RFS), urban food insecure (UFI), and urban food secure (UFS) are given for each country in table 2.2. East Timor, Kenya, and Niger all continue to see a concentration of households in rural areas. In both East Timor and Kenya most households (79 percent) live in rural areas, while in Niger 83 percent of households are located in rural areas. The incidence of household food insecurity is also higher in rural areas in East Timor and Niger. In East Timor 16 percent of rural households are food insecure households, compared to 8 percent of households in urban areas. In Niger 56 percent of rural households are food insecure compared to 36 percent of urban households.

In Kenya, however, the incidence of household food insecurity is higher in urban areas at 42 percent than rural areas at 35 percent. Ecuador in unique in that the majority of households live in urban areas (60 percent), but rates of food insecurity remain much higher in rural areas at 75 percent compared to 42 percent for urban households.

2.4.2 Consumption

For each commodity group, the share of the commodity that is consumed by each of the four household types is also provided in table 2.2. If a household type consumes a disproportionately small share of a commodity then its share will be below its share of the households in the country. For East Timor the only commodity consumed disproportionately by RFI households is corn, while the share of consumption of fish, meat, and fruits are particularly low when compared to RFI households as a share of all households in the country. UFI households, as mentioned, represent a very small share of all households but are still disproportionately low consumers of fish, meat, and legumes. Disproportionately low shares of food consumption are also found among food insecure households in Kenya and Niger. In Kenya, the cereal consumption share for RFI households is about one-third of household population share and consumption of other food groups is disproportionately even lower. Similarly, in Niger the RFI show a disproportionately low share of consumption for every commodity group, but the difference is less for sorghum millet and beans than for other commodity groups. The UFI in Niger are, on the other hand, actually disproportionately high consumers of corn and rice.

Differences in dietary patterns of food insecure and food secure households are even more apparent when examining the share of total household expenditures spent on each commodity group by household type (table 2.3). For instance, in East Timor the major food commodities in the analysis account for 64 percent of total expenditures for RFI households, compared to 53 percent for RFS households. Expenditure share differences are even greater for urban households, with the UFI spending 66 percent on food compared to 38 percent for UFS households. Expenditures on specific commodities also differ within East Timor. Food insecure households in both rural and urban areas allocate a higher share of total expenditures to staple cereals (corn, local and imported rice) and a smaller share to meat. Food expenditures as a share of total expenditures are also higher for rural households than urban households in Kenya and Niger. In the Kenya case food expenditure shares are also higher for food insecure households than food secure households. In addition, RFI households in Kenya are particularly reliant on corn and wheat relative to other household types. In Niger RFS households actually have a slightly higher share of expenditures on food than RFI households. The strong reliance of rural households on sorghum millet is also apparent. In urban areas cereal consumption is more diversified between sorghum millet, rice, and corn particularly among food secure households.

2.4.3 Revenue

Household reliance on commodity groups as sources of revenue also differs by household type (table 2.4). Of note, in all countries but Kenya urban households rely on agricultural commodities as a significant source of revenues. In East Timor the food commodities included in the analysis account for 65 percent of revenues of the RFI and 67 percent of revenues of the UFI. However revenue sources differ in rural and urban areas of East Timor. Fruit is the major source of agricultural revenue for the UFI and local rice is the major source for the RFI. The RFS show a more diversified revenue base, with the food commodity groups accounting for 53 percent of household revenue. The UFS show the greatest diversification outside of agriculture, as the food commodity groups account for only 30 percent of revenues.For Niger, agricultural revenues are a higher share of total revenues for both RFI and RFS households (60 percent and 58 percent, respectively) compared to UFI households (24 percent and 19 percent, respectively). For both rural household types revenues come primarily come from sorghum-millet and animal products. Only in Kenya are revenues a very small share of urban household income. Revenues from the agricultural commodity groups in the analysis represent 42 percent of total revenues of RFI households and 44 percent of total revenues of RFS households. However, agricultural revenues comprise only 12 percent of UFI household revenues and 6 percent of UFS household revenues. For all household types in Kenya, corn and fish-meat are the major sources of revenue.

2.4.4 Elasticities

Price and income demand elasticities and supply elasticities are reported in tables 2.5, 2.6 and 2.7 respectively and are drawn from the USDA Economic Research Service International Food Consumption Patterns (IFCP) database for major food commodity groups in 114 countries.[1]

For East Timor the own-price and income elasticities employed in the model are based on IFCP estimates for closely associated food groups in neighboring Indonesia. Own-price elasticity for corn is set at -0.304 for all household types. Own-price elasticities for the fruit and vegetables groups are set at -0.468. The own-price elasticity for the fish group is set at -0.654 and the own-price elasticities for the legume and tuber groups are set at - 0.588. Again, cross-price elasticities are not available, but small positive cross-price elasticities of 0.05 are assumed among the major cereal groups (local rice, imported rice and corn) because some limited substitution effects are expected.

In the East Timor model, imported rice and local rice are identified as two distinct commodities with separate markets. Obviously, imported and domestic rice are close substitutes. We would expect both commodities to have large own-price demand elasticities because households can easily substitute between the two types of rice. The cross-price elasticities of demand for local and imported rice are correspondingly high. In the East Timor simulations, the own-price demand elasticities of local and imported rice are set at -20 and cross-price demand elasticities between the two commodities are

[1]See http://www.ers.usda.gov/Data/InternationalFoodDemand/

set at 20.

Based on IFCP estimates for closely associated food sub-groups in neighboring Indonesia, income elasticities for the major cereal groups (corn, imported rice and local rice) are set at 0.376 for all household types. The income elasticity estimate for the fish group is set at 0.809. The income elasticity estimates for the fruit and vegetables groups are set at 0.579, while the income elasticities for the legume and tuber groups are set at 0.728 and the income elasticity for the meat group is set at 0.73.

For Kenya the IFCP database has own-price demand and income elasticity estimates for major food sub-groups or closely related food groups. The own-price elasticites for the major cereal groups (corn, rice, wheat and other cereal) are set at -0.471 for all household types. The own-price elasticity for the fish/meat group is set at -0.721, the own price elasticity estimate for the fruit/tuber group is set at -0.5, and the own-price elasticity estimates for the legume and vegetables groups are set at -0.538. No estimates on cross- price elasticities are available, but small positive cross-price elasticities of 0.05 are assumed among the cereal groups (corn, rice, wheat and other cereal) because some limited substitution among cereals occurs.

Income elasticity estimates for major food sub-groups are also based on IFCP database estimates for Kenya. The income elasticities for the major cereal groups (corn, rice, wheat and other cereal) are set at 0.583 for all household types. The income elasticities for the legume and vegetables groups are set at 0.665, while the income elasticity for the fish/meat group is set at 0.892 and the income elasticity for the fruit/tuber group is set at 0.6.

For Niger the own-price and income demand elasticities employed in the model are based on IFCP estimates for closely associated food groups in neighboring Mali. Own price elasticities for the major cereals (sorghum and millet, corn, and rice) and for grains are set at -0.48 for all household types. Own price elasticities for the roots and beans commodity groups are set at -0.67, estimates for the fruits and vegetables groups are set at -0.55, and estimates for the meats group are set at -0.827. No estimates of cross-price demand elasticities are available, but small positive cross-price elasticity estimates of 0.05 are assumed between the major cereal groups (sorghum and millet, corn, and rice), as some limited substitution between cereals occurs.

Initial guidance on income elasticity of demand estimates in Niger is also provided by the IFCP database. However, income elasticities for food commodities are commonly assumed to be lower for the food secure than for the food insecure and, correspondingly, lower when food is a smaller share of total expenditures. Therefore, income elasticities of demand are assumed to be 0.80 for the rural and UFI household types, 0.60 for the RFS, and 0.50 for the UFS for all food commodity groups except meat. Income elasticity of demand estimates for the meat products group is set at 1.00 for the rural and UFI, 0.80 for the RFS, and 0.60 for the UFS.

Supply elasticity estimates are not available for the four countries in the model. For Niger, we follow the general guidance in the literature and assume relatively inelastic short run supply elasticities of 0.50 for all crop commodity groups except sorghum millet (e.g. Alston, Norton, and Pardey). As the basic non-tradable staple, the price elasticity for sorghum millet is set at 0.25. Limited short-run cross-crop substitution in the production of corn and sorghum - millet is also allowed for through cross-price elasticities of

-0.05 for the two commodity groups. A larger supply elasticity of 0.75 is specified for the meat group, as animal stocks can be adjusted in the short term to take advantage of favorable prices.

Considering the fact that East Timor is a food insecure country highly dependent on the agricultural sector, we follow the general guidance in the literature and assume relatively inelastic short run supply elasticities of 0.30 for all crop commodity groups. We also assume no cross-crop supply elasticities in this case. A larger supply elasticity of 0.6 is specified for the meat group, as animal stocks can be adjusted in the short term to take advantage of favorable prices. For Kenya we follow the general guidance in the literature and assume relatively inelastic short run supply elasticities of 0.50 for all crop commodity groups.

2.4.5 Model Structure

The structure of each multimarket model is summarized in table 2.8. East Timor has 70 equations and 70 endogenous variables in the system. Kenya has 64 equations and 64 endogenous variables, while Niger has 71 equations and 71 endogenous variables.

2.4.6 Price shocks

International prices of the major tradable commodities for East Timor, Kenya and Niger are drawn from World Bank Commodity Price Data (Pink Sheet). International food prices have been highly volatile since 2007, reaching a first peak in 2008 and second peak in 2011. This paper focuses on most recent price shocks and in particular looks at the price changes from 2010 to 2011. Food prices increased substantially during this period. The average annual rice price increased by 16.2 percent, average annual price of wheat increased by 35.6 percent and the annual price of corn increased by 56.9 percent.

For East Timor, imported rice is the only tradable commodity and the price increase of rice is simulated. For Kenya, rice and wheat are the tradable commodities and price shocks of the two commodities are simulated simultaneously. Similarly, rice, wheat and corn are the tradable commodities for Niger and price shocks of all three commodities are simulated simultaneously.

2.5 Results

For East Timor, imported rice is the major tradable commodity and the first simulation presents a 16.2 percent increase in international price of rice as observed from 2010 to 2011 in the international rice market. Strong substitution effects between local and imported rice cause the demand and supply of local rice to go up by 4.8 percent and the price of local rice to increase by 16.0 percent. Both imports and demand of imported rice decrease by 4.6 percent because of the higher international price. Nominal income goes up for each household type because both production and price of local rice increase. Real income, however, decreases for all household types except the RFS whose real income increases by 0.03 percent. This is because the RFS households have the largest discrepancy between their revenue and expenditure on local rice (13.2 and 9.5 percent respectively) and spend relatively little on imported rice (8.7 percent). The greatest real income declines happens to the UFI type

(2.4 percent), because they are the only net consumers of local rice and have the highest expenditure share on imported rice (16.7 percent). For the RFI and UFS, real income also declines by 0.8 and 0.3 respectively mainly due to the increased international price of rice. For the entire agricultural sector, declines in household real income shift commodity demands inward and result in market clearance at lower levels of prices and supplies for all commodities except local rice and corn, which are substitutes for imported rice. Indirect decreases in demands caused by higher international rice price are most pronounced in fish, tuber and legume because these three commodities have relatively large income elasticities (between 0.728 and 0.809) and are, therefore, more adversely affected by lower real income among households.

The second simulation approximates the impact of cash transfer food assistance targeted to the RFI. The simulation maintains a 16.2 percent price increase in international rice market, but mimics the cash transfer by increasing the RFI type's real income by 2.0 percent (equivalent to the decrease in real income due to an increase in the price of rice). Results show that the targeting of food aid to the RFI effectively offsets the negative impact of price increase in imported rice and now real income increases by 1.2 percent for the RFI. Increased real income causes the RFI households' demands for all commodities to go up and in some cases offset demand decreases from the UFI and UFS, resulting in new increases in aggregate demands and prices for fruits, legume, tuber and vegetables. Similarly, price and demand of corn goes up even more by 2.9 percent (compared with 2.7 percent in Simulation 1) because of higher demand from the RFI. Moreover, when the economy is injected with food assistance funds in the face of price spikes, the outward shift in demand for all commodities result in higher levels of commodity supplies and prices compared with Simulation 1 where only price spike is considered. With cash transfer targeted to the RFI, for the untargeted groups real income either further increases (the UFI) or decreases by a smaller magnitude (the RFS and UFS) because the three household types are net producers of most of the above commodities with price increases. In particular, compared with Simulation 1, the biggest real income increase happens to the UFI, by 0.06 percentage points, because as net producers of corn, fruits, legume and tuber, they have on average the largest discrepancy in revenue and expenditure shares.

For Kenya, rice and wheat are the two major tradable commodities. The third simulation mimics simultaneous increases of 16.2 percent in rice price and 35.6 percent in wheat price as observed in the world markets between 2010 and 2011. The results indicate that demands of rice and wheat decrease by 8.4 percent and 16.7 percent respectively and as a result imports of rice and wheat decrease by 11.1 percent and 36.9 percent. Also in response to the price changes, domestic supplies of rice and wheat increase by 8.1 percent and 17.8 percent. Nominal income goes up for all household types because of price and production increases in the rice and wheat markets. However, real income declines for all household types because all household types are net consumers of rice and wheat. Moreover, the negative real income effect is most pronounced for the RFI (3.0 percent) who have the largest discrepancy in revenue and expenditure shares and least pronounced for the UFS who have the smallest discrepancy between revenue and expenditure shares. Lower real incomes among all households in turn lower aggregate demand

and commodity prices for all commodities except corn and other cereals that are substitutes for rice and wheat and have a cross-price elasticity of 0.05. The above two commodity groups have higher aggregate demand and prices because substitution occurs among the cereals (a cross-price demand elasticity of 0.05 is assumed among the cereals). The new market clearance causes domestic supplies of non-tradable commodities to decrease except corn and other cereals that are substitutes and have increased demand and prices. The smallest indirect demand decrease resulting from spikes in international rice and wheat prices happens to the commodity group of fruits/tuber, 4.5 percent, because this group has lowest income elasticity and is therefore least affected by real income declines.

The fourth simulation shows the impact of food assistance targeted to the RFI in the form of cash transfer. The simulation maintains 16.2 percent increase in the price of rice and 35.6 percent increase in the price of wheat in the international markets, but mimics the cash transfer by increasing the nominal income of the RFI by an amount (3.1 percent) equivalent to their real income loss due to higher rice and wheat prices. The results indicate that cash transfer targeted to the RFI effectively buffers the initial negative impact of higher rice and wheat price and now real income increases by 0.12 percent for the RFI. Due to higher real income for RFI type, demand of all commodities goes up for RFI households as well, resulting in a relative outward shift (compared with Simulation 3 where only price spikes are simulated) in aggregate demand for all commodities. This in turn causes relative increases in production and prices for all commodities at market clearance. Consequently, production and commodity prices either further increase (for substitutes of rice and wheat: other cereal and corn) or decrease by smaller magnitudes (all other commodities). The cash transfer targeted to the RFI group also has moderate impacts on the untargeted groups (the UFI, RFS, and UFS). Compared with the price increases only scenario, real income further decreases by 0.03 and 0.02 percentage points for the UFI and UFS, while increases by 0.05 percentage points for the RFS. This is because the RFS are net producers of corn, fish-meat, legume and other cereals and the discrepancies between revenue and expenditure shares are sufficient enough to reflect the benefits of relative price and production increases in these commodities under cash transfer.

For Niger, the major tradable commodities are corn, rice and wheat. The fifth simulation mimics simultaneous increases of 56.9 percent in international price of corn, 16.2 percent in international price of rice and 35.6 percent in international price of wheat. In response to the price changes, demand for corn, rice and wheat decrease by 29.0, 7.5 and 19.7 percent and production increases by 28.2, 8.1 and 17.8 percent respectively. Imports of the three commodities all decrease as a result of decreased demand. The nominal income of all household types increases due to increases in prices and production of the major tradable commodities. However, after the change of price indexes is accounted for, real income decreases for all household types, all of which are net consumers of corn, rice and wheat. Compared to the previous simulations of East Timor and Kenya, the real income decreases are rather large for Niger, varying from 3.2 percent to 6.1 percent, not only because Niger has more tradable commodities, but more importantly, because of the relatively big discrepancies between revenue and expenditure shares for these tradable commodities. Not surprisingly, real income decreases are more pronounced for the UFI and UFS (6.1 percent and 5.2 percent respectively), which in general have larger deficits in the three tradable commodities than the other two household types. In response to lower real income for all household types, demand declines for all commodities, resulting in declines for all non-tradable commodities in production and prices (except sorghum-millet). Unlike in previous simulations, sorghum-millet, a substitute for corn and rice, has declines in both demand and production. This is because a -.05 cross supply-elasticity is assumed between sorghum-millet and corn and supply is shifted inward due to price increase in corn. Again, the commodity group of meat has the largest decrease in demand caused indirectly by international food price spikes because meat has highest income elasticity and the demand is most adversely affected by real income declines due to high food prices.

The last simulation approximates the impact of cash transfer targeted to the RFI household type when the households are faced with high international food prices. The simulation maintains the price spikes as mentioned in the previous simulation, but mimics cash transfer targeted to the RFI introducing a 2.1 percent increase in their nominal income, which is equivalent to their real income loss due to high prices of corn, rice and wheat. The results again are suggestive of the efficacy of cash transfer targeted to the RFI, with a much lower decrease in real income (0.9 percent as opposed to 3.2 percent in the previous simulation). Unlike in previous simulations for East Timor and Kenya, RFI types real income still decreases after cash transfer is considered, probably because of the relatively big initial decrease in real income. The signs of all other endogenous variables remain the same as in simulation 5 but the magnitudes change. Compared to simulation 5 where only price increases are considered, cash transfer leads to much smaller decrease in real income for the RFI, and consequently smaller decreases in aggregate demand of all commodities. Prices either decrease less or increase more (for sorghum-millet only). Production for all commodities also declines less at market clearance. The untargeted groups (UFI, RFS and UFS) are slightly better off as opposed to price shocks only because their production surplus in commodities such as animal products, beans and fruits are sufficient enough to outweigh possible negative effects by production deficit in other commodities when prices increase for all commodities from simulation 5 to 6. The positive impact of cash transfer on untargeted groups is most pronounced for the RFS (0.1 percent) because they have the largest production surplus in general.

2.6 Discussion

Employing a parsimonious multimarket model for the agricultural sector, this paper examines the impacts of recent global price spikes in major food commodities as well as the efficacy of food assistance in the face of increasing international food prices. Synthesis of the results from three developing countries analyzed in the model yields several important points.

First, although nominal income tends to increase for households encountering higher food prices because of their agricultural production activities, real income decreases in most cases and hence household welfare are in fact compromised as a result. The severity of welfare deterioration depends to a large extent on the discrepancy between revenue and expenditure shares of the commodities exposed to price shocks. However, it is worth noting that whether a household type is a net consumer or a net producer of the commodities subject to price shocks is not the only factor determining the change in real income because substitution effects among commodities may also play an important role. Real income can in fact increase for certain households even when they are net consumers because they may be a net producer of an important substitute and therefore benefit from resulting price and production increases of the substitute commodity.

Second, higher international prices of commodities encourage their domestic production and also boost production and price levels for commodities that are substitutes for commodities at shock because of substitution effects. Meanwhile higher prices of commodities at shock discourage production for all other commodities due to households weakened purchasing power. The magnitudes of production declines depend largely on income-elasticity of these commodities. It is worth pointing out that the magnitudes of changes are much smaller for these indirect effects on non-shock commodities when compared to the direct effects on the markets of commodities exposed to price shocks, but policy makers need to be aware of the possible indirect impacts of international food prices and adjust policy mandate if necessary.

Third, cash transfer targeted to the low-income groups (the RFI) in each country all effectively offset the negative impacts of higher food prices, either partially or completely. In some cases, cash transfer outweighs the negative impact of high food prices resulting in higher real income than pre-price shocks while other times the negative impact of high food prices is dominant but real income decreases by a much smaller magnitude. The impact of cash transfer on untargeted households, however, is ambiguous. It is likely to be positive for household types that are net producers of at least some of the commodities that have increased production and prices under cash transfer and the production surplus is sufficiently big. On the other hand, when the households are net consumers of most commodities or the production surplus is rather small, the untargeted households can be hurt by the cash transfer targeted to the poor households.

It also bears reiterating that in the multimarket framework even non-tradable commodities with inelastic demand are assumed to adjust to a new quantity and price equilibrium in response to simulated production or price shocks. This assumption must be viewed with caution because producers are assumed they have some time to respond to the shocks. Specifically, limited (inelastic) supply responses are assumed in the model simulations. However for some shocks producers may have very limited opportunities to respond, at least in the short-run. Assuming no supply response increases the magnitude of market price change in response.

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Table 2.1: Commodity Groups and Import Ratios

East Timor			
		Supply/Import	Demand/Import
Tradables	Imported Rice	NA	NA
Non-Tradables	Corn	11.4	12.4
	Fish	NA	NA
	Fruit	0.9	1.9
	Legume	NA	NA
	Local Rice	NA	NA
	Meat	5.2	6.2
	Tuber	NA	NA
	Vegetable	2.6	3.6
Kenya			
		Supply/Import	Demand/Import
Tradables	Rice	0.2	1.2
	Wheat	0.6	1.6
Non-Tradables	Corn	25.9	28.7
	Fish/Meat	-41.1	-40.1
	Fruit/Tuber	-32.0	-31.0
	Legume	12.0	14.0
	Other Cereal	12.4	13.4
	Vegetable	-22.9	-21.9
Niger			
		Supply/Import	Demand/Import
Tradables	Corn	0.2	1.2
	Other Grains	0.1	1.1
	Rice	0.3	1.3
Non-Tradables	Animal Products	NA	NA
	Beans	NA	NA
	Fruits	NA	NA
	Root Crops	NA	NA
	Sorghum-Millet	NA	NA
	Vegetable	NA	NA

Source: FAO Food Balance Sheet. `http://faostat.fao.org/site/368/DesktopDefault.aspx?PageID=368#ancor`.

Table 2.2: Consumption Shares for Each Commodity Group across Household Types (%)

East Timor	Household (%)	Corn	Fish	Fruit	Imported Rice	Legume	Local Rice	Meat	Tuber	Vegetable
RFI	12.71	13.52	2.03	4.93	6.27	7.92	8.76	1.32	10.93	7.75
UFI	1.59	1.13	0.67	1.13	1.37	0.51	1.85	0.28	1.09	1.37
RFS	66.20	72.26	58.87	67.56	63.97	65.03	72.75	71.04	71.86	64.52
UFS	19.50	13.09	38.43	26.38	28.39	26.53	16.64	27.37	16.12	26.37
Total	100	100	100	100	100	100	100	100	100	100

Kenya	Household (%)	Corn	Fish/Meat	Fruit/Tuber	Legume	Other Cereal	Rice	Vegetable	Wheat
RFI	27.93	10.03	3.25	4.93	8.03	10.03	10.03	6.81	10.03
UFI	4.60	0.91	0.51	0.84	0.66	0.91	0.91	1.03	0.91
RFS	50.97	69.36	56.62	67.24	74.03	69.36	69.36	58.45	69.36
UFS	16.50	19.69	39.62	26.99	17.28	19.69	19.69	33.72	19.69
Total	100	100	100	100	100	100	100	100	100

Niger	Household (%)	Animal Product	Bean	Corn	Fruit	Other Grain	Rice	Root Crop	Sorghum/ Millet	Vegetable
RFI	46.80	23.62	26.29	19.43	13.96	5.62	17.68	18.14	33.35	16.33
UFI	6.20	3.86	4.23	9.02	3.39	2.16	10.94	2.68	2.60	6.20
RFS	36.20	48.85	50.67	40.86	50.12	67.00	41.89	46.96	56.03	52.94
UFS	10.80	23.68	18.81	30.69	32.53	25.22	29.49	32.22	8.03	24.53
Total	100	100	100	100	100	100	100	100	100	100

Table 2.3: Expenditure Shares on Food Commodity Groups by Household Types (%)

East Timor										
	Corn	Fish	Fruit	Imported Rice	Legume	Local Rice	Meat	Tuber	Vegetable	*Total*
RFI	10.11	0.75	2.42	12.49	3.23	13.43	2.34	8.50	10.30	63.58
UFI	6.21	2.60	3.44	16.74	1.18	16.39	2.81	5.61	11.37	66.36
RFS	5.57	2.44	2.75	8.71	2.19	9.49	9.23	5.11	7.76	53.26
UFS	3.90	2.41	2.28	5.80	1.36	7.85	5.60	2.88	6.15	38.24
Kenya										
	Corn	Fish/Meat	Fruit/Tuber	Legume	Other Cereal	Rice	Vegetable	Wheat	*Total*	
RFI	15.65	5.23	6.81	6.14	0.49	2.55	7.65	7.65	52.17	
UFI	9.72	4.86	6.80	3.13	0.31	1.58	7.33	4.75	38.47	
RFS	9.79	7.27	8.15	5.16	0.31	1.59	6.11	4.78	43.18	
UFS	4.37	7.31	4.84	1.84	0.14	0.71	5.24	2.13	26.58	
Niger										
	Animal Product	Bean	Corn	Fruit	Other Grain	Rice	Root Crop	Sorghum/ Millet	Vegetable	*Total*
RFI	7.45	1.70	2.36	0.37	0.48	3.74	0.44	38.05	1.69	56.28
UFI	5.99	1.67	5.86	0.41	0.97	12.31	0.37	16.05	3.18	46.81
RFS	9.35	2.08	3.01	0.52	1.23	6.02	0.56	35.33	2.80	60.90
UFS	9.19	1.78	5.00	0.93	2.74	9.35	0.93	8.34	3.34	41.60

Table 2.4: Revenue Shares on Food Commodity Groups by Household Types (%)

East Timor	Corn	Fish	Fruit	Legume	Local	Meat	Tuber	Vegetable Rice	*Total*	
RFI	12.74	0.87	14.21	3.42	15.45	2.55	12.38	3.73	65.36	
UFI	14.70	1.39	18.42	3.03	12.54	1.32	9.70	5.43	66.55	
RFS	11.04	0.20	9.75	2.82	13.17	2.94	10.55	2.35	52.82	
UFS	5.25	0.25	5.91	1.21	8.73	1.49	4.29	2.78	29.91	
Kenya	Corn	Fish/Meat	Fruit/Tuber	Legume	Other Cereal	Rice	Vegetable	Wheat	*Total*	
RFI	16.04	15.26	2.99	5.10	1.39	0.00	0.82	0.02	41.62	
UFI	4.89	4.71	0.66	1.17	0.41	0.00	0.15	0.00	11.99	
RFS	15.46	14.18	4.33	6.23	0.85	0.15	2.07	0.25	43.52	
UFS	1.81	2.53	0.42	0.90	0.07	0.10	0.23	0.01	6.06	
Niger	Animal Product	Bean	Corn	Fruit	Other Grain	Rice	Root Crop	Sorghum/ Millet	Vegetable	*Total*
RFI	17.44	5.37	0.27	0.60	0.49	0.95	0.58	32.35	1.64	59.69
UFI	7.62	2.22	0.20	0.50	0.13	0.76	0.19	11.14	1.66	24.42
RFS	16.86	3.00	0.52	0.73	0.40	1.40	0.55	28.85	5.23	57.53
UFS	4.87	1.65	0.47	0.94	0.21	1.43	0.25	7.27	1.65	18.76

Table 2.5: Demand Elasticities

East Timor	Corn	Fish	Fruit	Imported Rice	Legume	Local Rice	Meat	Tuber	Vegetable
Corn	-0.304	0	0	0.05	0&0.05	0	0	0	
Fish	0	-0.654	0	0	0	0	0	0	0
Fruit	0	0	-0.468	0	0	0	0	0	0
Imported Rice	0.05	0	0	-0.304	0	20	0	0	0
Legume	0	0	0	0	-0.588	0	0	0	0
Local Rice	0.05	0	0	20	0	-0.304	0	0	0
Meat	0	0	0	0	0	0	-0.59	0	0
Tuber	0	0	0	0	0	0	0	-0.588	0
Vegetable	0	0	0	0	0	0	0	0	-0.468

Kenya	Corn	Fish/Meat	Fruit/Tuber	Legume	Other Cereal	Rice	Vegetable	Wheat
Corn	-0.471	0	0	0	0.05	0.05	0	0.05
Fish/Meat	0	-0.721	0	0	0	0	0	0
Fruit/Tuber	0	0	-0.5	0	0	0	0	0
Legume	0	0	0	-0.538	0	0	0	0
Other Cereal	0.05	0	0	0	-0.471	0.05	0	0.05
Rice	0.05	0	0	0	0.05	-0.471	0	0.05
Vegetable	0	0	0	0	0	0	-0.538	0
Wheat	0.05	0	0	0	0.05	0.05	0	-0.471

Niger	Corn	Sorghum/ Millet	Rice	Other Grain	Root Crop	Bean	Fruit	Vegetable	Animal Products
Corn	-0.48	0.05	0.05	0	0	0	0	0	0
Sorghum/Millet	0.05	-0.48	0.05	0	0	0	0	0	0
Rice	0.05	0.05	-0.48	0	0	0	0	0	0
Other Grain	0	0	0	-0.48	0	0	0	0	0
Root Crop	0	0	0	0	-0.67	0	0	0	0
Bean	0	0	0	0	0	-0.67	0	0	0
Fruit	0	0	0	0	0	0	-0.55	0	0
Vegetable	0	0	0	0	0	0	0	-0.55	0
Animal Products	0	0	0	0	0	0	0	0	-0.83

Table 2.6: Supply Elasticities

East Timor	Corn	Fish	Fruit	Imported Rice	Legume	Local Rice	Meat	Tuber	Vegetable
Corn	0.3	0	0	0	0	0	0	0	0
Fish	0	0.3	0	0	0	0	0	0	0
Fruit	0	0	0.3	0	0	0	0	0	0
Imported Rice	0	0	0	0.3	0	0	0	0	0
Legume	0	0	0	0	0.3	0	0	0	0
Local Rice	0	0	0	0	0	0.3	0	0	0
Meat	0	0	0	0	0	0	0.6	0	0
Tuber	0	0	0	0	0	0	0	0.3	0
Vegetable	0	0	0	0	0	0	0	0	0.3

Kenya	Corn	Fish/Meat	Fruit/Tuber	Legume	Other Cereal	Rice	Vegetable	Wheat
Corn	0.5	0	0	0	0	0	0	0
Fish/Meat	0	0.65	0	0	0	0	0	0
Fruit/Tuber	0	0	0.5	0	0	0	0	0
Legume	0	0	0	0.5	0	0	0	0
Other Cereal	0	0	0	0	0.5	0	0	0
Rice	0	0	0	0	0	0.5	0	0
Vegetable	0	0	0	0	0	0	0.5	0
Wheat	0	0	0	0	0	0	0	0.5

Niger	Corn	Sorghum/ Millet	Rice	Other Grain	Root Crop	Bean	Fruit	Vegetable	Animal Products
Corn	0.5	-0.05	0	0	0	0	0	0	0
Sorghum/Millet	-0.05	0.5	0	0	0	0	0	0	0
Rice	0	0	0.5	0	0	0	0	0	0
Other Grain	0	0	0	0.5	0	0	0	0	0
Root Crop	0	0	0	0	0.5	0	0	0	0
Bean	0	0	0	0	0	0.5	0	0	0
Fruit	0	0	0	0	0	0	0.5	0	0
Vegetable	0	0	0	0	0	0	0	0.5	0
Animal Products	0	0	0	0	0	0	0	0	0.75

Table 2.7: Income Elasticities

East Timor		Kenya		Niger			
					RFI/UFI	RFS	UFS
Corn	0.376	Corn	0.583	Corn	0.8	0.6	0.5
Fish	0.809	Fish/Meat	0.892	Sorghum/ Millet	0.8	0.6	0.5
Fruit	0.579	Fruit/Tuber	0.6	Rice	0.8	0.6	0.5
Imported Rice	0.376	Legume	0.665	Other Grain	0.8	0.6	0.5
Legume	0.728	Other Cereal	0.583	Root Crop	0.8	0.6	0.5
Local Rice	0.376	Rice	0.583	Bean	0.8	0.6	0.5
Meat	0.73	Vegetables	0.665	Fruit	0.8	0.6	0.5
Tuber	0.728	Wheat	0.583	Vegetables	0.8	0.6	0.5
Vegetables	0.579			Animal Products	1	0.8	0.6

Table 2.8: Summary

Country	East Timor	Kenya	Niger
Number of Equations	70	64	71
Number of Endogenous Variables	70	64	71
Number of Exogenous Variables	6	6	10

Table 2.9: Simulation Results (East Timor)

Percentage Change in Endogenous Variables	Simulation 1 (16.2% Increase in International Rice Price)	Simulation 2 (Cash Transfer)
Demand of Corn	0.74	0.79
Demand of Fish	-0.03	-0.02
Demand of Fruit	-0.02	0.00
Demand of Imported Rice	-4.63	-4.48
Demand of Local Rice	4.79	4.79
Demand of Legume	-0.03	0.01
Demand of Meat	-0.03	-0.01
Demand of Tuber	-0.04	0.03
Demand of Vegetable	-0.03	0.01
Supply of Corn	0.80	0.86
Supply of Fish	-0.03	-0.02
Supply of Fruit	-0.04	0.00
Supply of Local Rice	4.79	4.79
Supply of Legume	-0.03	0.01
Supply of Meat	-0.03	-0.01
Supply of Tuber	-0.04	0.03
Supply of Vegetable	-0.04	0.01
Import of rice	-4.63	-4.48
Price of Corn	2.67	2.87
Price of Fish	-0.11	-0.05
Price of Fruit	-0.12	0.00
Price of Legume	-0.11	0.04
Price of Meat	-0.05	-0.01
Price of Tuber	-0.12	0.09
Price of Vegetable	-0.13	0.03
Price of Local Rice	15.96	15.97
Nominal Income (RFI)	3.59	5.72
Nominal Income (UFI)	3.05	3.17
Nominal Income (RFS)	3.07	3.16
Nominal Income (UFS)	1.97	2.01
Real Income (RFI)	-0.81	1.25
Real Income (UFI)	-2.41	-2.35
Real Income (RFS)	0.03	0.07
Real Income (UFS)	-0.31	-0.29

Table 2.10: Simulation Results (Kenya)

Percentage Change in Endogenous Variables	Simulation 3 (16.2% increase in international rice price and 35.6% increase in international wheat price)	Simulation 4 (Cash Transfer)
Demand of Corn	0.85	0.95
Demand of Fruit/Tuber	-0.45	-0.40
Demand of Legume	-0.48	-0.39
Demand of Fish/Meat	-0.58	-0.53
Demand of Other Cereal	0.86	0.97
Demand of Rice	-8.39	-8.17
Demand of Vegetable	-0.53	-0.42
Demand of Wheat	-16.72	-16.49
Supply of Corn	0.94	1.06
Supply of Fruit/Tuber	-0.44	-0.39
Supply of Legume	-0.56	-0.46
Supply of Fish/Meat	-0.56	-0.51
Supply of Other Cereal	0.93	1.04
Supply of Rice	8.10	8
Supply of Vegetable	-0.51	-0.40
Supply of Wheat	17.80	18
Price of Corn	1.88	2.11
Price of Fruit/Tuber	-0.88	-0.77
Price of Legume	-1.11	-0.92
Price of Fish/Meat	-0.87	-0.79
Price of Other Cereal	1.86	2.09
Price of Vegetable	-1.02	-0.80
Import of Rice	-11.13	-10.88
Import of Wheat	-36.86	-36.51
Nominal Income (RFI)	0.15	3.39
Nominal Income (UFI)	0.05	0.08
Nominal Income (RFS)	0.23	0.34
Nominal Income (UFS)	0.02	0.04
Real Income (RFI)	-3.04	0.12
Real Income (UFI)	-1.87	-1.90
Real Income (RFS)	-1.66	-1.62
Real Income (UFS)	-0.76	-0.78

Table 2.11: Simulation Results (Niger)

Percentage Change in Endogenous Variables	Simulation 5 (56.9% increase in international corn price, 16.2% increase in international rice price, and 35.6% increase in international wheat price)	Simulation 6 (Cash Transfer)
Demand of Corn	-28.97	-28.55
Demand of Sorghum/Millet	-1.50	-1.28
Demand of Rice	-7.47	-7.08
Demand of Wheat	-19.72	-19.57
Demand of Root	-1.10	-0.95
Demand of Bean	-1.12	-0.90
Demand of Fruit	-1.24	-1.10
Demand of Vegetable	-1.27	-1.11
Demand of Meat	-1.58	-1.31
Supply of Corn	28.18	28.14
Supply of Sorghum/Millet	-1.50	-1.28
Supply of Rice	8	8
Supply of Grain	18	18
Supply of Root	-1.10	-0.95
Supply of Bean	-1.12	-0.90
Supply of Fruit	-1.24	-1.10
Supply of Vegetable	-1.27	-1.11
Supply of Meat	-1.58	-1.31
Price of Sorghum/Millet	5.39	6.26
Price of Root	-2.21	-1.90
Price of Bean	-2.23	-1.80
Price of Fruit	-2.48	-2.20
Price of Vegetable	-2.53	-2.22
Price of Meat	-2.11	-1.75
Import of Corn	-41.54	-41.54
Import of Rice	-12.15	-12.15
Import of Other Grain	-21.59	-21.59
Nominal Income (RFI)	0.75	0.75
Nominal Income (UFI)	0.19	0.19
Nominal Income (RFS)	0.56	0.56
Nominal Income (UFS)	0.27	0.27
Real Income (RFI)	-3.17	-3.17
Real Income (UFI)	-6.09	-6.09
Real Income (RFS)	-4.13	-4.13
Real Income (UFS)	-5.16	-5.16

CHAPTER 3

CHILD FOOD INSECURITY AND THE FOOD STAMP PROGRAM: WHAT A DIFFERENCE MONTHLY DATA MAKES

3.1 Introduction

Most Americans believe that children should not have either persistent concerns about the quality and quantity of food they eat or lack of actual access to food due to low household resources. However, in 2007, approximately 3.3 million households (8.3 percent of households with children) had food insecurity among children who did not have consistent access to adequate and safe foods (Nord, 2009). This implies less than complete protection of children by the food-assistance safety net.

The United States's Supplemental Nutrition Assistance Program (SNAP), historically and commonly known as the Food Stamp Program (FSP), is a federal-assistance program designed to provide food assistance via benefit credits to low- and no-income households that can be used to purchase food in any participating store.[1] The FSP is the largest component of the USDA's nutrition program. During fiscal year 2011, an average of 44.7 million persons per month (on average 14 percent of Americans) participated in the FSP program. Federal spending for the program in fiscal year 2011 was $75.3 billion, comprising 73 percent of all Federal food and nutrition spending (USDA 2011). With so much of the nation's food assistance resources devoted to the FSP, it is important to document the effectiveness of the FSP in providing basic protection to food insecure populations, and to food insecure children in particular.

Child food insecurity often occurs in response to a negative shock to household economic well-being and close attention needs to be paid to the dynamic relationship between food security status and FSP participation. Most studies have examined and measured both food security and FSP participation on a yearly basis, but a household (and children in the household) may move in and out of food security and participate in the FSP at subintervals within a year. Descriptive statistics from the Panel Study of Income Dynamics (PSID)1999, 2001 and 2003 waves indicate that 10-15 percent (depending on the year) of PSID households classified as food insecure reported that they "had difficulty getting enough food" in only one month while between 32 and 43 percent reported difficulties in only two months. More than half of food insecure households only reported problems in three months

[1] The data used in this study were collected before the introduction of SNAP as the program acronym, and "Food Stamp Program" or "FSP" are used as generic references.

or less during each survey year. FSP participation also shows considerable within year variation. Among PSID wave 1999, 2001 and 2003 households that reported FSP participation, 24-29 percent reported participation for six months or less. The intra-annual dynamics of FSP participation and food security will be masked in an analysis with annual data. This may lead to incorrect inference with annual data about the effectiveness of the FSP in addressing food security, particularly if a substantial portion of FSP participants enter in response to a recent negative economic shock. Therefore, in this paper interaction between child food security and FSP participation is investigated using monthly, instead of annual, measures. Further, unlike most previous literature that examines the effectiveness of the FSP by comparing FSP participants with eligible non-participants, the paper specifically focuses on households that at some point participate in the FSP. This eliminates concerns about unobserved heterogeneity between participant and non-participant households.

3.2 Literature Review

Food security, defined as access at all times to enough food for an active, healthy life, is often measured using the Food Security Questionnaire Core Module developed by the USDA.[2] The module contains a set of 18 questions for households with children and 10 questions for households without children that focus on a 12-month recall period. The questions are designed

[2]Food insecurity, on the other hand, refers to "limited or uncertain availability of nutritionally adequate and safe foods or limited or uncertain ability to acquire acceptable foods in socially acceptable ways" (Bickel et al. 2000).

to capture the following major manifestations of food insecurity: anxiety or perception of inadequate food budget or food supply, perceptions of inadequate food quality, reported instances of reduced food intake or consequences of reduced food intake for adults and (or) children (see Appendix A for the module). Household food insecurity is simply defined as three or more affirmative answers out of the 18 questions. As noted, eight of the 18 questions pertain specifically to the food security status of children in the household. Households with children that respond affirmatively to two or more of these child-referenced conditions are classified as having *food insecurity among children* (Nord 2009).

The FSP provides recipients benefit transfers that can be used to purchase non-alcoholic food items at grocery stores. Although the use of FSP benefits is limited to food items, there is concern that recipients may use freed up cash to purchase non-food items and therefore may not necessarily experience improved food security condition. However, it has been estimated that low-income Americans spend about 5-15 cents of each additional dollar of cash income on food (Fraker 1990). Past research finds that FSP benefits do reduce out-of-pocket food spending but also increase overall food expenditures (Hoynes and Schanzenbach 2009). Further, the marginal propensity to spend on food has been found to be larger for food stamps than for cash income (Levedahl 1995). Hence, there is evidence to believe that FSP benefits should increase household spending and, at least partially, mitigate both household and child food insecurity.

But the analysis of FSP effects on child food security in large survey samples is complicated by endogeneity, i.e. self-selection bias. That is, households with low food security among children are more likely to participate in the FSP because of unobserved household characteristics that affect both food security and the FSP participation decision. Unobserved household heterogeneity may cause FSP participation to be an endogenous variable when quantifying its effect on food security. Many early studies that attempted to control for endogeneity found either no effect, or sometimes a paradoxical negative effect of FSP participation on food security. Most studies have focused on the food security status of households, rather than children within households. Gundersen and Oliveira (2001) and Huffman and Jensen (2006) employ simultaneous equation models to control for endogeneity and find no effect of FSP in participating households' food insecurity. Gibson-Davis and Foster (2006) use propensity score matching to address the participant and non-participant heterogeneity problem and also find no ameliorative effect of the FSP on food insecurity.

Several recent studies that take advantage of FSP policy related instrumental variables to control for endogeneity of FSP participation do, however, find an ameliorative effect of FSP participation on household food insecurity. Yen et al. (2008) find a small but negative effect of the FSP on food insecurity using data from the 1996-97 National Food Stamp Program Survey, a survey of roughly 2,200 FSP participants and income-eligible nonparticipants. Mykerezi and Mills (2010) employ both instrumental variable models and a natural experiment based on losing FPS benefits due to government interruption using 1999 Panel Study of Income Dynamics data and find a negative and significant effect of FSP participation on food insecurity. Ratcliffe and McKernan (2010) control for endogeneity with state program rules as instruments and use state and year fixed effects to control for endogeneity of policy changes and find that FSP participation reduces instances of both low food security and very low food security.

Interestingly, several studies using panel datasets to examine FSP effects on household food insecurity have not found a strong relationship between participation in the FSP and reduced food insecurity (e.g. Ribar and Hamrick, 2003; Wilde and Nord, 2005). The lack of effect of FSP uptake on food security in a panel data setting may stem in part from the aggregate timeframe used for measuring FSP participation and food security in these analyses. Specifically, deterioration of food security that may lead a household to enter the FSP usually occurs within a time period shorter than one year. As mentioned, aggregated annual measures may mask the transition in and out of the FSP and the timing of spells of food insecurity and thereby temper the true effects of FSP participation on food security. A notable exception is Nord and Golla (2009), who examine the relationship between the time of FSP entrance and food security status in the month of December of the years 2001 to 2006 with the Current Population Survey. They document that food security deteriorates in the 6 months prior to entrance into the FSP and then improves after commencing FSP use. The Nord and Golla (2009) result highlights the need to view food security as a dynamic, not static process.

The above studies focus on the relationship between the FSP and *household* food security, rather than food security among children within the household. However, the link between the FSP and child food security is itself an important research question. Food insecurity can lead to a variety of undesirable outcomes in children's health and development: a less healthy food consumption pattern (Casey et al., 2001; Kaiser et al. 2002), higher risks of being overweight (e.g.Casey et al., 2006; Jyoti et al., 2005), adverse physical health outcomes among young children (Cook et al., 2004, Cook et al., 2006, and Skalicky et al., 2006), as well as comprised mental health, social skills and academic performance (Dunifon and Kowaleski-Jones, 2003; Howard, 2011; Alaimo, Olson and Frongillo, 2001).

Recent studies have investigated the effects of Food Stamp benefits on child poverty and the effects of children-targeting food assistance programs on the food security of children-resided households as well as the effects on children's dietary outcomes. The findings provide some indirect evidence that food assistance programs do affect child food security. Jolliffe et al. (2005) calculate large reductions in the depth and severity of child poverty when FSP benefits are added to family income despite only a moderate reduction in the incidence of child poverty. Policy simulations also show that increased FSP benefits targeted to poor and extreme-poor FSP households with children effectively reduce the depth and severity of child poverty. Kabbani and Yezbeck (2004) find that the NSLP helps households with school age children to avoid hunger. Nord and Romig (2006) utilizes the seasonal differences in availability of the NSLP between spring and summer and find greater seasonal differences in food security households with school-age children and in states with lower numbers of Summer Food Service Programs and other summer time school lunch programs. Bartfeld and Dunifon (2006) examine state-level predictors for food security and find that greater state participation rates of both the Summer Food Service Program and Summer Time

School Lunches are associated with lower risk of food insecurity. Gundersen, Kreider and Pepper (2011) provide more direct evidence for the effectiveness of the NSLP, in that the receipt of free and reduced-price lunches leads to substantial reductions in food insecurity for households with children.

The literature examining the effectiveness of food assistance programs on children's nutritional outcomes is extensive. Early studies find substantial positive effect of the school lunch program on children's nutrient consumption (e.g.Akin, Guilkey, and Popkin, 1983; Price et al. 1978). Carlson and Senauer (2003) find a significant positive effect of the Women, Infants, and Children (WIC) Program on children's health in participating households. More recent studies show mixed results with respect to the effectiveness of the NSLP: the NSLP leads to increased intake of desirable nutritions such as vitamins and minerals as well as undesirable higher intake of dietary fat (Gleason and Suitor, 2003) and NSLP participants consume higher quantity rather than higher quality lunches (Campell et al., 2011).

This study fills a gap in the literature by directly focusing on the effect of the FSP on food security among children in households that participate in the FSP. More importantly, the paper employs novel monthly measurements of child food security and FSP participation and examines how child food security changes before and after a household enters the FSP. Utilization of panel data and a fixed effect model effectively controls for time-invariant unobserved heterogeneity that is prevalent across FSP participants, while focusing only on households with children that at some point participate in the FSP eliminates concerns about participant and non-participant heterogeneity that is prevalent in the literature to date.

3.3 Data and Methods

The Panel Study of Income Dynamics (PSID) is employed to estimate the dynamic effect that FSP participation has on child food security. The PSID was first conducted in 1968 with a nationally representative sample of over 18,000 individuals living in 5,000 families in the United States. Information on these individuals and their descendants have been collected continuously and immigrant families have been added to the survey in more recent years to represent the changing demographics. PSID data were collected annually 1968-97 and biennially after 1997. The 1999, 2001, and 2003 waves of the PSID provide detailed information on month-to-month variations in food security in the previous calendar year. These three waves are used in the analysis because Food Security Questionnaire Core Module discontinued and food security information is not available in later years.

Monthly measures of food insecurity among children in the household are derived as follows. First, both household food insecurity and food insecurity among children in the household for the year (1998, 2000 and 2002) are determined following standard guidelines (see paragraph one of Literature Review). Second, households that are determined to be food insecure in the year are also asked in the survey about difficulty in getting enough food in each month of the year. The measure of monthly food security among children is generated by assuming that if the household was food insecure in a certain month and children in the household experienced food insecurity for the year, then children in the household also experienced food insecurity in that month.[3] For instance, if a household has food insecure children in 1998 and reports difficulty getting enough food in January of that year, children in the household are considered to be food insecure in January. It is worth noting that this approximation of monthly food insecurity status of children is likely to overestimate food insecurity, as parents are often able to main normal or near-normal diets for their children even when the parents themselves are food insecure (Nord 2009). However, this paper focuses on the changes of food security among children before and after FSP enrollment, rather than the levels in each month. Universal overestimation of food insecurity may not affect the multivariate results, if the bias is not systematically related to FSP participation decisions. However, on the other hand, if respondents justify their use of FSP benefits by reporting food difficulties in the months immediately preceding and after take-up of benefits, greater caution is needed when utilizing the data.

In each wave, detailed information on households' month-to-month FSP participation is also collected from January two years back to the interview month of the reference year. This information is used to construct FSP status variables introduced below. As noted, households are asked to recall their FSP participation and experience of food difficulty in the survey and this raises some concern for reliability of recall data. To check the robustness of our results, the model is also estimated with recall time (temporal distance from interview month and the month of interest) as a control and key results

[3] Most households with food insecure children are also food insecure in the dataset and therefore asked about monthly difficulty getting enough food. However, five households in 2002 have food insecure children but are food secure by definition. Since monthly food security status is unknown, these households are dropped in the analysis.

do not change.

This paper explores the effectiveness of the FSP by investigating how food security among children evolves before and after a household enters the FSP. A household's interaction with the FSP is divided into pre-FSP, in-FSP, and post-FSP periods. The pre-FSP period is disaggregated into 1, 2, 3 months before entering the FSP and a 4-12 months aggregate pre-FSP period.[4] Similarly the in-FSP period is disaggregated into 1, 2, 3 months in the FSP and an aggregate 4-12 months in-FSP period. A two-month post-FSP period is also identified and disaggregated into 1 and 2 months after exiting the program. Distinguishing between pre-FSP and post-FSP periods allows for possible short-term asymmetric effects of entering and exiting the program.

The model is estimated using monthly observations of the food security status of children in 1998, 2000 and 2002. More importantly, only household-waves that had a FSP spell in the previous calendar year lasting 12 months or shorter are included in the sample in order to focus on how food security among children changes before and after FSP enrollment. FSP status is determined for each month in 1998, 2000 and 2002 by the timing of the month when child food security is identified, in relation to FSP entry. During an FSP spell, the FSP status of a month is determined by the temporal distance between the current month and the starting month of the spell. For instance, if a household enters the program in August and stays for the rest of the year,

[4] The non-immediate pre-FSP period (4-12 months before FSP entry) and long-term participation period (4-12 months in the FSP) are aggregated to maintain adequate observations in the groups, as the number of observations decreases significantly with the duration of time before and after entering FSP.

then August is one month in the FSP, September is two months in the FSP, October is three months in the FSP and November and December belong to the aggregate 4-12 month in the FSP period. The months before an FSP spell are categorized as the pre-FSP period and the FSP status of a month is again determined by the temporal distance between the current month and the starting month of the spell. Using the same example, July is one month before entering the FSP, June is two months before entering the FSP, May is three months before entering the FSP, and April-January all belong to the aggregate 4-12 months before entering the FSP period. The months after an FSP spell are categorized as post-FSP period and the FSP status of a month is determined by the temporal distance between the last month of the spell and the current month. For instance, if a household is in the FSP from January to October, then November is one month after exiting the FSP and December is two months after exiting the FSP.

When multiple FSP spells are present in a year, identification of the months between two adjacent spells is more complex because they can be defined as pre-FSP or post-FSP months. Since exiting the FSP is unlikely to have a prolonged influence on food security and the focus of this paper is to compare child food security before and after entering the FSP, the months that are three months or more after exiting the previous spell are categorized as pre-FSP period of the next spell, if applicable. For instance, if a household is in the FSP from January to March and from September to December, April and May are defined as one and two months after exiting the FSP while June, July and August are three, two and one months before entering the FSP. [5]

Our main sample (column 1 of table 3.4) only includes household-waves if there was an FSP spell in the previous year and the spell lasts 12 months or shorter because long-term participants of the FSP may be systematically different from short-term participants. This yields an unbalanced panel of 491 households with 6,480 household-month observations. To check the robustness of including only short-term participants, two alternative samples are also examined where all waves of a household are included if they had an FSP spell in the previous year and the FSP spell is 12 months or shorter in at least one wave (column 2 of table 3.4) or if they had an FSP spell in the previous year, regardless of the duration (column 3 of table 3.4).

A fixed effect model is employed to account for potential endogeneity of FSP participation arising from time invariant unobserved household characteristics. Household fixed effects largely eliminate the need to control for time invariant characteristics and the model is estimated with a parsimonious specification of monthly observations of food insecurity status among children, FSP participation status relative to month of observed food security status, and employment status in the month of observed food security status.[6]

[5]Only 18 households had multiple spells in a year and our results do not change after dropping out those observations.

[6]School meal programs that provide free or reduced-price breakfast and lunch to children are not included in our model specification because only annual measures are available in the data. Therefore there is very little variation since our model is estimated with monthly observations, which is not best for fixed effects model. Moreover, even when the school meal programs are controlled for in the model, parameter estimates remain largely unchanged.

$$
\begin{aligned}
FI_{it} \quad = \quad & \eta_1 FSPP3_{it} + \eta_2 FSPP2_{it} + \eta_3 FSPP1_{it} + \eta_4 FSP1_{it} + \eta_5 FSP2_{it} + \eta_6 FSP3_{it} \\
& + \eta_7 FSP4_{it} + \eta_8 FSPE1_{it} + \eta_9 FSPE2_{it} + \theta UNEM_{it} + \kappa OLF_{it} + \boldsymbol{m}_{it}\boldsymbol{\omega} + \mu_i + \varepsilon_{it}
\end{aligned}
$$

FI_{it} is a binary variable that is equal to 1 if children in household i are food insecure in month t, and 0 otherwise. $FSPP3$, $FSPP2$, and $FSPP1$ represent 3, 2, and one months prior to FSP entry, while $FSP3$, $FSP2$, $FSP1$ represent 3, 2, and 1 months in the FSP, and $FSP4$ represent the aggregate period of 4-12 months in the program. $FSPE1$ and $FSPE2$ represent 1 and 2 months after exiting the FSP. The non-immediate pre-FSP period (4-12 months prior) is the baseline period. $UNEM_{it}$ is a binary variable that indicates if the head of household i is unemployed in month t and OLF_{it} is a binary variable that indicates if the head of household i is out of labor force in month t[7]. $\boldsymbol{m}_{it}$ is a 1×11 vector of month dummies used to capture seasonal effects, μ_i is the household specific fixed effect, and $\eta's$, θ, κ, and $\boldsymbol{\omega}$ (11×1 vector) are coefficients.

The specification effectively compares the base food security status of children in participating households 12 to 4 months prior to entering the program with the food insecurity status of children in participating households three to one months prior to entering the FSP, the status of children in participating households from one month to up to 12 months after entering

[7]Being unemployed is defined as not having a job but actively looking for employment whereas being out of labor force denotes not having a job and not actively looking for employment.

the program, and the status of children in participating households in the first two months after program exits. A fixed effect Linear Probability Model (LPM) is used to estimate the relationships.[8]

3.4 Results

The PSID includes 3,393 households with children in 1998, 3,484 households with children in 2000, and 3,540 households with children in 2002. Food insecurity rates among children are 5.72 percent, 5.51 percent, and 6.32 percent, respectively, in 1998, 2000, and 2002 (table 3.1). Consistent with the literature, food insecurity among children is lower than food insecurity in the household, because children are usually the last household members to be exposed to food insecurity (Nord, 2009). It is also worth noting that food insecure rates among children are significantly higher for households that have at least some interactions with the FSP in the same years. As shown in table 1, among those with exposure to the FSP, 15 percent children were food insecure in 1998, 18 percent children were food insecure in 2000, and around 17 percent were food insecure in 2002. The rates of food insecurity among children in the restricted sample are statistically different from those in the entire sample of all households with children at 0.1% level. The simple descriptive statistics suggest the presence of self-selection among FSP

[8]Fixed effect probit models do not yield consistent estimates (Baltagi 2008). Conditional fixed effects logit models yield consistent estimates but drop households where the dependent variable does not change over time; i.e. households with no change in food security status over time are dropped. Another popular method to estimate panel datasets with binary dependent variables is the random effect probit model. Random effect probit model estimates do not substantially differ from the LPM estimates and are available from the authors upon request.

participants in terms of lower pre-existing child food security.

Descriptive statistics on child food insecurity rates at the different periods before and after interaction with the FSP are presented in table 3.2 for households with some interaction with the FSP in 1998, 2000, or 2002. Food insecurity among children increases in the months prior to FSP participation, with the rate of food insecurity going up from 2 percent in the 4-12 months pre-FSP period to 7.7 percent in the month immediately prior to participation. The rate of food insecurity among children then declines once the household participates in the FSP, dropping to 5.3 percent in the first month in FSP and to 3.8 percent in the second month. The food insecurity rate bounces back up slightly by 0.5 percentage point in the third month. In the 4-12 month in-FSP period, the food insecurity rate among children actually reaches its highest level along the timeline, at 9.9 percent. This may be because households that stay in the FSP for a relatively long time are chronically food insecure, rather than a result of exposure to the FSP. The fixed effect model will control for this possible self-selection by controlling for effects of time-invariant unobservables. After exiting the program, the rate of food insecurity among children decreases for households that are one month out of the FSP, to 3.4 percent and then bounces back up to 6.3 percent for households that are two months out of the FSP. This suggests that after households exit the program the child food security more or less returns immediately to the level seen 4-12 months prior to FSP entry. But the sample size is small so care is needed in making this inference.

Similarly, the relationship between parent labor market shocks and child food insecurity is examined in table 3.3. Food insecurity among children appears to be relatively constant before exposure to unemployment and then deteriorates in the months after a parent becomes unemployed, with child food insecurity increasing from 2.5 percent in the 1st month after unemployment to 11.2 percent in the 4th month after unemployment. Thus, a change in parental employment status appears to have a relatively strong immediate effect on child food insecurity. Given the moderate sample size, we only control for current employment status in the empirical specification.

Results from the fixed effect LPM model that examines how food insecurity among children changes before and after the FSP entry and when controlling for changes in food security associated with employment status are presented in table 3.4. All independent variables are binary and the omitted categories for the independent variables (by table row) are employed household heads, the month of January, and the non-immediate (4-12 months) pre-FSP participation period.

The first column provides parameter estimates for the main sample in which household-waves are included only if there was an FSP spell in the previous year and the spell lasted 12 months or shorter. Parameter estimates indicate that the change in the probability of food insecurity among children with respect to the timing of FSP participation largely shows a similar pattern to that found in the descriptive statistics presented in table 3.2 until the last (the long-term participation) period. Compared to the non-immediate pre-FSP period (the baseline), children are estimated to be 2.5 percentage points more likely to be food insecure in a household 3 months before FSP entry, and the probability continues to increase as the household gets closer to FSP entry, reaching a peak of 4.6 percentage points more likely to be food insecure the month before a household enters FSP. The probability of children being food insecure then starts to decrease once the household enters the FSP. After one month in the program, the probability of children being food insecure declines to 3.3 percentage points above the baseline and continues to decline to 2.8 percentage points above the baseline when the household is 2 months into the program. Food insecurity then increases slightly, as children are 3.2 percentage points more likely to be food insecure 3 months into the program compared to the baseline. Finally when the household enters the 4-12 month in-FSP period, children are only 2.3 percentage points more likely to be food insecure compared to the baseline, which is the same as the level seen 3 months prior to participation. In the first two months after exiting the program, children in the household are no more likely to be food insecure compared to the baseline of 4-12 before program entry, although numerically the probability increases in the second month out of the FSP. Thus child food security reverts back to pre-FSP levels after program exit.[9]

It is worth noting that in the descriptive statistics in table 3.2, the child food insecurity rate is much higher in the 4-12 month in-FSP period than in other periods, while results from fixed effect LPM show that children are less likely to be food insecure during the long-term participation period compared to immediately prior to and after FSP entry. This difference arises because unobserved household heterogeneity is controlled for in the fixed

[9]There are also statistically significant differences between some of the "non-baseline" pre- and in-FSP periods. Of note, child food insecurity one month before entering the program is statistically higher than 4-12 months in the program and also higher than at one month after exiting the program.

effect model and, therefore, the parameter only captures the difference in food insecurity relative to timing of FSP participation of the same household. This eliminates selection bias associated with long-term FSP participation. Figure 1 presents a straightforward illustration of the change in the probability of food insecurity among children in each period relative to the base period of 4-12 months prior to FSP participation.

Employment status indicator variables for the model in column one also have expected signs. Compared to the baseline case of working, an unemployed household head increases the probability of child food insecurity by 4.0 percentage points, while a household head out of the labor force increases the probability by 2.5 percentage points. As for seasonal effects, the probability of a child being food insecure is numerically lower in most months from February to November, compared to the baseline of January. While the probability is higher in December than in the January baseline. However, none of the month coefficients are statistically significant. The results weakly suggest that children's food insecurity tend to get worse at the beginning and end of the year, possibly due to financial stresses from heating expenses or the holidays faced by households. Contrary to previous findings, children do not appear to be more protected from food insecurity during the school year in the PSID sample (Nord and Romig, 2006; Bartfeld and Dunifon, 2006). But, again, our sample is different in that it focuses on households with some exposure to the FSP.

Results in columns 2 and 3 of table 3.4 are based on the same specification of the model, but with slightly different samples. Unlike column 1, which only includes household-waves that had an FSP spell in the previous year lasting 12 months or shorter, column 2 includes the larger sample where all waves of a household are included if they had an FSP spell in the previous year and the spell lasts 12 months or shorter in at least one wave. Column 3 presents an even larger sample, where all household-waves that had an FSP spell in the previous year are included, regardless of the duration. Parameter estimates in columns 2 and 3 are very similar to those of column 1, with the same estimated trends of increasing food insecurity among children in the pre-FSP periods and stabilization of rates on food insecurity in the in-FSP period. There is also a consistent jump in the probability of food insecurity when a household is 3 months into the program, but the likelihood then goes back down in the long-term participation period. The consistent increase in child food insecurity 3 months in the program may be related to the prevalence of a short FSP recertification period of 3 months in the late 1990s and early 2000s.[10] The finding is also consistent with concerns that short recertification periods can exclude needy households from the FSP and raise rates of food insecurity.

In order to test the robustness of the results to the FSP lead and lag structure, the model is re-estimated with the pre-FSP period disaggregated into 1, 2, 3, 4 months before and a non-immediate pre-FSP period of 5-12 months before FSP entrance and in-FSP periods disaggregated into 1, 2, 3, 4 months in FSP and an aggregate period of 5-12 months in the program. The post-FSP period is extended by one month. The results, table 3.5, are

[10]Kabbani and Wilde (2003) noted that in the late 1990s and early 2000s, many states drastically increased their use of short recertification periods (three months or less) to lower Food Stamp error rates. Nationally the rate of short recertification periods reached 36% for participants in working households and around 24% for all participants in fiscal year 2000.

presented for the same household-wave samples; those that had an FSP spell in the previous year and the spell is 12 months or shorter in each wave, those that had an FSP spell in the previous year and the spell is 12 months or shorter in at least one wave, and those that had an FSP spell in the previous year, regardless of the duration. Estimates for the major parameters of interest are similar to those in table 3.4. The probability of children in a household being food insecure is not statistically different 4 months before FSP entry from the non-immediate pre-FSP period (5-12 months). Then as the household gets closer to FSP entry, children are more likely to be food insecure, with the probability increasing from around 3 percentage points above the baseline 3 months before FSP entry to almost 5 percentage points above the baseline the month before FSP entry. Once the household enters the FSP, the likelihood of children being food insecure begins to decline to 4 percentage points and 3 percentage points above the baseline one and two months in the program, respectively. At 3 months in the program the probability again increases slightly before going back down to around 2 percentage points above the baseline in the 5-12 in-FSP period. When the household first exits the FSP, children are statistically no more likely to be food insecure compared to the baseline, 5-12 months before program entry. Then in the second month out of the FSP, the probability of children being food insecure increases to around 3 percentage points above the baseline and the difference is statistically significant. In the third month out of the program the probability difference becomes statistically insignificant again, although the magnitude of the parameter estimate is similar to that two months after program exit.

The use of intra-annual measures and incorporation of pre- and in-FSP dynamics are the key novel components in our model specification. Table 3.6 presents fixed effect LPM regressions of children's food insecurity on FSP participation and parent's employment status using annual measures of food insecurity and FSP participation to determine if evidence of FSP effects exist with more temporally aggregated data.[11] Estimates in the first column are based on the sample of households that had a change in FSP status in the year (in correspondence with column 1 of table 3.4), estimates in column 2 are based on the sample of households that had a change in FSP status in at least one out of the three years (in correspondence with column 2 of table 3.4) and column 3 is based on the entire sample of households with children in waves 1999, 2001, and 2003 of the PSID. As indicated in the table, the coefficients for the indicator for annual FSP participation are -0.078, -0.024 and -0.001, respectively. Importantly, the estimates are not statistically significant. Thus, no evidence of FSP effects on children's food insecurity is found with annual measures. This result suggests that a dynamic model containing monthly food insecurity and FSP participation measures may be crucial to uncovering the true nature of the effects that FSP participation has on food security.

[11] Annual child food security is determined using the eight questions pertaining to child food security in the USDA Food Security Module. Following the literature, a household is determined to be FSP participant for the year if FSP benefits are received for at least a month in that year.

3.5 Conclusions

Our results indicate that the FSP plays an important role in protecting the well-being of children in low-income households by effectively ameliorating declining food security conditions among children in the face of negative economic shocks. Instead of focusing on the effect of the FSP on children's food security at a single point in time, this paper uses monthly measures of both household FSP participation and child food insecurity to examine how, among participating households, food security evolves before and after a household enters the FSP. Unlike most previous literature that examines the effectiveness of the FSP by comparing participants with eligible non-participants, our paper focuses on the change of food security conditions in the subset of the population with children that are program participants at some point in time. Results indicate that children's food security starts deteriorating a few months before a household enters the FSP, but the FSP partially ameliorates participants' worsening food security conditions, once enrolled. After 4 months in the program the food security of children returns to the levels seen 3 months before FSP entry. The evidence of FSP exit effects on child food security is mixed, and further research is needed in this area. The results also indicate that intra-annual effects are masked by annual measures, as an annual indicator of FSP participation does not show a significant effect on an annual measure of children's food security using the same data, years, and fixed effect model.

The documented dynamics of program effects suggest that the FSP is effective in absorbing short-term negative shocks and helping families cope with urgent food difficulties. Some indirect evidence from our results suggests that the 3 month recertification window may increase child food insecurity. Most states started lengthening FSP certification period in early 2000s, when the data used in our analysis was collected (SNAP Policy Database). Also, the strengthening of linkages between the FSP and unemployment application should be explored when a larger dataset is available, as unemployment of adult household members is strongly related to deteriorating child food security.

This paper uses a new and novel indicator of child food security and finds supportive evidence for the effectiveness of the FSP in ameliorating food insecurity among children, but with some drawbacks. Both FSP participation and food security information are recalled month-to-month by survey respondents, which may need a more careful scrutiny of its reliability. Monthly child food security measure is generated based on the assumption that child food insecurity in a year translates into monthly child food insecurity in the months when the household as a whole is food insecure. Possible impacts of this assumption on multivariate fixed effect estimates that focus on a change, not levels, are uncertain.

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3.7 Appendix A

Food Security Questionnaire Core Module

1. "We worried whether our food would run out before we got money to buy more." Was that often, sometimes, or never true for you in the last 12 months?

2. "The food that we bought just didn't last and we didn't have money to get more." Was that often, sometimes, or never true for you in the last 12 months?

3. "We couldn't afford to eat balanced meals." Was that often, sometimes, or never true for you in the last 12 months?

4. In the last 12 months, did you or other adults in the household ever cut the size of your meals or skip meals because there wasn't enough money for food? (Yes/No)

5. (If yes to Question 4) How often did this happen-almost every month, some months but not every month, or in only 1 or 2 months?

6. In the last 12 months, did you ever eat less than you felt you should because there wasn't enough money for food? (Yes/No)

7. In the last 12 months, were you ever hungry, but didn't eat, because there wasn't enough money for food? (Yes/No)

8. In the last 12 months, did you lose weight because because there wasn't enough money for food? (Yes/No)

9. In the last 12 months did you or other adults in your household ever not eat for a whole day because there wasn't enough money for food? (Yes/ No)

10. (If yes to Question 9) How often did this happen-almost every month, some months but not every month, or in only 1 or 2 months?

(Questions 11-18 were asked only if the household included children ages 0-18)

11. "We relied on only a few kinds of low-cost food to feed our children because we were running out of money to buy food." Was that often, sometimes, or never true for you in the last 12 months?

12. "We couldn't feed our children a balanced meal, because we couldn't afford that." Was that often, sometimes, or never true for you in the last 12 months?

13. "The children were not eating enough because we just couldn't afford enough food." Was that often, sometimes, or never true for you in the last 12 months?

14. In the last 12 months, did you ever cut the size of any of the children's meals because there wasn't enough money for food? (Yes/No)

15. In the last 12 months, were the children ever hungry but you just couldn't afford more food? (Yes/No)

16. In the last 12 months, did any of the children ever skip a meal because there wasn't enough money for food? (Yes/No)

17. (If yes to Question 16) How often did this happen-almost every month, some months but not every month, or in only 1 or 2 months?

18. In the last 12 months did any of the children ever not eat for a whole day because there wasn't enough money for food? (Yes/No)

Table 3.1: Prevalence of Food Insecurity among Children in the Household(%)

Household type	1998	2000	2002	1998	2000	2002
	Raw sample			Restricted sample		
Households with food security among children	94.28	94.49	93.68	84.57	82.03	83.4
Households with low food security among children	4.98	4.88	5.47	12.07	15.44	14.48
Households with very low food security among children	0.74	0.63	0.85	2.96	2.53	2.12
Total number of households	3,393	3,484	3,540	439	395	518

NOTE: The raw sample includes all households with children in 1999, 2001 and 2003 waves of the PSID. The restricted sample includes only households that had a FSP spell in the previous calendar year. The rates are not statistically different between years within each sample, but are statistically different at 0.1% level across samples in each year.

Table 3.2: FSP Status and Prevalence of Food Insecurity among Children in the Household (%)

Month	Households with food security among children	Households with food insecurity among children	Total number of observations
4-12 months before FSP entrance	98.0	2.0	1,925
3 months before FSP entrance	95.6	4.4	342
2 months before FSP entrance	93.8	6.2	370
1 month before FSP entrance	92.3	7.7	426
1 month in the FSP	94.7	5.3	417
2 months in the FSP	96.2	3.8	445
3 months in the FSP	95.7	4.3	445
4-12 months in the FSP	90.1	9.9	1,984
1 month out of the program	96.6	3.4	219
2 months out of the program	93.7	6.3	142

Pairwise tests of two adjacent categories indicate that food insecurity rates among children in the household are statistically different at 0.1% level between the following pairs; 4-12 months before FSP entrance and 3 months before FSP entrance, 3 months in the FSP and 4-12 months in the FSP, and 4-12 months in the FSP and 1 month out of the program. Statistical indifference between the rest of the pairs may result from the moderate sample size of other groups.

Table 3.3: Parent's Labor Market Shock (Unemployment) and Food Security Status of Children (%)

Month	Households with food security among children	Households with food insecurity among children	Total number of observations
4 months before unemployment	99.1	0.9	346
3 months before unemployment	98.4	1.6	430
2 months before unemployment	98.8	1.2	481
1 month before unemployment	98.5	1.5	540
1st month of unemployment	97.5	2.5	518
2nd month of unemployment	95.3	4.7	339
3rd month of unemployment	94.9	5.1	198
4th month of unemployment	88.9	11.1	144

NOTE: The sample is limited to households with children in which household head was unemployed at some point in 1998, 2000 and 2002. Food security status of children is a monthly measure and the duration of pre- and post-unemployment spells are up to four months because longer time span renders much fewer observations. Pairwise tests indicate that food insecurity rates among children in the household are statistically different between 1st month of unemployment and 2nd month of unemployment at 10% level, and are statistically different between 3rd month of unemployment and 4th month of unemployment at 5% level.

Table 3.4: Food Insecurity among Children and FSP Participation (Fixed Effects LPM)

Variables	Sample 1	Sample 2	Sample 3
Head is unemployed	0.040***	0.016*	0.022**
	(0.011)	(0.009)	(0.009)
Head is out of the labor force	0.025**	-.003	-.008
	(0.010)	(0.008)	(0.006)
February	-.005	-.004	-.007
	(0.010)	(0.009)	(0.007)
March	0.005	-.002	-.007
	(0.010)	(0.009)	(0.007)
April	-.005	-.009	-.010
	(0.010)	(0.009)	(0.007)
May	-.003	-.007	-.008
	(0.010)	(0.009)	(0.007)
June	-.003	-.004	-.008
	(0.009)	(0.009)	(0.007)
July	-.002	0.001	-.002
	(0.010)	(0.009)	(0.007)
August	-.008	-.006	-.006
	(0.010)	(0.009)	(0.007)
September	-.014	-.016*	-.017**
	(0.009)	(0.008)	(0.007)
October	-.008	-.010	-.008
	(0.011)	(0.009)	(0.007)
November	-.002	0.003	0.007
	(0.011)	(0.010)	(0.008)
December	0.011	0.012	0.015*
	(0.012)	(0.010)	(0.008)
3 months before participation	0.025***	0.027***	0.025**
	(0.010)	(0.010)	(0.010)
2 months before participation	0.040***	0.039***	0.036***
	(0.011)	(0.011)	(0.011)
1 month before participation	0.046***	0.047***	0.044***
	(0.011)	(0.011)	(0.011)
1 month in the program	0.033***	0.037***	0.034***
	(0.010)	(0.010)	(0.010)
2 months in the program	0.028***	0.032***	0.029***
	(0.011)	(0.011)	(0.011)
3 months in the program	0.032***	0.038***	0.036***
	(0.012)	(0.013)	(0.013)
4-12 months in the program	0.023**	0.023***	0.019***
	(0.010)	(0.007)	(0.007)
1 month out of the program	0.010	0.008	0.005
	(0.013)	(0.012)	(0.012)
2 months out of the program	0.020	0.017	0.015
	(0.017)	(0.016)	(0.016)
Number of observations	6,480	9,372	15,420
Number of groups	491	555	874

NOTE: Heteroskedastic robust standard errors are in parentheses. Asterisks indicate levels of significance: ***=1%, **=5%, *=10% in two-tailed t-tests. Sample 1 includes all household-waves that had an FSP spell in the previous year lasting 12 months or shorter. Sample 2 includes all waves of a household if they had an FSP spell in the previous year and the spell lasted 12 months or shorter in at least one wave. Sample 3 includes all household-waves that had an FSP spell in the previous year, regardless of the duration.

Table 3.5: Robustness checks (Extending the lead and lag structure)

Variables	Sample 1	Sample 2	Sample 3
Head is unemployed	0.038***	0.013	0.021**
	(0.011)	(0.009)	(0.009)
Head is out of the labor force	0.024**	-.001	-.007
	(0.010)	(0.008)	(0.006)
February	-.003	-.003	-.006
	(0.010)	(0.009)	(0.007)
March	0.004	-.002	-.008
	(0.010)	(0.009)	(0.007)
April	-.006	-.010	-.010
	(0.009)	(0.008)	(0.007)
May	-.001	-.005	-.007
	(0.009)	(0.008)	(0.007)
June	-.002	-.003	-.007
	(0.009)	(0.008)	(0.007)
July	0.002	0.003	-.0004
	(0.009)	(0.009)	(0.007)
August	-.005	-.005	-.005
	(0.009)	(0.008)	(0.007)
September	-.012	-.013	-.017**
	(0.009)	(0.008)	(0.007)
October	-.006	-.007	-.007
	(0.010)	(0.009)	(0.007)
November	0.001	0.007	0.008
	(0.011)	(0.010)	(0.008)
December	0.013	0.013	0.015**
	(0.011)	(0.010)	(0.008)
4 months before participation	0.002	0.004	0.004
	(0.008)	(0.008)	(0.008)
3 months before participation	0.025**	0.027**	0.026**
	(0.010)	(0.010)	(0.010)
2 months before participation	0.038***	0.037***	0.036***
	(0.011)	(0.011)	(0.011)
1 month before participation	0.045***	0.046***	0.044***
	(0.011)	(0.011)	(0.011)
1 month in the program	0.038***	0.042***	0.04***
	(0.011)	(0.011)	(0.011)
2 months in the program	0.031***	0.035***	0.033***
	(0.011)	(0.011)	(0.011)
3 months in the program	0.036***	0.041***	0.04***
	(0.013)	(0.013)	(0.013)
4 months in the program	0.035***	0.039***	0.036***
	(0.012)	(0.013)	(0.012)
5-12 months in the program	0.024**	0.024***	0.022***
	(0.011)	(0.008)	(0.008)
1 month out of the program	0.016	0.014	0.011
	(0.013)	(0.012)	(0.012)
2 months out of the program	0.031*	0.027*	0.025*
	(0.016)	(0.015)	(0.015)
3 months out of the program	0.028	0.024	0.025
	(0.018)	(0.017)	(0.017)
Number of observations	6,864	9,804	15,696
Number of groups	518	580	890

NOTE: Heteroskedastic robust standard errors are in parentheses. Asterisks indicate levels of significance: ***=1%, **=5%, *=10% in two-tailed t-tests. Sample 1 includes all household-waves that had an FSP spell in the previous year lasting 12 months or shorter. Sample 2 includes all waves of a household if they had an FSP spell in the previous year and the spell lasted 12 months or shorter in at least one wave. Sample 3 includes all household-waves that had an FSP spell in the previous year, regardless of the duration.

Table 3.6: Child Food Insecurity and FSP Participation (Annual Measures; Fixed Effects LPM)

Variables	At least a change every year	At least one change in 3 years	Including no changes
FSP participation	-.079 (0.239)	-.024 (0.135)	0.001 (0.018)
Head is unemployed	0.006 (0.315)	-.017 (0.089)	-.006 (0.013)
Head is out of the labor force	-.036 (0.271)	-.021 (0.071)	0.016 (0.015)
Number of observations	540	781	10,375
Number of groups	491	555	4,846

NOTE: Heteroskedastic robust standard errors are in parentheses. Asterisks indicate levels of significance: ***=1%, **=5%, *=10% in two-tailed t-tests.

CHAPTER 4

A CLOSER LOOK AT PATIENT-PHYSICIAN RELATIONSHIP AT "INTERNET AGE": FROM A PRINCIPAL-AGENT PERSPECTIVE

4.1 Introduction

The healthcare market is characterized by agency problems, which arise when different parties have unaligned incentives and asymmetric information (Gaynor 1994). One area of agency problem arises between patients and physicians because patients often desire the highest quality of care possible under a given budget while both diagnosis and treatment are costly to physicians to whom provision of best physician services may not be optimal. Meanwhile physicians in general possess professional medical training and knowledge that is, in most cases, not available to the patient. Information asymmetry also manifests after diagnosis when physicians acquires private information about the patient's condition that is not necessarily fully disclosed to the patient.

Insurance plays an indispensable role in contemporary healthcare system. Insured patients only pay a small fraction of the pecuniary costs of medical care, the majority of which is born by insurers. A second area of agency problem in the healthcare market exists between physicians and insurers because physicians' input (or effort) in treating the patient is not observable and neither is the actual quantity of treatment.[1] Several papers have studied the agency relationship between physicians and insurers, the insurer's interest in having physicians act as their agents and economize on the use of health services, or the possibility of physicians acting on their patients' behalf and untruthfully reporting the quantity of treatment when patients are responsible for a copayment of health services (Blomqvist 1991, Ma and McGuire 1997). A third area of agency problems emanate from patients and insurers, and previous studies have examined patients' over-demand of healthcare services when they are fully insured, and insurance contracts with copayments that bring patients into cost sharing (e.g. Ellis and McGuire 1990).

The wide spread popularity of internet has made its mark in the present healthcare system. 'internet informed' patients are exposed to more medical information than ever before, which may have a profound influence on patient-physician and physician-insurer dynamics. Information outlets on-

[1] The quantity of treatment is not verifiable, even *ex post*. In practice, insurers contract on the basis of report of treatments, or claims, rather than the quantity of treatment itself because verifying the quantity of treatment is costly. Distinguishing between the report and actual quantity of treatment immediately reveals agency problems between physicians and insurers (Ma and McGuire 1997).

line are a significant source of health information in the U.S. For instance, 80 percent internet users (or 59 percent adults) in the U.S. have looked online about health topics such as a specific disease or treatment (Fox 2011). Patients search for medical information on the internet before or after a visit to the physician, use the internet to learn about drug side effects or complications of medical therapy, share personal experience in virtual communities or educate themselves with general health information found online (Diaz et al. 2002 and McMullan 2006).

Interactions between patients, physicians and insurance are characterized by information asymmetry. Patients' behavior of health information seeking on the internet has a potential to partially bridge the information gap between patients and physicians and therefore, to some extent, mitigate agency problems. On the other hand, the quality of medical information online is highly variant and patients can find it very confusing (Diaz et al. 2002 and McMullan 2006). Incomprehensible online health information can mean longer explaning time and less efficient consultations for physicians (Murray et al. 2003 and Sommerhalder et al. 2009). Indeed, "internet Age" may present both advantages and challenges to physician practices and insurer contracts. This paper introduces internet health information to a principal-agent framework between patients, physicians and a public insurer and investigate how internet information affects insurance contracts, physician effort and patient's expected health loss.

4.2 Literature Review

Health information seeking has become one of the most common activities online (Hesse et al. 2005). Women, younger adults, and those with more education and higher income are more likely than other demographic groups to gather health information on the internet (Fox 2011). The majority of online health information seekers search for medical information about a specific condition, while others search information regarding a visit to the physician, use the internet to investigate drug side effects or complications of medical therapy, share commentary or experience in virtual communities, and self educate with nutrition and diet information (Diaz et al. 2002, Fox 2011, McMullan 2006 and Powell, Darvell and Gray 2003).

The quality of internet health information is highly variant. Information is often incomplete and sometimes inaccurate, although good material can be found (Powell, Darvell and Gray 2003). An early study surveys internet advice on managing fever in children at home and find only four out of 41 websites examined provide complete and accurate information for this common condition(Impicciatore et al.). A more recent study on the quality of internet oncology information also finds a lack of validation among most oncologic sites and less than a quarter of the sites are HON credited (Lawrentschuk et al. 2012).[2] Although some studies find that most patients find the quality of internet health information to be "very good" or "good", there is now increasing evidence that information can be overwhelming, con-

[2]Health on the Net (HON) Foundation is a non-profit, non-governmental organization founded in 1995. An ethical standard aimed at providing quality health information, the HONcode certification is the most used ethical and trustworthy code for medical and health related information available on the internet.

flicting and confusing for patients (e.g. Diaz et al. 2002, McMullan 2006). As a result patients often experience difficulties when searching the internet for health-related information, and often do not achieve a final clarification of their health-related problems and treatment options (Sommerhalder et al. 2009). Most studies still find that patients rely on health professionals as the most trustworthy and number one source for health information (e.g. Fox 2011, McMullan 2006). What's more, patients do not see internet as replacement for health professionals. It is often found that patients' seeking for internet information does not affect their decision for a physician visit, or sometimes searching for health information has a positive sizable effect on an individual's demand for health care (Wagner and Jimison 2003, Suziedelyte 2012).

The timing of health information search is often related to consultations. Patients seek health-related information both before a consultation to better explore whether symptoms are related to clinically meaningful diseases or after a consultation to confirm and fully understand a diagnosis or treatment procedure (McMullan 2006 and Sommerhalder et al. 2009). Internet is perceived to be particularly useful by patients for confirming and expanding information given by the physician who often has a limited time constraint (Stevenson et al. 2007). Patients' use of internet health information to better understand their physicians is not surprising given that being able to talk to the physician, understanding of the doctor's explanations, and the amount of information transferred to the patient are found to be the three most important attributes to a patient in time-constrained consultations (Scott and Vick 1999). Some patients discuss health related internet information with their physicians, while others avoid talking about it in fear of interfering with the diagnosis process or the physician's authority (Sommerhalder et al. 2009). Patients bring internet information to consultations because they want physicians' opinion on it, or sometimes want a change in medication, a test, or referral to a specialist. Physicians usually completely or partially do what the patients want. Reluctant to jeopardize patient satisfaction which directly or indirectly affects their income, physicians sometimes even acquiesce to patients' requests for tests or treatments that may not be clinically appropriate (Murray et al. 2003). When patients bring internet information to consultations, some physicians feel that their authority is challenged and patients distrust their professionalism especially when they are confronted by the patients to validate their irrational view based on misleading internet health information (Murray et al. 2003, Sommerhalder et al. 2009, McMullan 2006).

Several empirical papers attempted to explore the direct effects of internet health information on the outcomes of clinical encounters. Surveying a nationally representative cross-sectional sample of physicians in the U.S., Murray et al. (2003) find that most physicians (75%) believed that information had made no difference to the patient's health outcome or quality of care, some (21%) believed that it had improved the outcome, and very few (4%) believed that it had been detrimental. They also find that 38% physicians believe patient bringing information to the consultation harmed their time efficiency, while only 16% believe it helped. Their findings are in line with some other analysis that raises the concern that physicians trying to explain the correct interpretation of health-related internet information is a time-consuming process (e.g. Sommerhalder et al. 2009). Another possible outcome of internet based health-related information search is the potential non-adherence to physicians' treatment or advice. Weaver III et al. (2009) use a sample of adults living in the Seattle-Tacoma designated market area and find that refusing or discontinuing treatment recommended by a physician or dentist based on health information obtained via internet is a fairly widespread behavior (11.2%). Females, those with a lower health status (both physically and mentally), and those who estimate more time spent on seeking internet health information about medications, illness or disease, treatments are more likely to be non-adherent patients.

Despite a handful of papers that examine the effect of internet information on health outcomes by asking physicians' opinions (e.g. Murray et al. 2003), more research is needed to better understand various aspects of a clinical encounter that may be affected by patients' search for health information on the internet. Several important questions remain unaddressed in current literature that examines the impact of internet health information. For instance, how does internet health information affect physicians' decision-making process during diagnosis and treatment? Is the accuracy of diagnosis affected? And how physicians' compensations may need to change given patients' bringing extra health information to medical consultations? This paper attempts to explore these questions utilizing a principal-agent framework, a powerful tool when it comes to agency problems.

Healthcare relationships have been studied, most noticeably, with principal-agent models in health economics literature. Previous studies unfold around different areas of agency problems that are pervasive in the healthcare market. One area of prominent agency problems stems from the startling information asymmetry between patients and physicians, which alone is not sufficiently studied in the literature. Instead, for instance, Gafni et al. (1998) considers two scenarios in an ideal world; the physician acts the patient's perfect agent and is delegated the authority to make medical decisions for the patient, or the physician transfers perfect information to the patient who has to make her own decisions. In the former case the challenge is for the physician to find out about the patient's preferences, while in the latter the key is perfect transfer of medical information. Gafni et al. find it easier and more feasible for the physician to transfer medical information to the patient, rather than find out about the patient's preferences. Rochaix (1998) stresses that agency relationship between physicians and insurers can not be overlooked for an adequate account of the complex interaction. Indeed, physician's role is better captured by introducing the concept of double agency: agent for the patient in patient-physician relationship to obtain better health outcomes and agent for health insurance provider in physician-insurance relationship to economize health care costs. Even though HMO insurance and prepayment (unlike third-party insurance and fee-for-service) eliminates inefficiency in physician-insurance provider relationship when physician is assumed to be a perfect agent for the insurance, information asymmetry between patients and physicians still leave the healthcare system with efficiency problem and liability rules may help correct to some extent (Blomqvist 1991).

A third area of agency problems, i.e. interactions between patients and insurers, is added into consideration in Ma and McGuire (1997). The agency relationship between physicians and insurers is tackled by insurer deriving optimal payment contracts for physicians while the agency relationship between patients and insurers is approached by insurer designing optimal insurance for patients. Incentive problems between patients and physicians are incorporated by acknowledging that insurance-payment contracts are based on reported quantity of treatment, or claims, rather than actual quantity of treatment, and patients have demand response, or chooses the amount of input after observing the physician's effort. Truthful reporting imposes constraints on contract parameters, which can be relaxed when physicians behave ethically or competition is present among physicians. On the other hand, desirable input combinations of quantity of treatment and level of effort may be prevented by the truthful reporting constraint.

Jelovac (2001) follows the footsteps of Ma and McGuire (1997) and let a public insurer design optimal payment contracts for physicians when neither physician's diagnosis effort nor physician's private information are contractible. Instead of covering all three areas of agency relationships, she focuses on the interactions between physicians and the public insurer but introduces treatment strategies and discussion of different payment mechanisms. In general when the patient is allowed to demand health care on more than on occasion, supply-side cost sharing is the optimal payment contract through motivating the physician to gather an informative signal and provide the most adequate treatment so that the likelihood of future cost sharing is decreased.

Several papers utilize agency relationships and principal-agent framework to examine different healthcare systems. Gate-keeping systems with mandatary General Physician (GP) referral is compared with non-gatekeeping systems with optional GP referral. Gatekeeping is more preferable wherever GP's incentives matter when information is asymmetric between the insurer and the GP regarding diagnosis effort and referral decisions and the GP's diagnosis and referral behavior are interdependent (Garcia-Marinoso and Jelovac 2003). Gonzalez (2010) show that which system is optimal depends on patient self-health information and referral pressure on the GP. When GP's incentives matter, a non-gatekeeping system is preferable only when patient pressure to refer is sufficiently high and the quality of the patient's self-health information is not at extremes (highly accurate or highly inaccurate). Patient's self-health information and referral pressure on the GP directly affect the expected health-care costs of patients and indirectly affect the diagnosis and referral behavior of the GP and thus have an impact on the expected primary and secondary costs of care.

Another systematic characteristic studied in the healthcare market using agency relationships is physicians' dual practices in countries where both public and private health care systems exist it is very common that some physicians work in both sectors. Gonzalez (2004) find the physician's dual practices have conflicting effects. On the one hand, the physician tend to over-provide public health services to obtain more effective treatment and gain prestige in the private sector. On the other hand, if the health authority have control over the incentives of over-provision, the physician's interest in making a more accurate diagnosis can be beneficial. Thus, when the priority of the health authority is to contain costs, the physician's dual practice is negative for the health authority. Dual practice is positive, however, when the health authority's priority is to minimize patients' health loss.

To the best of our knowledge, online health information that has a potential to mitigate information asymmetry between patients and physicians has not been introduced into studies of agency relationships in the healthcare market despite the prevalence of patients' health information seeking on the Internet. This paper bridges the gap in the literature by incorporating internet health information into the examination of agency relationships, particularly between physicians and a public insurer and investigates how the quality of internet health information affects healthcare outcomes.

4.3 The Model

This paper develops a principal-agent model to understand how internet information might affect clinical consultations. Three players are introduced in the model: a patient, a physician, and a public insurer. A public insurer is considered in the model because most patients are insured and insurers plays an important role in contemporary medical relationships.

Following Jelovac (2001), we use a simplified version of clinical encounter to facilitate the analysis. Suppose when a patient becomes ill, there are only two possibilities, i.e. the patient either has a serious illness or a minor illness with probability of 0.5 each. The probability is determined by nature and known to everyone as common sense. Both illnesses are curable by the correct treatment: the serious illness is only cured by a strong (or expensive) treatment and the minor illness is only cured by a mild (or inexpensive) treatment. Therefore, whether the patient is cured after a visit completely hinges on the accuracy of the physician's diagnosis. But diagnosis of the illness is not straightforward. That is, the physician correctly diagnoses a patient with a probability of $p(\varepsilon)$, rather than a certainty. The probability depends on the effort (ε) exerted by the physician. Effort is the physician's input to diagnosing the patient. It can be thought of as how hard the physician tries to communicate with and diagnose the patient. The function $p(\varepsilon)$ is increasing and concave in ε where $\varepsilon \in [0, \infty), p(0) = 0.5, p_\varepsilon(0) > 0$ and $p(\infty) \leq 1$. Because of his medical training and knowledge, the physician always knows better than common sense as long as some effort is exerted in diagnosing the patient. That is, $p(\varepsilon) > 0.5$ for any $\varepsilon > 0$.

The physician gives a treatment based on his diagnosis. That is, if the patient is diagnosed with a serious illness, she will be given a strong treatment and vise versa. In this model we suppose the patient can not switch physicians and therefore if she is misdiagnosed and given the wrong treatment, she will have to come back for a second visit. Since there are only two possible illnesses, the physician will know to the patient suffers from the other illness and give the other treatment during the second visit and the patient will be cured. Illnesses can incur health loss to the patient.[3] When the patient is cured after the first visit, we normalize the health loss to be zero because the cure comes just in time. When the patient is only cured after a second visit, the health loss depends on the kind of illness the patient has and needs to be taken into consideration since the cure is delayed. Specifically, if the

[3] In our model the public insurer is responsible for the patient's current and future medical expenses and therefore acts as the patient's agent to maximize her utility. Illnesses incur indirect costs to the insurer in that detrimental effects on the patient's current health status may increase future medical expenses on the patient. This provides another justification for the insurer's objective function which is to minimize the patient's health loss (discussed in greater detail in the next section).

patient has serious illness and only cured after two visits, the health loss is monetarized to be $\bar{l}$. On the other hand, if the patient has minor illness and cured after two visits, the health loss is monetarized to be $\underline{l}$.

The cost of strong treatment ($\bar{c}$) is higher than that of mild treatment ($\underline{c}$). The physician gets paid by the public insurer an amount net of treatment costs. The insurer designs the contract based on the number of visits paid by the patient and the kind of treatment used by the physician. If a patient is cured after one visit with a strong treatment, the physician gets a net payment of $\bar{R}_1$. If the patient is cured after one visit with a mild treatment, the physician gets a net payment of $\underline{R}_1$. If the patient is cured after two visits, the physician gets paid by R_2, regardless of the order of treatments given. Figure 3.1 gives a more straightforward illustration of different scenarios and relevant parameters.

It has been suggested that internet information is likely to affect the (time) efficiency of a clinical encounter (Murray et al. 2003). When the patient is misled by some information found online, the physician would have to spend extra time to explain her conditions and treatments (Sommerhalder et al. 2009). Therefore, given the potential influence of information quality on physician's time efficiency, physician's effort cost is modeled in monetary terms as a function of both effort level and quality of internet information, $\varphi(\varepsilon, i)$. i is an indicator of internet information quality and equals the difference between the percentage of accurate information and the percentage of inaccurate information. That is, denote I as the percentage of accurate internet information, then $1 - I$ is the percentage of inaccurate information.[4] It follows that $i = I - (1 - I) = 2I - 1$ for $I \in [0, 1]$. When there is no information, assume it is equivalent to having half of the information accurate and let $i = 0$. $\varphi(\varepsilon, i)$ is convex in ε and decreasing in i, i.e. $\varphi_\varepsilon(\varepsilon, i) > 0, \varphi_{\varepsilon\varepsilon}(\varepsilon, i) > 0, \varphi_i(\varepsilon, i) < 0$. Further, assume $\varphi_{\varepsilon i}(\varepsilon, i) < 0$. That is, the marginal cost of physician's effort decreases as the quality of health information improves. When the physician exerts no effort, the cost is naturally 0, i.e. $\varphi(\varepsilon, i) = 0$ when $\varepsilon = 0$.

The physician's reward is in the form of payments by the public insurer, who is essentially the principal here in this model. In the first stage the public insurer designs the payment contract $(\bar{R}_1, \underline{R}_1, R_2)$ and offers it to the physician. In the second stage the physician decides on whether or not to accept the offer. If the physician rejects the contract, the game ends. If the physician accepts the contract and the patient becomes ill, she decides on whether to seek medical information online before paying a visit to the physician. Then finally the physician exerts effort in diagnosing the patient and chooses the corresponding treatment.

The patient's utility is separable in health and money. We assume that the patient is fully insured and except for health loss her health and income is the same in all contingencies. Therefore, maximizing the patient's utility is equivalent to minimizing her health loss. The physician is risk-neutral in money and has a utility that depends on the payment and effort. Since effort is not contractible in realistic cases, the physician does not get paid based on effort level but rather healthcare outcomes $(\bar{R}_1, \underline{R}_1, R_2)$. Effort is meanwhile

[4] We simplify the analysis by assuming information is either accurate or inaccurate and the quality of internet health information is observable to both physicians and the insurer.

costly for the physician and the function is $\varphi(\varepsilon, i)$ as defined above. The physician has a reservation utility that is normalized to zero.

4.3.1 Benchmark

In reality the physician's effort is probably unobservable to the insurer, but our analysis starts with a benchmark case under symmetric information, i.e. the physician's effort is verifiable and thus contractible. In this case the insurer contracts both the desired effort level from the physician and physician's payments in different scenarios.

Specifically, it is assumed that all the medical costs (both treatment costs and physician's payments) are born the public insurer, who acts entirely in the patient's interest and maximizes her expected utility.[5] As discussed earlier, this is equivalent to minimizing the health loss. Meanwhile assume the insurance is actuarially fair and therefore the public insurer has a fixed budget of m to spend on a patient. In our model insurance premium is pre-determined so the fixed budget m is exogenously given.

The patient's health loss can be derived as following:

$$HL = \frac{1}{2}[1 - p(\varepsilon)]\bar{l} + \frac{1}{2}[1 - p(\varepsilon)]\underline{l} = \frac{1}{2}[1 - p(\varepsilon)](\bar{l} + \underline{l})$$

[5]It is often assumed in the literature that a health authority minimizes social costs (including treatment costs, physician payments and patients' health loss), or in this case, a public insurer maximizes patients' expected utility (Gonzalez 2004, Gonzalez 2006, Jelovac 2001, and Ma and McGuire 1997). The public insurer is responsible for patients' current and future medical expenses and any detrimental outcomes on the patient's health status now may increase future medical costs. This explains why the objective is to maximize the patient's utility, or minimize her health loss when her income is the same in all contingencies.

The insurer's expected cost is comprised of expected treatment costs and physician payments.

$$\begin{aligned} ETC &= \frac{1}{2}\{p(\varepsilon)(\bar{R}_1+\bar{c})+[1-p(\varepsilon)](R_2+\bar{c}+\underline{c})\}+\frac{1}{2}\{[1-p(\varepsilon)](R_2+\bar{c}+\underline{c})+p(\varepsilon)(\underline{R}_1+\underline{c})\} \\ &= [1-p(\varepsilon)]R_2+\frac{1}{2}p(\varepsilon)(\bar{R}_1+\underline{R}_1)+[1-\frac{1}{2}p(\varepsilon)](\bar{c}+\underline{c}) \end{aligned}$$

The physician's expected gain is expected payments less effort costs.

$$\begin{aligned} EP &= \frac{1}{2}\{p(\varepsilon)\bar{R}_1+[1-p(\varepsilon)]R_2\}+\frac{1}{2}\{[1-p(\varepsilon)]R_2+p(\varepsilon)\underline{R}_1\}-\varphi(\varepsilon,i) \\ &= [1-p(\varepsilon)]R_2+\frac{1}{2}p(\varepsilon)(\bar{R}_1+\underline{R}_1)-\varphi(\varepsilon,i) \end{aligned}$$

When effort is contractible, the insurer's problem is essentially to design a contract $(\bar{R}_1,\underline{R}_1,R_2,\varepsilon)$ so that the patient's expected health loss is minimized. i.e.

$$\text{Min}\,\frac{1}{2}[1-p(\varepsilon)](\bar{l}+\underline{l})$$

$$\text{s.t.}[1-p(\varepsilon)]R_2+\tfrac{1}{2}p(\varepsilon)(\bar{R}_1+\underline{R}_1)+[1-\tfrac{1}{2}p(\varepsilon)](\bar{c}+\underline{c})=m\ (B.C.)$$
$$\bar{R}_1\geq 0,\underline{R}_1\geq 0,R_2\geq 0\ (LLC)$$
$$[1-p(\varepsilon)]R_2+\tfrac{1}{2}p(\varepsilon)(\bar{R}_1+\underline{R}_1)-\varphi(\varepsilon,i)\geq 0\ (IRC)$$

The equality is a budget constraint for the insurer implying the expected total cost is equivalent to a fixed budget for each patient. The non-negativity constraints imply limited liability for the physician, or the payments need to be greater or equal to zero. The last inequality constraint states that the expected gain for the physician is at least his reservation utility, which is normalized to be zero in this model. Solving this problem IRC is actually satisfied as an equality at optimum because under symmetric information and contractible effort the physician earns zero information rent.

Hence solutions for the insurer's problem is $\varepsilon = \varepsilon^*(i, \bar{c}, \underline{c}, m)$ where:

$$\varphi(\varepsilon, i) + [1 - \frac{1}{2}p(\varepsilon)](\bar{c} + \underline{c}) = m \tag{4.1}$$

$$\frac{1}{2}p(\varepsilon)(\bar{R}_1 + \underline{R}_1) + [1 - p(\varepsilon)]R_2 = \varphi(\varepsilon, i) \tag{4.2}$$

where $\bar{R}_1 \geq 0, \underline{R}_1 \geq 0, R_2 \geq 0$.

There is a multiplicity of optimal solutions for physician payments. For a given information quality (i) introduced by the patient, equation (4.1) defines the optimal effort desired and also contracted by the insurer. At optimum, the expected total costs (treatment costs and physician payments) are equal to the fixed budget m.

To better understand the optimal effort level that satisfies equation (4.1) we need to take a closer look at the expected total costs $ETC = \varphi(\varepsilon, i) + [1 - \frac{1}{2}p(\varepsilon)](\bar{c} + \underline{c})$. When $\varepsilon = 0, ETC = 0.75(\bar{c} + \underline{c}) > 0$. Take the first and second order derivatives of ETC we have

$$\frac{\partial ETC}{\partial \varepsilon} = \varphi_\varepsilon(\varepsilon, i) - \frac{1}{2}p_\varepsilon(\varepsilon)(\bar{c} + \underline{c}) \tag{4.3}$$

$$\frac{\partial^2 ETC}{\partial \varepsilon^2} = \varphi_{\varepsilon\varepsilon}(\varepsilon, i) - \frac{1}{2}p_{\varepsilon\varepsilon}(\varepsilon)(\bar{c} + \underline{c}) \tag{4.4}$$

When $\varepsilon = 0$, $\frac{\partial ETC}{\partial \varepsilon} = -\frac{1}{2}p_\varepsilon(\varepsilon)(\bar{c} + \underline{c}) < 0$. Since $\varphi_{\varepsilon\varepsilon}(\varepsilon, i) > 0$ and

$p_{\varepsilon\varepsilon}(\varepsilon)(\bar{c} + \underline{c}) < 0$, $\frac{\partial^2 ETC}{\partial \varepsilon^2} > 0$. Therefore if ε has no upper bound, we know $\frac{\partial ETC}{\partial \varepsilon}$ is first negative when ε is small, but eventually becomes positive since the first order derivative is increasing in ε. Hence, the expected total cost ETC itself is a function that starts out decreasing in ε but then increases in ε when effort level is large enough.

Figure 4.2 gives a more straightforward illustration for the shape of ETC. Suppose a solution exists, there can be one or two intersection points depending on the value of fixed budget m. When there is only one intersection point, the corresponding effort level is the optimal level of effort desired by the insurer and solution to the problem. When there are are two intersection points between the horizontal line (fixed budget m) and the total expected cost ETC, the insurer would always prefer and contract the higher effort level since the patient's health loss is decreasing in physician's effort.

Information quality is a simple shifter of the total expected costs. When information quality improves, the efficiency of a clinical encounter increases and hence lower effort costs for the physician and subsequently lower total costs for the insurer. On the other hand, when information quality worsens, effort is more costly for the physician and the insurer has to bear higher costs. As indicated in the graph, compared with when internet information is absent, effort is more costly and total expected costs are higher when information quality is "bad" (or defined as $i \in [-1, 0)$), which results in a lower effort that can be elicited by the insurer from the physician for a given budget m. On the other hand, when internet information is of "good" quality (or $i \in (0, 1]$), effort is less costly for the physician and therefore a higher effort can be elicited from the physician at a fixed budget m.

Indeed, we know the optimal effort is a function of i and other exogenous factors in the model. i.e. $\varepsilon^* = \varepsilon(i, \bar{c}, \underline{c}, m)$. Moreover, from the above analysis we know when effort is contractible, the optimal effort that can be contracted by the insurer is increasing in information quality, i.e. $\frac{\partial \varepsilon^*}{\partial i} > 0$. Hence,

$$\frac{\partial p(\varepsilon^*)}{\partial i} = p_\varepsilon(\varepsilon^*)\frac{\partial \varepsilon^*}{\partial i} > 0 \tag{4.5}$$

$$\frac{\partial HL}{\partial i} = -\frac{1}{2}p_\varepsilon(\varepsilon^*)\frac{\partial p(\varepsilon^*)}{\partial i} < 0 \tag{4.6}$$

That is, when information quality improves, given the effort level contracted by the insurer, the physician will diagnose the patient with a higher probability and the patient will endure lower expected health loss. Since the probability of correct diagnosis ($p(\varepsilon^*)$) increases for a better information quality, $\varphi(\varepsilon^*, i)$ has to decrease for equation (4.1) to be satisfied at optimum. According to equation (4.2), the expected physician payment for the insurer is now higher.

When information is symmetric, the insurer will contract an effort level that minimizes the patient's expect health loss. In this case, if the quality of internet health information possessed by the patient is better, the diagnosis efficiency improves and diagnosis becomes less costly for the physician. Therefore the insurer can contract a higher effort level from the physician while maintaining the same fixed budget. When a higher effort level is elicited from the physician, the diagnosis will be more accurate, which also leads to lower expected health loss. The physician's net earnings will still be zero because under symmetric information the physician makes no information rent.

The insurer now expects to pay the physician a higher compensation because a much higher effort level is desired from the physician (high enough that the effort cost increases even though better information quality can lower effort cost).

4.3.2 Moral Hazard

When effort is not contractible, the physician will choose an effort level that is optimal for him and possibly earn information rent. The public insurer will design a payment contract so that a desired effort level will be elicited from the physician, even though the effort can not be contracted. Using backward deduction we start with the physician's problem, which is to maximize the expected gain based on the payments. i.e.

$$\text{Max}\,\frac{1}{2}p(\varepsilon)(\bar{R}_1 + \underline{R}_1) + [1 - \frac{1}{2}p(\varepsilon)]R_2 - \varphi(\varepsilon, i)$$

Solving this maximization problem gives

$$\varepsilon = \begin{cases} 0 & \gamma \leq 0 \\ \frac{\varphi_\varepsilon(\varepsilon,i)}{p_\varepsilon(\varepsilon)} = \gamma & \gamma > 0 \end{cases} \quad (ICC)$$

where $\gamma = .5(\bar{R}_1 + \underline{R}_1) - R_2$.

Knowing how the physician is going to react to the payment contract (ICC), the insurer minimizes the expected health loss for the patient by choosing appropriate physician payments. The insurer's problem can be written as following:

$$\text{Min}\,\frac{1}{2}[1-p(\varepsilon)](\bar{l}+\underline{l})$$

$$\text{s.t.}[1-p(\varepsilon)]R_2+\tfrac{1}{2}p(\varepsilon)(\bar{R}_1+\underline{R}_1)+[1-\tfrac{1}{2}p(\varepsilon)](\bar{c}+\underline{c})=m\ (B.C.)$$
$$\bar{R}_1\geq 0,\underline{R}_1\geq 0,R_2\geq 0\ (LLC)$$
$$\varepsilon=\begin{cases}0 & \gamma\leq 0\\ \frac{\varphi_\varepsilon(\varepsilon,i)}{p_\varepsilon(\varepsilon)}=\gamma & \gamma>0\end{cases}\ (ICC)$$
$$[1-p(\varepsilon)]R_2+\tfrac{1}{2}p(\varepsilon)(\bar{R}_1+\underline{R}_1)-\varphi(\varepsilon,i)\geq 0\ (IRC)$$

Because of the properties of the probability and effort cost functions, IRC is always satisfied when ICC holds (see Appendix 4.7 for proof). Rearrange the terms in $(B.C.)$ the above problem simplifies to

$$\text{Min}\,\frac{1}{2}[1-p(\varepsilon)](\bar{l}+\underline{l})$$

$$\text{s.t.}\,R_2+\gamma p(\varepsilon)+[1-\tfrac{1}{2}p(\varepsilon)](\bar{c}+\underline{c})=m\ (B.C.)$$
$$\bar{R}_1\geq 0,\underline{R}_1\geq 0,R_2\geq 0\ (LLC)$$
$$\varepsilon=\begin{cases}0 & \gamma\leq 0\\ \frac{\varphi_\varepsilon(\varepsilon,i)}{p_\varepsilon(\varepsilon)}=\gamma & \gamma>0\end{cases}\ (ICC)$$

Minimizing health loss is equivalent to maximizing physician's effort. Moreover, $\gamma=\frac{\varphi_\varepsilon(\varepsilon,i)}{p_\varepsilon(\varepsilon)}$ is increasing in physician's effort. Therefore, to minimize health loss the insurer will maximize γ. Hence, the optimal solutions are:

$$\frac{\varphi_\varepsilon(\varepsilon,i)}{p_\varepsilon(\varepsilon)}p(\varepsilon)+[1-.5p(\varepsilon)](\bar{c}+\underline{c})=m \tag{4.7}$$

$$R_2 = 0, \bar{R}_1 + \underline{R}_1 = 2\frac{\varphi_\varepsilon(\varepsilon, i)}{p_\varepsilon(\varepsilon)}$$

Equation (4.7) again implies that at optimum the expected total costs (ETC) need to be equal to the fixed budget m. Also, $\varepsilon^* = \varepsilon(i, \bar{c}, \underline{c}, m), p = p(\varepsilon^*(i, \bar{c}, \underline{c}, m))$. Apply the Implicit Function Theorem gives us the following:

$$\frac{\partial \varepsilon^*}{\partial i} = -\frac{\frac{\partial ETC}{\partial i}}{\frac{\partial ETC}{\partial \varepsilon^*}}$$

$\frac{\partial ETC}{\partial i} = \frac{\varphi_{\varepsilon i}(\varepsilon,i)}{p_\varepsilon(\varepsilon)} < 0$ since $\varphi_{\varepsilon i}(\varepsilon, i) < 0, p_\varepsilon(\varepsilon) > 0$.

Moreover, at optimum, it can shown that $\frac{\partial ETC}{\partial \varepsilon^*} > 0$. To see why this is the case, first suppose $\frac{\partial ETC}{\partial \varepsilon^*} < 0$. i.e. total expect cost decreases as effort level increases in the neighborhood of ε^*. Then the equation (4.7) will not be satisfied as equality. Instead, the insurer can choose an effort level as high as possible since total expected cost is decreasing in effort. The optimal effort would then be positive infinity. Also from equation (4.7) it is obvious that when effort level is extremely high (e.g. infinity), total expected cost will be infinity as well since the expected physician payment is increasing in effort. Then total expected cost for the insurer will not be less than or equal to a fixed budget m and this equation/inequality will not be satisfied. Therefore, it is not possible for $\frac{\partial ETC}{\partial \varepsilon^*} < 0$ to be negative at the neighborhood of optimal effort level.

Hence, $\frac{\partial \varepsilon^*}{\partial i} > 0$. Then we know

$$\frac{\partial p(\varepsilon^*)}{\partial i} = p_\varepsilon(\varepsilon^*)\frac{\partial \varepsilon^*}{\partial i} > 0 \tag{4.8}$$

$$\frac{\partial HL}{\partial i} = -\frac{1}{2}p_\varepsilon(\varepsilon^*)\frac{\partial p(\varepsilon^*)}{\partial i} < 0 \tag{4.9}$$

Our results indicate that when information quality is better, effort is less costly for the physician and therefore insurer can design the payment contract so that a higher effort level is elicited from the physician. Because the physician exerts more effort in diagnosing the patient, the diagnosis is now more accurate. The expected health loss for the patient is thus lower and the total expected treatment costs are lower as well since the patient is less likely to go through the wrong treatment. The fixed budget for each patient is spent by the insurer to pay for the physician's compensation and the patient's treatment costs. Consequently the physician can expect to get paid more since the expected treatment costs are now lower.

In a more realistic setting where the physician's effort is not contractible and the insurer induces an optimal effort from the physician through designing the payment contract, higher quality of information possessed by the patient makes it possible for the insurer to increase the payments to the physician and elicit higher effort from the physician. As a result, the diagnosis will be more accurate and the patient will endure less health loss. This has important policy implications in today's era when a majority of internet users have searched for health information on the internet. Health information online can potentially act as a useful tool to facilitate the communication between patients and physicians, lubricate clinical encounters and make medical consultations more efficient. As a result, now the insurer can pay the physician a compensation that is not as high as would be needed at the old quality of information for a given budget. A higher effort and more accurate diagnosis will follow.

4.4 Policy Implications

Our results demonstrate beneficial effects of improvement in health information quality and lends theoretical support for public health education programs sponsored by government agencies and medical clinics. To illustrate how this model can be used to address a policy question such as the impact of an increase in health information quality, consider a specific example and parametrize the model.

4.4.1 Model Parameterization

We will use two specific examples for the effort cost function and diagnosis probability. Let

$$\varphi(\varepsilon, i) = \frac{\varepsilon^3}{10^{i+2}}$$

and

$$p(\varepsilon) = \frac{e^{\frac{\varepsilon}{10}}}{1 + e^{\frac{\varepsilon}{10}}}$$

The physician's effort ε is defined in this illustration as the percentage of effort exerted out of the physician's full capacity and effort cost is in dollars. Moreover, suppose the inexpensive treatment cost 100 dollars, the expensive treatment costs 400 dollars, the patient's health loss are 200 and 500 dollars respectively for minor and serious illnesses, and the insurer's per patient budget is 500 dollars. i.e. $\bar{c} = 300$, $\underline{c} = 100$, $m = 500$, $\bar{l} = 500$, and $\underline{l} = 200$.

To see how model predictions change as the quality of information changes, consider the percentage of accurate information at 0, 25, 50, 75, and 100 percent respectively. i.e. I=0, 0.25, 0.5, 0.75, and 1.

4.4.2 Contractible Effort

Table 4.1 summarizes physician's effort contracted, diagnosis accuracy, physician's payment, effort cost and net earnings, and patient's health loss in different scenarios. The total expected cost function is plotted in figure 4.3. Consistent with the findings in section 4.3.1, when the quality of health information improves, insurer will contract higher effort from the physician, which leads to more accurate diagnosis and less health loss. In this example, the physician's effort cost also increases when information quality improves, due to the more dominant effect of higher effort level. Consequently, the physician needs to get paid more but net earnings is zero because the physician does not earn information rent when effort is contractible.

When accurate health information changes from 0 to 25 percent, the optimal effort contracted by the insurer increases from 13.7 percent to 20.6 percent of the physician's full capacity. The probability of correctly diagnosing the patient improves from significantly from 0.80 to 0.89 by 9 percentage points. The patient's expected health loss decreases from \$70.7 to \$39.5 and physician's payment (effort cost) increases from \$259.6 to \$277.4. If a public health education program is effective in helping the patient obtain more accurate information, say, from 50 percent of accurate information to 75 percent, the effort contracted by the insurer will increase from 30.8 percent of the physician's full capacity to 45.5 percent, and the probability of correctly diagnosing the patient increases from 0.956 to 0.990. The patient's health loss decreases from $15.4 to $3.7 and the physician's payment (effort cost) increases from $291.2 to $297.9. The same 25 percent improvement in information quality leads has more significant impacts when the initial quality of information is poor because physician's effort has prominent diminishing returns especially when effort level is relatively high.

4.4.3 Non-contractible Effort

Simulation results under moral hazard are presented in table 4.2. The total expected cost function is plotted in figure 4.4. Consistent with findings in section 4.3.2, when the quality of health information improves, the insurer can induce higher effort from the physician and the diagnosis will be more accurate. As a result, the patient will suffer less health loss. Physician's are compensated with higher payment since lower treatment costs free up some of the fixed budget. The change in effort cost is ambiguous, while physician's net earnings consistently increase in our examples.

Compared with table 4.1, the physician's induced effort is much lower than their contracted effort at each information quality and diagnosis is less accurate. The patient suffers a much higher health loss and the physician makes positive net earnings. This is not surprising because under moral hazard the principal can only induce lower effort from the agent, *ceteris* *paribus*, and the agent will earn information rent. Compared with the case of contractible effort, information quality has a much more significant impact in improving diagnosis accuracy and reducing health loss in the case of non-contractible effort.

If a policy intervention can improve the quality of health information found by patients online from a 50 percent accuracy to 75 percent accuracy, the percentage of physician's effort induced by insurance contract will increase from 13.4 percent to 19.2 percent. The probability of physician correctly diagnosing the patient will increase from 0.79 to 0.87. The patient's expected health loss is reduced from $72.7 to $ 44.7. Insurance contract pays the physician a higher compensation with an increase of $16.0 from $258.4to $274.5 and the physician makes a higher net earning of $252.0.

4.5 Conclusions

This paper examines how health information on the internet affects the status-quo interactions between patients, physicians and a public insurer. Using a principal-agent framework where the public insurer acts as the principal and the physician is the agent, we find that when the physician's effort is contractible, improved quality of internet health information leads to higher physician effort that can be contracted by the insurer for any given fixed budget. This is because when health information is more accurate, the efficiency of communication between the patient and the physician increases and exerting efforts to diagnose the patient becomes less costly for the physician. Hence, it is possible for the insurer to desire a higher level of effort from the physician under the same budget. Consequently, the physician's diagnosis becomes more accurate and the expected health loss for the patient decreases.

A more realistic scenario considered in the paper is when physician's effort is not verifiable, and thus not contractible. In this case, although the insurer can not directly contract an effort level by the physician, a desired level of effort can be induced by properly designing the payment contract. When the quality of internet health information possessed by the patient improves, the effort cost for the physician decreases, which eventually leads to lower total costs for the insurer. Therefore, when the insurer aims at minimizing the patient's health loss at a given budget, a higher effort level can be induced. Consequently, the probability of correctly diagnosing the patient increases and the expected treatment costs decrease. The physician will get higher expected compensation from the insurer and the patient's health loss is lower.

It is assumed in this paper that physicians are homogenous in their knowledge and skills and affected in the same way by internet information. Real-world observations of the health care industry suggest the heterogenous nature of physicians. Future research can take into account that the same effort may lead to different diagnosis probabilities and same internet information can affect physicians' effort costs differently as well. Moreover, we assume that the patient stays with her physician in the model, and this assumption can be relaxed as well so that the patient can switch to other physicians if not satisfied with their first visit. This relaxation may have important implications for the physician's incentives.

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Table 4.1: Illustration of Model Predictions When Effort is Contractible

Percentage of accurate information	I=0	I=25	I=5	I=75	I=100
Quality indicator	-1	-0.5	0	0.5	1
Physician effort (in percentage)	13.7	20.6	30.8	45.5	66.9
Probability of correct diagnosis	0.798	0.887	0.956	0.990	0.999
Patient health loss ($)	70.665	39.48	15.435	3.675	0.42
Physician payment ($)	259.6	277.4	291.2	297.9	299.8
Effort cost ($)	259.6	277.4	291.2	297.9	299.8
Physician net earnings ($)	0	0	0	0	0

Table 4.2: Illustration of Model Predictions When Effort is Non-Contractible

Percentage of accurate information	I=0	I=25	I=5	I=75	I=100
Quality indicator	-1	-0.5	0	0.5	1
Physician effort (in percentage)	5.3	8.7	13.4	19.2	25.9
Probability of correct diagnosis	0.629	0.704	0.792	0.872	0.930
Patient health loss ($)	129.8	103.6	72.7	44.7	24.5
Physician payment ($)	225.8	240.8	258.4	274.5	286.0
Effort cost ($)	14.8	20.6	24.0	22.4	17.3
Physician net earnings ($)	211.1	220.2	234.5	252.0	268.7

Figure 4.1: Illustration of the Medical Encounter

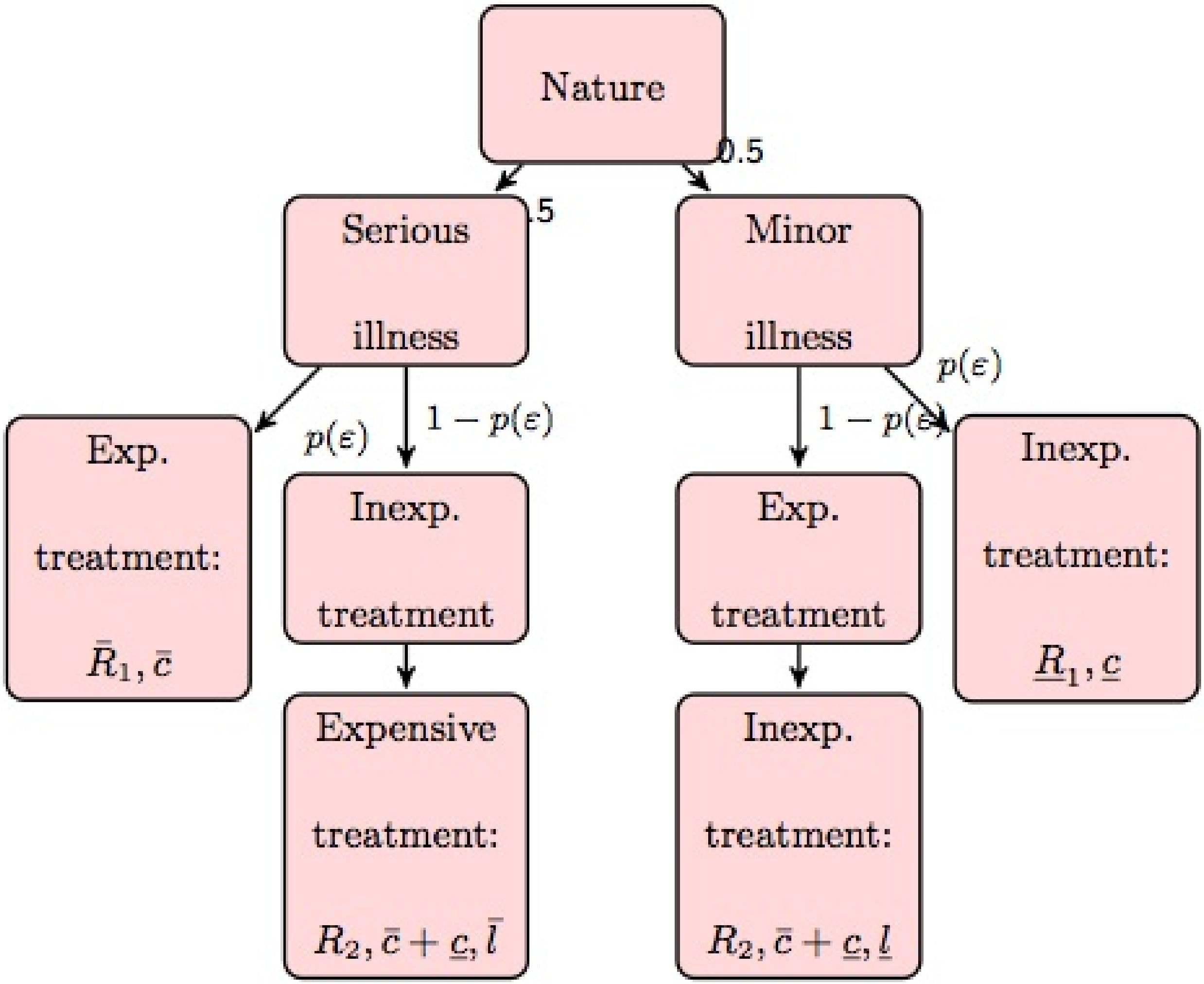


Figure 4.2: Total Expected Cost When Effort is Contractible

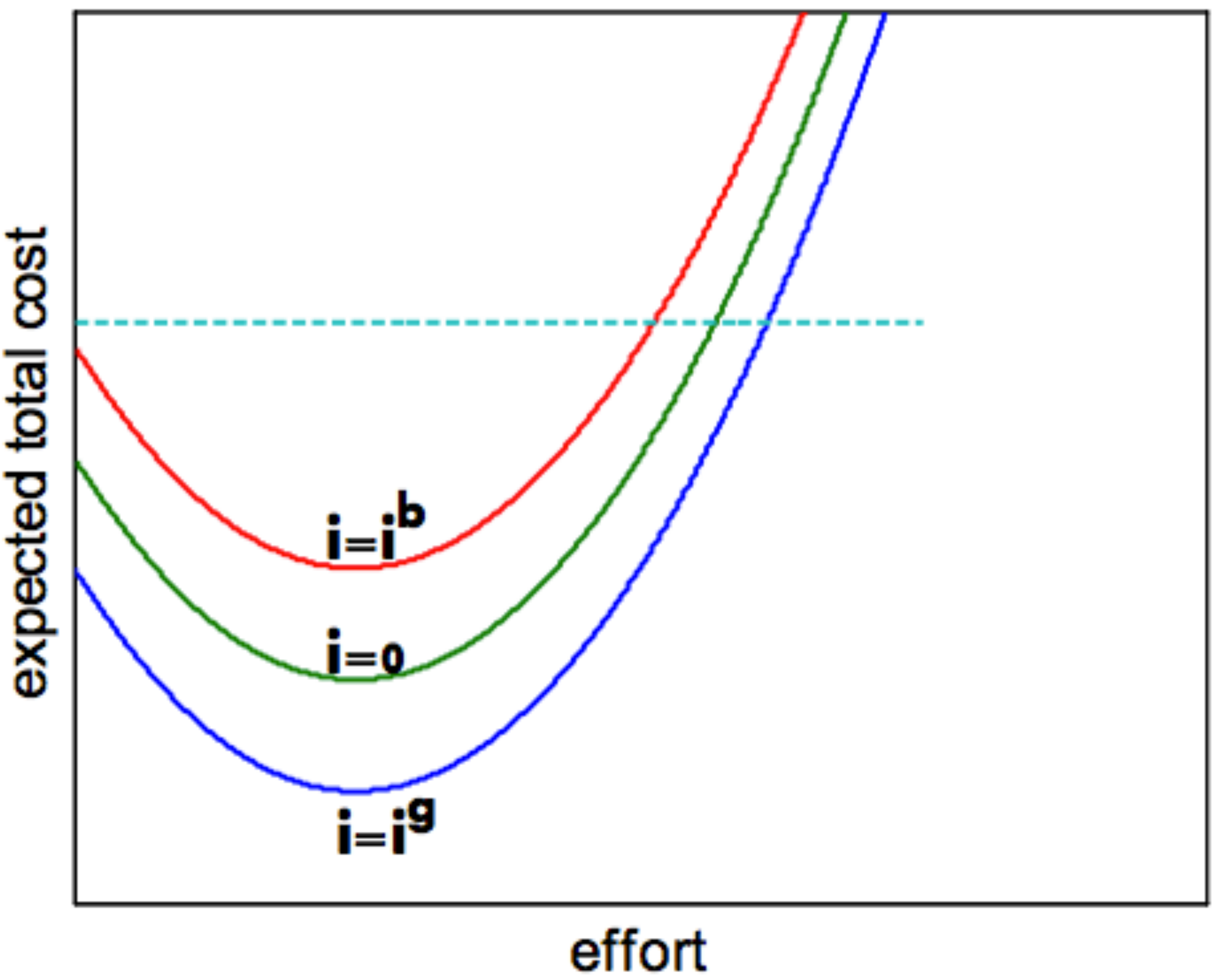


Figure 4.3: Total Expected Cost under Contractible Effort (Example in section 4.4.2)

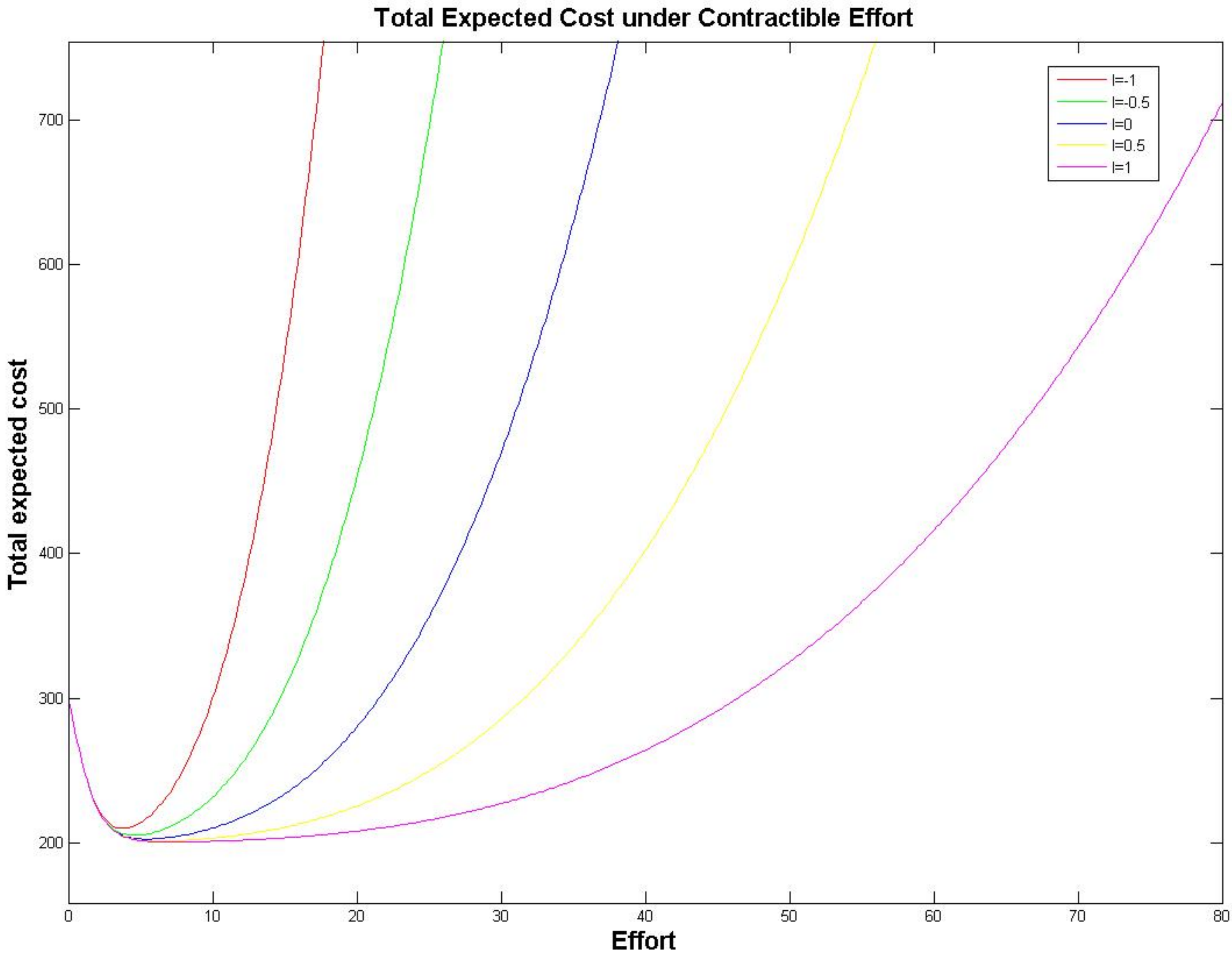
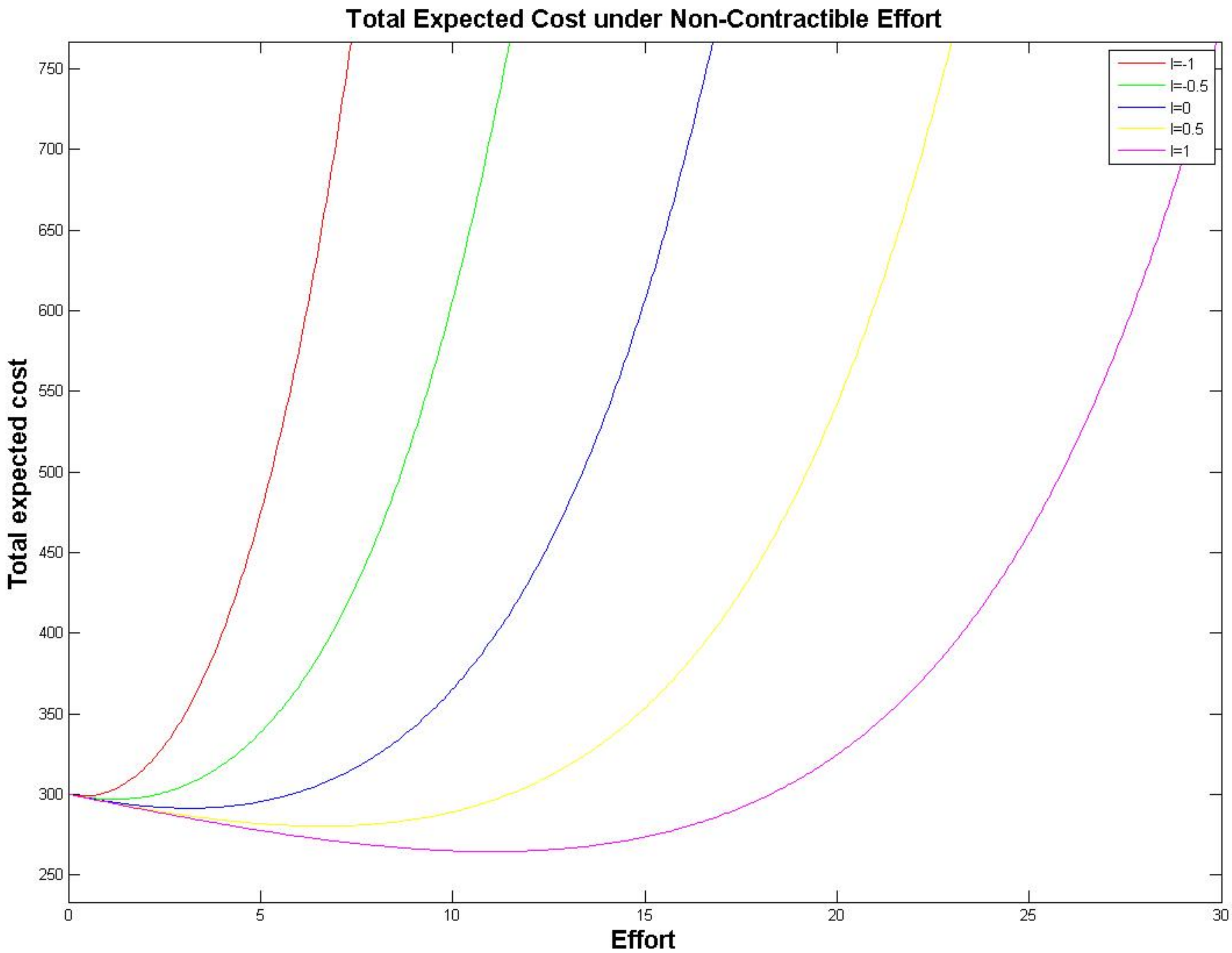


Figure 4.4: Total Expected Cost under Non-Contractible Effort (Example in section 4.4.3)



4.7 Appendix B

This appendix provides proof that when IRC is always satisfied when ICC holds in the insurer's problem under moral hazard (Section 4.3.2).

First prove

$$\varphi(\varepsilon, i)p_\varepsilon(\varepsilon) \leq \varphi_\varepsilon(\varepsilon, i)[p(\varepsilon) - \frac{1}{2}] \leq \varphi_\varepsilon(\varepsilon, i)p(\varepsilon)$$

Let $X = \varphi(\varepsilon, i)p_\varepsilon(\varepsilon) - \varphi_\varepsilon(\varepsilon, i)[p(\varepsilon) - \frac{1}{2}]$, we know $X = 0$ when $\varepsilon = 0$.

$$\begin{aligned}
\frac{\partial X}{\partial \varepsilon} &= \varphi_\varepsilon(\varepsilon, i)p_\varepsilon(\varepsilon) + \varphi(\varepsilon, i)p_{\varepsilon\varepsilon}(\varepsilon) - \varphi_{\varepsilon\varepsilon}(\varepsilon, i)p(\varepsilon) - \varphi_\varepsilon(\varepsilon, i)p_\varepsilon(\varepsilon) + \frac{1}{2}\varphi_{\varepsilon\varepsilon}(\varepsilon, i) \\
&= \varphi(\varepsilon, i)p_{\varepsilon\varepsilon}(\varepsilon) - \varphi_{\varepsilon\varepsilon}(\varepsilon, i)p(\varepsilon) + \frac{1}{2}\varphi_{\varepsilon\varepsilon}(\varepsilon, i) \\
&= \varphi(\varepsilon, i)p_{\varepsilon\varepsilon}(\varepsilon) + (\frac{1}{2} - p(\varepsilon))\varphi_{\varepsilon\varepsilon}(\varepsilon, i)
\end{aligned}$$

According to the properties of the probability and effort cost functions, $\frac{\partial X}{\partial \varepsilon} \leq 0$. Therefore, $X \leq 0$ for any $\varepsilon \geq 0$. Hence,

$$\varphi(\varepsilon, i)p_\varepsilon(\varepsilon) \leq \varphi_\varepsilon(\varepsilon, i)[p(\varepsilon) - \frac{1}{2}] \leq \varphi_\varepsilon(\varepsilon, i)p(\varepsilon)$$

Rewrite IRC as following:

$$R_2 \geq \varphi(\varepsilon, i) - \gamma p(\varepsilon)$$

ICC may hold in two scenarios

- When $\gamma \leq 0$, $\varepsilon = 0$,

  $$R_2+\gamma p(\varepsilon) = R_2+[\frac{1}{2}(\bar{R}_1+\underline{R}_1)-R_2]p(\varepsilon) = [1-p(\varepsilon)]R_2+\frac{1}{2}(\bar{R}_1+\underline{R}_1) \geq 0$$

  i.e.$R_2 \geq \varphi(0,i) - \gamma p(\varepsilon)$ and IRC holds.

- When $\gamma > 0$, $\gamma = \frac{\varphi_\varepsilon(\varepsilon,i)}{p_\varepsilon(\varepsilon)}$,

  IRC is equivalent to

  $$R_2 \geq \varphi(\varepsilon,i) - \frac{\varphi_\varepsilon(\varepsilon,i)}{p_\varepsilon(\varepsilon)}p(\varepsilon) = \frac{1}{p_\varepsilon(\varepsilon)}[\varphi(\varepsilon,i)p_\varepsilon(\varepsilon) - \varphi_\varepsilon(\varepsilon,i)p(\varepsilon)]$$

  We know from inequalities (4.7) that $\frac{1}{p_\varepsilon(\varepsilon)}[\varphi(\varepsilon,i)p_\varepsilon(\varepsilon) - \varphi_\varepsilon(\varepsilon,i)p(\varepsilon)] \leq 0$. Since $R_2 \geq 0$, IRC again holds in this case when ICC is satisfied.