# Adverse Food Price Shocks, Employment, and Wage Income: Evidence from Tanzania

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**Abstract**

This paper studies the effects of adverse food price shocks–large and sudden increases in food prices–on employment and wage income. Substantial research exists on household food insecurity as a result of food price spikes, but studies on households' coping strategies involving labour markets have so far been limited. In this paper, I use a simple agricultural household model to study whether individuals in a household seek additional employment opportunities and/or earn more income when faced with adverse food price shocks. I employ an individual-level panel data set from Tanzania that covers the years 2008, 2010, and 2012 and use a Heckman correction model to account for self-selection into the labor market. My results suggest adverse food price shocks are correlated with a significant 15% decrease in income for urban individuals and no significant wage income effect for rural households. The effect of the shock on the probability of employment is negative but statistically insignificant. These results likely originate from negative general equilibrium effects and entrepreneurial effects due to Tanzania's status as a net food-importer, outcomes that my simple theoretical model fails to capture.

*Keywords:* Labor Supply, Food Crises, Household Agricultural Model

## 1. INTRODUCTION

Between December 2007 and June 2008, a multitude of demand and supply factors caused international food prices to skyrocket, a shock commonly referred to as the 2007/08 global food crisis. In the span of six months, rice prices tripled and wheat prices doubled (Christiaensen, 2009). Tiwari and Zaman (2010) claim that 63 million individuals might have become malnourished in 2008 as a result of the price spikes. In general, the literature suggests a strong negative impact on most Sub-Saharan African countries. A study by Headey (2013) finds that the largest increase in self-assessed food insecurity in Sub-Saharan Africa occurred in Tanzania, where 23% of the population became more insecure as a result of the food price spike. This substantial increase in food insecurity in Tanzania stems from the country's status as a net food-importer. 85% of the Tanzanian households in my sample of study are net food-consumers, which makes the vast majority of the population vulnerable to adverse price shocks.

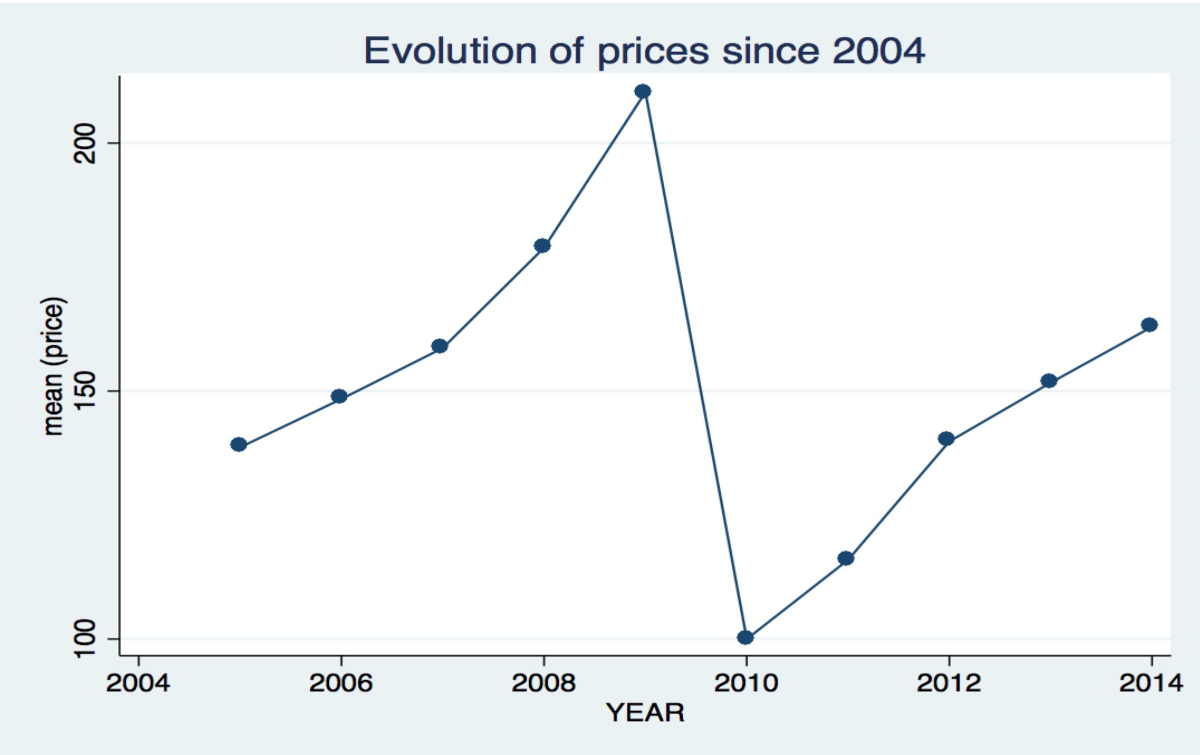


Figure 1: Evolution of prices in Tanzania between 2004 and 2014

Today, food prices are much lower than they were between 2007 and 2010, but periods of sharp rises still persist. Figure 1 above plots food price indices in Tanzania from the International Labor Office (ILO) between 2005 and 2014. Prices peaked around 2009, dropped to their lowest level in 2010 and started spiking again. Substantial research exists on household food insecurity as a result of food crisis, but studies on households' coping strategies involving labour markets have so far been limited. Some empirical studies suggest that, in some cases, individuals within a household seek additional job opportunities to cope with these price shocks. Researchers, however, often ignore the self-selection implied with studying the effects of these shocks on wage income. Moreover, only a few papers have acknowledged the positive impacts that can originate from adverse shocks for food producers predominantly located in rural areas.

In this paper, I use a simple agricultural household model to study whether and how individuals within a households work more or less when faced with adverse food price shocks and whether or not their wage income increases when taking into account self-selection and potential positive effects for food producers. Using panel data from the Living Standards Measurement Study (LSMS) on Tanzania, I estimate regression equations for wage and employment, correcting for self-selection using a Heckman model. This research is important because understanding how households choose to cope is key to designing safety nets that assist vulnerable populations at times of price shocks.

The rest of the paper proceeds in six steps. Section 2 briefly reviews the literature on the effects of adverse price shocks on employment and wages. Section 3 proposes a household decision-making theory. Section 4 presents the data and summary statistics of the main variables used in my regressions. Section 5 and 6 present an empirical strategy and the results, respectively. Section 7 concludes the study, discusses some limitations, and offers directions for future research. My results suggest adverse food price shocks are correlated with a significant 15% decrease in income for urban individuals and no significant wage income effect for rural households. The effect of the shock on the probability of employment is negative for both rural and urban households but statistically insignificant.

## 2. LITERATURE REVIEW

As welfare is closely linked with employment and wage income, I start by briefly reviewing the literature on the effects of adverse price shocks on welfare, which is more common.

### *2.1. Food price shocks and welfare*

Adverse food price shocks are also known as food crises. Authors often use the agricultural household model that predicts a positive welfare effect of food price spikes on net food-producers and a negative effect on net food-consumers.

Applying the agricultural household model to a sample of West and Central African countries, Wodon and Zaman (2010) find, using simulations, that an increase in the price of cereals of 50% could increase the share of the population in poverty by 4.4% if only the impact on consumers is taken into account. When factoring potential gains for producers, this effect drops to 2.5%. They also find that in countries such as Liberia that are highly dependent on food imports, a 50% increase in rice prices increases poverty by 8%. Benson et al. (2008) find evidence supporting a more negative impact of the 2008 food crisis in Rwanda on those for whom maize constitutes a large share of calorie intake. Arndt et al. (2008), use data from Mozambique and find that urban households and those who live in the south are more severely hit by food price changes compared to those in the north and in the center, with relatively wealthier farmers reaping benefits from the crisis.

Studies looking at the implications of adverse food price shocks in terms of employment and wage income are less ubiquitous.

### *2.2. Food price shocks and labour market outcomes*

The literature has explored the effects of soaring food prices on labour market outcomes from different perspectives. One body of the literature looks at household coping mechanisms when faced with the adverse price shock. Results from these studies suggest that households seek additional wage income opportunities to cope against the adverse effects of the shock. Reyes et al. (2010) find that, in the Philippines during the 2008 price spikes, 6.3 percent of households reported that at least one member of their household looked for work in addition to their existing job.

A second body of the literature explores the transmission effect of price spikes on labor market outcomes. Results indicate that rising food prices increase wage income in competitive agricultural sectors since the nominal wage is equal to marginal revenue product. This increase in agricultural wages mitigate the poverty impacts resulting from lower purchasing power (Ravallion, 1990; Ferreira et al., 2011). Earlier work by Dejanvry and Subbarao (1986), however, assumes a fixed exogenous wage in the agricultural sector, which implies a zero food price elasticity and thus an adverse impact on rural households.

A third body of the literature explores changes in business costs and demand for competing products and services. Rodgers and Menon (2012) explore the effects of the 2008 fuel and food price surges on employment and daily wage incomes in the Philippines. They find that the likelihood of employment decreased by 1% and wages decreased by 6%. They explain that this decline originates from reduced local demand for small-scale products and services and reduced entrepreneurial activities due to higher operating costs associated with higher food and fuel prices.

The current state of the literature thus indicates that labor market outcomes at times of adverse food price shocks do not only depend on increased labor supply from individuals coping with the shock, but also on general equilibrium effects, entrepreneurial activities, and demand effects. In general, the literature suggests negative employment and wage effect in net food-importing countries. When disaggregated, however, these impacts vary from household to household depending on their market status as net food-consumers or net food-producers. Studies looking at wages, however, often fail to take into account the biases caused by self-selection. In this paper I use detailed individual-level data from Tanzania and correct for self-selection using a Heckman correction model.

In the next section, I propose a theory of labor market-based coping behavior for individuals evolving in different types of households.

## 3. THEORY

Consider a farm or non-farm household that earns a fixed labor income, consumes a set of commodities (rice, corn, wheat) that they may or may not produce, and trades in the commodities market. Following a similar framework by Deaton (1991), I represent the household's living standards by the following indirect utility function:

$$u_h = \psi(I + A + \pi, p), \tag{1}$$

where $\psi$ is a utility function, I is wage income, A is the household's asset holdings, and $\pi$ is the household's profits from farming or other family businesses.

Wage income is given by the product of the wage rate and the total number of hours the members of the household work (for wage):

$$I = w \times L. \tag{2}$$

Since profits are maximized, I can represent $\pi$ as the value of a profit function from food production, $\pi(p, v)$, where p is the vector of food prices, and v is a vector of input prices such that:

$$\pi(p, v) = Q \times p - B \times v, \tag{3}$$

where Q denotes food production and B is a vector of input quantities.

The change in production income as a result of a change in the price of food is given by:

$$\frac{\partial \pi}{\partial p} = Q.$$

Let $C$ denote household consumption. The change in living standards ($du_h$) resulting from a change in the price, $p_i$, of food item $i$ is given by the sum of the expenditure effect ($\Delta p_i(Q_i - C_i)$) and the household labour supply effect ($\Delta L$):

$$du_h = \Delta p_i(Q_i - C_i) + \Delta L \times w. \tag{4}$$

I can rewrite equation (4) to obtain an expression for the amount of money (positive or negative) the household would require in order to maintain its previous level of living ($d_L$)[1]:

$$dL = [\Delta p_i(C_i - Q_i)] + [\Delta L \times w] \,. \tag{5}$$

The first term in equation (5) implies that, when an adverse food price shock, $dp_i$, occurs, net food-producing households become wealthier and net food-consuming households become poorer. To maintain its previous level of living, the net food-consumer would need to work more hours to compensate for the loss in purchasing power. The net food-producer, on the hand, can afford to work less hours and keep the same living standard. Assuming wages stay the same, this simple model predicts that net food-consumers will work more and earn more income. The opposite is true for net food-producers.

This simple framework models changes in the labor market as originating from households' coping strategies to keep their living standards constant in the face of adverse price shocks. It makes numerous assumptions. The first assumption is that the wage rate is fixed and exogenous similar to Dejanvry and Subbarao (1986). The model ignores general equilibrium effects on wages, which have been found to be significant. The model also assumes zero substitution effect and fails to take into account the effect of income transfers from remittances or government programs. I will discuss the implications of these assumptions in the conclusion and discussion section. The next section introduces the data used and presents summary statistics.

[1]Notice in the first term I subtract production from consumption. In equation 4 I do the opposite.

## 4. DATA AND SUMMARY STATISTICS

I use individual-level data from the three rounds of the Tanzania National Panel Survey (TNPS). These nationally representative surveys are a part of the Living Standards Measurement – Integrated Surveys (LSMS – IS) conducted by the World Bank. The first round of the TNPS was implemented between October 2008 and 2009 and covered 3,265 households and 16,707 individuals. The second round was implemented between October 2010 and September 2011 and covered new households in addition to all the households in the first round for a total of 3,924 households and 20,559 individuals. The third and most recent round was conducted between October 2012 and November 2013 and covered all the households in the previous two waves for a total of 5,010 households and 25,412 individuals.

The final sample used in my analysis consists of a panel of 45,948 observations. In the next subsections, I compare the key variables for rural and urban individuals.

### *4.1. Shock Variable*

Table 1: **Comparing the summary statistics of shock variables for rural and urban households**

| **Household type** | **min** | **mean** | **max** | **N** |
|---|---|---|---|---|
| **Rural households** | | | | |
| Food price spike | 0 | .604 | 1 | 29416 |
| Livestock death | 0 | .305 | 1 | 25510 |
| Droughts/Floods | 0 | .389 | 1 | 25557 |
| Severe illness | 0 | .110 | 1 | 23385 |
| Crop price fall | 0 | .338 | 1 | 25661 |
| Input price spike | 0 | .347 | 1 | 25818 |
| **Urban households** | | | | |
| Food price spike | 0 | .695 | 1 | 12663 |
| Livestock death | 0 | .172 | 1 | 9565 |
| Droughts/Floods | 0 | .222 | 1 | 9778 |
| Severe illness | 0 | .119 | 1 | 9463 |
| Crop price fall | 0 | .115 | 1 | 9434 |
| Input price spike | 0 | .172 | 1 | 9666 |
| **Overall** | | | | |
| Food price spike | 0 | .632 | 1 | 42079 |
| Livestock death | 0 | .268 | 1 | 35075 |
| Droughts/Floods | 0 | .343 | 1 | 35335 |
| Severe illness | 0 | .113 | 1 | 32848 |
| Crop price shock | 0 | .278 | 1 | 35095 |
| Input price spike | 0 | .299 | 1 | 35484 |

I use the self-reported food price shock measure from the “Shocks” module of the LSMS-IS data on Tanzania included in all the three survey rounds and control for the covariant shocks listed in the module. Households were asked to respond with “yes” or “no” to whether they experienced a list of shocks over the five years prior to the survey. For those responding “yes”, additional questions were asked to collect details on the timing and severity of the shocks. The shocks include “large rises in the price of food” (Food crisis dummy), “large rises in input prices”, “severe flood or drought”, and “fall in the price of crops”. Table 1 shows the percentage of households that reported to have experienced each type of shock. For instance, about 60% of the rural households reported to have experienced large rises in food prices compared to 70% of urban households. Notice the shocks appear to be more severe in rural than urban households, as expected, given the shocks affect productive activities.

### *4.2. Labour variables*

Table 2: **Comapring the summary statistics of labour market outcomes for rural and urban households**

| **Household type** | **min** | **mean** | **max** | **N** | **sd** |
|---|---|---|---|---|---|
| **Rural households** | | | | | |
| Wage work | 0 | .119 | 1 | 32248 | .323 |
| Income | 100 | 9622.854 | 1680000 | 3827 | 65766.356 |
| **Urban households** | | | | | |
| Wage work | 0 | .171 | 1 | 13682 | .376 |
| Income | 200 | 15380.741 | 2000000 | 2336 | 77596.294 |
| **Overall households** | | | | | |
| Wage work | 0 | .134 | 1 | 45930 | .341 |
| Income | 100 | 11805.302 | 2000000 | 6163 | 70533.536 |

Individuals were asked to respond “yes” or “no” to whether they had a job that paid a wage income in the past seven days. Those who responded “yes” were asked to report their last wage income. The pay period ranged from a few hours to a year. I transformed all the incomes to the same unit by computing daily incomes for all the individuals. Table 2 above compares the statistics for employment and wage income for rural and urban households. On average 12% of individuals work for wage in rural areas compared to 17% in the urban areas. The mean daily income in rural areas is 9,623 Tanzanian Shillings (4.41 USD) compared to 15,380 shillings (7.05 USD) in urban areas. The minimum daily income is 100 shillings (0.05 USD) in rural areas and 200 (0.1 USD) in urban areas, respectively. The maximum daily income is 1,680,000 shillings (770 USD) in rural areas and 2,000,000 shillings (916 USD) in urban areas, respectively. Notice the high standard deviations in income, which signal a high income inequality. In the robustness checks, I will remove individuals with unusually high incomes (above 1,091,000 shillings or 500 USD per day) or unusually low incomes (below 2,180 Or 1 USD per day) to test the sensitivity of my estimates.

### *4.3. Control variables*

Table 3: **Comapring the summary statistics of control variables for rural and urban households**

| Household Type | min | mean | max | N | sd |
|---|---|---|---|---|---|
| **Rural households** | | | | | |
| Gender | 0 | .487 | 1 | 31252 | .500 |
| Age | 0 | 23.672 | 107 | 31252 | 19.475 |
| Education | 1 | 17.248 | 45 | 11095 | 3.519 |
| Marital status | 0 | .499 | 1 | 20578 | .500 |
| Household size | 1 | 6.998 | 55 | 32248 | 4.432 |
| Market status | 0 | .193 | 1 | 32248 | .394 |
| Age of head | 17 | 48.139 | 107 | 32248 | 14.469 |
| Gender of head | 0 | .807 | 1 | 32248 | .395 |
| Productive asset index | 1 | 29.018 | 876 | 32248 | 44.800 |
| Unproductive asset index | 1 | 55.081 | 1054 | 32248 | 44.557 |
| **Urban households** | | | | | |
| Gender | 0 | .479 | 1 | 13246 | .500 |
| Age | 0 | 25.214 | 101 | 13246 | 17.968 |
| Education | 1 | 19.233 | 45 | 6181 | 5.253 |
| Marital Status | 0 | .433 | 1 | 9739 | .495 |
| Household size | 1 | 6.066 | 22 | 13682 | 3.137 |
| Market status | 0 | .056 | 1 | 13682 | .231 |
| Age of head | 18 | 46.825 | 101 | 13682 | 14.555 |
| Gender of head | 0 | .781 | 1 | 13682 | .414 |
| Productive asset index | 1 | 14.100 | 708 | 13682 | 26.597 |
| Unproductive asset index | 0 | 88.698 | 1110 | 13682 | 72.136 |
| **Overall households** | | | | | |
| Gender | 0 | .485 | 1 | 44498 | .500 |
| Age | 0 | 24.131 | 107 | 44498 | 19.0515 |
| Education | 1 | 17.959 | 45 | 17276 | 4.328 |
| Marital Status | 0 | .477 | 1 | 30317 | .500 |
| Household size | 1 | 6.721 | 55 | 45930 | 4.11 |
| Market status | 0 | .152 | 1 | 45930 | .359 |
| Age of head | 17 | 47.748 | 107 | 45930 | 14.5066 |
| Gender of head | 0 | .799 | 1 | 45930 | .401 |
| Productive asset index | 1 | 24.574 | 876 | 45930 | 40.822 |
| Unproductive asset index | 0 | 65.095 | 1110 | 45930 | 56.394 |

I control for various variables that might affect outcomes in the labor market. These variables include education, marital status, age, and household characteristics. Table 3 on the previous page compares rural and urban households in terms of these variables. Comparing the key variables, some facts emerge. On average urban individuals are more educated, older, more likely to be single, and possess more unproductive assets and less productive assets than rural households. I use the asset indices as a proxy for household wealth [2]. The market status variable is a dummy variable equal to 1 if the individual's household is a net-producer of maize. I define a household as a net food-producer if it reported selling maize in the goods market and a net food-consumer otherwise. As expected, rural households are more likely to be producers. A key take-away from the summary statistics for this variable is that, based on my definition of net-producer, only 15% of the households are net-producers. This makes sense given Tanzania is a net food-importer.

### *4.4. Apparent Relationship*

Figure 2 shows the employment status for urban and rural households who reported to have or not have experienced adverse price shocks. I intend to communicate two key facts from the figure. The first is that wage work is significantly higher in urban and rural areas. The second fact is that rural households experiencing adverse food price shocks tend to work more. The same is true for urban households in 2012 but not in 2010.

Figure 3 shows income over time for urban and rural households who reported to have or not have experienced adverse food price shocks and suggests three key facts. The first is that income is slightly higher in urban than rural areas. The second fact is that income does not appear to be significantly different between individuals who live in households who did or did not report to have experienced adverse price shocks. The third fact is that, in 2010 and 2012, individuals in rural households who did report the shock had slightly lower incomes than those in rural households who did not.

Note that in 2008, during the global food crisis, all the households reported to have expe-

[2] The computation of these indices is described in the additional document attached.

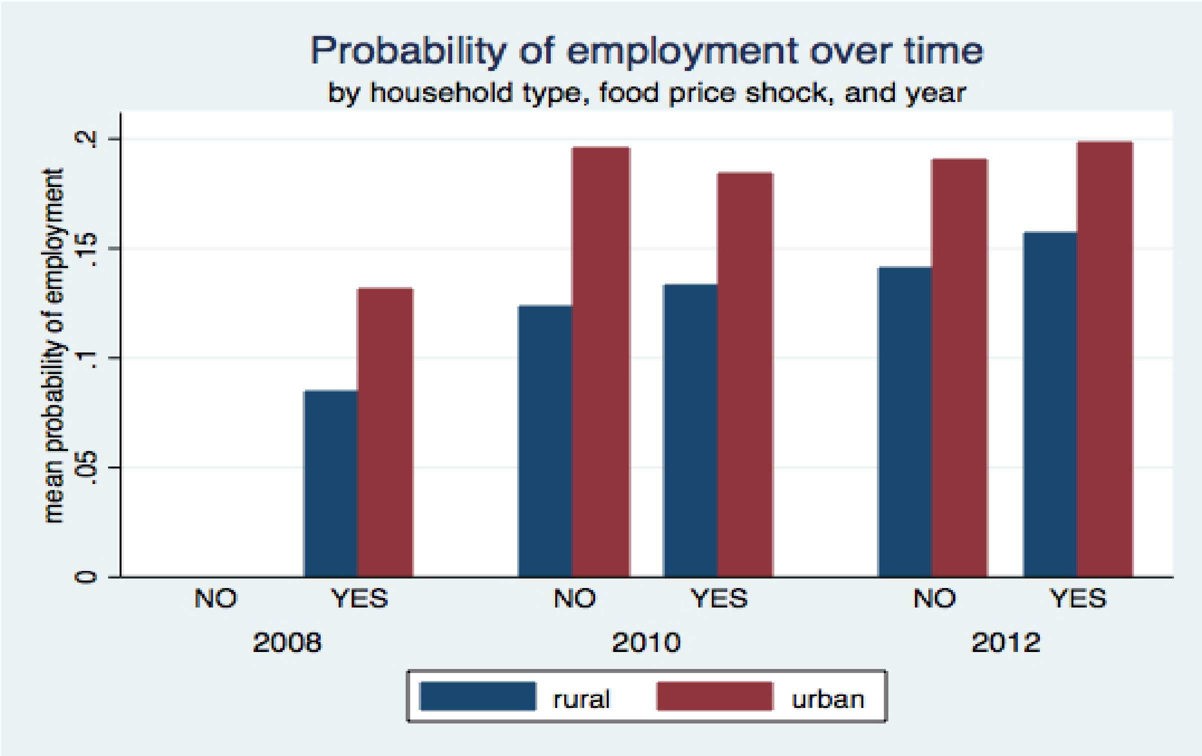


Figure 2: Probability of employment over time for urban and rural households who reported to have or not have experienced adverse price shocks

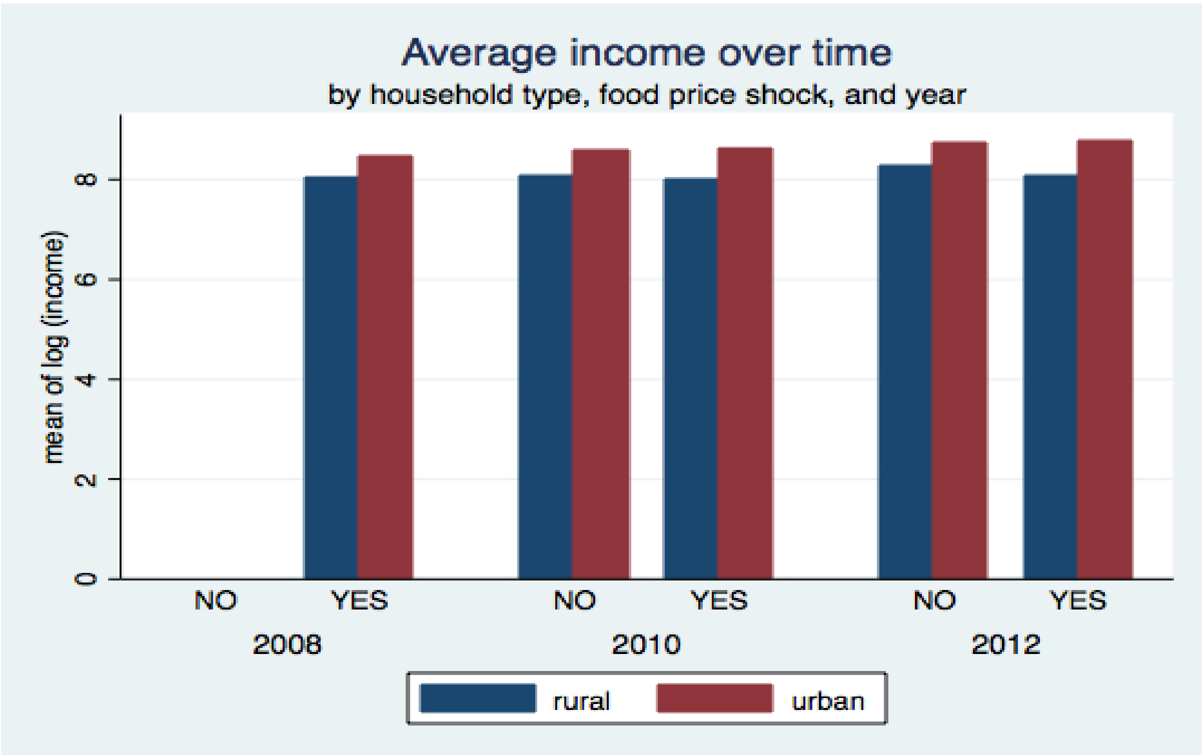


Figure 3: Income over time for urban and rural household who reported to have or not have experienced adverse price shocks

rienced adverse food price shocks. These two graphs, however, do not include keys control variables. In the next section, I present an empirical model that test these relationships, when other variables are controlled for.

## 5. EMPIRICAL STRATEGY

I use a Heckman correction model to account for self-selection into the labor market. My sample includes non-head of household individuals aged between 14 and 60. The minimum working age in Tanzania is 14 and the retirement age is 60 (SSRA, 2014). I exclude the heads of household as I am using variables relating to them to control for household characteristics. The selection equation models the probability of working for wage as a function of individual variables, household characteristics, the food price shock variable, and covariant shock variables. Household characteristics include household size, asset stocks, and variables relating to the head of household. The income equation models daily income as a function of gender, education, age, food price shocks, and regional and year dummies. I estimate the model for both urban and rural individuals.

**First Stage:** *work = f(gender, age, education, marital status, household size, age of the head, gender of the head, productive assets, unproductive assets, food crisis, livestock crisis, drought or flood crisis, severe illness, crop price crisis, agricultural input crisis)*

**Second Stage:** *income = f(gender, education, age, food crisis, year dummies, regional dummies)*

All the continuous variables are logged to correct for heteroskedasticity. According to my theory, I would expect a negative sign on the the food shock dummy for rural households in the first stage indicating that they spend less time on wage work. For urban households, I would expect the opposite, given the income effect is negative. The signs of standard control variables must also be in accordance with theory. Education and age are expected to positively related to income and employment. Males are expected to work more and earn more than women. Married individuals are expected to work less.

# 6. RESULTS

## *6.1. General results*

Table 4: **Two-stage Heckman**

| VARIABLES | (1) Overall Log(income) | (2) Overall Selection | (3) Urban Log(income) | (4) Urban Selection | (5) Rural Log(income) | (6) Rural Selection |
|---|---|---|---|---|---|---|
| Gender | 0.618*** | 0.569*** | 0.626*** | 0.643*** | 0.649*** | 0.543*** |
| | (5.565) | (13.70) | (3.993) | (8.804) | (4.712) | (10.64) |
| Log(age) | 0.719*** | 0.207*** | 1.006*** | 0.353*** | 0.630*** | 0.112 |
| | (8.433) | (3.407) | (7.310) | (3.149) | (5.778) | (1.532) |
| Log(education) | 1.232*** | 0.330*** | 1.117*** | 0.644*** | 1.318*** | 0.0314 |
| | (10.34) | (4.114) | (6.401) | (5.328) | (7.697) | (0.296) |
| Married | | -0.133*** | | -0.378*** | | 0.0114 |
| | | (-2.902) | | (-4.748) | | (0.200) |
| Log(household size) | | -0.0891** | | -0.0729 | | -0.112** |
| | | (-2.229) | | (-0.999) | | (-2.295) |
| Log(age of head) | | -0.0739 | | -0.210* | | -0.0132 |
| | | (-1.155) | | (-1.836) | | (-0.170) |
| Gender of head | | -0.171*** | | -0.208*** | | -0.131** |
| | | (-3.912) | | (-2.764) | | (-2.400) |
| Log(productive asset) | | -0.0825*** | | -0.0209 | | -0.108*** |
| | | (-3.301) | | (-0.435) | | (-3.294) |
| Log(unproductive asset) | | 0.115*** | | 0.156*** | | 0.0640* |
| | | (4.075) | | (2.990) | | (1.683) |
| Food crisis shock | -0.116** | -0.0426 | -0.152* | -0.0457 | -0.101 | -0.0533 |
| | (-2.140) | (-1.136) | (-1.895) | (-0.737) | (-1.382) | (-1.106) |
| Livestock death shock | | -0.0226 | | -0.00759 | | -0.0196 |
| | | (-0.457) | | (-0.0749) | | (-0.343) |
| Droughts/Flood | | 0.0514 | | -0.0215 | | 0.0877* |
| | | (1.190) | | (-0.242) | | (1.752) |
| Severe illness shock | | 0.109* | | -0.00419 | | 0.145* |
| | | (1.767) | | (-0.0410) | | (1.841) |
| Crop price fall shock | | 0.0672 | | -0.0516 | | 0.0752 |
| | | (1.340) | | (-0.401) | | (1.356) |
| Ag. input price shock | | 0.208*** | | 0.182* | | 0.213*** |
| | | (4.419) | | (1.777) | | (3.943) |
| Region fixed effects | YES | | YES | | YES | |
| Year fixed effects | YES | | YES | | YES | |
| Constant | 1.835** | -2.261*** | 1.307 | -3.305*** | 1.696* | -1.137** |
| | (2.222) | (-6.522) | (1.340) | (-5.535) | (1.684) | (-2.573) |
| Lambda | | 0.3101 | | 0.1463 | | 0.5094 |
| Rho | | 0.3114 | | 0.1716 | | 0.47055 |
| Sigma | | 0.9959 | | 0.8524 | | 1.0827 |
| Wald $\chi^2$ Test Statistic | | 441.70 | | 283.58 | | 247.73 |
| Observations | 7,175 | 7,175 | 2,389 | 2,389 | 4,786 | 4,786 |
| Censored observations | 5,587 | 5,587 | 1798 | 1,798 | 3,789 | 3,789 |

The dependent variable is log(income) for models 1, 3, and 5 and the wage dummy for models 2, 4, and 6.
All continuous variables are transformed into logs.
The region and year fixed effects are omitted for clarity.
z-statistics in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 5: **FE Results**

| VARIABLES | (7)<br>Overall FE<br>Log(income) | (8)<br>Overall Logit FE<br>Wage work | (9)<br>Urban FE<br>Log(income) | (10)<br>Urban Logit FE<br>Wage work | (11)<br>Rural FE<br>Log(income) | (12)<br>Rural Logit FE<br>Wage work |
|---|---|---|---|---|---|---|
| Log(age) | 1.430 | 2.631** | 2.615 | 3.170 | -0.0682 | 2.981** |
| | (1.229) | (2.553) | (1.605) | (1.324) | (-0.0377) | (2.367) |
| Log(education) | -0.0497 | 0.186 | -0.0441 | -6.200** | -0.174 | 2.177 |
| | (-0.161) | (0.386) | (-0.138) | (-2.516) | (-0.206) | (1.565) |
| Married | | -0.551** | | -0.255 | | -0.820** |
| | | (-2.100) | | (-0.510) | | (-2.334) |
| Log(household size) | | 0.217 | | -0.335 | | 0.182 |
| | | (0.839) | | (-0.606) | | (0.570) |
| Log(age of head) | | -1.079** | | -0.358 | | -1.166** |
| | | (-2.392) | | (-0.384) | | (-2.090) |
| Gender of head | | -0.983*** | | -0.887 | | -0.950** |
| | | (-3.115) | | (-1.457) | | (-2.288) |
| Log(productive asset) | | -0.306** | | -0.0168 | | -0.355* |
| | | (-2.010) | | (-0.0476) | | (-1.880) |
| Log(unproductive asset) | | 0.0428 | | 0.0287 | | 0.137 |
| | | (0.294) | | (0.0898) | | (0.741) |
| Food crisis shock | -0.166 | -0.0840 | 0.0772 | -0.262 | -0.427*** | 0.113 |
| | (-1.538) | (-0.548) | (0.460) | (-0.949) | (-2.698) | (0.554) |
| Livestock death shock | | 0.102 | | 0.513 | | -0.0920 |
| | | (0.567) | | (1.174) | | (-0.427) |
| Droughts/Flood | | 0.428** | | 0.715 | | 0.355* |
| | | (2.495) | | (1.489) | | (1.804) |
| Severe illness shock | | 0.132 | | 0.104 | | 0.222 |
| | | (0.605) | | (0.214) | | (0.830) |
| Crop price fall shock | | -0.272 | | -1.124** | | -0.142 |
| | | (-1.399) | | (-2.032) | | (-0.647) |
| Ag. input price shock | | 0.249 | | 1.251*** | | -0.0478 |
| | | (1.329) | | (2.714) | | (-0.212) |
| Region fixed effects | YES | | YES | | YES | |
| Year fixed effects | YES | | YES | | YES | |
| Constant | 3.247 | | -1.029 | | 8.340 | |
| | (0.839) | | (-0.191) | | (1.318) | |
| LRT $\chi^2$ Statistic | | 41.08 | | 31.03 | | 36.95 |
| F Statistic | 1.13 | | 1.37 | | 1.19 | |
| R-squared within | 0.091 | | 0.165 | | 0.162 | |
| R-squared between | 0.0117 | | 0.0639 | | 0.0005 | |
| R-squared overall | 0.0190 | | 0.0855 | | 0.0041 | |
| Observations | 1,906 | 1,193 | 739 | 350 | 1,167 | 785 |
| Number of panels | 1,441 | 595 | 541 | 175 | 931 | 392 |

The dependent variable is log(income) for models 7, 9, and 11 and the wage dummy for models 8, 10, and 12.
All continuous variables are transformed into logs.
The region and year fixed effects are omitted for clarity.
t-statistics and z-statistics in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 4 shows the Heckman regression estimates. Models 1 and 2 show the second and first stage estimates, respectively, when I pool all the individuals. Models 3 and 4 show the the second and first stage estimates, respectively, for urban households. Finally, models 5 and 6 show the the second and first stage estimates for rural households. Adverse food price shocks are associated with an overall 12% decrease in daily income, significant at the 5% level. For urban households the decrease is 15%, significant at the 10% level. For rural households, the decrease is an insignificant 10%. The adverse shock is also negatively correlated with wage employment. The marginal effects in the appendix (section 9.1) suggest that the shock decreases the probability of wage employment by 1.2% overall, 1.4% for urban households, and a little below 1.4% for rural households, but these estimates are insignificant. All the standard variables– education, age, marriage – are in accordance with theory. For instance, the results show that men are more likely to work and earn more income than women. Married individuals work less and older people work more. The wald chi squared statistic is large for all the models, which suggest my model significantly explain the outcomes.

In addition to the Heckman model, I also estimate fixed effect regressions [3]. Table 5 shows the coefficient estimates from panel logit regressions with fixed effects. The signs on my variable of interest change for some of the models. Models 7 and 8 are analogous to models 1 and 2 and suggest that, overall, the shock is associated with a 17% decrease in income and an 0.2% decrease in wage employment, both insignificant. Models 9 and 10 indicate that for urban households, the shock is associated with a 7% increase in income and a practically 0% decrease in employment [4], both insignificant. Model 11 suggests that for rural households, the shock is associated with a 43% decrease in income, significant at the 1% level. Model 12 indicates that the shock increases wage employment by practically 0% for rural households.

My Heckman and fixed effects models yield opposite results. The former indicates that urban households are significantly poorer while the latter suggests the opposite. There are two reasons why the Heckman model is better than the fixed effects model. The first reason is that the fixed effects model does not correct for self-selection. The second reason is that the signs

[3] I conducted a Hausman test and rejected the Null hypothesis of random effects being more appropriate than fixed effects.

[4] See appendix, section 9.2 for marginal effects.

on education from the fixed effects models suggest that education is negatively correlated with income, which is inconsistent with theory. I thus adopt the Heckman estimates as my best model and run robustness checks.

## *6.2. Robustness checks*

Table 6: **Two-stage Heckman after excluding outliers**

| VARIABLES | (13) Overall Log(income) | (14) Overall selection | (15) Urban Log (income) | (16) Urban selection | (17) Rural Log (income) | (18) Rural selection |
|---|---|---|---|---|---|---|
| Gender | 0.292** | 0.827*** | 0.449** | 0.863*** | -0.00965 | 0.834*** |
| | (2.003) | (16.66) | (2.384) | (10.54) | (-0.0447) | (13.12) |
| Log(age) | 0.388*** | 0.393*** | 0.512*** | 0.544*** | 0.228 | 0.293*** |
| | (3.410) | (5.424) | (3.280) | (4.317) | (1.390) | (3.270) |
| Log(education) | 0.933*** | 0.860*** | 1.102*** | 1.058*** | 0.670** | 0.622*** |
| | (5.126) | (8.848) | (4.693) | (7.756) | (2.449) | (4.412) |
| Married | | -0.000158 | | -0.215** | | 0.157** |
| | | (-0.00289) | | (-2.403) | | (2.228) |
| Log(household size) | | -0.0374 | | -0.0118 | | -0.0751 |
| | | (-0.804) | | (-0.147) | | (-1.286) |
| Log(age of head) | | 0.0292 | | -0.0958 | | 0.0857 |
| | | (0.383) | | (-0.746) | | (0.895) |
| Gender of head | | -0.149*** | | -0.212** | | -0.0906 |
| | | (-2.909) | | (-2.551) | | (-1.369) |
| Log(productive asset) | | -0.113*** | | -0.0758 | | -0.0999** |
| | | (-3.894) | | (-1.427) | | (-2.554) |
| Log(unproductive asset) | | 0.207*** | | 0.210*** | | 0.135*** |
| | | (6.206) | | (3.561) | | (2.926) |
| Food crisis shock | -0.104* | -0.0189 | -0.174** | 0.0307 | -0.0527 | -0.0802 |
| | (-1.849) | (-0.432) | (-2.236) | (0.445) | (-0.661) | (-1.374) |
| Livestock death shock | | -0.0650 | | -0.0492 | | -0.0589 |
| | | (-1.086) | | (-0.431) | | (-0.831) |
| Droughts/floods | | 0.0280 | | 0.0217 | | 0.0562 |
| | | (0.543) | | (0.219) | | (0.914) |
| Severe illness shock | | 0.138* | | 0.00839 | | 0.186** |
| | | (1.947) | | (0.0755) | | (1.993) |
| Crop price fall shock | | -0.0377 | | -0.141 | | -0.0120 |
| | | (-0.606) | | (-0.928) | | (-0.172) |
| Ag. input price shock | | 0.174*** | | 0.0896 | | 0.218*** |
| | | (3.073) | | (0.762) | | (3.292) |
| Region fixed effects | YES | | YES | | YES | |
| Year fixed effects | YES | | YES | | YES | |
| Constant | 6.846*** | -5.651*** | 3.096** | -6.197*** | 9.550*** | -4.708*** |
| | (5.081) | (-13.39) | (2.249) | (-9.007) | (5.207) | (-8.330) |
| Lambda | | 0.1138 | | 0.1446 | | -0.2252 |
| Rho | | 0.14301 | | 0.20654 | | -0.26465 |
| Sigma | | 0.7955 | | 0.7002 | | 0.8512 |
| Wald $\chi^2$ Test Statistic | | 155.21 | | 160.01 | | 70.64 |
| Observations | 6,591 | 6,591 | 2,244 | 2,244 | 4,347 | 4,347 |
| Censored observations | 5587 | 5587 | 1798 | 1798 | 3789 | 3789 |

The dependent variable is log(income) for models 13, 15, and 17 and the wage dummy for models 14, 16, and 18.
All continuous variables are transformed into logs.
The region and year fixed effects are omitted for clarity.
z-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7: **Two-stage Heckman for net-maize producers and net-maize consumers.**

| | (19) | (20) | (21) | (22) |
|---|---|---|---|---|
| | Household is a net consumer | | Household is a net producer | |
| VARIABLES | Log (income) | Consumer Selection | Log (income) | Producer Selection |
| Gender | 0.619*** | 0.604*** | 0.390* | 0.337*** |
| | (5.080) | (13.53) | (1.727) | (2.902) |
| Log(age) | 0.760*** | 0.237*** | 0.378 | 0.0376 |
| | (8.072) | (3.593) | (1.642) | (0.234) |
| Log(education) | 1.204*** | 0.316*** | 1.512*** | 0.529* |
| | (9.813) | (3.788) | (3.281) | (1.791) |
| Married | | -0.122** | | -0.232* |
| | | (-2.471) | | (-1.775) |
| Log(household size) | | -0.0887** | | -0.0872 |
| | | (-2.038) | | (-0.799) |
| Log(age of head) | | -0.0503 | | -0.160 |
| | | (-0.725) | | (-0.923) |
| Gender of head | | -0.174*** | | -0.168 |
| | | (-3.728) | | (-1.292) |
| Log(productive asset) | | -0.0915*** | | -0.0378 |
| | | (-3.353) | | (-0.474) |
| Log(unproductive asset) | | 0.124*** | | 0.0400 |
| | | (4.109) | | (0.466) |
| Food crisis shock | -0.153*** | -0.0319 | 0.00937 | -0.106 |
| | (-2.581) | (-0.789) | (0.0643) | (-0.974) |
| Livestock death shock | | -0.0145 | | -0.0444 |
| | | (-0.259) | | (-0.408) |
| Droughts/Flood | | 0.0490 | | 0.0923 |
| | | (1.032) | | (0.860) |
| Severe illness shock | | 0.108 | | 0.0999 |
| | | (1.625) | | (0.577) |
| Crop price fall shock | | 0.0371 | | 0.156 |
| | | (0.654) | | (1.393) |
| Ag. input price shock | | 0.219*** | | 0.174* |
| | | (4.038) | | (1.665) |
| Region fixed effects | YES | | YES | |
| Year fixed effects | YES | | YES | |
| Constant | 2.104** | -2.451*** | 1.243 | -1.591 |
| | (2.301) | (-6.622) | (0.640) | (-1.469) |
| Lambda | | 0.2322 | | 0.3517 |
| Rho | | 0.23560 | | 0.3912 |
| Sigma | | 0.9856 | | 0.8992 |
| Wald $\chi^2$ Test Statistic | | 397.02 | | 74.26 |
| Observations | 6,136 | 6,136 | 1,039 | 1,039 |
| Censored observations | 4,777 | 4,777 | 810 | 810 |

The dependent variable is log(income) for models 19 and 21 and the wage dummy for models 20 and 22.
All continuous variables are transformed into logs.
The region and year fixed effects are omitted for clarity.
z-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8: **Two-stage Heckman for net-rice producers and net-rice consumers.**

| | (23) | (24) | (25) | (26) |
|---|---|---|---|---|
| | Household is a net consumer | | Household is a net producer | |
| VARIABLES | Log(income) | Consumer selection | Log(income) | Producer selection |
| Gender | 0.581*** | 0.563*** | 0.649** | 0.700*** |
| | (5.058) | (12.95) | (2.194) | (4.753) |
| Log(age) | 0.696*** | 0.201*** | 0.816*** | 0.283 |
| | (7.814) | (3.160) | (3.356) | (1.301) |
| Log(education) | 1.225*** | 0.376*** | 0.322 | -0.583 |
| | (9.610) | (4.565) | (0.585) | (-1.430) |
| Married | | -0.139*** | | -0.127 |
| | | (-2.891) | | (-0.812) |
| Log(household size) | | -0.0977** | | 0.00416 |
| | | (-2.323) | | (0.0280) |
| Log(age of head) | | -0.0858 | | 0.211 |
| | | (-1.296) | | (0.788) |
| Gender of head | | -0.148*** | | -0.292* |
| | | (-3.218) | | (-1.841) |
| Log(productive asset) | | -0.0838*** | | -0.105 |
| | | (-3.199) | | (-0.999) |
| Log(unproductive asset) | | 0.142*** | | -0.258** |
| | | (4.820) | | (-2.124) |
| Food crisis shock | -0.127** | -0.0504 | -0.262 | 0.0459 |
| | (-2.247) | (-1.296) | (-1.281) | (0.300) |
| Livestock death shock | | -0.0220 | | -0.0254 |
| | | (-0.419) | | (-0.163) |
| Droughts/floods | | 0.0534 | | 0.0338 |
| | | (1.174) | | (0.219) |
| Severe illness shock | | 0.0910 | | 0.201 |
| | | (1.393) | | (0.978) |
| Crop price fall shock | | 0.0486 | | 0.196 |
| | | (0.917) | | (1.133) |
| Ag. input price shock | | 0.195*** | | 0.204 |
| | | (3.863) | | (1.410) |
| Region fixed effects | YES | | YES | |
| Year fixed effects | YES | | YES | |
| Constant | 1.914** | -2.435*** | 4.835*** | 0.516 |
| | (2.212) | (-6.788) | (2.707) | (0.323) |
| Lambda | | 0.245 | | 0.191 |
| Rho | | 0.249 | | 0.250 |
| Sigma | | 0.987 | | 0.762 |
| Wald $\chi^2$ Test Statistic | | 392 | | 102 |
| Observations | 6,638 | 6,638 | 537 | 537 |
| Censored Observations | 190 | 190 | 397 | 397 |

The dependent variable is log(income) for models 23 and 25 and the wage dummy for models 24 and 26.
All continuous variables are transformed into logs.
The region and year fixed effects are omitted for clarity.
z-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

I run several robustness checks to test the sensitivity of my results to various samples. Figure 7 in the appendix (section 9.1), plotting the actual versus fitted values from the Heckman models in table 4, indicates the presence of outliers. For the first robustness check, I exclude all individuals with daily income lower than 2,180 shillings (2,036 observations) or greater than 1,091,000 million shillings (8 observations). The results from the regressions, displayed in table 6, are similar to the results in table 4. The coefficient on food for urban households has become more negative and more significant. For urban households, the adverse food price shock is associated with a 15% decrease in income, significant at the 1% level. The first stage coefficients remain practically the same.

For my second robustness check, I place individuals in two categories of households: net food-producers and net food-consumers. As mentioned earlier, I define a household as a net food-producer if it reported selling maize in the goods market. From table 3, notice that only 19% of rural households and 6% of urban households can be classified as net food-producers. Results shown in table 7 mirror the estimates for urban and rural households in table 4. Models 19 and 20 show the second and first stage estimates for individuals in net food-consuming households. Models 21 and 22 show the second and first stage estimates for individuals in net food-producing households. The marginal effects [5] on the food shock dummy show that the probability of employment is 0.7% lower for individuals belonging to net food-producing households and 3% lower for individuals residing in net food-consuming households, but these estimates remain statistically insignificant. The estimates also show that income decreases by a significant 15% for net food-consuming households. For net food-producing households, the adverse price shock is associated with a small and insignificant 0.9% increase in income. Given net food-consumers are more likely to live in urban areas and net food-producers in rural areas, these results are consistent with my previous estimates.

I repeat the same process defining a net food-producer as a household reported selling rice (paddy) in the goods market and obtain similar results, as shown by Table 8. For urban households, the adverse food price shock is associated with a 13% decrease in income, significant at the 5% level. The other results remain practically the same as those in table 7.

[5] See appendix, section 9.4 for these marginal effects.

Adverse food price shocks therefore significantly decrease daily income in urban areas. In rural areas, there is no significant evidence supporting adverse effects of price spikes. While my theory fails to explain these results, the general findings are consistent with the literature that suggest that positive income effects of soaring food prices in the agriculture sector mitigate the adverse general equilibrium effects of higher food prices in a predominantly food-consuming society.

## 7. CONCLUSION AND DISCUSSION

This paper investigates the effects of large and sudden increases in food prices such as those that occurred worldwide between 2007 and 2009 on the probability of employment and daily wage income. I use a simple theoretical framework to model how individuals within a household use labor markets to cope with adverse food price shocks. I employ a detailed individual-level panel data set from Tanzania that covers the years 2008, 2010, and 2012. I estimate regressions using a Heckman correction model, separating rural and urban households. In addition, I check for robustness by excluding outliers and categorizing individuals further based on the market status of their respective households. My results suggest adverse food price shocks are correlated with a significant 15% decrease in income for urban individuals. This effect likely originates from a negative general equilibrium and entrepreneurial effect that occur as a result of food price spikes in net food-importing countries. The effects in the rural areas are, in general, negative, but not statistically different. These negative effects might be mitigated in the rural areas by the positive wage effect of food price increases. The effects on the probability of employment are negative but statistically insignificant for both types of households. While my simple theoretical model fails to explain these outcomes, my results are consistent with general findings in the literature.

My results are suggestive rather than conclusive for it involves many weaknesses. The first and foremost weakness stems from endogeneity due to omitted variables such as loans, other income transfers, and macroeconomic variables. Furthermore, my model also does not take into account substitution effects of individuals. While food can be expected to be price inelastic, households might substitute towards other staples which can lead to biases in my estimates. A second limitation comes from the use of the self-reported shock dummy variables. Households were asked to report having experienced specific shocks over the last five years. While most households reported experiencing negative food price shocks around the time period of the survey rounds, some reported having experienced shocks in earlier years.

Future research should address the key limitations outlined above. Stronger evidence in support of negative employment and wage effects of food price spikes would help policymakers and governments identify those that are most vulnerable to changes in prices and provide them with safety nets in times of food insecurity.

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# 9. Appendix

## *9.1. Table 4 results: marginal effects and predicted versus actual values plot*

```
. margins, dydx(food_crisis)

Average marginal effects                        Number of obs     =      7,206
Model VCE    : OIM

Expression   : Pr(dinc), predict()
dy/dx w.r.t. : food_crisis
```

| | dy/dx | Delta-method Std. Err. | z | P>\|z\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| food_crisis | -.01187 | .0105739 | -1.12 | 0.262 | -.0325945 | .0088546 |

Figure 4: Model 2: marginal effects

```
. margins, dydx(food_crisis)

Average marginal effects                        Number of obs     =      2,397
Model VCE    : OIM

Expression   : Pr(dinc), predict()
dy/dx w.r.t. : food_crisis
```

| | dy/dx | Delta-method Std. Err. | z | P>\|z\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| food_crisis | -.0140462 | .0177513 | -0.79 | 0.429 | -.048838 | .0207457 |

Figure 5: Model 4: marginal effects

```
. margins, dydx(food_crisis)

Average marginal effects                        Number of obs     =      4,809
Model VCE    : OIM

Expression   : Pr(dinc), predict()
dy/dx w.r.t. : food_crisis
```

| | dy/dx | Delta-method Std. Err. | z | P>\|z\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| food_crisis | -.0138361 | .0132655 | -1.04 | 0.297 | -.0398359 | .0121637 |

Figure 6: Model 6: marginal effects

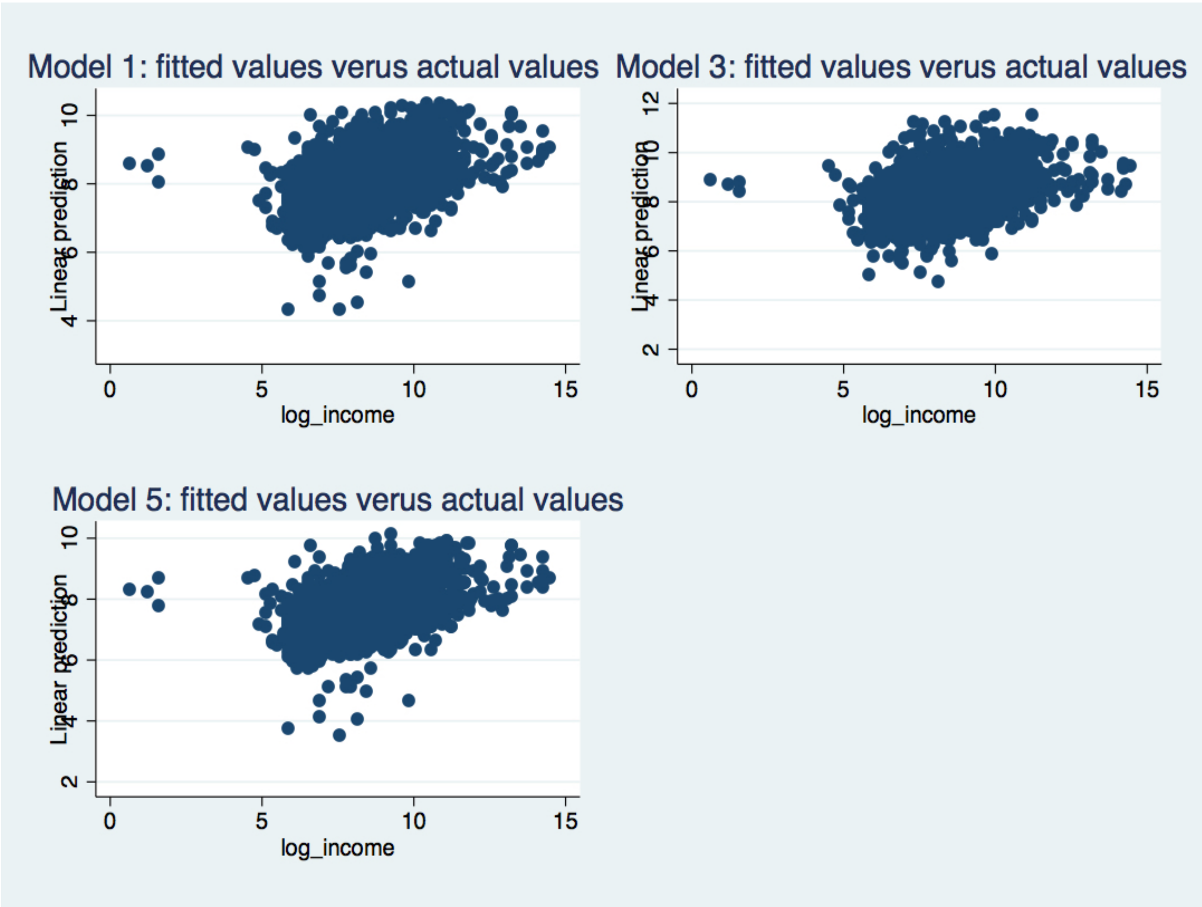


Figure 7: “Predicted versus actual values” for models 1, 3, and 5

## 9.2. *Table 5 results: marginal effects and "predicted versus actual values plot"*

```
. margins, dydx(food_crisis)

Average marginal effects                          Number of obs     =      1,193
Model VCE    : OIM

Expression   : Pr(dinc|fixed effect is 0), predict(pu0)
dy/dx w.r.t. : food_crisis

------------------------------------------------------------------------------
             |            Delta-method
             |      dy/dx   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
 food_crisis |  -.0024061   .0090884    -0.26   0.791     -.020219    .0154068
------------------------------------------------------------------------------
```

Figure 8: Model 8: marginal effects

```
. margins, dydx(food_crisis)

Average marginal effects                          Number of obs     =        350
Model VCE    : OIM

Expression   : Pr(dinc|fixed effect is 0), predict(pu0)
dy/dx w.r.t. : food_crisis

------------------------------------------------------------------------------
             |            Delta-method
             |      dy/dx   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
 food_crisis |  -.0000411    .000271    -0.15   0.879    -.0005723    .0004901
------------------------------------------------------------------------------
```

Figure 9: Model 10: marginal effects

```
. margins, dydx(food_crisis)

Average marginal effects                          Number of obs     =        785
Model VCE    : OIM

Expression   : Pr(dinc|fixed effect is 0), predict(pu0)
dy/dx w.r.t. : food_crisis

------------------------------------------------------------------------------
             |            Delta-method
             |      dy/dx   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
 food_crisis |   9.95e-06   .0000566     0.18   0.860     -.000101    .0001209
------------------------------------------------------------------------------
```

Figure 10: Model 12: marginal effects

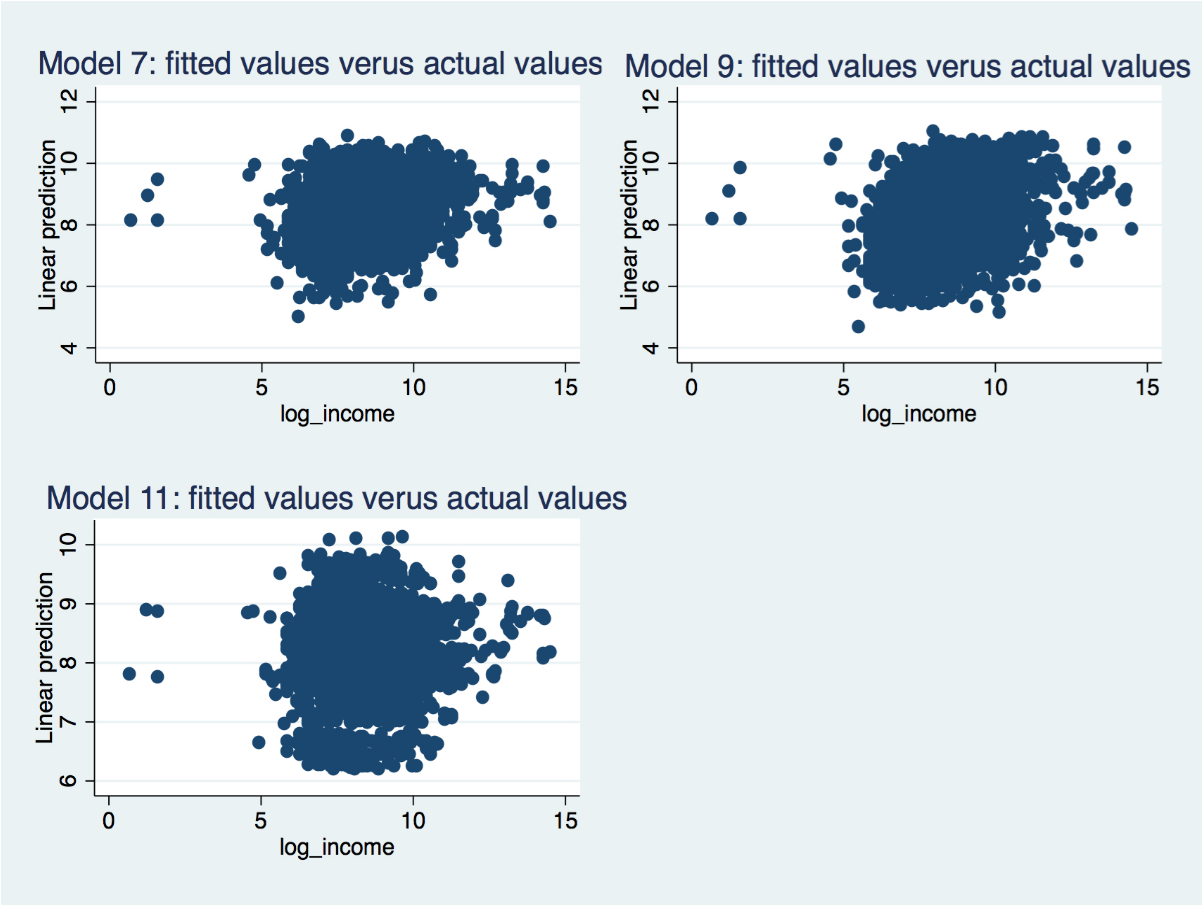


Figure 11: “Predicted versus actual values” plots for models 7, 9, and 11

*9.3. Table 6 results: predicted versus actual values*

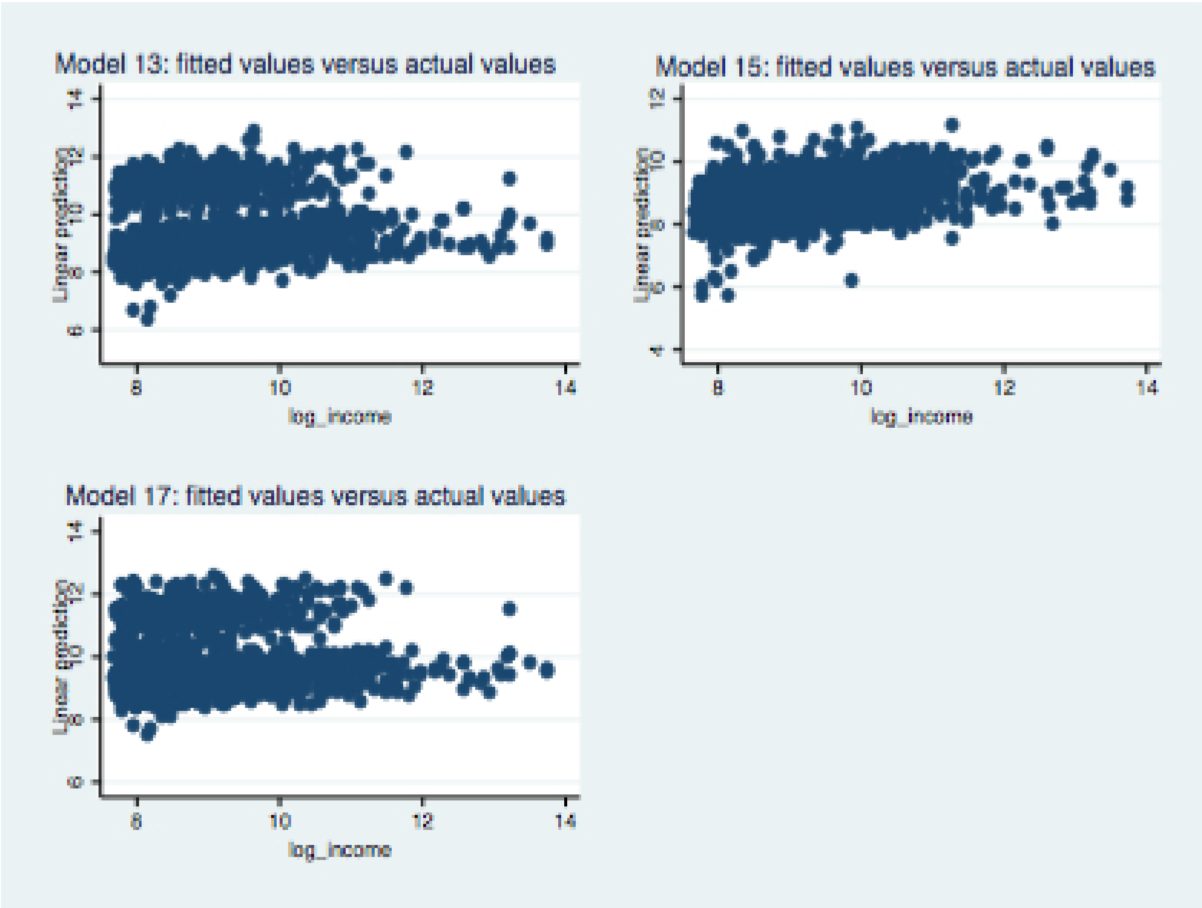


Figure 12: “Predicted versus actual values” plots for models 13, 15, and 17

### 9.4. *Table 7 results: marginal effects and predicted versus actual values*

```
. margins, dydx(food_crisis)

Average marginal effects                        Number of obs     =      6,161
Model VCE    : OIM

Expression   : Pr(dinc), predict()
dy/dx w.r.t. : food_crisis
```

| | dy/dx | Delta-method Std. Err. | z | P>\|z\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| food_crisis | -.0078684 | .011343 | -0.69 | 0.488 | -.0301003 | .0143635 |

Figure 13: Model 20: marginal effects

```
. margins, dydx(food_crisis)

Average marginal effects                        Number of obs     =      1,045
Model VCE    : OIM

Expression   : Pr(dinc), predict()
dy/dx w.r.t. : food_crisis
```

| | dy/dx | Delta-method Std. Err. | z | P>\|z\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| food_crisis | -.0364032 | .0310056 | -1.17 | 0.240 | -.0971731 | .0243667 |

Figure 14: Model 22: marginal effects

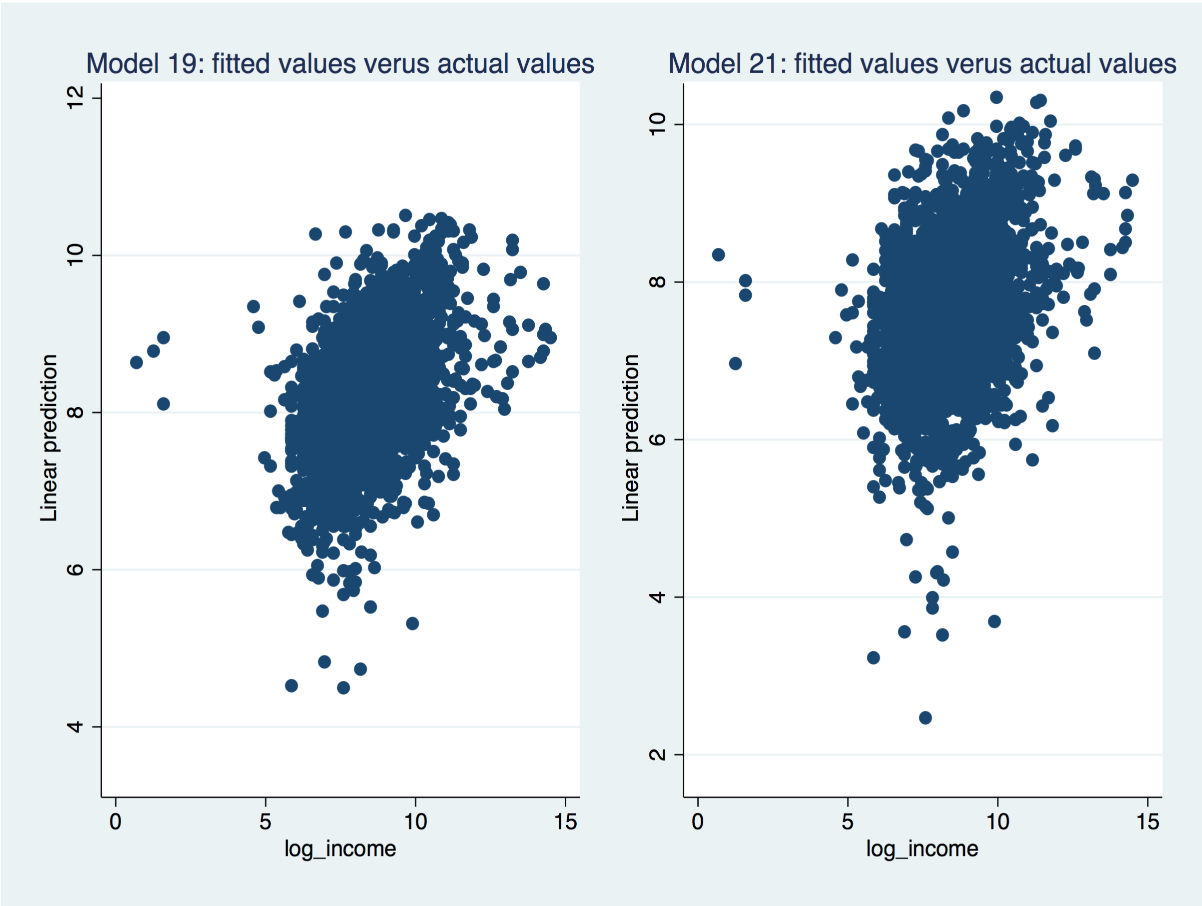


Figure 15: “Predicted versus actual values” plots for models 19 and 21

*9.5. Table 8 results: predicted versus actual values*

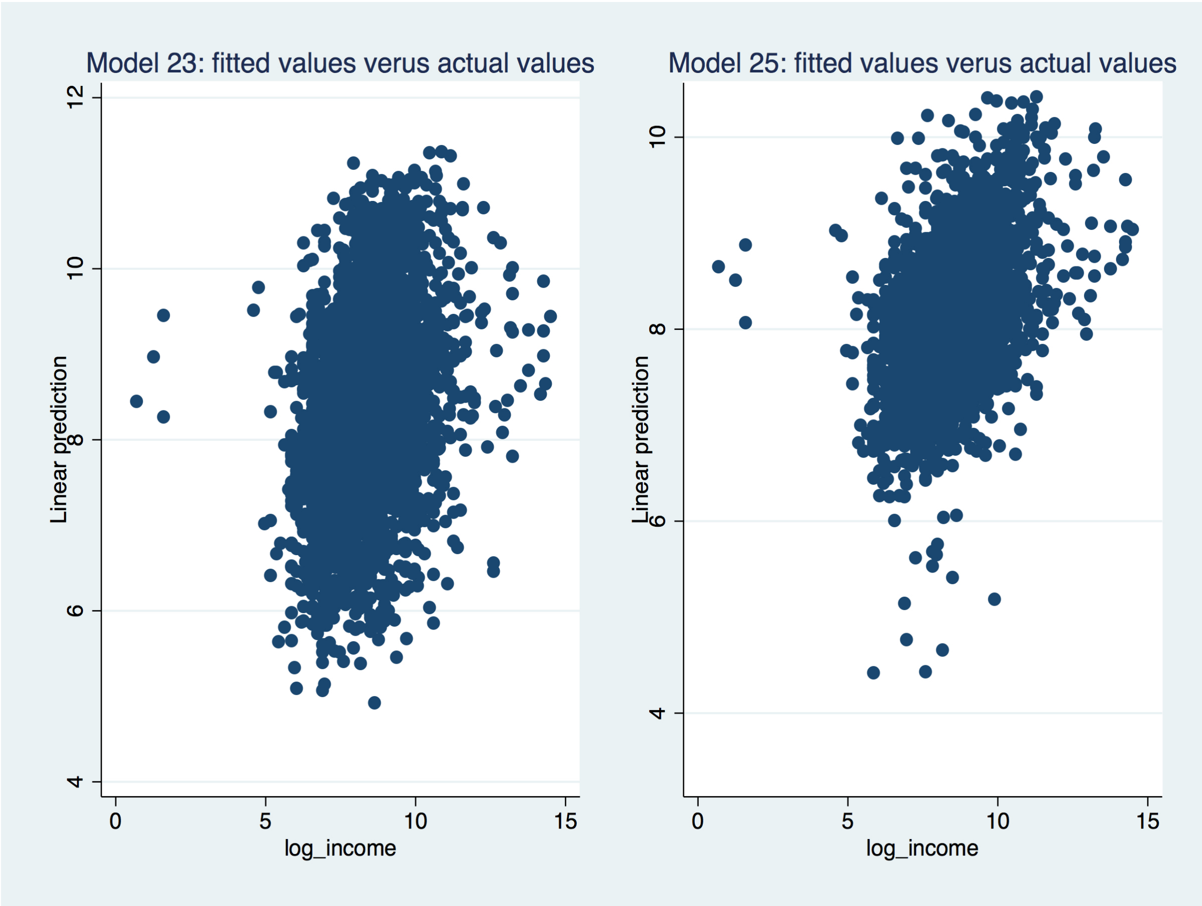


Figure 16: "Predicted versus actual values" plots for models 23 and 25