EXAMINING THE DEMAND FOR PROCESSED FOODS AND THE ROLE OF FOOD PROCESSING ENTERPRISES IN WEST AFRICA

By

Hanna Carlson

A DISSERTATION

Submitted to
Michigan State University
in partial fulfillment of the requirements
for the degree of

Agricultural, Food, and Resource Economics – Doctor of Philosophy

2025

ABSTRACT

The demand for processed convenience foods and ready-to-eat foods has increased globally in recent decades with increases in household income and urbanization. This increase in demand for processed convenience foods has led to an expanded supply of these foods, but little is known about these suppliers, their business choices, and the viability of their enterprises. In this dissertation, I first seek to understand how West African households change their food consumption in response to changes in income and food prices. Then, I provide a characterization of small and medium-sized food processing enterprises (SMEs) in West Africa, analyzing their performance and efficiency to provide insight into the characteristics of successful food processing SMEs.

Understanding how changes in household income and food prices affect dietary composition is key to improving food and nutrition security. Utilizing Mali's 2018 Harmonized Survey on Households Living Standards, Chapter 1 estimates demand for food by food group and by processing level through the calculation of price and expenditure elasticities for 3,847 rural households and 2,745 urban households. A two-stage Working-Leser and Quadratic Almost Ideal Demand System (QUAIDS) model is employed to calculate elasticities for rural and urban households of different income levels. Following the estimation of the demand system, I estimate the amount a household would need to be compensated to restore their original utility under hypothetical price shocks to different food groups. Findings indicate that both rural and urban Malians are increasing their food consumption, in value terms, as they increase their total household expenditure. Within a household's food budget, the consumption in value terms of animal products, fruits, and vegetables increases as household food expenditure increases. The budget share of cereals declines as expenditure increases but remains relatively high across rural and urban households. Additionally, households demand more processed foods as their incomes grow. Simulated price shocks to cereals and animal products have stronger impacts on household utility than any other food groups. Policymakers should focus on supporting and expanding sustainable food supply chains, particularly for cereals and animal products.

Shifting focus to the supply side, in Chapter 2, I utilize a unique dataset of 320 processed food vendors in 82 open-air markets across Senegal in 2021 to examine what factors contribute to a market food vendor's decision to process cowpea and the quantity they process. In addition to being locally produced, cowpea is a nutritious food source that can be processed for convenience.

I provide a characterization of market processed food vendors, then employ a double hurdle model to examine how various regional, sociodemographic, market, business, and product portfolio characteristics affect the probability of processing cowpea and the expected value of cowpea processed by a vendor each week, allowing the factors that affect the participation decision to differ from those that affect the intensity of participation. I find that vendors of processed food products in open-air markets in Senegal are mostly women. The results indicate that vendors in rural markets are more likely to process cowpea and to process more, on average, than urban market vendors. Results from postestimation analysis indicate that nearly two-thirds of the processors most likely to process cowpea operate out of physical structures compared to only a quarter of the processors least likely to process any cowpea. This could be related to the risk of pest infestation for improperly stored cowpea grain. Overall, this study highlights the importance of cowpea processing as a channel for entrepreneurial women to start small businesses and earn income to support their families, warranting further research and investment into this sector.

In Chapter 3, I describe the second-stage grain processing small and medium enterprises (SMEs) across urban areas of Senegal, estimate their technical efficiency (TE), and examine the factors that contribute to higher levels of technical efficiency using a Stochastic Frontier Analysis. I employ a dataset collected in 2018 under the Agricultural Policy Support Program that includes information on 552 grain processing street vendors and 200 semi-industrial enterprises. I find that women own and operate the majority of both of these types of grain processing SMEs. Additionally, both types of enterprises rely heavily on manual processing methods, exhibiting low levels of adoption of mechanized processing technologies. I estimate efficiencies separately for both groups of food processors and find the mean TE score of semi-industrial enterprises to be 0.642 and the mean TE score of street vendors to be 0.637. I find that street vendors relying on shared resources are less efficient. I also find that semi-industrial processors are more efficient if they are connected to formal networks through membership in a processor's organization, providing evidence that policies that improve access to and provide support for processor's organizations may effectively reduce inefficiency of second-stage grain processing SMEs.

TABLE OF CONTENTS

CHAPTER 1. AN EXPLORATION OF THE DIETARY LANDSCAPE IN RURAL AND URBAN AREAS OF MALI....1
1.1 Introduction....1
1.2 Food Demand Analysis....5
1.3 Data and Descriptive Statistics....12
1.4. Results....25
1.5. Conclusions and Policy Implications....34
REFERENCES....38
APPENDIX A: TESTING FOR THE INCLUSION OF QUADRATIC TERMS....44
APPENDIX B: FOOD GROUP CLASSIFICATIONS....45
APPENDIX C: PROCESSING LEVEL CLASSIFICATIONS....46
APPENDIX D: STAGE 1 REGRESSION COEFFICIENTS....47
APPENDIX E: STAGE 2 REGRESSION COEFFICIENTS – FOOD GROUP MODEL....48
APPENDIX F: CROSS PRICE ELASTICITIES BY FOOD GROUP....50
APPENDIX G: STAGE 2 REGRESSION COEFFICIENTS – PROCESSING MODEL....52

CHAPTER 2. DETERMINANTS OF PRODUCT CHOICE FOR FOOD MARKET VENDORS IN SENEGAL: THE CASE OF PROCESSED COWPEA....53
2.1 Introduction....53
2.2 Conceptual Model....58
2.3 Data....59
2.4 Estimation Strategy....62
2.5 Results....67
2.6 Conclusions....82
2.7 Policy Implications....84
REFERENCES....86
APPENDIX A: REGIONAL SAMPLING....91
APPENDIX B: TEST FOR POOLED VS RESTRICTED SAMPLE....92
APPENDIX C: COMPARING THE FIT OF TOBIT AND DOUBLE HURDLE SPECIFICATIONS....94

CHAPTER 3. TECHNICAL EFFICIENCY OF GRAIN PROCESSORS IN URBAN SENEGAL....96
3.1 Introduction....96
3.2 The Senegalese Context....99
3.3 Conceptual Model....101
3.4 Data....102
3.5 Empirical Model....103
3.6 Results....108
3.7 Policy Implications....122
3.8 Conclusions....124
REFERENCES....126
APPENDIX A: INDEPENDENT VARIABLE TRANSFORMATION COMPARISONS....131
APPENDIX B: META FRONTIER EXPLORATION....132
APPENDIX C: RESULTS OF MODEL WITHOUT ENDOGENEITY CORRECTION....133

CHAPTER 1. AN EXPLORATION OF THE DIETARY LANDSCAPE IN RURAL AND URBAN AREAS OF MALI

1.1 Introduction

Malians are heavily dependent on agriculture not only for food, but also for their livelihoods. Over 80% of the population is employed in the agri-food systems (Organization for Economic Cooperation and Development Sahel and West Africa Club [SWAC/OECD], 2021). Yet, food insecurity and malnutrition remain problematic. In 2012, the United Nations World Food Programme (WFP) declared the food crisis in the Sahel region of West Africa a level 2 emergency, which has since been upgraded to a level 3 emergency (WFP, 2020). This is the highest level of emergency, indicating an issue that requires global attention. An estimated 1.26 million Malians were acutely food insecure in the June – August 2023, the lean season in Mali (WFP, 2023).

The Malian agri-food system has experienced major shocks over the past decade. The agri-food system has been subject to drastic weather fluctuations due to climate change (Biasutti, 2019). Droughts and floods have negatively affected agricultural yields (Traoré et al., 2013). Violent conflict has escalated in the northern regions of the country, slowly pushing its way south and impacting the food trade routes both within the country and with neighboring countries (WFP, 2019). Malians are highly reliant on food markets, as both rural and urban consumers are net buyers of food (Smale, Thériault, & Vroegindewey, 2020).

Food production overall within the country is growing each year, but this does not mean that the food is available to all people, when and where it is needed, or that it is affordable (SWAC/OECD, 2021). Chronic malnutrition affects 26% of children in Mali (WFP, 2023). Additionally, 55% of rural households and 43% of urban households cannot meet their food needs (WFP, 2020). The global Coronavirus pandemic that began in 2020 impacted incomes and food security. Average daily per capita income decreased by 12% in Mali during the pandemic, ~ 30% of households reported consuming lower quantities and quality of food, and 16% reported skipping meals with similar effects across rural and urban households (Maredia et al., 2022). In contrast, Adjognon et al. (2021) found that the short-term effects of the Coronavirus pandemic on food security were larger for urban households.

While food insecurity in calorie terms is a major issue, it is also important to understand how dietary patterns are shifting to get a full picture of food demand in Mali. Bennett's Law (1941) states that dietary transformation involves the shift from starchy staple goods such as cereals towards foods such as meats, dairy, fruits, and vegetables, as incomes rise. Dietary transformation also encompasses the increase in consumption of processed foods as incomes increase since, the opportunity cost of food preparation rises and advertising for processed foods increases (Reardon et al., 2021). In Mali, GDP per capita rose quickly in the early 2000's, growing from $256 (current US Dollars) in 2000 to $789 in 2011, however, since 2011 it has fluctuated between a low of $704 in 2015 and a high of $869 in 2023 (World Bank, 2025). Gerbens-Leenes et al. (2010) found that in higher GDP countries, people get more of their calories from fats, whereas people in lower GDP countries are much more dependent on carbohydrates for their calories. Kearney (2010) similarly found that as incomes rise, people consume more diverse nutrients, including fat and animal proteins, and less carbohydrates.

Urban consumers tend to drive the dietary transformation process, demanding more processed and diversified foods than rural consumers (SWAC/OECD, 2021). Reardon et al. (2014) studied the impacts of urbanization on diets in Asian countries and found that urban households consume more meat, fruits, vegetables, processed food, and food away from home (FAFH). Urban areas often have better marketing and distribution channels, better infrastructure, and supermarkets providing access to more food choices and FAFH options (Kearney, 2010).

In Mali, the total population has grown from 11.2 million in 2000 to 22.6 million in 2022, with the urban percentage of the population growing from 28% to 45% during the same time frame (World Bank, 2023a; World Bank, 2023b). In urban Mali, supermarkets are not common and small, traditional shops and markets dominate over larger, more modernized retailers (Theriault et al., 2018). In inventorying processed grain and dairy products, Theriault et al. (2018) found that there is more processed product diversity in high income urban neighborhoods than in lower income urban neighborhoods. Although the urban middle and upper class have been seen as the primary drivers of diet transformation, particularly as it relates to dietary diversity, in the last few decades researchers have found evidence that household dietary changes are also happening at lower income levels than in the past (Dolislager et al., 2022; Popkin 2002). Popkin (2002) found that fat consumption was increasing at lower income levels. Additionally, a recent study suggests that in East and West Africa, the urban and rural poor are actually at the forefront of dietary transformation, as they have shifted large portions of their food budget to processed foods (Dolislager et al., 2022). This raises questions about how similar or different rural and urban consumption patterns are in Mali, and how consumption differs across expenditure levels.

Smale, Thériault, and Mason (2020) found that the dietary diversity scores for rural Malians women were low, indicating that they were not eating a wide variety of food groups and nutrients. Olabisi et al. (2021) found that in Nigeria, dietary diversity scores were lower for households that consumed more food from their own production, particularly rural households. According to the Food and Agriculture Organization (2017), the top three commodities available for consumption in Mali are rice, millet, and sorghum, with cereals making up more than 67% of Mali's dietary energy supply. Mali has the highest annual per capita cereal consumption in West Africa at 247 kg of cereals per person per year, 84 kg more than the average for West Africa (Food and Agriculture Organization [FAO], 2022). The dominance of cereals in the Malian diet and evidence of low dietary diversity raise some concerns about nutrition security, particularly in regard to micronutrient deficiencies. Cereals are affordable, calorie dense carbohydrates, but they alone do not provide all the necessary protein, fat, vitamins, and minerals for nutritious diet. An unbalanced diet can lead to serious health problems. Protein Energy Malnutrition (PEM), for example, can cause stunting, wasting, kwashiorkor, and an increased risk of infectious disease (Ahmed et al., 2020).

In order to improve food and nutritional security in Mali, it is essential for policymakers to understand how rural and urban Malians change the composition of their diet in response to changes in food prices, as well as changes in their income. Many food assistance programs either provide funds to households to allow them to increase their consumption, or institute subsidies, or price ceilings on food products to increase affordability of staple goods (FAO, 2017; Famine Early Warning System Network [FEWS NET], 2020; WFP, 2023). Knowing how Malians' consumption patterns change with changes in prices and income will inform policymakers on the types of interventions they could support to improve food and nutrition security.

This study examines demand for food products by food group and by processing group for rural and urban Malians in 2018/2019 utilizing a nationally representative household survey dataset. We utilize a two-stage demand system to calculate price and expenditure elasticities, which tell us how consumers change their behavior when prices change or when they increase their food budgets. The first stage utilizes a Working-Leser demand equation. For the second stage, we employ a Quadratic Almost Ideal Demand System (QUAIDS). Utilizing the estimates from our QUAIDS model, we look at changes in consumer welfare resulting from hypothetical price increases using compensating variation. Compensating variation allows us to see how much additional money a household would need to achieve their original utility level under the new prices.

We contribute to the literature in several ways through our analysis. First, we are unaware of any recent studies that extensively examine food demand in Mali. One prior study calculated elasticities of food groups in Bamako, Mali using the AIDS model with data from 2001 (Camara, 2004). They found that households absorb most income shocks in non-food expenditure categories and that consumption of staples was less responsive to income changes than consumption of non-staples. Another study employed the QUAIDS model using 2006 data but focused particularly on cereals (Me-Nsope & Staatz, 2016). They found higher income elasticities for coarse grains like millet and sorghum and indicated that demand for millet and sorghum may be increasing due to the rise in mechanical processing, reducing the preparation times. The unique set of circumstances surrounding the political, environmental, and socio-economic climates of Mali over the past two decades call for an updated analysis of the full system of food groups that allows for non-linear Engel curves.

Second, we are able to provide estimates for both rural and urban households separately. This is valuable because previous literature has found significant differences between demand elasticities for rural and urban consumers, with urban consumers generally being less sensitive to price changes than rural consumers (Boysen, 2015; Cheng & Larochelle, 2016; Hussein et al., 2021). Yet, much of the food demand literature provides pooled estimates for rural and urban consumers together (Colen et al., 2018).

Third, we estimate elasticities based on processing level. We are aware of only one other study that has done this, which was focused on Nigeria only (De Brauw & Herskowitz, 2020). Our estimated processing group elasticities will provide insight into the dietary transformation process occurring in a less populous and landlocked country.

Fourth, we generate elasticities by per capita expenditure quartiles, allowing us to look at food consumption patterns for households at different income levels. Finally, we use our calculated elasticities to estimate the amount of additional expenditure households would have to allocate towards food to reach their original utility level under simulated price changes to each food and processing group.

1.2 Food Demand Analysis

1.2.1 Theoretical Background

Examining elasticities can provide important insights for policy makers, allowing them to predict how people will change their consumption when prices and incomes change. The larger the magnitude of an elasticity estimate, the more responsive consumption is to changes in price or income. A positive elasticity means consumption is predicted to increase in response to an increase in the variable in question (price or income). A negative elasticity means consumption is predicted to decrease in response to the variable in question. In our study we calculate both price and expenditure elasticities. We utilize expenditure as a proxy for income as it is frequently and more accurately reported in developing nations and closely approximates income as savings rates are generally low (Elbadawi & Mwega, 2000).

An own-price elasticity describes the percentage change in consumption of a good when the price of that particular good changes (Hutchinson, 2017). A negative own-price elasticity indicates that as the price rises, people consume less of a good. We hypothesize that all food and processing groups we analyze will have negative own-price elasticities. If the own-price elasticity for a good is greater than one in absolute value, the good is said to be price elastic. If the own-price elasticity for a good is less than 1 in absolute value, the good is said to be price inelastic (Hutchinson, 2017).

Cross-price elasticities refer to the change in consumption of good *j* when the price of good *i* increases (Hutchinson, 2017). Generally, if consumption of *j* increases when the price of *i* increases, the two goods are regarded as substitutes. This is the case if the cross-price elasticity of good *j* with respect to good *i* is positive. If consumption of j decreases with an increase in the price of *i,* then the two goods are considered to be complementary. In this case, the cross-price elasticity of good *j* with respect to *i* would be negative (Hutchinson, 2017).

Expenditure elasticities refer to the consumption change in good *j* when the household increases overall expenditure. If an expenditure elasticity is positive, the good is considered normal and if it is between zero and one, good *j* is called a necessity (Hutchinson, 2017). If positive and greater than one, it is considered a luxury. If negative, the good is called inferior because people consume less of it when their income rises. Expenditure inelastic means that when household expenditure increases, expenditure on good *j* increases less than proportionally. Expenditure elastic means that when household expenditure increases, expenditure on good *j* increases more than proportionally. An Engel curve shows how the proportion of household consumption of a good changes as income levels rise. The shape and slope of the curve depend on a variety of factors (Hutchinson, 2017).

We hypothesize that the expenditure elasticity of food overall will be positive and less than one, indicating that food is expenditure inelastic. As households spend more money, we expect that food will take up a smaller percentage of their overall budget. We expect the price elasticity of food to be negative and less than one, indicating that food is also price inelastic. This is supported by the logic that if food prices rise, households still need to consume food, so their consumption decreases less than proportionally. If food prices fall, however, there is a point at which a household satisfies their food needs, and they will diversify that additional expenditure into non-food goods. This follows Engel's law (Chakrabarty & Hildenbrand, 2011; Engel, 1857) which states that households will dedicate larger portions of their budget to non-food commodities as incomes rise. We also hypothesize that many cereals and roots and tubers may serve as substitutes for one another as they are affordable and calorie dense starches. We expect that animal proteins and legumes will be substitutes, as they both provide essential protein. We expect to see lower elasticities for staple foods like cereals, and higher elasticities for animal proteins and other foods that may be seen as more of a luxury. We expect that processed foods have become essential for both rural and urban households and are growing in importance, therefore expenditure elasticities may be high and own-price elasticities may be lower. We expect that overall, rural households may be more sensitive to price changes and exhibit higher price elasticities than urban households.

In order to generate our elasticity estimates, we employ a two-stage budgeting model. As we are only interested in examining food demand in this study, the two-stage method allows us to limit our demand system to only include food commodities, thus limiting the number of parameters that need to be estimated by assuming consumer preferences are weakly separable (Deaton & Muellbauer, 1980). The household decision making process is broken down into two stages. In the first stage, households allocate expenditure between food and non-food commodities. After this stage, we estimate the price and expenditure elasticities for food in general.

In the second stage, households allocate their food budget to each of the available food groups or processing groups. We estimate two separate demand systems, one where individual food products are grouped with other similar foods (e.g., animal proteins, roots and tubers), and one where they are grouped by processing level. After this stage, we calculate the price and expenditure elasticities for the various food groups and processing levels. There are several papers preceding ours that use a two-stage approach employing a Working-Leser demand equation in the first stage and a Quadratic Almost Ideal Demand System (QUAIDS) in the second stage (Boysen, 2015; Cheng & Larochelle, 2016). The QUAIDS model has been widely used to estimate demand for both non-food commodities (Chukwuemeka & Emmanuel, 2020) and food commodities (Han & Chen, 2016; Korir et al. 2018; Kharisma et al., 2020; Mittal 2010; Obayelu et al., 2009; Rasyid, 2022). Finally, we estimate compensating variation (CV) using our second stage results to calculate how much additional income a household would need to spend to achieve their original utility level under simulated price changes of each food or processing group. CV is frequently used to estimate the impacts of food price changes (Ackah & Appleton, 2007; Cranfield and Haq, 2010; Osei-Asare and Eghan, 2013; Wood et al., 2012).

1.2.2 Stage 1 Specification: Working-Leser

We use the Working-Leser (WL) equation (Leser, 1963; Working, 1943) in the first stage of our model, where households allocate their expenditure between food and non-food commodities. This is a single equation model (1), specified with the Pollak and Wales (1981) adaptation to include demographic variables. This stage models the Engel curve for food in total household expenditure.

$$\omega_F = \alpha_F + \Sigma c_{Fk} z_k + \rho_F \, ln(P_F) + \beta_F \, ln(M) + \varepsilon \qquad (1)$$

The terms of the equation are defined as follows: ω_F is the budget share of food, α_F is the intercept, and z_k is the vector of demographic variables. The parameters are c_{Fk}, ρ_F and β_F. P_F is the price index for food. M is total expenditure. For rural households it is recommended to test equation (1) with the inclusion of a quadratic term in the natural log of total expenditure since some of the poorest households may be facing such severe food insecurity that for each additional dollar of total expenditure, they may increase more than proportionally their expenditure on food and the share of food in their total budget may actually grow (Boysen, 2015; Deaton, 1981). We find that the model with the quadratic term is a better fit for rural households (see Appendix A). We also test the inclusion of a quadratic term for urban households and find it to be unnecessary, supporting the hypothesis that consumption behavior for rural and urban households is different and our decision to model urban and rural consumption separately. This first step of the model is estimated separately for both urban and rural households with ordinary least squares (OLS). The estimated coefficients are then used to calculate the expenditure (η_F) and price (ε_F) elasticity for food. The predicted food budget share ($\widehat{\omega_F}$) is multiplied by total weekly household expenditure (*M*) to generate the predicted weekly household food expenditure ($\widehat{M_F}$) which enters into the stage 2 QUAIDS model.

$$\eta_F = 1 + \frac{\beta_F + 2\,\lambda_F \ln(M)}{\omega_F} \qquad (2)$$

$$\varepsilon_F = -1 + \frac{\gamma_F}{\omega_F} \qquad (3)$$

1.2.3 Stage 2 Specification: QUAIDS

The second stage of the demand system models the budget share of individual food groups or processing groups within the total food budget. This stage is estimated using the Quadratic Almost Ideal Demand System (QUAIDS). In 1980, Deaton and Muellbauer developed the QUAIDS predecessor, the Almost Ideal Demand System (AIDS) model to improve upon models of demand commonly used during that time. The model comes from the Price-Independent Generalized Log (PIGLOG). PIGLOG represents a class of functional forms that models aggregate consumer behavior as the outcome of one rational, representative consumer, which is recommended to satisfy the properties of demand at an aggregate level (Deaton & Muellbauer, 1980).

In 1997, Banks, Blundell, and Lewbel developed the QUAIDS expansion of the AIDS model. They found that the AIDS model was insufficient for non-linear Engel curves – where the income elasticities varied across not only goods, but also across different points within the income distribution. Adapting to fit non-linear Engel curves would allow for some goods to be luxuries at certain income levels and necessities at others. In choosing QUAIDS for our study, we considered that in countries with high levels of poverty, the lack of dietary diversity for the poorest households may best be represented by non-linear Engel curves. Food products such as dairy and fish may be luxuries for many households in the lowest income brackets who rely heavily on staples with less dietary diversity. These same products may be considered necessities at higher income levels, where households have enough money to have diversified diets. Applying the AIDS model, or another linear demand system model, would not account for this non-linearity.

We test the validity of our assumption of non-linear Engel curves by conducting likelihood ratio tests between the QUAIDS and AIDS specifications of our models. We find that the QUAIDS model is a better fit than the AIDS model for the rural and urban food demand systems by food group and by processing level. We found that there was no need for a quadratic term in estimating the rural demand system of food by processing level. This is likely due to the fact that the processing groups are much more aggregated than food groups, so the quadratic nature of individual items is more likely to be overpowered by items in the same processing group that do not have a quadratic Engel curve.

The model has been adapted following Ray (1983) and Poi (2002) to include scaling for demographic variables. It is valuable to control for sociodemographic characteristics, such as education of the head of the household, which has been shown to influence the consumption decisions of the household (Kearney, 2010). The budget share equation is specified as follows:

$$\omega_i = \alpha_i + \sum_j \gamma_{ij}\, ln\left(p_j\right) + (\beta_i + \eta_i' z)\, ln\left(\frac{M_F}{\bar{m}_0(z)a(p)}\right) + \frac{\lambda_i}{b(p)c(p.z)}\left[ln\left(\frac{M_F}{\bar{m}_0(z)a(p)}\right)\right]^2 \qquad (4)$$

The variables in the equation are budget share for good *i* (ω_i), price of good j (p_j), the vector of demographic variables (*z*), and predicted food expenditure from stage 1 (M_F). The parameters are: $\alpha_i, \gamma_{ij}, \beta_i, \eta_i', \lambda_i$. If $\lambda_i = 0$, the quadratic term is also equal to zero, and we are left with the AIDS model.

Following Banks et al. (1997), the function *a(p)* is the transcendental price index (5).

$$ln\, a(p) = \alpha_0 + \sum_i \alpha_i\, ln(p_i) + \frac{1}{2}\sum_i \sum_j \gamma_{ij}\, ln(p_i)\, ln\left(p_j\right) \qquad (5)$$

The function *b(p)* is the Cobb-Douglas price aggregator (6). These price functions deflate expenditure to put things in real terms, as opposed to nominal. The specific functional forms were selected to maintain functional flexibility while also satisfying desirable demand properties.

$$b(p) = \Pi p_i^{\beta_i} \qquad (6)$$

Following Ray (1983) and Poi (2002) the function $\overline{m_0}(z)$ scales expenditure, accounting for demographic information. The parameterization of this function for the QUAIDS model is given by equation (7).

$$\overline{m_0}(z) = 1 + \rho' z \qquad (7)$$

The combination of this function and *c (p, z)* (8) allows us to control for differences between households in terms of demographic characteristics and prices faced by the household.

$$c(p, z) = \prod_j^k p_j^{\eta_j' z} \qquad (8)$$

To be consistent with the theory of demand, the model must satisfy the adding up condition (i.e., the sum of the budget shares must equal the total budget) and must be homogeneous of degree zero in prices and expenditure. In the AIDS model, the restrictions in equation (9) are imposed to satisfy these conditions (Banks et al. 1997).

$$\sum_i \alpha_i = 1, \quad \sum_i \beta_i = 0, \quad \sum_i \gamma_{ij} = 0, \quad \sum_j \gamma_{ij} = 0 \qquad (9)$$

Since we include demographic scaling following Ray (1983), we must add a constraint on the demographic parameters (10) for all demographic variables *r* in the vector *z*.

$$\sum_i \eta_{ir} = 0 \qquad (10)$$

Due to the addition of the quadratic term for the QUAIDS model, we also need to impose a restriction on the parameter of the quadratic term (11) (Poi, 2002).

$$\sum_i \lambda_i = 0 \tag{11}$$

Additionally, the model must satisfy the Slutsky symmetry condition (12).

$$\gamma_{ij} = \gamma_{ji} \tag{12}$$

The elasticities are then computed using the following formulas. Equation (13) is the income elasticity of good *i*. Equation (14) is the uncompensated price elasticity of good *i* with respect to good *j,* or the percent change in consumption of good *i* when there is a change in the price of *j*.

$$\mu_i = 1 + \frac{1}{\omega_i}\left[\beta_i + \eta_i{}'z\frac{2\lambda_i}{b(p)c(p,z)}\left\{ln\left[\frac{M_F}{\bar{m}_0(z)a(p)}\right]\right\}\right] \tag{13}$$

$$\epsilon_{ij} = -\delta_{ij} - \frac{1}{\omega_i}\left(\gamma_{ij} - \left[\beta_i + \eta_i{}'z\frac{2\lambda_i}{b(p)c(p,z)}ln\left\{\frac{M_F}{\bar{m}_0(z)a(p)}\right\}\right] \times \left(\alpha_j + \sum_k \gamma_{jk}\, ln\, P_k\right) - \frac{\lambda_i(\beta_j + \eta_i{}'z)}{b(p)c(p,z)}\ln\left[\frac{M_F}{\bar{m}_0(z)a(p)}\right]^2\right) \tag{14}$$

As in the first stage, we run the second stage separately for rural and urban households. We also run the model that separates food by food group separately from the model that separates food by processing level and, therefore, have 4 total models in the second stage. We test the QUAIDS specification versus the AIDS specification for all these models and find that for all models, QUAIDS has a better fit. The likelihood ratio test results are available in Appendix A.

This second stage of the model is estimated with iterated feasible generalized nonlinear least-squares (IFGNLS) with bootstrapped standard errors. The IFGNLS estimates are equal to the maximum likelihood estimates for this system (Poi, 2012). The system of equations is estimated together with one equation dropped to ensure satisfaction of the adding up condition.

The coefficients for this equation can then be calculated using the coefficients from the other equations and the adding up property.

1.2.4 Compensating Variation

After estimating our models, we will also calculate compensating variation under a few hypothetical price changes. Compensating variation (CV) is a measure of consumer welfare (Chipman & Moore, 1980; Hicks, 1942). The purpose of CV is to predict how expenditure would need to change in response to a price change for a household to maintain the same level of utility they achieved prior to the price change. CV is used frequently by researchers to study the effects of food price increases on household food budgets (Ackah & Appleton, 2007), expenditure on non-durable goods (Cranfield & Haq, 2010), total household budgets (Osei-Asare & Eghan, 2013; Wood et al., 2012). CV is defined by equation (15), where M is household food expenditure, p^1 is the price vector with the price change, p^0 is the price vector before the price change, u^1 is the utility level after the price change, and u^0 is the utility level before the price change.

$$\begin{aligned} CV &= e(p^1, u^1) - e(p^1, u^0) \\ &= M - e(p^1, u^0) \qquad (15) \end{aligned}$$

1.3 Data and Descriptive Statistics

1.3.1 Data

In determining household demand, we need data on prices, expenditures, and household consumption of food products. We use the Mali National Institute of Statistics (INSTAT) Harmonized Survey on Households Living Standards (HSHLS) dataset (2022) collected in 2018/2019 as part of a joint project between the World Bank and the West African Economic Monetary Union (WAEMU) Commission (INSTAT, 2022). This is the most recent dataset available that includes the detailed food consumption report needed for the analysis. The consumption module includes questions on individual households' food consumption over the previous seven days in quantities. Enumerators also asked household respondents to recall the most recent transaction in which they purchased each product. They collected quantity and value purchased. In the HSHLS dataset, half of the sample was surveyed in the first wave (harvest season) and the remaining half was sampled in the second wave (lean season). In wave one, enumerators interviewed 1338 urban and 1570 rural households. In wave two, enumerators interviewed 1414 urban and 2280 rural households.

1.3.2 Food and Processing Groups

In our demand system, we focus on food commodities. However, it is not practical to estimate demand for each individual food product because the datasets provide information for 138 different food products. Aggregation into groups is necessary to reduce the number of parameters in our second stage QUAIDS model and reduce the bias caused by non-consumption. For individual food products, non-consumption is a significant issue. We referenced existing food demand papers (Boysen, 2015; Cheng & Larochelle, 2016) and the groupings given within the dataset when determining our food groups and settled upon the following seven categories: (1) cereal products, (2) animal products, (3) legumes, (4) fruits and vegetables, (5) roots and tubers, (6) sugars and sugar-sweetened beverages (SSBs), and (7) oils, spices and other foods.

The cereal products group captures cereals, cereal flours, and products primarily made of cereals such as bread, pasta, and cookies. The animal product group includes fish, meat, eggs, and dairy products. The legumes group includes foods like groundnuts, peas, and cowpeas. Fruits and vegetables include fresh items like mangos and lettuce, as well as fruit and vegetable-based products like dried okra and tomato paste. The roots and tubers group contains starchy items such as potatoes, yams, and cassava and roots like carrots and onions (Harvard Health Publishing, 2021; University of California Cooperative Extension, 2020; United States Department of Agriculture [USDA], n.d.). Roots and tubers are unique because the edible portion is grown underground. Though some roots and tubers are quite starchy, and others are not, the products in this category have long shelf lives when stored properly (Cantwell & Kasmire p. 435, 2002). The sugar and SSB group contains sweeteners and sweets like cane sugar, honey, and candies, as well as sweetened beverages like juices and sodas. The oils, spices and other category includes cooking oils, condiments, seasonings, and mineral and filtered water. We do not include alcohol or tobacco products in our study. See Appendix B for a full list of commodities in each food group.

In determining our processing groups, we first considered the NOVA classification system. The NOVA system classification system is comprised of 4 categories: (1) unprocessed or minimally processed foods, (2) processed culinary ingredients, (3) processed foods, and (4) ultra-processed foods (Monteiro et al., 2019). In the context of a country where the dietary transformation process is likely to be at an early stage, we find that the NOVA system's aggregation of unprocessed and minimally processed foods groups would not allow us to look at the demand for low-processed convenience foods, like grain flours. Sauer et al. (2021) and Kebe et al. (2024) modified the NOVA system to be more applicable to developing economies. We construct our three processing groups based on these adaptations, (1) unprocessed, (2) minimally processing and (3) highly processed. We define unprocessed food as food harvested/extracted from a source that may be cut, shelled, butchered, hulled, or otherwise modified to remove inedible parts before purchase. We define minimally processed food as food that was ground, milled, pressed, dried, preserved, evaporated, reduced, or pasteurized one time before purchase. We define highly processed food as food items comprised of multiple ingredients or additives, or items that have undergone multiple steps of processing before purchase. See Appendix C for a list of commodities in each processing group.

Our classifications differ from the NOVA classifications in a few ways. First, we include transformed single ingredients like grain flours in the minimally processing category since they have added value as convenience foods, but they would fall under the single unprocessed/minimally processed category in the NOVA system. If we used the NOVA system, we would lose out on interesting detail about the demand for convenience foods because the classification system would dictate that labor-saving products like grain flours should be included with unprocessed and minimally processed goods. Additionally, the NOVA system distinguishes between processed foods made of multiple ingredients and ultra-processed foods made from multiple industrial-use ingredients processed with industrial techniques, but for this analysis we aggregate all multi-ingredient products together into the highly processed group as we don't have detailed information on the processed products to further disaggregate them.

1.3.3 Prices and Consumption Value

The dataset provides some food prices in the community level survey, although prices are not available for all food-commodities reported in the consumption survey. Additionally, many observations in the dataset are measured in non-standard units (e.g., "a pile") for which respondents were asked to provide a qualifier (small, medium, or large). Given that we are provided with no quantitative information on the relationship between sizes, we treat the sizes of each unit of measure as individual units of measurement. For example, a small pile of a product is considered to be a different unit of measurement than a medium pile or large pile of that product, even though they are all piles. Under this treatment, we have 86 unique units of measurement.

We establish a numeraire unit for each product based on the unit in which most people reported purchasing an item. When we have community price data for, we assign the item's price as the group (cluster) price in the numeraire unit, or if the price is unavailable at the group level, we assign the departmental seasonal median, or regional seasonal median. There are still a large number of items for which we do not have prices. We then turn to unit values and follow a similar process. We calculate the median unit value at the group level in the numeraire unit, then fill in with departmental seasonal medians or regional seasonal medians if group unit values are unavailable. Items that do not have prices in the community survey are then assigned the most precise median unit value.

As we run our models across aggregated food and processing groups, we cannot include prices for individually consumed items and therefore we need aggregate price indexes for each food and processing group. We employ the corrected Stone Price Index, which is invariant to units of measurement, recommended by Moschini (1995), and frequently used in demand system estimation (Boysen, 2015; Cheng & Larochelle, 2016). Let p_{ic} be the price index for food or processing group i that contains goods $g \in G$ for cluster c. Let p_{gc} be the price of good g in cluster c and $\bar{p}_g$ be the seasonal median rural or urban price for good g. Finally, $\bar{w}_g$ is the mean rural or urban budget share for good g in group i.

$$p_{ic} = \sum_{g=1}^{G} \bar{w}_g \frac{p_{gc}}{\bar{p}_g} \qquad (16)$$

We also construct a price index for food to use in the first stage of our model where we examine food vs. non-food expenditure. For the food price index, we follow the same procedure as above but as if there is just one food group containing all items $g \in G$.

In addition to prices, we also need to know the value consumed by each household of each good. Enumerators asked household respondents to report the quantity they consumed from their purchases, from their own production, and the quantity of the product they received as a gift. However, since the questionnaire does not include the value consumed, we need to calculate the value by multiplying the quantity consumed by the price of the item. As consumption quantities are reported in such a wide variety of units, yet our prices are for the numeraire unit, we first need to convert the consumed quantity from the original units into the numeraire units. Unfortunately, the dataset does not include any conversion factors and upon examining conversion factors from similar datasets collected in surrounding countries, we were unable to find conversion factors for the units of measure used in the Malian survey. Therefore, we created our own by using the community survey data to generate conversion factors as the ratio of the unit price to the numeraire price. If we did not have community price data for certain units of measure, we used the ratio of the unit value for the unit of measure to the community numeraire price. Finally, if we did not have numeraire pricing from the community data, we employed the ratio of the unit value for the unit of measure to the numeraire unit value for that commodity.

We generated the mean conversion factor for each unit of measurement for each good and multiplied this by the quantity consumed from purchases, own production, and gifts to obtain total quantity consumed in the numeraire unit. We then multiplied price by total quantity consumed to measure total value consumed for each good. As many rural households consume significant portions of their diet from their own production, it is essential that we include the value of what they consume from their own production. For our analysis, we value own production at market value. This essentially values the household's own consumption as the opportunity cost since shadow prices for individual households are household specific. In the absence of shadow prices, this technique is widely used in the literature (Boysen, 2015; Me-Nsope & Staatz, 2016).

For household total expenditure and food expenditure, we use the annual values given in the dataset and divide by 52 to get the average weekly expenditure. To examine differences in food demand between households of different expenditure levels, we break the rural and urban sample into per capita expenditure quartiles. We consider the households in the lower expenditure quartiles to be relatively poorer, and the households in higher expenditure quartiles to be relatively wealthier.

1.3.4 Descriptive Statistics

Table 1.1 shows average household per capita expenditure across quartiles for both rural and urban households. On average, urban households are better off than rural households, as evidenced by the fact that in each quartile as well as in total, urban households have greater expenditure than rural households. The lowest rural per capita expenditure quartile spends almost 800 FCFA less per week per person on food than the lowest urban per capita expenditure quartile. Higher expenditure quartiles see larger spending gaps between rural and urban households per person for food goods, and much higher spending gaps in total expenditure. The top expenditure quartile of urban households spends over 5,000 FCFA more per capita per week on food than households in the top rural expenditure quartile, and almost 13,000 FCFA more per capita in total each week. Total expenditure per capita per week in the top rural quartile is similar to that of the second highest urban quartile, however the food budget share for the rural households is higher than the food budget share for urban households. A similar pattern is seen for the second quartile of rural households compared to the first (lowest) urban per capita expenditure quartile. This demonstrates that at similar total expenditure levels, rural households dedicate a larger portion of their budget to food, but generally the share of the budget dedicated to food is high across all groups, ranging from about 55 to 61% for rural households and about 45 to 56% for urban households.

Table 1.1: Average Household Expenditure for Rural and Urban Households by Per Capita Expenditure Quartiles

	Rural					**Urban**				
	Total	**Q1**	**Q2**	**Q3**	**Q4**	**Total**	**Q1**	**Q2**	**Q3**	**Q4**
Food Expenditure Per Capita (FCFA/week)	3,597	1,751	2,645	3,642	6,289	6,125	2,527	3,970	5,772	10,763
Total Expenditure Per Capita (FCFA/week)	6,329	2,876	4,403	6,228	11,673	12,893	4,526	7,701	11,794	24,086
Food Budget Share	0.586	0.608	0.601	0.585	0.549	0.500	0.562	0.517	0.490	0.450
n	3845	962	961	961	961	2741	686	685	685	685

Source: Authors' own calculations using HSHLS data. Estimates account for survey design characteristics, such as sampling weights, using Stata svy commands for specified subpopulations.

Table 1.2 describes the sociodemographic characteristics for the rural and urban subpopulations that we control for in our analysis. Heads of households in urban areas are more likely to have attended school than rural household heads. In both rural and urban areas, heads of households with higher per capita expenditure are more likely to be educated. Urban households have on average fewer members than their rural counterparts. All households are predominantly headed by men, though there are more female heads of households in higher expenditure quartiles. Heads of households in both rural and urban areas across all expenditure quartiles are in their late 40's on average.

Table 1.2: Sociodemographic Characteristics of Rural and Urban Subpopulations

	Rural					Urban				
	Total	**Q1**	**Q2**	**Q3**	**Q4**	**Total**	**Q1**	**Q2**	**Q3**	**Q4**
Gender of HOH										
Male	92.7%	94.2%	94.2%	92.2%	90.4%	87.3%	88.6%	88.3%	88.4%	84.7%
Female	7.3%	5.8%	5.8%	7.8%	9.6%	12.7%	11.4%	11.7%	11.6%	15.3%
Education of HOH										
No schooling	78.8%	88.7%	82.8%	78.6%	65.5%	51.4%	76.7%	60.7%	45.2%	32.0%
Schooling	21.2%	11.3%	17.2%	21.4%	34.5%	48.6%	23.3%	39.3%	54.8%	69.0%
Age of HOH	48.8	50.9	48.9	47.9	47.5	46.4	48.9	47.8	45.1	44.7
Size of Household	7.4	9.4	7.5	6.9	5.7	6.6	7.9	7.4	6.5	5.1
n	3845	962	961	961	961	2741	686	685	685	685

Source: Authors' own calculations using HSHLS data. Estimates account for survey design characteristics, such as sampling weights, using Stata svy commands for specified subpopulations.

The dataset we use in our analysis does not provide sufficient information on consumption of food away from home (FAFH) for us to include this as a group in our model. However, we can calculate the average expenditure per capita on FAFH for households who report meals, snacks, or beverages consumed outside the household by two or more members of the household over the past seven days (Table 1.3). Some households in all quartiles have two household members or more who consume FAFH, however, a higher proportion of urban households consume FAFH than rural households. Households in higher expenditure quartiles are more likely to have two household members or more who consume FAFH. Less than 5% of the poorest rural households have two members of more who consume FAFH, compared to around 22% of the wealthiest rural households. In the poorest quartile of urban households, nearly 12% have two members or more who consume FAFH. This is more than double the rate for the poorest rural households. Around 23% of the wealthiest urban households have two members or more who consume FAFH, so the urban-rural gap in the consumption rate is much smaller for the wealthiest households. Higher expenditure households also spend more money per week on FAFH. The budget share of FAFH ranges from 1.2% for the poorest rural households, to 6.3% for the wealthiest urban households. The majority of FAFH consumed by households is purchased, however some households also receive gifted FAFH. Higher expenditure households are also more likely to receive gifted FAFH. Rural households are more likely to receive gifted FAFH than urban households. The finding that urban households are more likely to consume and spend more on FAFH than rural households is in line with the dietary transformation literature on urbanization (Reardon et al. 2014).

Table 1.3: Value of Food Away From Home (FAFH) Purchased & Gifted by Rural and Urban Per Capita Expenditure Quartile

	Rural					Urban				
	Total	**Q1**	**Q2**	**Q3**	**Q4**	**Total**	**Q1**	**Q2**	**Q3**	**Q4**
All FAFH										
Households consuming	12.3%	4.2%	9.9%	12.7%	22.2%	17.1%	11.6%	14.4%	17.2%	23.1%
Avg. weekly value consumed (FCFA)	955	239	585	954	2014	2307	834	1217	1361	5134
Budget share of FAFH in food budget	0.032	0.012	0.027	0.034	0.055	0.043	0.029	0.040	0.035	0.063
Purchased FAFH										
Households purchasing	10.5%	4.0%	8.7%	10.5%	18.7%	15.7%	10.5%	13.0%	15.7%	23.1%
Avg. weekly value purchased (FCFA)	721	182	393	735	1554	2064	779	1109	1184	4587
Gifted FAFH										
Households receiving	3.6%	1.1%	3.3%	3.4%	6.4%	2.6%	1.4%	2.2%	2.6%	3.8%
Avg. weekly value received (FCFA)	234	58	192	219	460	243	55	109	177	547
n	3845	962	961	961	961	2741	686	685	685	685

Source: Authors' own calculations using HSHLS data. Estimates account for survey design characteristics, such as sampling weights, using Stata svy commands for specified subpopulations. Averages include non-consumers (i.e., zeros). Note: These estimates are for households with at least two members consuming food away from home. Those estimates would likely be higher if they were for households with at least one member instead of two.

Table 1.4 breaks down household food budgets by food groups and processing level over the last seven days. All households across rural and urban expenditure quartiles consume cereal products and nearly all consume oils and condiments. Animal products, fruits, and vegetables are consumed by over 95% of households in all quartiles. Legumes are the least commonly consumed group. They are consumed by just over 70% of the rural poor and nearly 90% of the wealthier rural households. For urban households, the legume consumption rate is steady. Between 85-90% of urban households in all quartiles consume legumes. Overall, consumption rates for most food groups and processing levels are consistent across expenditure quartiles and between rural and urban households, suggesting that consumption of different categories of food is relatively homogenous across the country, however, the quantity of individual food items within a food group and the quality of food consumed are likely heterogenous. See tables 1.5 and 1.6 below for further discussion of intra-food group consumption differences for animal products and roots and tubers, respectively. The budget shares of each group and processing level vary across quartiles and across rural and urban households, indicating the expenditure on different food categories is relatively heterogenous across the country.

As expected, the budget share of cereals is much higher for rural households than for urban households. The poorest rural households spend 40.8% of their food budget on cereals. The wealthiest rural households spend around half that, 21.6% of their food budget. The poorest urban households spend an average of 21.1% of their food budget on cereal products and the wealthiest urban households spend only 14.9% of their food budget on cereal products. The largest food group in the budget share of all rural households, except the wealthiest, is cereal products.

The wealthiest rural households spend the largest portion of their budget on animal products. The poorest urban households spend the largest portion of their budget on cereal products, then the second quartile spends the most on animal products. The households in the two highest urban expenditure quartiles spent the most on fruits and vegetables in the seven days preceding the survey enumeration. Our results are in line with previous research that has shown households of higher expenditure levels spend more on animal products, fruits, and vegetables (Kearney, 2010; Reardon et al. 2014).

All households consumed food from every processing level in the past seven days. The budget share of unprocessed products is smaller in higher expenditure rural households. For urban households this is also true, except for the wealthiest urban households. This could be in part due to the increase in the budget share for fruits and vegetables that we see for high expenditure urban households, as most fruits and vegetables are purchased unprocessed (See Table 1.4). For minimally processed foods, rural households on average spend more on this category than their urban counterparts, whereas the budget share of the high processing category is higher for urban households. Wealthier households spend more on highly processed foods than poorer households. The wealthiest urban households spend ~23% of their food budget on highly processed food compared to the wealthiest rural households that spend ~13% of their food budget on highly processed foods. This suggests that urban households play a larger role in the dietary transformation of Mali, as urban households spend around 10 percentage points more of their total food budget on highly processed foods than rural households. The average rural household spends 63% of their food budget on unprocessed foods, ~23% on minimally processed, and ~14% on highly processed. Urban households also spend ~60% on unprocessed foods but spend ~17% on minimally processed and ~23% on highly processed foods.

Table 1.4: Average Budget Share by Food Group & Processing Level by Rural and Urban Per Capita Expenditure Quartiles

	Rural					Urban				
	Total	**Q1**	**Q2**	**Q3**	**Q4**	**Total**	**Q1**	**Q2**	**Q3**	**Q4**
					Food Group					
Cereal Products										
Households consuming	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
Avg. budget share	0.312	0.408	0.334	0.291	0.216	0.211	0.294	0.236	0.193	0.149
Animal Products										
Households consuming	98.4%	96.4%	97.8%	99.7%	99.9%	99.3%	98.7%	98.8%	99.6%	100%
Avg. budget share	0.240	0.188	0.210	0.265	0.296	0.254	0.258	0.260	0.252	0.249
Legumes										
Households consuming	80.7%	70.8%	77.9%	84.7%	89.2%	85.7%	76.2%	90.1%	87.0%	87.5%
Avg. budget share	0.055	0.048	0.054	0.059	0.060	0.042	0.034	0.040	0.040	0.050
Fruits & Vegetables										
Households consuming	97.5%	97.3%	98.0%	96.9%	97.6%	99.0%	97.0%	99.1%	99.7%	99.7%
Avg. budget share	0.135	0.125	0.133	0.135	0.146	0.181	0.131	0.167	0.183	0.226
Roots & Tubers										
Households consuming	82.6%	76.4%	81.9%	82.7%	89.2%	96.6%	92.0%	97.4%	98.7%	97.2%
Avg. budget share	0.085	0.067	0.093	0.087	0.093	0.106	0.116	0.108	0.115	0.090
Sugars & SSB										
Households consuming	99.7%	99.2%	99.9%	99.9%	99.9%	99.7%	99.2%	100%	99.6%	100%
Avg. budget share	0.060	0.063	0.060	0.057	0.061	0.061	0.054	0.063	0.065	0.060
Oils, Condiments, Other										
Households consuming	100%	100%	100%	100%	99.8%	99.8%	100%	99.9%	99.8%	99.5%
Avg. budget share	0.113	0.100	0.115	0.106	0.129	0.145	0.113	0.127	0.151	0.176
					Processing Level					
Unprocessed										
Households consuming	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
Avg. budget share	0.630	0.662	0.632	0.617	0.607	0.601	0.634	0.583	0.581	0.611
Minimally Processed										
Households consuming	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
Avg. budget share	0.234	0.225	0.234	0.247	0.231	0.174	0.190	0.196	0.174	0.145
High processed										
Households consuming	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
Avg. budget share	0.136	0.112	0.134	0.136	0.162	0.225	0.176	0.221	0.245	0.244
n	3845	962	961	961	961	2741	686	685	685	685

Source: Authors' own calculations using HSHLS data. Estimates account for survey design characteristics, such as sampling weights, using Stata svy commands for specified subpopulations. Averages include non-consumers (i.e., zeros).

To understand Malian's animal product consumption habits more in depth, in Table 1.5 we look at household consumption of animal products over the past seven days broken down into smaller sub-categories: dairy, eggs, meat, and fish. Within the household budget for animal products, the average Malian household spends the most on fish, followed by meat, aside from the top two urban expenditure quartiles. Those households spend the most on meat, followed by fish. The budget share of milk, eggs, and meat in the animal product budget grows as per capita expenditure grows, whereas the share of fish in the animal product budget shrinks. Additionally, fish makes up a larger proportion of the animal product budget of rural consumers than urban consumers. Thus, by looking at trends in budget shares by food groups we find evidence that points towards a decrease in the relative importance of fish in the animal product budget with both urbanization and increasing expenditure.

Table 1.5: Average Budget Share of Animal Products by Rural and Urban Per Capita Expenditure Quartile

	Rural					Urban				
	Total	**Q1**	**Q2**	**Q3**	**Q4**	**Total**	**Q1**	**Q2**	**Q3**	**Q4**
Share of Total Food Budget										
Animal Products	0.240	0.188	0.210	0.265	0.296	0.254	0.258	0.260	0.252	0.249
Share of Animal Product Budget										
Milk	0.115	0.096	0.106	0.130	0.129	0.176	0.122	0.155	0.179	0.227
Eggs	0.009	0.003	0.004	0.010	0.021	0.049	0.013	0.036	0.054	0.080
Meat	0.264	0.198	0.255	0.294	0.309	0.372	0.284	0.355	0.399	0.421
Fish	0.596	0.668	0.613	0.584	0.539	0.397	0.569	0.442	0.363	0.271
n	3845	962	961	961	961	2741	686	685	685	685

Source: Authors' own calculations using HSHLS data. Estimates account for survey design characteristics, such as sampling weights, using Stata svy commands for specified subpopulations. Averages include non-consumers (i.e., zeros).

Table 1.6 breaks down consumption of roots and tubers into smaller subcategories: starches and non-starches. Starches include items like potatoes, yams, cassava, cassava flour, and cassava couscous. Non-starches include roots such as carrots, onions, and garlic. Roots and tubers comprise less than 10% of rural households' overall food budgets. Most expenditure in this category is on non-starches. Starches comprise less than 10% of the expenditure on roots and tubers for the lowest expenditure rural households, however, rural households with higher expenditure levels dedicate more of their budget to starches. Similarly, for urban households, roots and tubers comprise around 10% of household food budgets with the largest expenditure on non-starches. For urban households, expenditure on non-starches decreases with total expenditure and the share of the starchy roots and tubers is increasing in expenditure.

Table 1.6: Average Budget Share by Type of Root/Tuber by Rural and Urban Per Capita Expenditure Quartiles

	Rural					Urban				
	Total	**Q1**	**Q2**	**Q3**	**Q4**	**Total**	**Q1**	**Q2**	**Q3**	**Q4**
Share of Total Food Budget										
Roots & Tubers	0.085	0.067	0.093	0.087	0.093	0.106	0.116	0.108	0.115	0.090
Share of Roots & Tubers Budget										
Starches	0.145	0.085	0.115	0.150	0.228	0.249	0.159	0.215	0.241	0.348
Non-starches	0.662	0.668	0.691	0.656	0.632	0.688	0.743	0.736	0.717	0.582
n	3845	962	961	961	961	2741	686	685	685	685

Source: Authors' own calculations using HSHLS data. Estimates account for survey design characteristics, such as sampling weights, using Stata svy commands for specified subpopulations. Averages include non-consumers (i.e., zeros).

Though the majority of household food consumption over the past seven days comes from households' purchases, gifted food and own production also factor into household food budgets and consumption decisions. Gifted food is food that the household received for free, from sharing within the community for example. Own production is food that the household grew, or produced, for itself. In our analysis, we value gifted food and own production at the value the household would have spent if they purchased the item. Table 1.7 shows mean budget shares of food from gifts in the last seven days. Around 59% of rural and 44% of urban households received gifted food. The average rural household receives 6.7% of the total value of the food as gifts. The average urban household receives 4.2% of their total food consumption value in gifts. Rural households in higher expenditure quartiles are more likely to receive gifted food, whereas urban households in higher expenditure quartiles are less likely to received gifted food. The budget shares by food group and processing level give the share of the total value consumed of group *i* that comes from gifts. The budget shares of gifted animal products, legumes, fruits, and vegetables are generally higher than the budget shares of gifts from other food groups for all households. The budget share of unprocessed foods from gifts is higher for urban households than the budget shares of medium or highly processed foods. For the three lowest expenditure quartiles of rural households, the medium processing level has the highest budget share from gifts. For the highest rural expenditure quartile, the unprocessed category has the largest budget share from gifts, similar to urban households.

Table 1.7: Budget Share of Gifted Food by Food Group & Processing Level by Rural and Urban Per Capita Expenditure Quartiles

	Rural					Urban				
	Total	**Q1**	**Q2**	**Q3**	**Q4**	**Total**	**Q1**	**Q2**	**Q3**	**Q4**
Gifted Food (all)										
Households consuming	59.4%	54.2%	60.5%	60.5%	62.3%	43.5%	53.5%	46.8%	39.9%	37.2%
Avg. budget share	0.067	0.053	0.073	0.068	0.072	0.042	0.058	0.049	0.035	0.032
Budget Share by Food Group										
Cereal Products	0.043	0.034	0.043	0.048	0.048	0.031	0.050	0.034	0.023	0.020
Animal Products	0.080	0.064	0.093	0.082	0.082	0.036	0.054	0.042	0.028	0.027
Legumes	0.079	0.083	0.079	0.081	0.076	0.040	0.066	0.039	0.027	0.036
Fruits & Vegetables	0.080	0.068	0.086	0.082	0.083	0.046	0.059	0.049	0.045	0.035
Roots & Tubers	0.062	0.056	0.082	0.060	0.052	0.031	0.049	0.039	0.027	0.018
Sugars & SSB	0.060	0.050	0.072	0.062	0.056	0.034	0.047	0.035	0.031	0.028
Oils, Condiments, Other	0.052	0.038	0.065	0.053	0.054	0.028	0.045	0.033	0.019	0.019
Budget Share by Processing Level										
Unprocessed	0.067	0.049	0.072	0.068	0.077	0.043	0.056	0.049	0.037	0.034
Minimally processed	0.069	0.058	0.077	0.074	0.065	0.037	0.049	0.044	0.029	0.033
Highly processed	0.054	0.048	0.064	0.056	0.049	0.031	0.051	0.036	0.023	0.020
n	3845	962	961	961	961	2741	686	685	685	685

Source: Authors' own calculations using HSHLS data. Estimates account for survey design characteristics, such as sampling weights, using Stata svy commands for specified subpopulations. Averages include non-consumers (i.e., zeros).

Own production (Table 1.8) is a more significant portion of food budgets than gifted food, particularly for rural households. Over 90% of rural households in the poorest quartile consumed food from their own production. Of the wealthiest rural households, around 64% consumed food from their own production. For urban households however, 46% of the poorest urban households consume food from their own production compared to 13% of those in the wealthiest quartile. The rural households with the lowest expenditure produce on average 24% of the cereal products they consume, 25% of the legumes they consume, and 19.5% of their fruits and vegetables. The urban households with the lowest expenditure consume on average 6.6% of their cereal products from own production, 4.9% of their legumes, and 7.5% of their fruits and vegetables. Overall, own production is a larger part of the budget shares of households in lower expenditure quartiles. For rural and urban households in all expenditure quartiles, own production makes up a larger portion of the budget share of the unprocessed and minimally processed goods. The share of own production in the high processing category is generally the smallest. Since highly processed products are more labor intensive and may require specialized equipment, it is logical that households are less likely to produce their own highly processed products.

Table 1.8: Budget Share of Own-Production Food by Food Group & Processing Level by Rural and Urban Per Capita Expenditure Quartiles

	Rural					Urban				
	Total	**Q1**	**Q2**	**Q3**	**Q4**	**Total**	**Q1**	**Q2**	**Q3**	**Q4**
Own-Production (all)										
Households consuming	80.6%	90.4%	87.9%	80.5%	64.1%	25.2%	46.3%	28.9%	19.8%	12.6%
Avg. budget share	0.148	0.199	0.164	0.135	0.096	0.024	0.066	0.023	0.011	0.006
Budget Share by Food Group										
Cereal Products	0.174	0.240	0.194	0.155	0.107	0.023	0.066	0.024	0.010	0.005
Animal Products	0.072	0.068	0.068	0.085	0.067	0.020	0.043	0.022	0.014	0.009
Legumes	0.188	0.250	0.228	0.175	0.116	0.021	0.049	0.026	0.014	0.005
Fruits & Vegetables	0.163	0.227	0.190	0.146	0.090	0.027	0.075	0.025	0.015	0.009
Roots & Tubers	0.048	0.062	0.060	0.038	0.034	0.006	0.020	0.005	0.003	0.002
Sugars & SSB	0.011	0.007	0.010	0.013	0.014	0.001	0.002	0.003	0.001	0.000
Oils, Condiments, Other	0.057	0.080	0.061	0.059	0.031	0.007	0.023	0.005	0.001	0.002
Budget Share by Processing Level										
Unprocessed	0.176	0.242	0.198	0.157	0.108	0.029	0.080	0.027	0.016	0.007
Minimally processed	0.106	0.115	0.115	0.116	0.082	0.018	0.043	0.022	0.009	0.007
Highly processed	0.026	0.039	0.033	0.020	0.013	0.003	0.011	0.003	0.000	0.001
n	3845	962	961	961	961	2741	686	685	685	685

Source: Authors' own calculations using HSHLS data. Estimates account for survey design characteristics, such as sampling weights, using Stata svy commands for specified subpopulations. Averages include non-consumers (i.e., zeros).

1.4. Results

1.4.1 Stage 1 Results

We run the first stage of our demand system separately for rural and urban households. The expenditure and price elasticities of food for urban and rural households by per capita expenditure quartile of the first stage are presented in Table 1.9. The elasticities are calculated at the quartile means. The full OLS regression output is available in Appendix D.

Table 1.9: Food Expenditure and Price Elasticities from Stage 1 by Per Capita Expenditure Quartiles

	Rural					Urban				
	Total	**Q1**	**Q2**	**Q3**	**Q4**	**Total**	**Q1**	**Q2**	**Q3**	**Q4**
Food Expenditure Elasticity	0.978	0.997	0.986	0.975	0.955	0.898	0.912	0.903	0.898	0.884
Food Price Elasticity	-0.983	-0.984	-0.983	-0.983	-0.981	-0.946	-0.953	-0.949	-0.946	-0.939
n	3845	962	961	961	961	2741	686	685	685	685

Source: Authors' own calculations using HSHLS data.

The overall food expenditure elasticity is less than one for all households, indicating that as household total expenditure increases, their expenditure on food increases less than proportionally. This supports Engel's law, which says that as a household's expenditure increases by 1%, their increase in food expenditure is less than 1%. Although a thorough analysis of elasticities over time is beyond the scope of this paper due to the use of cross-sectional data, comparing our estimated food elasticities to the food elasticity estimated for Malian households twenty years ago (0.51) by Camara (2004) indicates that food expenditure elasticities are much higher now (to 0.88-0.98), which may suggest that households, on average, have made a shift from subsistence consumption to consumption of more expensive and diversified food products. As incomes continue to grow, we expect to see food expenditure elasticities decrease as households reach their optimal food consumption and dedicate less of their additional disposable income to food. Food is less expenditure elastic for households in higher expenditure quartiles in both rural and urban areas, aligning with Engel's law. Food is also less expenditure elastic for rural households than urban households. The price elasticity of food is negative for all households. As food prices rise, food consumption falls.

1.4.2 Stage 2 Results

The expenditure and own-price elasticities from our stage 2 rural and urban QUAIDS models by food group are reported in Tables 1.10 & 1.11. The regression output for these models can be found in Appendix E. For the full set of cross-price elasticities, see Appendix F. The expenditure, own-price, and cross price elasticities from our stage 2 QUAIDS procedure for rural and urban households by processing level are reported in Tables 1.12 & 1.13. The output from the processing level regression models can be found in Appendix G.

Table 1.10 provides the expenditure elasticities for each of our seven food groups for rural and urban households by per capita expenditure quartile. Elasticities less than 1 indicate that as household food expenditure increases, the proportion of the food budget dedicated to these items shrinks. The poorest rural households increase their expenditure on cereals more than proportionally to an increase in total food expenditure, whereas wealthier rural households and urban households increase their expenditure on cereals less than proportionally. Elasticity estimates at quartile means are closer to 0 for wealthier households, indicating that their consumption of cereals is less responsive to expenditure changes. These findings align with our expectations that cereals are staples that provide calories, but as households spend more on food they spend less on cereals, opting to spend their additional money on food from other food groups. Both rural and urban households increase their expenditure on legumes, fruits and vegetables, and oils and condiments more than proportionally to an increase in total food expenditure. The proportion of animal products in household budgets increases more for wealthier households and more for urban households with increased expenditure. Expenditure elasticities of roots and tubers for rural households are higher than for urban households, indicating that consumption of roots and tubers for rural consumers is more sensitive to a change in the overall food budget. Recall from Table 1.6 that non-starches comprise the largest portion of household expenditure on roots and tubers, thus the elasticities for non-starchy roots likely dominate these results. In future work, it could be of interest to disaggregate cereals and roots and tubers to explore elasticities of particular starchy staples in depth. Sugars and SSBs are the least elastic category for all groups except the wealthiest urban households. Our finding that sugar and SSBs make up 5.3-6.3% of household food budgets across all quartiles and are expenditure inelastic across all quartiles indicates that households likely purchase a relatively small but consistent amount of sugars and SSBs that does not change very much when they increase or decrease their overall food consumption. Comparing rural and urban elasticities across expenditure quartiles, there is a more pronounced wealth effect in urban households than rural households. The difference in the estimated elasticities between low and high expenditure urban households are generally much larger than the differences between the low and high expenditure rural households.

In an analysis that examined a variety of existing elasticity estimates for food products in Sub-Saharan Africa, Colen et al. (2018) found that income elasticities for meat, fish, eggs, and dairy were generally quite high indicating these commodities were most responsive to changes in income. Meat, fish, eggs, and dairy all fall under our *animal products* category. In Mali, we do find that animal products are expenditure elastic for urban households, but both rural and urban expenditure elasticities are relatively close to 1 indicating the proportion of animal products in the food budget scales relatively proportionally with any increase in food expenditure. We find that fruits, vegetables, and legumes are more expenditure elastic in Mali, thus more sensitive to any change in overall food expenditure. Camara (2004) estimated the elasticity of staples (cereals, roots, and tubers) using the AIDS model as 0.418, which is lower than our estimated elasticities for any quartile. We find cereals to be more expenditure elastic, particularly for rural households and those with lower expenditure levels.

Table 1.10: Expenditure Elasticities for Food Groups by Rural and Urban Per Capita Expenditure Quartile

	Rural					Urban				
Food Group	**Total**	**Q1**	**Q2**	**Q3**	**Q4**	**Total**	**Q1**	**Q2**	**Q3**	**Q4**
Cereal Products	0.976***	1.043***	1.002***	0.958***	0.902***	0.737***	0.898***	0.785***	0.687***	0.494***
Animal Products	0.938***	0.881***	0.909***	0.956***	0.987***	1.047***	1.090***	1.046***	1.032***	1.024***
Legumes	1.189***	1.139***	1.176***	1.217***	1.221***	1.326***	1.098***	1.270***	1.340***	1.438***
Fruits & Vegetables	1.216***	1.203***	1.211***	1.243***	1.217***	1.284***	1.318***	1.303***	1.291***	1.256***
Roots & Tubers	1.108***	1.081***	1.099***	1.109***	1.140***	0.876***	0.856***	0.883***	0.882***	0.887***
Sugars & SSB	0.617***	0.625***	0.629***	0.571***	0.643***	0.556***	0.515***	0.542***	0.572***	0.637***
Oils, Condiments, Other	1.070***	1.070***	1.085***	1.058***	1.073***	1.171***	1.032***	1.151***	1.196***	1.231***
n	3845	962	961	961	961	2741	686	685	685	685

*Source: Authors' calculations using HSHLS data, Bootstrap standard errors using 100 replications, *** = significant at 1%, ** = significant at 5%, * = significant at 1%.*

Table 1.11 shows the own price elasticities for each of the seven food groups by rural and urban per capita expenditure quartile. All own-price elasticities by food group are negative, meaning that as the prices in each food group rise, consumption will fall, except the sugars and SSB group for a few quartiles for which the elasticity estimates are not statistically significant. For rural households, fruits and vegetables, and oils, condiments and other have group own-price elasticities greater than 1 absolute value, meaning that consumption of these groups will change by more than 1% in response to a 1% price change. For urban households, animal products and legumes are the most price elastic. The price elasticity of cereal products for an average rural household is -0.503 and -0.461 for urban households.

It is somewhat surprising that urban households exhibit such price sensitivity to animal products whereas rural households are less price sensitive, but one reason why rural households may be less price sensitive according to our estimates is the inclusion of own production in the value of food consumed. Comparing our results to Camara's (2004) estimates using the AIDS model, the price elasticity of staples (-0.506) is close to our estimates for rural households in particular. Camara's price elasticity of vegetables is -0.958, close to our estimate for an average urban household's price elasticity of fruits and vegetables (-0.926). Camara's estimates do not include own production, and they are not separated between rural and urban areas, so we must consider that when interpreting the differences.

Table 1.11: Own-Price Elasticities for Food Groups by Rural and Urban Per Capita Expenditure Quartile

	Rural					Urban				
Food Group	**Total**	**Q1**	**Q2**	**Q3**	**Q4**	**Total**	**Q1**	**Q2**	**Q3**	**Q4**
Cereal Products	-0.503***	-0.555***	-0.522***	-0.474***	-0.447***	-0.461***	-0.582***	-0.501***	-0.420***	-0.248*
Animal Products	-0.275	-0.205	-0.237	-0.325**	-0.329**	-1.287***	-1.289***	-1.291***	-1.292***	-1.290***
Legumes	-0.934***	-0.931***	-0.933***	-0.933***	-0.935***	-1.028***	-1.027***	-1.029***	-1.028***	-1.026***
Fruits & Vegetables	-1.120***	-1.122***	-1.121***	-1.124***	-1.117***	-0.926***	-0.904***	-0.923***	-0.930***	-0.936***
Roots & Tubers	-0.800***	-0.801***	-0.805***	-0.796***	-0.796***	-0.704***	-0.717***	-0.715***	-0.703***	-0.692***
Sugars & SSB	-0.372	-0.379	-0.380	-0.377	-0.377	0.055	-0.087	0.009	0.048	0.118
Oils, Condiments, Other	-1.448***	-1.468***	-1.444***	-1.447***	-1.435***	-0.806***	-0.736***	-0.794***	-0.826***	-0.853***
n	3845	962	961	961	961	2741	686	685	685	685

*Source: Authors' calculations using HSHLS data, Bootstrap standard errors using 100 replications, *** = significant at 1%, ** = significant at 5%, * = significant at 1%.*

The cross-price elasticities between all seven food groups are too extensive to be displayed here, so we will just highlight a few relationships of interests. The full table of cross-price elasticities by quartile can be found in Appendix F.

When cereal product prices increase, not only does consumption of cereals decrease, but consumption of fruits, vegetables and legumes decreases as well for both urban and rural households. The cross-price elasticity for legumes with respect to cereals is -0.940 for rural households and -0.678 for urban households. Rural households increase their consumption of roots and tubers when cereal product prices increase, and they decrease consumption of roots and tubers when animal product prices increase with cross price elasticities of +0.549 and -1.236 respectively. For rural households, animal product price increases lead to decreased consumption of cereals (-0.437) and increased consumption of legumes (+0.695). We also find that when prices of fruits and vegetables rise, rural households tend to decrease their consumption of legumes (-0.566), and urban households tend to increase their consumption of legumes (+0.206). In comparing estimated price elasticities for various food groups, we find that rural and urban households have heterogenous demand responses to price changes.

Table 1.12 contains the expenditure elasticities for rural and urban per capita expenditure quartiles by processing group. We find that for rural households, demand for the highly processed category is the least expenditure elastic, whereas demand for unprocessed food is the most expenditure across expenditure quartiles. For urban households, minimally processed foods are the least expenditure elastic, and the elasticity decreases with higher expenditure. Our estimated elasticities are in line with those of De Brauw and Herskowitz (2020) who estimated elasticities for processing levels in Nigeria. They categorize foods into three processing groups, comparable to the groups we use. De Brauw and Herskowitz (2020) estimate the elasticity of the unprocessed group as 1.044, their estimate for the minimally processed group is 0.847, and their highly processed group estimate is 1.065. Our third quartile of urban households has the most similar profile to the estimates from De Brauw and Herskowitz with elasticities of 1.011, 0.872, and 1.083 respectively. Our estimates show that an increase in food expenditure in urban Malian households is on average associated with a more than proportional increase in expenditure on highly processed foods. For rural households, however, highly processed foods are slightly less elastic, ranging from 0.862 to 1.000 for the lowest to highest expenditure quartiles. For rural households, unprocessed foods are the most elastic, but across all processing levels, elasticities approach 1.000 for the highest expenditure quartiles.

Table 1.12: Expenditure Elasticities for Processing Levels by Rural and Urban Per Capita Expenditure Quartile

	Rural					Urban				
Processing Level	**Total**	**Q1**	**Q2**	**Q3**	**Q4**	**Total**	**Q1**	**Q2**	**Q3**	**Q4**
Unprocessed	1.019***	1.038***	1.023***	1.017***	1.000***	1.005***	0.951***	0.985***	1.011***	1.055***
Minimally Processed	0.995***	0.990***	1.003***	0.993***	0.999***	0.906***	1.053***	0.948***	0.872***	0.757***
Highly Processed	0.934***	0.862***	0.907***	0.946***	1.000***	1.076***	1.094***	1.091***	1.083***	1.055***
n	3845	962	961	961	961	2741	686	685	685	685

*Source: Authors' calculations using HSHLS data, Bootstrap standard errors using 100 replications, *** = significant at 1%, ** = significant at 5%, * = significant at 1%*

Table 1.13 shows the own-price and cross-price elasticities for the processing levels. All own-price elasticities are negative and significant, except for the minimally processed category for rural households. The small, positive own-price elasticities for rural households may be driven in part by the inclusion of own production at market value. Based on our finding that own production makes up a substantial portion of rural households' food consumption, it is reasonable to infer that rural households may be less likely to change their consumption of products they produce when prices increase. When prices of unprocessed foods increase, urban households respond by decreasing consumption of unprocessed foods more than proportionally, but their consumption of minimally and highly processed foods is not significantly impacted. Rural households, on the other hand, decrease not only their consumption of unprocessed foods, but also their consumption of minimally processed foods. For increases in prices of highly processed foods, rural households decrease their consumption of both highly and minimally processed foods. Urban households consume less minimally and highly processed foods when prices of either rise. Overall, our demand estimates show that rural and urban households respond to changes in food prices and household food budgets in different ways.

Table 1.13: Price Elasticities for Processing Levels by Rural and Urban Per Capita Expenditure Quartile

	Rural					Urban				
Processing Level	**Total**	**Q1**	**Q2**	**Q3**	**Q4**	**Total**	**Q1**	**Q2**	**Q3**	**Q4**
Unprocessed										
Unprocessed	-0.680***	-0.696***	-0.685***	-0.675***	-0.663***	-1.047***	-1.021***	-1.038***	-1.049***	-1.066***
Minimally Processed	-0.824***	-0.853***	-0.857***	-0.808***	-0.786***	0.134	0.055	0.110	0.152	0.210
Highly Processed	-0.058	-0.016	-0.039	-0.062	-0.097	-0.002	0..005	-0.008	-0.012	-0.006
Minimally Processed										
Unprocessed	-0.311***	-0.310***	-0.310***	-0.314***	-0.312***	0.028	0.041	0.033	0.026	0.013
Minimally Processed	0.282*	0.333**	0.325*	0.260	0.219	-0.655***	-0.697***	-0.673***	-0.639***	-0.578***
Highly Processed	-0.643***	-0.631***	-0.621***	-0.633***	-0.659***	-0.399***	-0.465***	-0.413***	-0.380***	-0.349***
Highly Processed										
Unprocessed	-0.028	-0.031	-0.029	-0.028	-0.025	0.015	0.029	0.020	0.012	-0.003
Minimally Processed	-0.453***	-0.469***	-0.470***	-0.444***	-0.432***	-0.385***	-0.412***	-0.385***	-0.386***	-0.389***
Highly Processed	-0.234**	-0.215	-0.247***	-0.251***	-0.244	-0.675***	-0.634***	-0.670***	-0.691***	-0.700***
n	3845	962	961	961	961	2741	686	685	685	685

*Source: Authors' calculations using HSHLS data, Bootstrap standard errors using 100 replications, *** = significant at 1%, ** = significant at 5%, * = significant at 1%.*

1.4.3 Compensating Variation

To further understand how Malian households would be impacted by a price shock, we calculate the compensating variation under a few hypothetical price increases. CV is the amount of additional money a household would need to spend to achieve their original level of utility under the simulated new prices for one group, holding the prices of other groups constant (Hicks, 1942; Chipman & Moore, 1980). To allow for more meaningful interpretation, we present the CV of each food or processing group as a percentage of the household's total food expenditure to understand how a household's food budget would need to change to maintain their original utility level (Ackah & Appleton, 2007). We simulate 10% and 30% increases in the corrected Stone price index used for our demand model for each of the 7 food groups and 3 processing levels, presenting the mean CV as a percentage of total food expenditure for rural and urban households by per capita expenditure quartile in Table 1.14.

Under a simulated 10% own-food group price increase for cereal products, we find that rural households on average would need to increase total food expenditure by 2.54% to 3.58% to achieve their pre-price change utility level. Under a simulated 30% price increase, the necessary compensation for rural households climbs to 7.58% to 10.61% of the total food budget. In both scenarios, those in higher expenditure quartiles require a relatively lower percentage increase in total food expenditure to achieve their original utility level, likely because cereals comprise a smaller budget share of the total food budget for these households as seen in Table 1.4. Urban consumers are slightly less negatively affected by a 10% price increase in cereal products, requiring increases in overall food expenditures between 1.77% to 2.74% to achieve their pre-price change utility level and 5.23% to 7.99% to achieve the pre-price change utility level under a 30% price increase. Similar to the rural households, we find that the urban households in lower expenditure quartiles require a relatively larger increase in the overall food budget to reach pre-price change utility levels. Price changes in cereals lead to the largest welfare losses for rural households and the second largest losses for urban households. If prices of cereals rise, Malian households would need to be compensated by a higher percentage of their food budget to be as well off as they were before.

Animal product price increases have the most substantial impact on urban household welfare. Under a 10% price increase, urban households would need compensation equal to 2.56% to 2.78% of their total food expenditure to achieve their original utility and under a 30%

price change, that rises to 7.05% to 7.66%. For urban households, the required compensation as a share of food expenditure is slightly lower for higher expenditure quartiles under both the 10% price increase and 30% price increase. On the other hand, rural households in higher expenditure quartiles would require higher compensation to reach their original utility level under both simulated animal product price increases than those in lower expenditure quartiles. This aligns with our findings that the poorest rural households are more reliant on staples. Wealthier rural households and urban households spend more on non-cereal foods, therefore, price increases to non-cereal foods have more significant impacts on these groups.

Table 1.14: Compensating Variation for Simulated Own-Group Price Increases as a % of Total Food Expenditure by Rural and Urban Per Capita Expenditure Quartiles

	Rural					Urban				
	Total	**Q1**	**Q2**	**Q3**	**Q4**	**Total**	**Q1**	**Q2**	**Q3**	**Q4**
10% Own-Food Group Price Increase										
Cereal Products	3.06%	3.58%	3.24%	2.86%	2.54%	2.27%	2.74%	2.40%	2.16%	1.77%
Animal Products	2.78%	2.47%	2.60%	2.95%	3.09%	2.63%	2.78%	2.62%	2.58%	2.56%
Legumes	0.49%	0.46%	0.49%	0.50%	0.50%	0.38%	0.33%	0.37%	0.37%	0.43%
Roots & Tubers	0.75%	0.72%	0.76%	0.74%	0.78%	0.98%	1.02%	1.01%	0.96%	0.92%
Fruits & Vegetables	1.20%	1.19%	1.22%	1.19%	1.22%	1.52%	1.16%	1.46%	1.63%	1.86%
Sugars & SSB	0.62%	0.58%	0.60%	0.63%	0.66%	0.59%	0.64%	0.59%	0.57%	0.55%
Oils, Condiments, Other	0.95%	0.83%	0.94%	0.97%	1.04%	1.33%	1.04%	1.26%	1.44%	1.61%
30% Own-Food Group Price Increase										
Cereal Products	9.07%	10.61%	9.59%	8.50%	7.58%	6.64%	7.99%	7.00%	6.33%	5.23%
Animal Products	8.46%	7.57%	7.93%	8.96%	9.37%	7.25%	7.66%	7.21%	7.09%	7.05%
Legumes	1.36%	1.29%	1.36%	1.38%	1.41%	1.04%	0.92%	1.02%	1.02%	1.19%
Roots & Tubers	2.12%	2.04%	2.14%	2.09%	2.20%	2.78%	2.90%	2.86%	2.72%	2.62%
Fruits & Vegetables	3.32%	3.28%	3.35%	3.27%	3.36%	4.31%	3.26%	4.12%	4.59%	5.26%
Sugars & SSB	1.78%	1.68%	1.73%	1.81%	1.89%	1.75%	1.89%	1.76%	1.70%	1.64%
Oils, Condiments, Other	2.55%	2.24%	2.53%	2.61%	2.82%	3.79%	2.96%	3.57%	4.07%	4.56%
10% Own-Processing Level Price Increase										
Unprocessed	6.13%	6.34%	6.21%	6.04%	5.92%	5.83%	5.99%	5.74%	5.70%	5.87%
Minimally Processed	2.47%	2.33%	2.39%	2.56%	2.61%	1.87%	2.02%	2.00%	1.85%	1.60%
Highly Processed	1.45%	1.38%	1.45%	1.44%	1.51%	2.10%	1.78%	2.06%	2.24%	2.34%
30% Own-Processing Level Price Increase										
Unprocessed	18.34%	19.00%	18.59%	18.06%	17.69%	16.83%	17.32%	16.55%	16.45%	16.99%
Minimally Processed	7.65%	7.23%	7.40%	7.90%	8.06%	5.39%	5.83%	5.75%	5.33%	4.64%
Highly Processed	4.31%	4.13%	4.33%	4.31%	4.49%	6.08%	5.15%	5.95%	6.48%	6.76%
n	3845	962	961	961	961	2741	686	685	685	685

Source: Authors' calculations using HSHLS data.

The magnitude of the required compensating variation for fruits and vegetables is the next highest after cereals and animal products for both rural and urban households, followed by oils, condiments, and other group. For both of these food groups as well as the legumes group, rural and urban households both require higher compensation levels at higher expenditure levels. For roots, tubers, and sugars and SSBs we find rural households in lower expenditure quartiles would need less compensation than those in higher expenditure quartiles to be as well off as they were before the price change, but for urban households we find that higher expenditure households require less compensation than those in lower expenditure quartiles. For cereal products, animal products, legumes, and sugars and SSBs, price changes have larger impacts as a percentage of a household's total food budget on rural households than on urban households. For the other groups, the opposite is true.

Examining the impacts of simulated price changes on processing groups reveals that a price increase of 10% or 30% across the unprocessed category has the by far largest impact on households of all the processing groups in both rural and urban areas. Both rural and urban consumers rely heavily on foods from the lowest processing category, as this category makes up over half of the food budget share on average for all quartiles. For the minimally processed category, we find that rural households in higher expenditure quartiles require higher compensation than lower expenditure quartiles. On the other hand, urban households in higher expenditure quartiles dedicate less of their budget to minimally processed food and therefore require less compensation to meet their pre-price change utility level. The results for the high processed food category across rural and urban expenditure quartiles show that households with higher expenditure levels need higher rates of compensation to meet their original utility levels under simulated price increases for highly processed foods. This finding aligns with the finding that households with higher expenditure levels dedicate larger portions of their food budget to highly processed foods, therefore, price increases for highly processed foods decrease household utility for these households more dramatically. Price changes for highly processed products have larger impacts on urban households, but price changes for unprocessed and minimally processed foods would translate to higher compensation needs for rural households on average to meet their original utility level.

1.5. Conclusions and Policy Implications

Inflation and volatility of food prices are major concerns, as the food prices faced by West Africans are up to 40% greater than in comparable regions based on per capita income (SWAC/OECD, 2021). In this study, we use the Harmonized Survey on Households Living Standards (HSHLS) from 2018/2019 in Mali (INSTAT, 2022) to estimate a two-stage demand system to examine the impacts of price changes and expenditure growth on household consumption of food (1) by food group and (2) by processing level. The dataset, collected by the National Institute of Statistics in Mali with support from the World Bank and West African Economic Monetary Union (WAEMU), provides detailed consumption information for the seven days preceding survey enumeration on a nationally representative sample of 3,847 rural and 2,745 urban households across the country. In our demand model, households allocate their expenditure to food or non-food commodities in stage one. This allows us to estimate the expenditure and price elasticities of food for rural and urban households separately in this stage with a Working-Leser budget share equation. We find food is expenditure inelastic, meaning the share of food in the total household budget declines as total expenditure rises. Food is more expenditure inelastic for all quartiles of urban households than any quartile of rural household. We also find that rural households are less sensitive to food price changes than urban households, however this is likely due to the fact that we include own production in household consumption, which is a much more significant part of the food budget for rural households than urban households.

In stage 2 of the demand model, households allocate their predicted total food expenditure to different food or processing groups. To generate our price and expenditure elasticities for our various food and processing groups, we model the budget share by group with QUAIDS. We have four separate stage two models: 1) rural demand by food group; 2) urban demand by food group; 3) rural demand by processing group and 4) urban demand by processing group. We generate the elasticities at the means for each expenditure quartile for rural and urban households.

Our calculated expenditure elasticities clearly support our hypotheses that as Malian households increase their food expenditure, they are diversifying their diets away from calorie dense cereals towards more legumes, fruits, and vegetables. Rural households are also increasing their consumption of roots and tubers, and urban households increase spending on animal products. Urban consumers spend more on highly processed products as their food budgets increase, whereas rural households increase their consumption of unprocessed foods (e.g., fresh fruits and vegetables). Overall, food is still a large portion of the total budget of rural and urban households at all income levels and cereals maintain a key role in the diets of all households, suggesting dietary transformation is underway but still in relatively early stages. Policies that lead to increased household incomes are likely to result in increased consumption of more diverse, non-cereal foods, including legumes, fruits, and vegetables.

As we expected, even in low expenditure quartiles, rural and urban households are reliant on processed foods, but we also find significant differences in results across rural and urban households. Urban households are demanding more highly processed foods as they increase their food budgets, whereas rural households demand more unprocessed foods. Price changes to different food groups have substantially different impacts on rural and urban household consumption patterns. For example, when prices of fruits and vegetables rise, rural households tend to decrease their consumption of legumes whereas urban households tend to increase their consumption of legumes. It is important for policymakers to understand that the spillover effects of price changes for one food group will have heterogenous impacts on rural and urban households, and on households of different wealth levels.

Mali has experienced a variety of climatic and geopolitical shocks, which have had impacts on food supply and food prices. After our two-stage demand system estimation, we use the results to calculate the compensating variation to estimate welfare changes for households under hypothetical price shocks to different food groups. When comparing the welfare impacts of the same level of price shock across different food groups, we find that price shocks to animal products and cereals have the largest impact on urban households at all income levels, but cereal price increases have the largest impact on rural households of all income levels. When looking at price shocks to foods based on processing level, we find that shocks to the unprocessed level have the largest impact by far for rural and urban households across all income levels. These findings suggests that policymakers should consider policies that reduce inefficiencies and support the sustainability along food supply chains, particularly prioritizing cereal supply chains, animal product supply chains, and other unprocessed foods. These initiatives would have positive impacts on rural and urban households at all income levels.

Closer examination of the compensating variation estimates for cereal products reveals that the lowest income households in both rural and urban areas require the highest relative compensation to achieve their original level of utility under a price increase for cereal products. For urban households, roots and tubers follow the same pattern. For most other food groups, the higher income households require a relatively equal or higher level of compensation than the lower income households under a simulated price shock. This reflects the enduring importance of staples in the dietary composition of households across Mali, particularly the lowest income households.

As the dataset we use is a cross-section, looking at the dietary change over time is beyond the scope of this paper. However, the findings from this study suggest dietary transformation is occurring in Mali as households, particularly urban households, shift their consumption towards more diverse diets with higher expenditure on animal products and highly processed foods. Both rural and urban households consume more fruits, vegetables, and legumes as their food budgets grow. Our findings motivate further analysis looking at the changes over time in dietary composition and food demand and their impact on nutritional outcomes.

Acknowledgements

This work was supported by the United States Agency for International Development (USAID)’s Bureau for Food Security under Agreement #7200AA18LE00003 as part of Feed the Future Innovation Lab for Legume Systems Research and USAID's Innovation Laboratory for Food Security Policy [AID-OAA-L-13-00001]. Any opinions, findings, conclusions, or recommendations expressed here are those of the author alone.

REFERENCES

Ackah, C., & Appleton, S. (2007). *Food price changes and consumer welfare in Ghana in the 1990s* (CREDIT Research Paper No. 07/03). The University of Nottingham. http://hdl.handle.net/10419/80310

Adjognon, G. S., Bloem, J. R., & Sanoh, A. (2021). The coronavirus pandemic and food security: Evidence from Mali. *Food Policy*, *101*, 102050. https://doi.org/10.1016/j.foodpol.2021.102050

Ahmed, T., Hossain, M. I., Islam, M. M., Ahmed, A., Afroze, F., & Chisti, M. J. (2020). Protein-Energy Malnutrition in Children. In *Elsevier eBooks* (pp. 1034–1041). https://doi.org/10.1016/b978-0-323-55512-8.00143-5

Banks, J., Blundell, R., & Lewbel, A. (1997). Quadratic Engel Curves and Consumer Demand. *The Review of Economics and Statistics*, *79*(4), 527–539. https://doi.org/10.1162/003465397557015

Bennett, M. K. (1941). International Contrasts in Food Consumption. *Geographical Review*, *31*(3), 365–376. https://doi.org/10.2307/210172https://www.jstor.org/stable/210172

Biasutti, M. (2019). Rainfall trends in the African Sahel: Characteristics, processes, and causes. *WIREs Climate Change*, *10*(4). https://doi.org/10.1002/wcc.591

Boysen, O. (2015). Food Demand Characteristics in Uganda: Estimation and Policy Relevance. *South African Journal of Economics*, *84*(2), 260–293. https://doi.org/10.1111/saje.12093

Cantwell, M. I., & Kasmire, R. F. (2002). Handling Systems: Underground Vegetables (Roots, Tubers, and Bulbs). *Postharvest technology of horticultural crops,* 3311, 435.

Camara, O. (2004). *The impact of seasonal changes in real incomes and relative prices on households' consumption patterns in Bamako, Mali* [PhD Dissertation]. Michigan State University. Available from ProQuest.

Chakrabarty, M., & Hildenbrand, W. (2011). Engel's law reconsidered. *Journal of mathematical economics*, *47*(3), 289-299.

Chipman, J. S., & Moore, J. C. (1980). Compensating Variation, Consumer's Surplus, and Welfare. *The American Economic Review*, *70*(5), 933–949. http://www.jstor.org/stable/1805773

Cheng, Z., & Larochelle, C. (2016). Estimating household demand for millet and sorghum in Niger and Nigeria. *ResearchGate*. https://doi.org/10.13140/RG.2.1.1351.0007

Chukwuemeka, E. N., & Osuji, E. (2020). Demand analysis for solid fuel and its substitutes as domestic energy in Imo State, Nigeria. *Finance & Economics Review*, *2*(2), 39–54. https://doi.org/10.38157/finance-economics-review.v2i2.141

Colen, L., Melo, P. C., Abdul-Salam, Y., Roberts, D., Mary, S., & Paloma, S. G. Y. (2018). Income elasticities for food, calories and nutrients across Africa: A meta-analysis. *Food Policy*, *77*, 116–132. https://doi.org/10.1016/j.foodpol.2018.04.002

Cranfield, J., & Haq, Z. U. (2010). *What impact has food price inflation had on consumer welfare: a global analysis* [Conference Paper]. Australasian Agricultural and Resource Economics Society (AARES) 2010 Conference (54th), February 10-12, 2010, Adelaide, Australia. https://ageconsearch.umn.edu/record/58894

De Brauw, A., & Herskowitz, S. (2020). Income Variability, Evolving Diets, and Elasticity Estimation of Demand for Processed Foods in Nigeria. *American Journal of Agricultural Economics*, *103*(4), 1294–1313. https://doi.org/10.1111/ajae.12139

Deaton, A. (1981). *Three essays on a Sri Lanka Household Survey* (Living Standard Measurement Study Working Paper No. 11). The World Bank. https://deaton.scholar.princeton.edu/publications/three-essays-sri-lanka-household-survey

Deaton, A., & Muellbauer, J. (1980). An Almost Ideal Demand System. *American Economic Review*, *70*(3), 312–326. https://econpapers.repec.org/article/aeaaecrev/v_3a70_3ay_3a1980_3ai_3a3_3ap_3a312-26.htm

Dolislager, M., Holleman, C., Liverpool-Tasie, L. S. O., & Reardon, T. (2023). *Analysis of food demand and supply across the rural–urban continuum for selected countries in Africa: Background paper for The State of Food Security and Nutrition in the World 2023* (FAO Agricultural Development Economics Working Paper, No. 23-09). Food and Agriculture Organization of the United Nations. https://www.fao.org/3/cc9119en/cc9119en.pdf

Dolislager, M., Liverpool-Tasie, L. S. O., Mason, N. M., Reardon, T., & Tschirley, D. L. (2022). Consumption of healthy and unhealthy foods by the African poor: Evidence from Nigeria, Tanzania, and Uganda. *Agricultural Economics*, *53*(6), 870–894. https://doi.org/10.1111/agec.12738

Elbadawi, I., & Mwega, F. (2000). Can Africa's Saving Collapse Be Reversed? *The World Bank Economic Review*, *14*(3), 415–443. https://doi.org/10.1093/wber/14.3.415

Food and Agriculture Organization. (2017). *Country Fact Sheet on Food and Agriculture Policy Trends - Mali*. https://www.fao.org/agrifood-economics/publications/detail/en/c/1132142/

Food and Agriculture Organization. (2022). *Cereal supply and demand balances for sub-Saharan African countries: Situation as of November 2022*. https://doi.org/10.4060/cc3273en

Gerbens-Leenes, P., Nonhebel, S., & Krol, M. S. (2010). Food consumption patterns and economic growth. Increasing affluence and the use of natural resources. *Appetite*, *55*(3), 597–608. https://doi.org/10.1016/j.appet.2010.09.013

Han, X., & Chen, Y. (2016). Food consumption of outgoing rural migrant workers in urban area of China: a QUAIDS approach. *China Agricultural Economic Review*, *8*(2). https://doi.org/10.1108/caer-06-2015-0067

Harvard Health Publishing. (2021). *The pros and cons of root vegetables.* https://www.health.harvard.edu/staying-healthy/the-pros-and-cons-of-root-vegetables

Hussein, M., Law, C., & Fraser, I. (2021). An analysis of food demand in a fragile and insecure country: Somalia as a case study. *Food Policy*, *101*, 102092. https://doi.org/10.1016/j.foodpol.2021.102092

Hutchinson, E. (2017). *Topic 4 Part 1: Elasticity. In Principles of Microeconomics.* Chapter, OpenStax.

Institut National de la Statistique [INSTAT]. (2022). *Harmonized Survey on Households Living Standards 2018-2019* World Bank, Development Data Group. https://doi.org/10.48529/90E9-4E91. Downloaded on February 11, 2022.

Kearney, J. (2010). Food consumption trends and drivers. *Philosophical Transactions of the Royal Society B*, *365*(1554), 2793–2807. https://doi.org/10.1098/rstb.2010.0149

Kharisma, B., Alisjahbana, A. S., Remi, S. S., & Praditya, P. (2020). Application of the Quadratic Almost Ideal Demand System (QUAIDS) model in the demand of the household animal sourced food in West Java. *AGRIS on-line Papers in Economics and Informatics.* https://doi.org/10.22004/ag.econ.303932

Korir, L., Rizov, M., & Ruto, E. (2018). *Analysis of household food demand and its implications on food security in Kenya: an application of QUAIDS model* [Conference Paper]. Agricultural Economics Society 92nd Annual Conference, April 16-18, 2018, UK https://doi.org/10.22004/ag.econ.273474

Leser, C. E. V. (1963). Forms of Engel Functions. *Econometrica*, *31*(4), 694–703. https://doi.org/10.2307/1909167https://www.jstor.org/stable/1909167

Maredia, M. K., Adenikinju, A., Belton, B., Chapoto, A., Faye, N. F., Liverpool-Tasie, S., Olwande, J., Reardon, T., Thériault, V., & Tschirley, D. L. (2022). COVID-19's impacts on incomes and food consumption in urban and rural areas are surprisingly similar: Evidence from five African countries. *Global Food Security*, *33*, 100633. https://doi.org/10.1016/j.gfs.2022.100633

Me-Nsope, N., & Staatz, J. M. (2016). *Household-Level Evidence of Cereals Demand and the Welfare Implications of Cereals Price Shocks in Rural and Urban Mali* [Invited Paper]. African Association of Agricultural Economists (AAAE) Fifth International Conference, September 23-26, 2016, Addis Ababa, Ethiopia. https://ideas.repec.org/p/ags/aaae16/246397.html

Mittal, S. (2010). Application of the Quaids Model to the Food Sector in India. *Journal of Quantitative Economics*, *8*(1), 42–54. https://EconPapers.repec.org/RePEc:jqe:jqenew:v:8:y:2010:i:1:p:42-54

Monteiro, C.A., Cannon, G., Lawrence, M., Costa Louzada, M.L. and Pereira Machado, P. 2019. Ultra-processed foods, diet quality, and health using the NOVA classification system. Rome, FAO.

Moschini, G. (1995). Units of Measurement and the Stone Index in Demand System Estimation. *American Journal of Agricultural Economics*, *77*(1), 63–68. https://doi.org/10.2307/1243889

Obayelu, A. E., Okoruwa, V. O., & Ajani, O. (2009). Cross-sectional analysis of food demand in the North Central, Nigeria. *China Agricultural Economic Review*, *1*(2), 173–193. https://doi.org/10.1108/17561370910927426

Olabisi, M., Obekpa, H. O., & Liverpool-Tasie, L. S. O. (2021). Is growing your own food necessary for dietary diversity? Evidence from Nigeria. *Food Policy*, *104*, 102144. https://doi.org/10.1016/j.foodpol.2021.102144

Osei-Asare, Y. B., & Eghan, M. (2013). Food Price Inflation and Consumer Welfare in Ghana. *International Journal of Food and Agricultural Economics*, *1*(1), 27–39. https://doi.org/10.22004/ag.econ.156140

Poi, Brian, (2002), From the help desk: Demand system estimation, *Stata Journal*, 2, issue 4, p. 403-410, https://EconPapers.repec.org/RePEc:tsj:stataj:v:2:y:2002:i:4:p:403-410.Poi, B. P. (2012). Easy Demand-System Estimation with Quaids. *The Stata Journal*, *12*(3), 433–446. https://doi.org/10.1177/1536867x1201200306

Pollak, R. A., & Wales, T. J. (1981). Demographic Variables in Demand Analysis. *Econometrica*, *49*(6), 1533–1551. https://doi.org/10.2307/1911416https://www.jstor.org/stable/1911416

Popkin, B. M. (2002). The dynamics of the dietary transition in the developing world. In *The Nutrition Transition* (pp. 111–128). https://doi.org/10.1016/b978-012153654-1/50008-8

Rasyid, M. (2022). Can unconditional cash assistance improve household welfare? QUAIDS model for food commodities in Indonesia. *Development Studies Research*, *9*(1), 1–11. https://doi.org/10.1080/21665095.2022.2027258

Ray, R. (1983). Measuring the costs of children. *Journal of Public Economics*, *22*(1), 89–102. https://doi.org/10.1016/0047-2727(83)90058-0

Reardon, T., Tschirley, D., Dolislager, M., Snyder, J., Hu, C., & White, S. (2014). *Urbanization, Diet Change, and Transformation of Food Supply Chains in Asia*. Global Center for Food System Innovation. https://www.fao.org/fileadmin/templates/ags/docs/MUFN/DOCUMENTS/MUS_Reardon_2014.pdf

Reardon, T., Tschirley, D. L., Liverpool-Tasie, L. S. O., Awokuse, T. O., Fanzo, J., Minten, B., Vos, R., Dolislager, M., Sauer, C., Dhar, R., Vargas, C. M., Lartey, A., Raza, A., & Popkin, B. M. (2021). The processed food revolution in African food systems and the double burden of malnutrition. *Global Food Security*, *28*, 100466. https://doi.org/10.1016/j.gfs.2020.100466

Smale, M., Thériault, V., & Mason, N. M. (2020). Does subsidizing fertilizer contribute to the diet quality of farm women? Evidence from rural Mali. *Food Security*, *12*(6), 1407–1424. https://doi.org/10.1007/s12571-020-01097-w

Smale, M., Thériault, V., & Vroegindewey, R. (2020). Nutritional implications of dietary patterns in Mali. *African Journal of Agricultural and Resource Economics*, *15*(3), 177–193. https://afjare.org/nutritional-implications-of-dietary-patterns-in-mali/

SWAC/OECD. (2021). *Food System Transformations in the Sahel and West Africa* (Maps&Facts, no. 4).

Thériault, V., Vroegindewey, R., Assima, A., & Keita, N. (2018). Retailing of Processed Dairy and Grain Products in Mali: Evidence from a City Retail Outlet Inventory. *Urban Science*, *2*(1), 24. https://doi.org/10.3390/urbansci2010024

Traoré, B. S., Corbeels, M., Van Wijk, M., Rufino, M. C., & Giller, K. E. (2013). Effects of climate variability and climate change on crop production in southern Mali. *European Journal of Agronomy*, *49*, 115–125. https://doi.org/10.1016/j.eja.2013.04.004

Tschirley, D. L., Snyder, J., Dolislager, M., Reardon, T., Haggblade, S., Goeb, J., Traub, L., Ejobi, F., & Meyer, F. (2015). Africa' s unfolding diet transformation: implications for agrifood system employment. *Journal of Agribusiness in Developing and Emerging Economies*, *5*(2), 102–136. https://doi.org/10.1108/jadee-01-2015-0003

United States Department of Agriculture [USDA]. (n.d.). *What do I do with root vegetables?*. WIC Works Resource System. https://wicworks.fns.usda.gov/topic/what-do-i-do-with/root-vegetables

Wood, B., Nelson, C. H., & Nogueira, L. (2012). Poverty effects of food price escalation: The importance of substitution effects in Mexican households. *Food Policy*, *37*(1), 77–85. https://doi.org/10.1016/j.foodpol.2011.11.005

Working, H. (1943). Statistical laws of family expenditure. *Journal of the American Statistical Association*, *38*(221), 43–56. https://doi.org/10.1080/01621459.1943.10501775

World Bank, World Development Indicators (2023a). *Urban population (% of total population) - Mali* [Data file]. Retrieved from https://data.worldbank.org/indicator/SP.URB.TOTL.IN.ZS?locations=ML

World Bank, World Development Indicators (2023b). *Total population - Mali* [Data file]. Retrieved from https://data.worldbank.org/indicator/SP.POP.TOTL?locations=ML

World Bank, World Development Indicators (2025). *GDP per capita (current US$ - Mali* [Data file]. Retrieved https://data.worldbank.org/indicator/NY.GDP.PCAP.CD?locations=ML

World Food Programme. (2019). *Mali country strategic plan (2020–2024)* (Executive Board Second Regular Session) [Operational matters - Country strategic plans]. Executive Board - Second Regular Session, Rome, Italy. https://www.wfp.org/operations/ml02-mali-country-strategic-plan-2020-2024

World Food Programme. (2020). *The Development of a Minimum Expenditure Basket in Mali*. https://www.wfp.org/publications/wfp-mali-development-minimum-expenditure-basket

World Food Programme. (2023). *WFP Mali Country Brief July 2023*. https://docs.wfp.org/api/documents/WFP-0000152900/download/

Zhou, Y., & Staatz, J. M. (2016). Projected demand and supply for various foods in West Africa: Implications for investments and food policy. *Food Policy*, *61*, 198–212. https://doi.org/10.1016/j.foodpol.2016.04.002

APPENDIX A: TESTING FOR THE INCLUSION OF QUADRATIC TERMS

Table 1.15: Testing Inclusion of Quadratic Terms (Stage 1 & Stage 2)

LR Test for the inclusion of the quadratic term in WL Stage 1 for rural households LR Chi2(1) = 8.56 Prob > Chi2 = 0.0034
LR Test for the inclusion of the quadratic term in WL Stage 1 for urban households LR Chi2(1) = 0.18 Prob > Chi2 = 0.6747
LR Test for the use of the Quadratic AIDS Stage 2 by food group for rural households LR Chi2(6) = 293.11 Prob > Chi2 = 0.0000
LR Test for the use of the Quadratic AIDS Stage 2 by processing level for rural households LR Chi2(5) = 159.10 Prob > Chi2 = 0.0000
LR Test for the use of the Quadratic AIDS Stage 2 by food group for urban households LR Chi2(11) = 115.15 Prob > Chi2 = 0.0000
LR Test for the use of the Quadratic AIDS Stage 2 by processing level for urban households LR Chi2(4) = 60.50 Prob > Chi2 = 0.0000

Source: Authors' calculations using HSHLS data.

APPENDIX B: FOOD GROUP CLASSIFICATIONS

Table 1.16: Food Group Classification

Cereal Products	Animal Products	Legumes	Fruits & Vegetables	Roots & Tubers	Sugars & SSB	Oils, Condiments, and Other
Wheat	Beef	Peas	Mango	Carrots	Sugar cane	Shea butter
Local rice variety 1	Camel	Dried peas	Pineapple	Onion	Sugar	Red palm oil
Local rice variety 2	Sheep	Other legumes	Orange	Garlic	Honey	Peanut oil
Imported aromatic rice	Goat	Dried beans, cowpeas	Banana	Cassava	Caramel, candy, confectionaries	Cottonseed oil
Imported broken grain rice	Offal, tripes	Fresh peanuts in shell	Lemon	Yam	Coffee	Refined palm oil
Maize on cob	Pork	Dried peanuts in shell	Other citrus	Plantain	Tea	Other oils
Maize grain	Free range chicken	Shelled or crushed peanuts	Avocados	Potato	Powdered chocolate	Salt
Millet	Chicken	Roasted peanuts	Melon, watermelon	Sweet potato	Other herbal teas and infusions	Pepper
Sorghum	Other domestic fowl	Peanut butter	Dates	Gari, tapioca	Carbonated beverages	Ginger
Fonio	Game	Sesame	Coconuts	Attieke	Powdered juice	Bouillon cube
Other cereals	Other meat		Other fruits			Aromatics
Maize flour	Fresh fish variety 1		Lettuce			Soumbala
Millet flour	Fresh fish variety 2		Cabbage			Mayonnaise
Wheat flour	Fresh fish variety 3		Green beans			Vinegar, mustard
Other flours	Fresh fish variety 4		Cucumbers			Other condiments
Pasta	Smoked fish variety 1		Eggplant, zucchini, squash			Mineral, filtered water
Modern bread	Smoked fish variety 2		Bell pepper			
Traditional bread	Dried fish		Tomato			
Croissants	Shellfish, other seafood		Dried tomato			
Cookies	Preserved fish		Okra			
Beignets, donuts	Fresh milk		Dried okra			
Cakes	Milk curd, yogurt		Sorrel leaves			
	Sweetened condensed milk		Baobab leaves			
	Evaporated milk		Bean leaves			
	Powdered milk		Local leaves			
	Cheese		Other leafy vegetables			
	Baby formula		Other fresh vegetables			
	Eggs		Tomato paste			
	Butter		Cola nuts			
			Fruit juice			

Source: Authors' design using HSHLS data.

APPENDIX C: PROCESSING LEVEL CLASSIFICATIONS

Table 1.17: Processing Level Classification

Unprocessed		Minimally Processed	Highly Processed
Local rice variety 1	Sugar cane	Maize flour	Pasta
Local rice variety 2	Other fruits	Millet flour	Modern bread
Imported aromatic rice	Lettuce	Wheat flour	Traditional bread
Imported broken grain rice	Cabbage	Other flours	Croissants
Maize on cob	Carrots	Smoked fish variety 1	Cookies
Maize grain	Green beans	Smoked fish variety 2	Cakes
Millet	Cucumbers	Dried fish	Beignets, donuts
Sorghum	Eggplant, zucchini, squash	Preserved fish	Sweetened condensed milk
Wheat	Mango	Fresh milk	Powdered milk
Fonio	Bell pepper	Milk curd, yogurt	Baby formula
Other cereals	Tomato	Evaporated milk	Refined palm oil
Beef	Okra	Cheese	Attieke
Camel	Onion	Butter	Sugar (crystalline)
Sheep	Garlic	Shea butter	Caramel, candy, confectionaries
Goat	Sorrel leaves	Red palm oil	Bouillon cube
Offal, tripes	Baobab leaves	Peanut oil	Soumbala
Pork	Bean leaves	Cottonseed oil	Mayonnaise
Free range chicken	Local leaves	Other oils	Vinegar, mustard
Chicken	Other leafy vegetables	Dried tomato	Other condiments
Other domestic fowl	Other fresh vegetables	Dried okra	Powdered chocolate
Other meat	Peas	Tomato paste	Carbonated beverages
Fresh fish variety 1	Other legumes	Dried peas	Powdered juice
Fresh fish variety 2	Fresh peanuts in shell	Dried beans, cowpeas	
Fresh fish variety 3	Sesame	Dried peanuts in shell	
Fresh fish variety 4	Cassava	Shelled or crushed peanuts	
Shellfish, other seafood	Yam	Roasted peanuts	
Eggs	Plantain	Peanut butter	
Game	Potato	Gari, tapioca	
Pineapple	Sweet potato	Salt	
Orange	Honey	Black Pepper	
Banana	Ginger	Coffee	
Lemon	Aromatics	Tea	
Other citrus	Cola nuts	Other herbal teas and infusions	
Avocados	Mineral, filtered water		
Melon, watermelon			
Dates			
Coconuts			

Source: Authors' design using HSHLS data.

APPENDIX D: STAGE 1 REGRESSION COEFFICIENTS

Table 1.18: Regression Coefficient Table – Stage 1 (Working Leser)

	Rural		Urban	
Variable	**Coefficient**	**Bootstrap SE**	**Coefficient**	**Bootstrap SE**
Age HOH	0.000	0.000	0.000	0.000
Schooling HOH	-0.043***	0.005	-0.038***	0.005
Household size	0.002***	0.001	0.003***	0.001
Survey wave	-0.022***	0.004	-0.011**	0.004
Budget share of own production	0.112***	0.014	0.182***	0.028
Food price index (ln)	0.010	0.010	0.025	0.018
Weekly expenditure (ln FCFA)	0.249***	0.089	-0.047***	0.004
Weekly expenditure squared (ln FCFA)^2	-0.012***	0.004	-	-
Constant	-0.628	0.470	1.038	0.048
Regional controls	Yes		Yes	
n	3,845		2,741	
Bootstrap replications	100		100	
F	67.12		71.98	
Prob > F	0.000		0.000	
R-squared	0.1855		0.2555	
Adjusted R-squared	0.1828		0.2519	

Source: Authors' calculations using HSHLS data.

APPENDIX E: STAGE 2 REGRESSION COEFFICIENTS – FOOD GROUP MODEL

Table 1.19: QUAIDS Parameter Estimates for Food Group Models

	Rural		Urban	
Parameter	**Coefficient**	**Bootstrap SE**	**Coefficient**	**Bootstrap SE**
Alpha				
Cereal products	0.273***	0.020	0.217***	0.039
Animal products	0.343***	0.043	0.366***	0.054
Legumes	0.029***	0.006	0.039***	0.010
Roots & Tubers	0.114***	0.010	0.130***	0.020
Fruits & Vegetables	0.077***	0.013	0.058***	0.015
Sugar & SSBs	0.073***	0.010	0.088***	0.021
Oils, Condiments, Other	0.091***	0.021	0.101***	0.035
Beta				
Cereal products	-0.053**	0.024	-0.054	0.050
Animal products	0.041	0.058	0.090	0.064
Legumes	0.007	0.007	-0.005	0.011
Roots & Tubers	0.005	0.011	-0.031	0.021
Fruits & Vegetables	0.049***	0.019	0.055***	0.016
Sugar & SSBs	-0.042***	0.009	-0.045**	0.020
Oils, Condiments, Other	-0.005	0.016	-0.010	0.031
Gamma				
Cereal # Cereal	0.150***	0.025	0.104***	0.025
Cereal # Animal	-0.135***	0.022	0.001	0.025
Cereal # Legume	-0.035***	0.010	-0.022**	0.010
Cereal # Root/Tuber	0.038**	0.016	0.011	0.014
Cereal # Fruit/Veg.	-0.030**	0.014	-0.052***	0.008
Cereal # Sugar	0.009	0.011	-0.012	0.012
Cereal # Oil	0.003	0.017	-0.030	0.019
Animal # Animal	0.220***	0.044	-0.079*	0.044
Animal # Legume	0.031**	0.015	0.011	0.013
Animal # Root/Tuber	-0.079***	0.020	-0.025	0.019
Animal # Fruit/Veg.	0.009	0.016	0.030***	0.010
Animal # Sugar	0.004	0.013	-0.017	0.018
Animal # Oil	-0.050*	0.026	0.080***	0.025
Legume # Legume	0.003	0.009	-0.001	0.008
Legume # Root/Tuber	-0.012	0.008	-0.004	0.009
Legume # Fruit/Veg.	-0.022***	0.006	0.010***	0.004
Legume # Sugar	-0.001	0.006	0.016**	0.007
Legume # Oil	0.036***	0.008	-0.010	0.009
Root/Tuber # Root/Tuber	0.014	0.015	0.028	0.017
Root/Tuber # Fruit/Veg.	0.004	0.007	0.020***	0.005
Root/Tuber # Sugar	-0.010	0.009	-0.006	0.012
Root/Tuber # Oil	0.044***	0.011	-0.024	0.023
Fruit/Veg. # Fruit/Veg.	-0.013	0.010	0.015**	0.006
Fruit/Veg. # Sugar	0.008	0.006	-0.006	0.004
Fruit/Veg. # Oil	0.044***	0.010	-0.017*	0.009
Sugar # Sugar	0.030**	0.013	0.054***	0.016
Sugar # Oil	-0.040***	0.009	-0.029*	0.015

Source: Authors' calculations using HSHLS data.

Table 1.19 (cont'd).

	Rural		Urban	
Parameter	**Coefficient**	**Bootstrap SE**	**Coefficient**	**Bootstrap SE**
Lambda				
Cereal products	-0.019***	0.005	-0.013	0.014
Animal products	0.019***	0.006	-0.003	0.013
Legumes	0.001	0.003	0.008*	0.005
Roots & Tubers	0.001	0.003	0.001	0.006
Fruits & Vegetables	-0.003	0.003	-0.005	0.007
Sugar & SSBs	0.004	0.004	0.005	0.004
Oils, Condiments, Other	-0.003	0.002	0.007	0.007
Rho				
Survey wave 1	-0.004	0.019	0.005	0.081
Age HOH	0.000	0.001	-0.006*	0.003
Schooling HOH	-0.005	0.030	0.033	0.058
Budget share of own production	-0.097	0.347	-0.886	0.613
Household size	0.000	0.003	0.018	0.022
Eta				
Cereal # Survey wave 1	-0.007	0.010	0.001	0.009
Animal # Survey wave 1	0.004	0.007	-0.016	0.011
Legumes # Survey wave 1	0.009*	0.005	-0.001	0.003
Root/Tuber # Survey wave 1	0.003	0.003	0.012**	0.005
Fruit/Veg. # Survey wave 1	0.003	0.003	0.012*	0.007
Sugar # Survey wave 1	-0.004	0.003	0.006**	0.003
Oil # Survey wave 1	-0.007*	0.004	-0.013**	0.005
Cereal # Age HOH	0.000	0.000	0.000	0.000
Animal # Age HOH	0.000	0.000	0.000	0.000
Legumes # Age HOH	0.000	0.000	0.000	0.000
Root/Tuber # Age HOH	0.000	0.000	0.000	0.000
Fruit/Veg. # Age HOH	0.000	0.000	0.000	0.000
Sugar # Age HOH	0.000	0.000	0.000*	0.000
Oil # Age HOH	0.000	0.000	0.000	0.000
Cereal # Schooling HOH	0.001	0.005	-0.006	0.007
Animal # Schooling HOH	-0.004	0.005	-0.005	0.006
Legumes # Schooling HOH	-0.003	0.003	-0.004*	0.002
Root/Tuber # Schooling HOH	0.001	0.002	-0.007**	0.003
Fruit/Veg. # Schooling HOH	0.001	0.002	0.006	0.005
Sugar # Schooling HOH	0.001	0.002	-0.001	0.002
Oil # Schooling HOH	0.004	0.003	0.017**	0.008
Cereal # Budget share of own production	0.156***	0.046	0.144**	0.069
Animal # Budget share of own production	-0.076**	0.034	0.100	0.091
Legumes # Budget share of own production	0.030***	0.011	0.001	0.025
Root/Tuber # Budget share of own production	-0.041*	0.021	-0.042	0.030
Fruit/Veg. # Budget share of own production	0.005	0.018	-0.041	0.034
Sugar # Budget share of own production	-0.021*	0.011	-0.024	0.016
Oil # Budget share of own production	-0.053**	0.026	-0.138***	0.049
Cereal # Household size	0.002**	0.001	0.004***	0.001
Animal # Household size	-0.001	0.001	-0.002**	0.001
Legumes # Household size	0.000	0.000	-0.001**	0.000
Root/Tuber # Household size	0.000	0.000	0.000	0.000
Fruit/Veg. # Household size	0.000	0.000	0.000	0.001
Sugar # Household size	0.000	0.000	-0.001	0.001
Oil # Household size	0.000	0.000	0.000	0.001

APPENDIX F: CROSS PRICE ELASTICITIES BY FOOD GROUP

Table 1.20: Cross Price Elasticities by Food Group by Rural and Urban Per Capita Expenditure Quartiles

	Rural					Urban				
	Total	Q1	Q2	Q3	Q4	Total	Q1	Q2	Q3	Q4
Cereals										
Cereals	-0.503**	-0.555***	-0.523***	-0.474***	-0.447***	-0.461***	-0.582***	-0.501***	-0.420***	-0.248*
Animal Products	-0.412***	-0.428***	-0.422***	-0.390***	-0.403***	-0.012	-0.023	-0.011	-0.008	-0.006
Legumes	-0.940***	-0.940***	-0.937***	-0.955***	-0.934***	-0.678**	-0.722**	-0.694**	-0.659**	-0.597***
Roots & Tubers	0.549**	0.549**	0.535**	0.560**	0.553**	0.146	0.145	0.140	0.145	0.149
Fruits & Vegetables	-0.300***	-0.299**	-0.299***	-0.313***	-0.297***	-0.398***	-0.502***	-0.421***	-0.384***	-0.339***
Sugar & SSB	0.262	0.255	0.256	0.276	0.257	-0.082	-0.046	-0.070	-0.083	-0.108
Oils, Spices, Other	0.021	0.024	0.017	0.023	0.018	-0.268*	-0.285	-0.273*	-0.257*	-0.243**
Animal Products										
Cereals	-0.437***	-0.431***	-0.436***	-0.449***	-0.441***	0.074	0.031	0.060	0.086	0.137
Animal Products	-0.275	-0.205	-0.237	-0.325**	-0.329**	-1.287***	-1.289***	-1.291***	-1.292***	-1.290***
Legumes	0.695*	0.728*	0.701*	0.690*	0.667*	0.192	0.300	0.223	0.182	0.116
Roots & Tubers	-1.236***	-1.211***	-1.199***	-1.259***	-1.277***	-0.222	-0.201	-0.215	-0.225	-0.238
Fruits & Vegetables	-0.020	-0.013	-0.018	-0.028	-0.023	0.114*	0.160**	0.119*	0.103*	0.091
Sugar & SSB	0.250	0.246	0.244	0.262	0.242	-0.213	-0.153	-0.193	-0.215	-0.258
Oils, Spices, Other	-0.631*	-0.658*	-0.630*	-0.622*	-0.617	0.547***	0.729***	0.579***	0.496***	0.426***
Legumes										
Cereals	-0.111***	-0.106***	-0.109***	-0.117***	-0.117***	-0.091**	-0.080**	-0.087**	-0.096**	-0.116**
Animal Products	0.096**	0.105**	0.101**	0.090**	0.090**	0.036	0.033	0.036	0.037	0.037
Legumes	-0.934***	-0.931***	-0.933***	-0.933***	-0.935***	-1.028***	-1.027***	-1.029***	-1.028***	-1.026***
Roots & Tubers	-0.177	-0.174	-0.172	-0.180	-0.182	-0.036	-0.033	-0.035	-0.036	-0.038
Fruits & Vegetables	-0.185***	-0.189***	-0.186***	-0.189***	-0.181***	0.048**	0.066**	0.051**	0.045**	0.039**
Sugar & SSB	-0.005	-0.004	-0.005	-0.004	-0.007	0.312**	0.271**	0.299**	0.310**	0.330**
Oils, Spices, Other	0.428***	0.446***	0.422***	0.427***	0.416***	-0.076	-0.088	-0.078	-0.071	-0.065

Table 1.20 (cont'd).

	Rural					Urban				
	Total	**Q1**	**Q2**	**Q3**	**Q4**	**Total**	**Q1**	**Q2**	**Q3**	**Q4**
Roots & Tubers										
Cereals	0.125**	0.112**	0.120**	0.133**	0.138***	0.079	0.053	0.071	0.088	0.121
Animal Products	-0.243***	-0.255***	-0.250***	-0.230***	-0.234***	-0.094	-0.097	-0.095	-0.095	-0.094
Legumes	-0.299	-0.301	-0.299	-0.303	-0.294	-0.140	-0.134	-0.140	-0.138	-0.133
Roots & Tubers	-0.800***	-0.801***	-0.805***	-0.796***	-0.796***	-0.704***	-0.717***	-0.715***	-0.703***	-0.692***
Fruits & Vegetables	0.022	0.022	0.021	0.021	0.022	0.087***	0.119***	0.091***	0.080***	0.069***
Sugar & SSB	-0.165	-0.162	-0.162	-0.159	-0.167	-0.053	-0.033	-0.047	-0.055	-0.068
Oils, Spices, Other	0.519***	0.542***	0.512***	0.519***	0.505***	-0.196	-0.223	-0.202	-0.185	-0.171
Fruits & Vegetables										
Cereals	-0.088*	-0.087*	-0.088*	-0.093*	-0.088*	-0.204***	-0.184***	-0.196***	-0.212***	-0.248***
Animal Products	0.027	0.034	0.030	0.025	0.020	0.105***	0.097***	0.106***	0.110***	0.112***
Legumes	-0.566***	-0.572***	-0.566***	-0.573***	-0.558***	0.206**	0.288***	0.229**	0.193**	0.134*
Roots & Tubers	0.053	0.054	0.052	0.055	0.053	0.211***	0.201***	0.203***	0.211***	0.218***
Fruits & Vegetables	-1.120***	-1.123***	-1.121***	-1.124***	-1.117***	-0.926***	-0.904***	-0.923***	-0.930***	-0.936***
Sugar & SSB	0.167	0.169	0.166	0.169	0.160	-0.104	-0.073	-0.094	-0.107	-0.134
Oils, Spices, Other	0.527***	0.550***	0.520***	0.526***	0.513***	-0.147**	-0.163*	-0.150**	-0.140**	-0.133**
Sugars & SSB										
Cereals	0.025	0.017	0.022	0.028	0.032	-0.030	-0.035	-0.031	-0.028	-0.025
Animal Products	0.023	0.029	0.026	0.020	0.019	-0.068	-0.069	-0.068	-0.068	-0.068
Legumes	-0.036	-0.031	-0.035	-0.039	-0.040	0.415**	0.500*	0.439**	0.400**	0.337**
Roots & Tubers	-0.153	-0.149	-0.149	-0.156	-0.160	-0.047	-0.042	-0.045	-0.047	-0.050
Fruits & Vegetables	0.039	0.043	0.040	0.038	0.037	-0.074***	-0.088**	-0.078***	-0.073***	-0.066***
Sugar & SSB	-0.372	-0.379	-0.380	-0.377	-0.377	0.055	-0.087	0.009	0.048	0.118
Oils, Spices, Other	-0.486***	-0.507***	-0.482***	-0.483***	-0.474***	-0.226**	-0.265*	-0.234**	-0.212**	-0.193**
Oils, Spices, Other										
Cereals	0.014	0.008	0.012	0.015	0.020	-0.103	-0.100	-0.101	-0.104	-0.114
Animal Products	-0.154*	-0.160*	-0.158*	-0.145**	-0.150**	0.274***	0.259***	0.277***	0.284***	0.285***
Legumes	0.891***	0.909***	0.893***	0.898***	0.873***	-0.292	-0.304	-0.298	-0.289	-0.269
Roots & Tubers	0.656***	0.651***	0.639***	0.668***	0.670***	-0.224	-0.208	-0.216	-0.226	-0.237
Fruits & Vegetables	0.349***	0.357***	0.350***	0.352***	0.342***	-0.135**	-0.170**	-0.143**	-0.130**	-0.113**
Sugar & SSB	-0.755***	-0.751***	-0.749***	-0.739***	-0.751***	-0.471*	-0.393*	-0.446*	-0.470*	-0.517*
Oils, Spices, Other	-1.448***	-1.468***	-1.444***	-1.447***	-1.435***	-0.806***	-0.736***	-0.794***	-0.826***	-0.853***

Source: Authors' calculation using HSHLS data.

APPENDIX G: STAGE 2 REGRESSION COEFFICIENTS – PROCESSING MODEL

Table 1.21: QUAIDS Parameter Estimates for Processing Level Models

	Rural		Urban	
Parameter	**Coefficient**	**Bootstrap SE**	**Coefficient**	**Bootstrap SE**
Alpha				
Unprocessed	0.520***	0.020	0.669***	0.020
Minimally Processed	0.287***	0.026	0.178***	0.013
Highly Processed	0.193***	0.015	0.154***	0.017
Beta				
Unprocessed	0.003	0.023	-0.126***	0.033
Minimally Processed	-0.020	0.028	0.028	0.018
Highly Processed	0.017	0.026	0.098***	0.022
Gamma				
Unprocessed x Unprocessed	0.203***	0.031	-0.035	0.046
Unprocessed x Minimally Processed	-0.189***	0.029	0.021	0.037
Minimally Processed x Minimally Processed	0.292***	0.037	0.065	0.041
Unprocessed x Highly Processed	-0.014	0.018	0.014	0.032
Minimally Processed x Highly Processed	-0.103***	0.016	-0.086***	0.019
Lambda				
Unprocessed	-0.010	0.013	0.031**	0.013
Minimally Processed	-0.003	0.011	-0.020**	0.008
Highly Processed	0.013***	0.005	-0.011	0.007
Rho				
Survey wave 1	0.056	0.053	-0.001	0.049
Age HOH	-0.003	0.003	-0.002	0.002
Schooling HOH	-0.024	0.031	-0.011	0.048
Budget Share of Own Production	-0.268	0.273	-0.335	0.382
Household size	0.004	0.004	0.021	0.016
Eta				
Unprocessed # Survey wave 1	0.008	0.010	0.029**	0.012
Minimally Processed # Survey wave 1	-0.003	0.004	-0.016*	0.008
Highly Processed # Survey wave 1	-0.005	0.009	-0.014**	
Unprocessed # Age HOH	0.000	0.000	0.000	0.000
Minimally Processed # Age HOH	0.000	0.000	0.001**	0.000
Highly Processed # Age HOH	0.000	0.000	0.000	0.000
Unprocessed # Schooling HOH	0.013	0.008	-0.001	0.007
Minimally Processed # Schooling HOH	-0.013*	0.007	-0.011	0.008
Highly Processed # Schooling HOH	0.001	0.005	0.011**	0.005
Unprocessed # Budget Share of Own Production	0.187***	0.061	0.111	0.067
Minimally Processed # Budget Share Own Production	-0.070**	0.035	0.077	0.092
Highly Processed # Budget Share of Own Production	-0.117***	0.043	-0.187***	0.070
Unprocessed # Household size	0.000	0.001	0.001	0.001
Minimally Processed # Household size	0.000	0.001	-0.001	0.001
Highly Processed # Household size	0.000	0.000	-0.001	0.001

Source: Authors' calculations using HSHLS data.

CHAPTER 2. DETERMINANTS OF PRODUCT CHOICE FOR FOOD MARKET VENDORS IN SENEGAL: THE CASE OF PROCESSED COWPEA

2.1 Introduction

Over the last few decades, urbanization, income growth and the modernization of food systems in Sub-Saharan Africa have driven up the demand for convenient and ready-to-eat foods (Reardon, Liverpool-Tasie, et al. 2021). Food processing and food away from home (FAFH) are rapidly growing parts of the agri-food value chains in developing economies that help meet this demand. Food processing refers to the transformation of food products from their original state as raw ingredients, such as milling grain to make flour (Albuquerque et al. 2022). FAFH refers to food that is prepared outside of the home and ready-to-eat at the time of purchase, though it may be taken home and consumed there (Farfan et al., 2015). There is some overlap between food processing and FAFH, as many FAFH vendors make and sell processed food products. Students and commuters often stop to get breakfast, lunch, or snacks from FAFH vendors on their way to or from their destination (Reardon, Tschirley et al. 2021). Changes in tastes and preferences also contribute to the shift towards more processed food and FAFH (Staatz & Hollinger, 2016). The rising opportunity cost of time (Reardon, Tschirley et al. 2021) and high fuel prices (Steyn et al., 2013) make these prepared foods relatively affordable, even for low-income urban workers (Mwangi et al., 2001; Staatz and Hollinger, 2016). Though processed food and FAFH comprise a larger portion of the food budget for urban households, their place in the food budget of rural households is still substantial, supporting prior evidence found in Chapter 1 of this dissertation and Sauer et al. (2021).

Processed food is categorized into different levels based on the degree of transformation of the food products from their original state. Following the categorization in Reardon, Liverpool-Tasie et al. (2021), first stage processing encompasses changes made to the raw ingredients such as removing the husk from cereals or milling grain into flour. These foods are considered minimally processed. Second stage processing results in highly processed foods made of multiple ingredients such as bread, or akara, which are small cowpea doughnuts. Additionally, it is important to distinguish between the different types of entities that process and sell processed foods. The agri-food processing sector broadly encompasses manufacturers of processed food products. This ranges from large factories that process and package food, selling their products to wholesalers or retailers for distribution, down to market vendors, who prepare ready-to-eat food and sell it directly to the consumer. In many Sub-Saharan nations, micro, small, and medium sized enterprises dominate the agri-food processing industry (Owoo & Lambon-Quayefio, 2018; Reardon, Liverpool-Tasie et al. 2021). Though researchers broadly understand that there are a variety of actors in this space, previous work on food market environments has largely focused on higher income countries and has not sufficiently paid attention to the different vendor typologies that are seen in low- and middle-income countries (Toure et al. 2021).

The agri-food processing sector is not just important for meeting the growing demand of consumers. The food processing, food marketing, and FAFH segments of the food economy are also major sources of employment, particularly for women. In West Africa, the FAFH sector accounts for about 10% of non-farm employment of the food sector, and 88% of FAFH employees are women (Allen et al. 2018). The proportion of women involved in the FAFH in rural areas is even higher (Allen et al. 2018). Many of these women are self-employed, resource constrained, have low levels of education, and their businesses are informal (Otoo et al. 2011; Otoo et al., 2012; Owoo & Lambon-Quayefio, 2018; Kpossilande et al., 2020). These women resort to food processing and preparation of FAFH to generate income for themselves and their families using their existing skills, which are often traditional domestic skills like cooking (Awusabo-Asare & Tanle, 2008; Boateng, 2017; Kpossilande et al., 2020). It is also fairly common for these women to rely on unpaid family labor (Awusabo-Asare & Tanle, 2008; Posner, 1983).

Some researchers argue small, informal economic activities should not be referred to as "enterprises" since they are focused on self-employment and income generation as opposed to profit maximization and growth (Sethuraman, 1981, p.189). Recent evidence from Ghana suggests that women who process palm kernel oil earn very little, with the highest earners making approximately the national minimum wage, which renders them unable to expand their business and vulnerable to external economic shocks (Awusabo-Asare & Tanle, 2008), indicating modern food processors activities may fall into this category that some have argued does not constitute an enterprise. Modern food processors activities may fall into this category that some would argue does not constitute an enterprise. Other researchers, however, contend that these operations are indeed microenterprises. They argue that the informal economy has been central to the overall economy in West Africa for centuries and informal enterprises are generally more adaptable in the face of uncertainty and unstable or inefficient governance (Boateng, 2017). In a study of cowpea street food vendors in Niger and Ghana, Otoo et al. (2011) found that many women made substantially more than the minimum wage, and that their businesses had withstood the test of time as they have been in operation for several years. Tinker (1999) argued that an enterprise's success should not be narrowly defined by their growth, as utilizing earned income for other expenses, such as funding a child's education, should be seen as success. In several instances, the resource constraints faced by women have prevented them from expanding and formalizing their businesses (Awusabo-Asare and Tanle, 2008; Boateng, 2017; Otoo et al., 2012).

Though street and market food vendors generally fall into this category of small-scale, informal, and under resourced operations, they have garnered increasing attention from researchers over the past few years. This is largely due to their rapid proliferation (Reardon, Tschirley et al., 2021). The precise definition of street food vendors differs somewhat between studies, however, these definitions broadly include traders that sell ready-to-eat foods and beverages that may or may not be processed, may or may not be prepared by the vendor directly, and are sold on the street or in open areas from mobile kiosks, stationary stalls, pushcarts, or other structures that are nonpermanent (Steyn et al., 2013). In this study, we focus on vendors who prepare and sell processed food items in open-air markets. We refer to them as processed food market vendors or FAFH market vendors.

West Africans, even those from rural farming households, are heavily dependent on food markets for food procurement (see Chapter 1 and Staatz & Hollinger, 2016; Smale et al., 2020). For those working in a market, the marketplace may provide a steady source of customers as both shoppers and other marketplace vendors may patronize these businesses. Shoppers may choose to purchase ready-to-eat foods from market vendors to eat while they complete their errands, or they may buy enough to feed their family and take it home with them once they've completed their shopping. Other vendors can purchase snacks and meals from these processed food market vendors. Additionally, food market vendors may obtain some of their inputs from other vendors within their marketplace, either conveniently purchasing small quantities in the morning, or potentially by making arrangements with the input vendors to pay for the inputs at the end of the day, once they've sold their prepared food products. Intra-market short-term credit of this nature has been documented, particularly between wholesalers and retailers of perishable products (Clark, 1994 p.160).

Previous research has looked at the types of products sold by street food vendors and found that these vendors often sell traditional dishes, or adaptations on traditional dishes (Mahopo et al., 2022; Reardon, Tschirley et al., 2021; Steyn et al., 2013). Additional research has looked at consumption of street foods and their nutritional value and have found that many street food products are calorie-dense and in other West African nations, including Mali and Nigeria, street food is a part of the daily diet and makes up a substantial portion (18-50%) of the energy intake of adults (Bouafou et al., 2021; Namugumya & Muyanja, 2012; Oguntona et al., 1998; Steyn et al., 2013). There is a growing strand of literature related to the lack of regulation of street food vendors and food safety concerns related to bacterial contamination and food-borne illness outbreaks (Alimi, 2016; Bouafou et al., 2021; Cudjoe et al., 2022; Okojie & Isah, 2019). A few studies have examined the financial performance of street food vendors in Benin (Kpossilande et al., 2020), Niger, and Ghana (Otoo et al., 2011; Otoo et al., 2012). Although some studies have looked at the characteristics of street food vendors descriptively, the only studies we were able to locate that have looked at factors related to the decisions made by these vendors focus on the level of formality of the enterprise (Ashaley-Nikoi & Abbey, 2023) and food safety practices (Usman et al., 2023).

This study contributes to the food market environment literature by exploring the factors that contribute to vendors' decisions related to the choice of products they process and sell as well as the quantity they choose to prepare on an average day. This is an area of vendor decision making that is currently unexplored, but it is important for many reasons. Understanding the factors that are associated with the sale of certain types of products may help policymakers who want to support production of these products to make more effective, targeted policy interventions. In this study, we focus on second stage processed cowpea products. Cowpea is a locally produced grain that is high in protein- it has been previous called "poor man's meat" (Otoo et al. 2011). Processed cowpea products are convenient and affordable and can provide essential nutrients to consumers.

We also contribute to the literature by providing a description of the processed food market vendors in open-air markets of Senegal. Existing characterization of the broader class of street food vendors in West Africa have mostly focused on vendors in major urban areas- either in individual cities or across a small number of cities within a country (Kpossilande et al., 2020;

Otoo et al., 2011; Otoo et al., 2012). Our study is unique, as we characterize processed food market vendors across the whole country, in both rural and urban markets.

Senegal is a unique setting for our study as there are very few studies that have looked at the street food sector or processed FAFH in general in Senegal. In 1983, a study was done to describe street food vendors in the city of Ziguinchor, which is located in the region of the same name in southern Senegal (Cohen, 1984; Posner, 1983). Though this study provided novel insights on street food vendors in this area, the findings are nearly 40 years old, and as previously discussed, the street food sector has grown immensely over the past few decades. Additionally, Ziguinchor is in the Casamance region of Senegal, which is notable because this region is separated from the northern portion of the country by the Gambia. In order to travel from Ziguinchor to regions outside of the Casamance, one would have to cross through another country (the Gambia) or go all the way around it. In the 1980's the Casamance region was growing significantly slower than the rest of Senegal, largely due to the poor transportation linkages (Cohen, 1984). For these reasons, the updated characterization of the processed food market vendors in this study provides information on a group of economic players that have received little attention in the literature, contributing to the broader understanding of market food environments and vendor typologies in low- and middle-income countries, a knowledge gap highlighted in Toure et al. (2021).

In order to examine the factors that contribute to FAFH market vendors choice to make and sell processed cowpea products, and the amount of cowpea they choose to process in an average day, we employ a double hurdle model. The first hurdle examines the factors that are associated with processing cowpea products. As women have historically dominated artisanal food processing and FAFH sectors in West Africa (Allen et al. 2018; Otoo et al., 2011), we expect that most of the FAFH vendors in the markets will be women. Previous research has found that the processed FAFH products that are commonly sold by men tend to be less labor-intensive products, such as grilled meat (Cohen, 1984). Given that that cowpea processed products can be labor intensive (Cohen, 1984; Gomez, 2004), we expect that fewer men will include cowpea in their portfolio of processed products. In Mali, Smale et al. (2022) and Sissoko et al. (2024) find that women are key players in the processing and marketing of cowpea and cowpea products. The labor intensity of cowpea processing also leads us to believe that vendors who employ family or hired labor may be more likely to process cowpea.

In the second hurdle, we examine the factors that are associated with processing a higher value of cowpea each week. We expect that location variables, such as being in an urban market or being in the densely populated capital region, will lead sellers to process more cowpea each day. We hypothesize that vendors who received financial assistance at startup may have been able to grow their business more quickly, therefore they may process more cowpea. We also believe those who employ family or hired labor may be able to process more each day due to the additional labor availability. Years of experience may also have a positive impact on the amount of cowpea a vendor processes, for many reasons such as the development of a loyal client base or an increase in processing efficiency. Vendors who operate out of physical structures such as storefronts or sheds within the marketplace may also have larger processing capacities and therefore may process more cowpea.

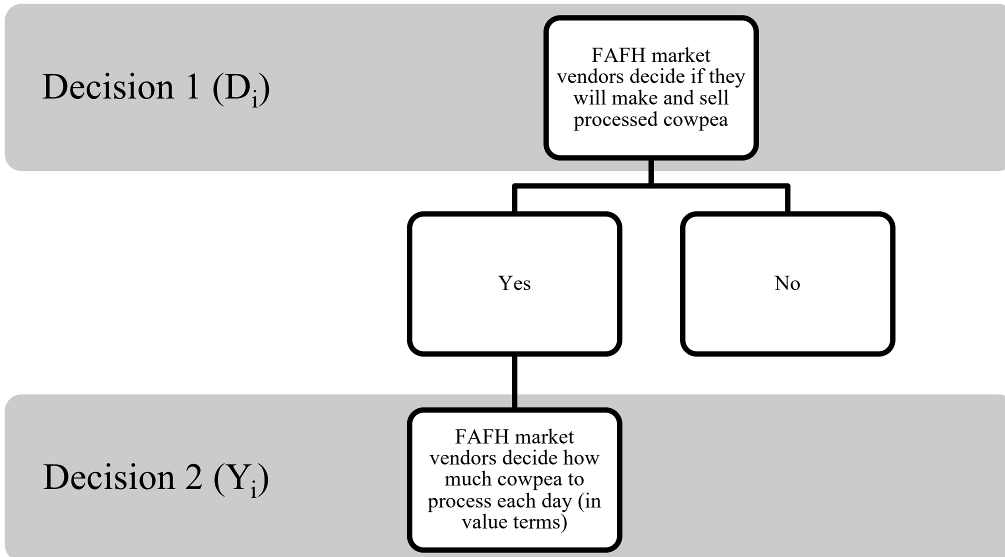
After estimating our hurdles, we compare key characteristics of the vendors with the highest and lowest predicted probability of processing cowpea to better understand how best to support different groups of vendors through interventions that could boost the production and sale of processed cowpea.

2.2 Conceptual Model

In this study, we are looking at FAFH market vendors' decision to make and sell processed cowpea products, as well as their choice of how much cowpea to process each week. The first decision represents a vendor's choice to participate in the processed cowpea market. The second decision represents their intensity of participation. Figure 2.1 shows a decision tree that represents our choice model. We assume that FAFH market vendors make the binary participation decision and intensity of participation decision that maximize their utility.

FAFH market vendor *i's* utility from participating in the processed cowpea market is a function of their binary participation decision D_i, and participation level Y_i, represented by $U_i = f(D_i, Y_i)$. The vendor chooses the values of D_i and Y_i that maximize their expected utility. Vendor *i* will only choose to process cowpea if their expected utility from processing cowpea exceeds 0. Though these choices- participation and intensity of participation- are related, they are not necessarily simultaneous therefore different characteristics may influence each decision. Each choice is a function of regional characteristics $\boldsymbol{r}$, sociodemographic characteristics $\boldsymbol{z}$, market characteristics $\boldsymbol{m}$, business characteristics $\boldsymbol{b}$, and product characteristics $\boldsymbol{p}$, represented as $D_i = d(\boldsymbol{r}_{1i}, \boldsymbol{z}_{1i}, \boldsymbol{m}_{1i}, \boldsymbol{b}_{1i}, \boldsymbol{p}_{1i})$ and $Y_i = y(\boldsymbol{r}_{2i}, \boldsymbol{z}_{2i}, \boldsymbol{m}_{2i}, \boldsymbol{b}_{2i}, \boldsymbol{p}_{2i})$ where the characteristics included in the vectors $\boldsymbol{r_1}$, $\boldsymbol{z_1}$, $\boldsymbol{m_1}$, $\boldsymbol{b_1}$, and $\boldsymbol{p_1}$ may differ from the characteristics included in $\boldsymbol{r_2}$, $\boldsymbol{z_2}$, $\boldsymbol{m_2}$, $\boldsymbol{b_2}$, and $\boldsymbol{p_2}$.

Figure 2.1: Processor's Decision Tree



Source: Produced by authors.

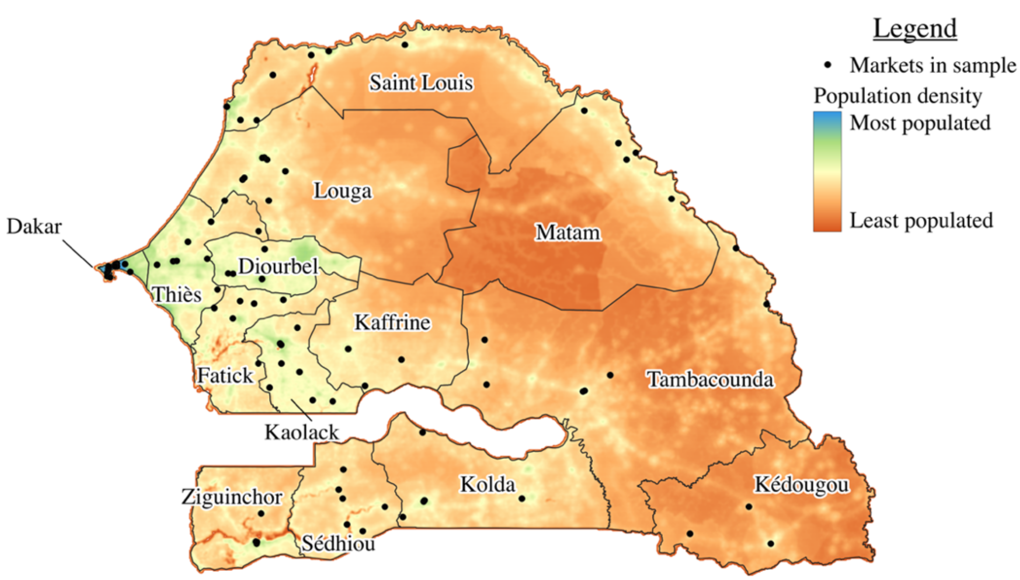
2.3 Data

We utilize a unique nationally representative survey dataset that was collected by the market information system of the Commissariat a la Securite Alimentaire, Universite de Thies and Michigan State University. The targeted population was cowpea grain and cowpea processed vendors in open-air markets of Senegal. A multi-stage stratified cluster design was used to randomly sample 1000 vendors in open-air markets in Senegal. The 14 regions of Senegal were the first-level stratification. The second level of stratification was the level of attendance in the market. The number of selected markets in each region was determined based on their relative population weights. To calculate these population weights, markets were subjectively classified as low, medium, or high attendance by the market information system to capture relative importance of market activities and assigned a corresponding attendance value (low=1, medium=2, high=3). The population weight of region *j* is the ratio of the sum of all attendance values of markets in region *j* to the sum of the attendance values of all markets in the country. The number of markets selected in each region was 100 x *Pj* where *Pj* is the population weight for region *j*, resulting in a sample spanning 100 of the 583 markets identified by the market information system in Senegal. The selection probability of markets with attendance below a certain threshold was set to zero, then markets were randomly selected within each region. Each selected market is considered a cluster of traders. See Diagne et al. (2020) for a detailed description of the sampling strategy.

Figure 2.2 depicts the 14 regions of Senegal with each dot representing one of the markets that was selected through the sampling procedure. Additionally, the population density is represented by the colored gradient with blue areas being the most densely populated and orange areas being the least densely populated. The capital region of Dakar located along the western coast of Senegal is the most densely populated part of the country. A fourth of the entire country's population lives in this region which comprises only 0.3% of the country's land (World Bank, 2024). Fatick, Diourbel, Thies and Louga, the regions surrounding Dakar, are the major cowpea producing regions in Senegal. Together, they produce 92% of the country's cowpea with Louga alone producing 66% (Diagne et al., 2020).

Within each of the 100 markets in the sample, the survey was designed to randomly collect responses from 3 cowpea grain traders, 2 non-cowpea grain traders, 3 cowpea processor-vendors, and 2 non-cowpea processor vendors, for a total anticipated sample size of 1000 market traders.

Figure 2.2: Map of Markets Sampled



Source: Produced by the authors in QGIS using geoBoundaries data (Runfola et al., 2020) for regional borders, WorldPop (2020) data for population density, and market GPS coordinates.

Survey enumeration began near the end of the hot season in May 2021 and ended at the start of the rainy season in June 2021. Fewer food processor vendors were in the markets in May, which coincided with the tail end of Ramadan, a holy month in the Islamic faith in which fasting is observed from dawn to dusk each day. As such, demand for ready-to-eat meals and snacks during the main operating hours of the markets was likely lower. At the end, the number of food processor vendors interviewed was around 80% of the planned sample size. It is worth noting that some markets had less than five food processor vendors. This indicates that some FAFH market vendors may face little competition within their marketplace and/or may face lower demand. The number of FAFH market vendors in some rural markets was especially low. Future research could investigate the heterogeneity in the concentration and competition of food processor vendors in different areas of Senegal, which could reveal important insights into the development of the processed FAFH sector. Appendix A provides information on the number of markets sampled in each region.

After cleaning the data and removing observations with key missing values, and extreme outliers[1], the number of food processor vendors is 339 located across 84 open-air markets in Senegal. Looking at the breakdown of processors in the sample by gender, we find there are only 19 men and only 5 of these men process cowpea. This is aligned with previous studies (Allen et al., 2018; Otoo et al., 2011) that women dominate the industry. Based on this finding, we focus the analysis to women processor-vendors only. Theoretically, modeling women food processors independently is justifiable because we expect potential heterogeneity in the impact of certain factors on men and women's decision-making processes. Statistically, the decision to exclude men is supported since the women-only model is a better fit than the model with the pooled sample of men and women (Appendix B). The final sample used for the analysis includes 320 FAFH market vendors across 82 markets. Out of 320, 203 of these vendors make and sell processed cowpea products. This final sample excludes the region of Ziguinchor, as there is only one-woman processor in this region in our data.

The dataset contains information on trading activities in the current period, as well as recall data on trading activities for each season in the previous year. The analysis is restricted to the 2020-2021 data. We average trading activity across the three seasons: hot, cold, and rainy.

[1] We exclude the six observations we determine to be outliers by calculating the z-score of the value of cowpea processed per week and set the cut off at $z > 3$.

The hot season spans from February to May, followed by the rainy season from June to September, and finally the cold season from October to January. The cold season is also the post-harvest commercialization season when grains stocks are the highest.

The Senegalese Market Information System (SIM) classifies markets within Senegal into 4 primary categories: rural collection markets, rural consumption markets, urban markets, and border markets, noting that the rural market types typically operate on a weekly basis, whereas most urban markets are open every day (SIM/CSA, n.d.). We classify markets open daily as permanent markets and those open weekly as non-permanent markets for the purpose of this analysis.

We also use data from the market information system (SIM/CSA, 2022) on cowpea prices in major grain markets across the country. The SIM/CSA dataset tracks the price of 1 kg of cowpea (and other staple crops) at various times throughout the year and across multiple open-air markets, including a few of those that were randomly selected into our sample. We include all price observations collected between June 1, 2020, and May 31, 2021. Prices derived from the SIM/CSA data are at the market level when available, or at the departmental or regional average if the market level price is unavailable. The prices were first averaged seasonally, as there are inconsistent numbers of observations for each market in each season. Then, we averaged across all seasons with data for each market. We also incorporate data from WorldPop (2020) on the population density (people/km^2) at the GPS coordinates nearest to the GPS coordinates for each market in our sample. Once we match the nearest coordinates, the measure of population density for each market is no more than 0.65 km away from the market itself.

2.4 Estimation Strategy

In addition to providing a characterization of the vendors, this study employs a double hurdle model to examine the factors that affect the decisions of FAFH market vendors to participation in cowpea processing and intensity of participation. There are several reasons why this model is the best choice to represent these vendors decisions. In the first decision, the vendors make a binary choice to participate in cowpea processing or not. Those who do not process cowpea are considered zero-types. The double hurdle model accommodates two different categories of zero-type vendors: (1) those who will always be zeros under any circumstances and (2) those vendors that are zeros based on their current circumstances but may choose to participate under different circumstances (Engel & Moffat, 2014). Additionally, the double hurdle model is unique because it does not assume that the participation and intensity decisions are made simultaneously, and thus it allows different factors to contribute to the participation decision and the intensity of participation decision. Overall, this model provides a more flexible framework than single tier models for corner solution variables, such as the Tobit model (Tobin, 1958).

Following Wooldridge (2001, p. 536-538), if y is the value of cowpea processed and **x** are the independent variables in each hurdle, the first and second hurdles can be defined as equations (1) and (2) respectively where equation (1) defines the probability that a vendor process cowpea and equation (2) imposes a lognormal distribution on $y \mid \boldsymbol{x}$ for $y > 0$.

$$P(y = 0 \mid x) = 1 - \Phi(\boldsymbol{x\gamma}) \tag{1}$$

$$\log(y) \mid (\boldsymbol{x}, y > 0) \sim Normal(\boldsymbol{x\beta}, \sigma^2) \tag{2}$$

The density for $y \geq 0$ is defined in equation 3.

$$f(y|\boldsymbol{x};\boldsymbol{\theta}) = [1 - \Phi(\boldsymbol{x\gamma})]^{1[y=0]} \left\{ \frac{\Phi(\boldsymbol{x\gamma})\phi\left[\frac{\{\log(y) - \boldsymbol{x\beta}\}}{\sigma}\right]}{y\sigma} \right\}^{1[y>0]} \tag{3}$$

The log likelihood for vendor i is defined in equation 4.

$$\ell_i = 1[y_i = 0] \log[1 - \Phi(\boldsymbol{x\gamma})] + \tag{4}$$

$$1[y_i > 0] \left\{ \log\Phi(\boldsymbol{x_i\gamma}) - \log(y_i) - \frac{\log(\sigma^2)}{2} - \frac{\log(2\pi)}{2} - \frac{[\log(y_i) - \boldsymbol{x_i\beta}]^2}{2\sigma^2} \right\}$$

The Maximum Likelihood Estimate (MLE) for $\boldsymbol{\gamma}$ is the probit estimate for whether or not a vendor processed cowpea. The MLE of $\boldsymbol{\beta}$ is the Ordinary Least Squares (OLS) estimate obtained from regressing the natural log of the value processed [*log(y)*] on $\boldsymbol{x}$ for those processors who do process cowpea. We can then define the conditional and unconditional estimated value of cowpea processed as in equations (5) and (6) respectively.

$$E(y|\boldsymbol{x}, y > 0) = e^{\left(\boldsymbol{x\beta} + \frac{\sigma^2}{2}\right)} \tag{5}$$

$$E(y|\boldsymbol{x}) = \Phi(\boldsymbol{x\gamma})e^{\left(\boldsymbol{x\beta}+\frac{\sigma^2}{2}\right)} \tag{6}$$

To account for the potential correlation between the error terms of the first and second hurdle, we estimate a version of the model where the Inverse Mills Ratio (IMR) is included as an added explanatory variable that impacts the second hurdle, treating it like an omitted variable following Heckman (1979). To do this, we first fit the model assuming no correlation between the errors, then we generate the IMR of the first component, and finally we re-estimate the model including the IMR as an explanatory variable for the second component. We use bootstrapping to account for the regional stratification and market clustering in the estimation of all parameters, as well as the Average Partial Effects (APEs).

The lognormal hurdle model above was introduced by Cragg (1971), who also proposed a truncated normal version of the model. We run the truncated normal double hurdle model and employ Vuong's test (1989) to compare the two non-nested models as suggested by Wooldridge (2001, p. 537). We find that the lognormal model is a better fit (Appendix C). For an additional robustness check, we run a Tobit model, which is nested in the truncated normal double hurdle model and using a likelihood ratio test we find it is not a better fit (Appendix C).

The variables included in our model are grouped into regional characteristics, sociodemographic characteristics, market characteristics, business characteristics, and product characteristics. We hypothesize that there are differences in the factors that contribute to the decision to participate in cowpea processing and the intensity of participation decision, therefore the set of independent variables selected for the first hurdle is not identical to the set of independent variables selected for the second hurdle. The variable definitions and related summary statistics are in Table 2.1.

We choose to include regional characteristics in our model, as we do not have sufficient observations to control for each region individually with regional dummies. In Kaffrine, all sampled vendors make and sell processed cowpea products, so being a vendor in these regions perfectly predicts the participation decision. We consider a variety of regional characteristics but ultimately choose to include a dummy variable for Dakar, the capital region, and a dummy variable for Louga, the region that produces nearly two-thirds of the country's cowpea (Diagne et al., 2020). These variables are consistent in both hurdles of our model. We predict that in comparison to the rest of the country, FAFH market vendors in the major cowpea producing region of Louga will be more likely to process cowpea and will process more cowpea since we would expect the supply of cowpea to be higher and the price of cowpea as an input to be lower. We also expect vendors in Dakar to process more cowpea than vendors in other regions since Dakar is very urban and has a much higher population density than other areas of Senegal (Africapolis, 2015).

In the first hurdle, the market characteristics include a dummy indicating if the market is monitored by the SIM/CSA, a dummy for rural markets, the market price of one kilogram of cowpea grain, the weekly market tax rate, and the number of different categories of cowpea products sold in the market.

We include the rural market dummy because we hypothesize that rural FAFH market vendors are more likely to process cowpea. We include the dummy for whether a market is monitored by the SIM/CSA, because this organization monitors major grain markets, which may be more well-established markets, and may have more supply of cowpea available for purchase. We contemplate the inclusion of population density, as we expect processing cowpea to be more popular in areas with higher population density, but the population density variable is very highly correlated with the indicator variable for Dakar ($\rho = 0.885$). We include the price of cowpea grain as high input prices may make cowpea processing less attractive. Market tax rates are incorporated into the model due to their potential role in deterring vendors facing resource constraints, as higher taxes may act as barriers to entry. This also helps account for potential differences in the formality of a market. The number of different categories of cowpea products sold in the market is included as well. The categories of cowpea include: (1) fodder, (2) fresh leaves, (3) dried leaves, (4) pods, (5) beignets, (6) flour, and (7) ndambe. We would expect that a wider variety of cowpea products in a market may indicate higher demand for cowpea.

The sociodemographic characteristics include a dummy if the vendor attended any school, a dummy if the vendor is married, the number of children the vendor has, and a dummy if the vendor participates in a secondary activity. The most commonly reported secondary activities are agriculture and domestic labor. Previous researchers have found that processors are often less educated and with families (Kpossilande et al., 2020; Otoo et al., 2011; Otoo et al., 2012).

We include a wide variety of business characteristics to account for various sources of labor, seasonality, tenure, and formality of the business. The labor related variables include a dummy if the vendor has employees working for them in their business, the number of hours per week the vendor is present in the market, and the number of family labor hours. In relation to the formality of the business, we include a dummy indicating if the vendor received any financial assistance when starting their business and a dummy indicating if the vendor operates out of a physical structure such as a storefront or shed. To account for seasonality of the business, we include a dummy if the vendor operates their business in all three seasons. As a measure of tenure, we include the natural log of the number of years the vendor has been operating in the market in the first hurdle. This variable is excluded from the second hurdle as we do not expect the number of years a vendor has been selling in the current market to influence the quantity of processed cowpea product sold. We hypothesize that the vendors who receive assistance from their family or employees are more likely to process cowpea due to the labor intensity of cowpea processing (Cohen, 1984; Gomez, 2004). We include the dummy for financial assistance at startup as previous research has found that lack of financial capital is a limiting factor in informal street vending businesses (Otoo et al., 2011; Posner, 1983). The dummy for financial assistance includes all types of financial assistance such as loans from a bank or from family members. We include the dummy for vendors selling out of a physical structure as researchers in Benin found that many akara processors operate out of physical structures like storefronts, but more commonly, they work in makeshift structures using umbrellas, sheets, or trees for shade (Kpossilande et al., 2020).

We also include variables related to the characteristics of the products the vendor makes and sells. In the first hurdle, we include a dummy if the vendor also sells any unprocessed food items, as well as a dummy if the vendor specialized in making and selling only one processed food item. In Nigeria, there are a mix of cowpea processors that specialize in only akara (i.e., beignets) and those that sell multiple products (Otoo et al., 2012). We also include dummies for making beignets, ready-to-eat meals, or other processed foods. The types of products vendors prepare influence the types of inputs they need to process to make their products. The beignets category includes akara, a popular cowpea fritter. The ready-to-eat meals category includes ndambe, a popular Senegalese stew made with cowpea that may be served on bread. The other processed foods category includes other snacks or processed foods that do not fall under the previous two categories, such as sauces, jams, and other FAFH processed products.

In the second hurdle, the regional, market, and product portfolio characteristics are the same as in the first hurdle. We drop the dummy for being married and the number of children from the list of explanatory variables in the second stage as we hypothesize their primary impact on FAFH market vendors is through their choices to enter the processed food market and the decision to process cowpea. We add four dummy variables to the business characteristics vector in the second hurdle to account for the cowpea supply sources of FAFH market vendors, which likely impact the quantity they process. We include dummies for (1) acquiring cowpea from the market the vendor is selling in, (2) acquiring cowpea from a vendor's own production or production by someone else in their household, (3) acquiring cowpea from an urban market, and (4) acquiring cowpea from a vendor's own village or another village. A vendor may acquire cowpea from any number or these sources.

2.5 Results

2.5.1 Characteristics of food processor vendors

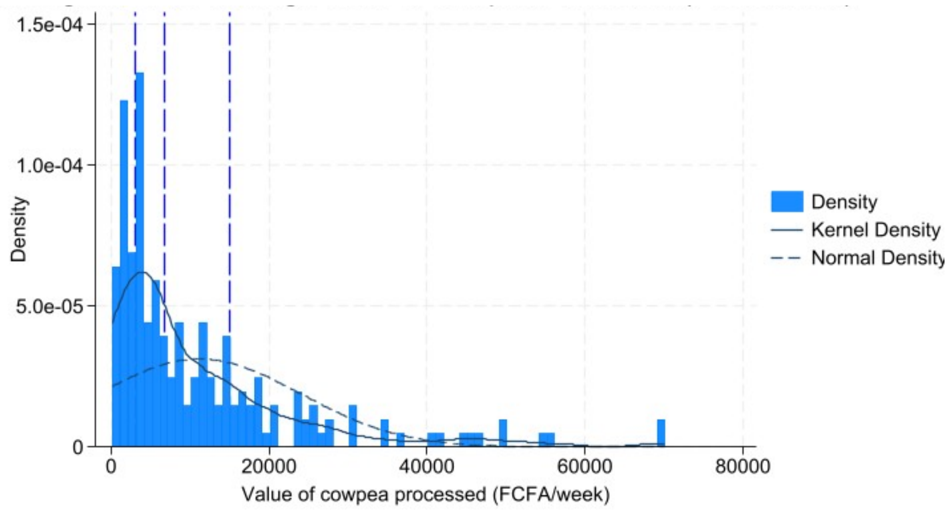
In Tables 2.1 through 2.3, we present descriptive statistics for FAFH market vendors in Senegal and the markets in which they operate. The statistics are presented by tier where we set the cut offs between tiers at the 25th, 50th, and 75th percentile of the value of cowpea processed Tier 0 includes all vendors who do not process cowpea (117 processors). Tier 1 includes all vendors who process less than 3,000 FCFA of cowpea per week (49 vendors). Tier 2 includes all vendors who process between 3,000 to 6,700 FCFA per week (52 vendors). Tier 3 includes vendors processing 6,700 to 15,000 FCFA of cowpea per week (48 vendors). Finally, Tier 4 includes the remaining vendors who process more than 15,000 FCFA per week (54 vendors). Figure 2.3 depicts a histogram of the average value of cowpea processed per week by cowpea processors with vertical reference lines delineating the 25th, 50th, and 75th percentile. In the discussion of our results, we will often refer to the vendors in tier 1 as small-scale cowpea processor-vendors, the vendors in tier 2 as medium-scale cowpea processor-vendors, and the vendors in tier 3 as large-scale cowpea processor-vendors. Note that this only describes the relative size of the cowpea processing (as an input) function of their business and not the production and sale of any other processed or unprocessed items.

Table 2.1: Variable Definitions and Summary Statistics

Variable	Definition	Mean	SD	Min	Max
Market Characteristics					
Dakar	=1 if the vendor is located in Dakar; =0 otherwise	0.097	0.296	0	1
Louga	=1 if the vendor is located in Louga; =0 otherwise	0.066	0.248	0	1
Market monitored by SIM	=1 if the market is monitored by the Senegalese Information System; =0 otherwise	0.575	0.495	0	1
Rural market	=1 if the market is rural; =0 otherwise	0.525	0.500	0	1
Number of categories of cowpea products sold	Number of different categories of cowpea products sold within the market (grain, leaves, fodder, etc.)	2.488	1.264	0	7
Price of cowpea (FCFA/kg)	Price of cowpea in the market (FCFA/kg), departmental or regional price substituted when market price not available (data from SIM/CSA, 2022)	547	154	261	859
Business Characteristics					
Operates in physical structure	=1 if the vendor if vendor operates in a physical structure (hangar, shed, storefront); =0 otherwise	0.388	0.488	0	1
Has employees (non-family labor)	=1 if the vendor uses non-family labor; =0 otherwise	0.091	0.288	0	1
Vendor received financial aid at startup	=1 if the vendor received any funding at startup; =0 otherwise	0.241	0.428	0	1
Vendor sources some cowpea supply from this market*	=1 if the vendor's closes cowpea source is within the market; =0 otherwise	0.484	0.501	0	1
Vendor sources some cowpea supply from home production*	=1 if the vendor processes any cowpea from own agricultural production; =0 otherwise	0.038	0.190	0	1
Vendor sources some cowpea supply from villages*	=1 if the vendor sources cowpea from villages; =0 otherwise	0.131	0.338	0	1
Vendor sources some cowpea supply from urban areas*	=1 if the vendor sources cowpea from urban areas; = 0 otherwise	0.400	0.491	0	1
Sells in all seasons	=1 if the vendor is present in this market in all seasons; =0 otherwise	0.844	0.364	0	1
Market tax rate paid by vendor (FCFA/week)	Value of tax paid by the vendor to the marketplace (FCFA/week)	465	551	0	4153
Family labor hours	Hours per week of family labor used	14.3	36.1	0	280
Number of years the seller has been in this market	Number of years the vendor has been selling in this market	10.7	8.0	1	50
Hours per week in this market	Hours per week the vendor operates in this market	36.9	24.9	2	114
Vendor Sociodemographic Characteristics					
Attended some school	=1 if the vendor has attended any school; =0 otherwise	0.547	0.499	0	1
Has secondary occupation	=1 if the vendor engages in another income generating activity; =0 otherwise	0.463	0.499	0	1
Married	=1 if the vendor is married; =0 otherwise	0.666	0.473	0	1
Number of children	The vendor's number of children	2.925	2.334	0	10
Product Portfolio Characteristics					
Sale of unprocessed food during the year	=1 if the vendor sells any unprocessed food items during any season; =0 otherwise	0.091	0.288	0	1
Specialize in 1 processed product	=1 if the vendor specializes in one type of processed product; =0 otherwise	0.403	0.491	0	1
Make and sell beignets	=1 if the vendor makes and sells beignets (akara); =0 otherwise	0.447	0.498	0	1
Make and sell ready-to-eat meals	=1 if the vendor makes and sells ready to eat meals; =0 otherwise	0.631	0.483	0	1
Make and sell other processed foods	=1 if the vendor makes and sells other types of processed foods; =0 otherwise	0.678	0.468	0	1
n					320

*Source: Authors' calculations. * indicates the variable is only in the second hurdle.*

Figure 2.3: Histogram of the Average Value of Cowpea Processed (FCFA/Week)



Source: Authors' calculations.

In Table 2.2, we examine characteristics of the regions and markets the FAFH market vendors operate in. We find that 48.7% of non-cowpea processing FAFH market vendors are located in rural markets. The small-scale cowpea processing FAFH market vendors in our sample are most commonly located in rural markets (67.3%) followed by the large-scale cowpea processors (61.1%). Half (50%) of the tier 2 processors and only 39.6% of the tier 3 processors are located in rural markets. Of the cowpea processor-vendors, those who process less cowpea per week are less frequently located in markets monitored by the SIM, whereas those that process more are more often located in markets that are monitored by the SIM. Similarly, vendors that process higher values of cowpea are also more commonly located in markets that charge tax than smaller scale cowpea processor-vendors. The non-cowpea FAFH market vendors are more often located in the permanent (daily) markets (57.3%). All tiers of cowpea FAFH market vendors except tier 2, on the other hand, are more likely to be located in non-permanent (weekly) markets. The tier 2 processors are a bit more likely to be found in permanent markets (59.6%).

Table 2.2: Regional and Market Characteristics

	Tier 0	Tier 1	Tier 2	Tier 3	Tier 4
Region					
Dakar	7.7%	0.0%	1.9%	25.0%	16.7%
Louga	12.0%	12.2%	1.9%	0.0%	0.0%
Market Characteristics					
Rural market	48.7%	67.3%	50.0%	39.6%	61.1%
Market monitored by SIM	53.0%	49.0%	59.6%	56.2%	74.1%
Consumption market	86.3%	77.6%	92.3%	97.9%	83.3%
Permanent market	57.3%	40.8%	59.6%	50.0%	40.7%
Vendor pays market tax	72.6%	53.1%	63.5%	77.1%	81.5%
Tax rate if vendor pays tax (FCFA/week)	599	356	827	894	538
	(420)	(381)	(663)	(686)	(492)
Number of categories of cowpea products sold	2.357	2.526	2.538	2.383	2.382
	(1.263)	(1.178)	(1.455)	(0.990)	(1.125)
Price of cowpea (FCFA/kg)	527	522	515	598	544
	(159)	(186)	(135)	(130)	(110)
Population density (people/km^2)	2,314	1,288	1,837	4,301	1,954
	(4,625)	(1,850)	(3,922)	(7,834)	(4,328)
n	117	49	52	48	54

Source: Authors' calculations. Means and standard deviations are survey weighted.

In Table 2.3 we present information about key sociodemographic and business characteristics. Though the majority of all FAFH market vendors are married, the marital rate for the large-scale processors is higher, over 85%. Though few FAFH market vendors use non-family labor, the medium-scale processors tier 2 and tier 3 processors are the most likely to employ non-family members. Larger-scale cowpea processors in tiers 3 and 4 are the most likely to sell in multiple markets, though few vendors sell in multiple markets overall. For large-scale processors, the higher frequency of selling in multiple markets is likely associated with the fact that many of these vendors operate in weekly markets, so they may rotate between different weekly markets that operate on different days of the week.

Although the majority of all FAFH market vendors operate in all three seasons, 100% of the large-scale cowpea processor-vendors in our sample sell in all three seasons. Less than 10% of vendors in each tier of cowpea processor-vendors source any of their cowpea from agricultural production from their own household. Few small-scale vendors source any of their cowpea from wholesalers, however nearly 60% of the large-scale tier 4 vendors get at least some of their cowpea from wholesalers.

Family labor seems less important for non-cowpea processor vendors. Only 23.1% of these vendors receive assistance from family, and those that do employ, have under 10 family labor hours per week on average. The tier 1 cowpea processors are a bit more likely to use family labor than non-cowpea processors, but their average hours per week are slightly lower. Family labor is most commonly employed by vendors in tier 4, the largest cowpea processing tier, where 55.6% of vendors employ family labor and these businesses employ just under 40 hours per week of family labor on average. Small scale cowpea processor-vendors also spend fewer hours in the market themselves (around 26 hours) compared to other processor-vendor groups who spend closer to 40 hours per week in this market on average. Note that this only captures time in the current market, so those splitting their time between markets may spend less time in each individual market.

Table 2.3: Sociodemographic and Business Characteristics of FAFH Market Vendors

	Tier 0	Tier 1	Tier 2	Tier 3	Tier 4
Vendor Sociodemographic Characteristics					
Married	61.5%	65.3%	67.3%	58.3%	85.2%
Attended some school	47.0%	49.0%	59.6%	68.8%	59.3%
Has secondary occupation	46.2%	59.2%	38.5%	52.1%	37.0%
Number of children	3.174	2.693	3.034	2.974	3.535
	(2.538)	(2.263)	(2.531)	(2.430)	(1.846)
Business Characteristics					
Vendor received financial aid at startup	16.2%	20.4%	19.2%	12.5%	9.3%
Operates in physical structure	30.8%	44.9%	40.4%	54.2%	35.2%
Has employees (non-family labor)	4.3%	4.1%	15.4%	18.8%	9.3%
Has family members helping in business	23.1%	26.5%	32.7%	29.2%	55.6%
Sells in multiple markets	6.0%	2.3%	2.4%	12.1%	4.7%
Vendor sells in this market in all seasons	77.8%	73.5%	90.4%	87.5%	100.0%
Vendor sources some of their cowpea supply from this market	-	95.9%	88.5%	66.7%	48.1%
Vendor sources some of their cowpea supply from home production	-	4.1%	5.8%	4.2%	9.3%
Vendor sources some of their cowpea supply from villages	-	16.3%	17.3%	16.7%	29.6%
Vendor sources some of their cowpea supply from urban areas	-	55.1%	71.2%	66.7%	53.7%
Vendor purchases some cowpea from a collector	-	40.8%	21.2%	20.8%	14.8%
Vendor purchases some cowpea from a wholesaler	-	14.3%	36.5%	33.3%	59.3%
Vendor purchases some cowpea from a retailer	-	83.7%	67.3%	60.4%	57.4%
Family labor (hours/per week) if have family assistance	8.570	6.660	14.796	24.703	38.171
	(23.609)	(17.042)	(38.975)	(51.590)	(67.963)
Number of years the seller has been in this market	10.062	10.975	9.241	11.856	12.516
	(8.502)	(8.833)	(7.578)	(6.579)	(6.839)
Hours per week in this market	38.969	26.170	42.138	39.929	38.474
	(24.897)	(24.383)	(24.387)	(23.236)	(26.890)
n	117	49	52	48	54

Source: Authors' calculations. Means and standard deviations are survey weighted.

We also find that across all tiers, FAFH market vendors have around a decade of experience or more on average, but those in cowpea processing tiers 1 and 2 have on average fewer years of experience than those in the larger cowpea processing tiers (3 and 4). This aligns with the findings in Otoo et al. (2011) that many cowpea street food vendors in Ghana and Nigeria have been in operation for several years, indicating that although their trading activity may be largely informal, FAFH vending can be a sustainable career.

Table 2.4 provides information on the types of products FAFH market vendors make and sell. We find that overall, most processor-vendors do not also sell any unprocessed foods, however non-cowpea processor-vendors and large-scale cowpea processor vendors do sell unprocessed food more often than small and medium scale cowpea processors. Additionally, the smaller scale cowpea processor-vendors are the most likely to specialize in only making and selling one processed product. We find that 57.1% of the tier 1 cowpea processor-vendors specialize in only one processed product, whereas only 25.9% of the tier 4 cowpea processor-vendors specialize in just one product.

Ready-to-eat meals are the least popular category for non-cowpea processor-vendors, with only 34.2% of these FAFH market vendors selling any ready-to-eat meals. For cowpea FAFH market vendors on the other hand, it is most common to sell ready-to-eat meals and in larger processing tiers, ready-to-eat meals are more prevalent than in smaller cowpea processing tiers. We find that beignets are only sold by about a third of the smallest scale cowpea processors, however they are sold by over two-thirds of the largest scale cowpea processors.

In examining the inputs used by vendors in different tiers, we find that in the non-cowpea processor-vendor tier, millet, wheat flour, and "other raw food" are the most commonly used inputs. For cowpea processor-vendors, clearly cowpea is used by all vendors in these tiers. In smaller-scale cowpea processing tiers, vendors frequently use wheat flour, vegetables, peas and other raw food in their processed products. In larger processing tiers, vendors often make products that include other grains such as millet and rely less on non-grain inputs. We note that the FAFH market vendors that make and sell beignets generally use millet and/or wheat flour in their inputs, so it is likely they are making beignets out of one of these other grain types. In examining the sales by product for the two most commonly sold processed cowpea products, akara and ndambe, we find that in smaller processing tiers, those that make and sell akara have substantially higher weekly sales from akara, whereas ndambe vendors make much less per week from ndambe sales on average. In Tier 3, the weekly sales from akara and ndambe are much closer to convergence.

Table 2.4: Characteristics of Product Portfolios of FAFH Market Vendors

	Tier 0	Tier 1	Tier 2	Tier 3	Tier 4
Product Portfolio Characteristics					
Vendor sells any unprocessed food	12.8%	4.1%	3.8%	6.2%	13.0%
Vendor specializes in 1 processed product	40.2%	57.1%	50.0%	29.2%	25.9%
Makes and sells beignets	39.3%	36.7%	42.3%	43.8%	66.7%
Makes and sells ready-to-eat meals	34.2%	71.4%	78.8%	81.2%	87.0%
Makes and sells other processed food	73.5%	55.1%	57.7%	68.8%	75.9%
Uses cowpea in 1 or more processed products	0.0%	100.0%	100.0%	100.0%	100.0%
Uses rice in 1 or more processed products	5.1%	8.2%	13.5%	16.7%	17.0%
Uses millet in 1 or more processed products	43.6%	8.2%	9.6%	18.8%	50.9%
Uses wheat flour in 1 or more processed products	35.9%	38.8%	34.6%	14.6%	7.5%
Uses peas in 1 or more processed products	23.1%	51.0%	44.2%	29.2%	35.8%
Uses vegetables in 1 or more processed products	27.4%	69.4%	44.2%	43.8%	9.4%
Uses livestock or fish in 1 or more processed products	20.5%	4.1%	1.9%	10.4%	1.9%
Uses other raw food in 1 or more processed products	55.6%	38.8%	40.4%	52.1%	37.7%
Cost of non-cowpea ingredients for processed cowpea	-	2,755	5,586	16,175	31,796
products (FCFA/week)	-	(2,982)	(10,166)	(48,042)	(20,128)
Value of cowpea processed (FCFA/week)	-	1,408	4,260	10,071	28,769
	-	(1,298)	(4,102)	(13,918)	(11,638)
Akara sales (FCFA/week) if vendor makes and sells	-	42,133	80,605	179,856	838,779
akara	-	(47,472)	(785,444)	(970,399)	(735,934)
Ndambe sales (FCFA/week) if vendor makes and sells	-	11,213	17,550	60,648	701,047
ndambe	-	(14,948)	(652,664)	(1,016,519)	(626,254)
n	117	49	52	48	54

Source: Authors' calculations. Means and standard deviations are survey weighted.

In addition to examining the differences between processors based upon the value processed, we also explore the differences between rural and urban processor-vendors. Table 2.5 provides the sample characteristics of FAFH market vendors in rural and urban markets with tests for statistically significant differences between the groups. We find that 60.5% of the urban FAFH market vendors in our sample process cowpea, which is quite close to the 66.1% of rural FAFH market vendors that process cowpea. The average value of cowpea processed (as in input) is not significantly different for rural and urban processor-vendors, when not controlling for other covariates. This implies that cowpea processing is not a particularly rural or urban phenomenon. We find that nearly all the markets in urban areas are permanent consumption markets. In rural areas, just over three quarters of the markets are consumption markets, however only 11.3% of the markets are permanent markets. Urban markets also tend to have a higher variety of cowpea products available for purchase.

The rural markets are somewhat surprisingly more likely to pay taxes, but the tax they are charged is substantially smaller than the tax charged to urban FAFH market vendors. The price of cowpea is not significantly different between rural and urban markets. The average population density near urban markets is more than ten times the population density near rural markets. Urban processor-vendors are more than twice as likely to have employees than rural vendors.

Urban vendors are also more likely to sell in all three seasons in comparison to rural vendors. Rural vendors are more likely to sell in multiple markets (8.3%) with less than 1% of urban vendors selling in multiple markets. The majority of both urban and rural vendors acquire some cowpea from within the market they are selling in. Though few cowpea vendor-processors use cowpea from auto-production, it is logical that we find rural vendors source from their own production more frequently than urban vendors. While 21.4% of vendors in rural areas source some of their cowpea from their own village or other villages, only 3.9% of urban vendors get any of their cowpea supply from villages. 53.3% of urban vendors source some of their cowpea from urban areas, compared to 28% of rural vendors. A higher percentage of rural vendors purchase cowpea from grain collectors and wholesalers, whereas a higher percentage of urban vendors purchase cowpea from retailers. The difference in family labor employed by rural and urban vendors is relatively small and statistically insignificant. Urban vendors are present for nearly 15 more hours per week on average than rural vendors.

Table 2.5: Sample Characteristics of Rural vs Urban FAFH Market Processors

	Urban	**Rural**	**Test**
Vendor processes cowpea	60.5%	66.1%	
Value of cowpea processed	6,894	7,312	
	(11,205)	(11,793)	
Regions			
Dakar	20.4%	0.0%	***
Louga	2.6%	10.1%	***
Market Characteristics			
Market monitored by SIM	56.6%	58.3%	
Consumption market	99.3%	76.2%	***
Permanent market	95.4%	11.3%	***
Number of categories of cowpea products sold	2.941	2.006	
	(1.500)	(0.711)	
Price of cowpea (FCFA/kg)	540	554	
	(145)	(162)	
Population density (people/km^2)	5,915	529	***
	(7,724)	(640)	
Vendor Sociodemographic Characteristics			
Married	63.8%	69.0%	
Attended some school	58.6%	51.2%	
Has secondary occupation	41.4%	50.6%	
Number of children	2.671	3.155	*
	(2.068)	(2.536)	

Table 2.5 (cont'd)

Business Characteristics			
Operates in physical structure	36.8%	40.5%	
Has employees (non-family labor)	12.5%	6.0%	**
Has family members assisting in business	28.9%	33.9%	
Sells in all seasons	92.8%	76.8%	***
Sells in multiple markets	0.7%	8.3%	***
Vendor pays market tax	61.8%	78.0%	
Tax rate if vendor pays tax (FCFA/week)	872	515	***
	(428)	(577)	
Vendor received financial aid at startup	12.5%	18.5%	
Vendor sources some of their cowpea supply from this market	89.5%	82.1%	
Vendor sources some of their cowpea supply from home production	2.0%	5.4%	
Vendor sources some of their cowpea supply from villages	3.9%	21.4%	***
Vendor sources some of their cowpea supply from urban areas	53.3%	28.0%	***
Vendor purchases some cowpea from a collector	11.8%	19.0%	*
Vendor purchases some cowpea from a wholesaler	21.1%	26.8%	
Vendor purchases some cowpea from a retailer	50.0%	36.9%	**
Family labor (hours/week) if have family assistance	14.565	17.672	
	(34.934)	(46.045)	
Number of years the seller has been in this market	10.658	10.738	
	(7.635)	(8.343)	
Hours per week in this market	44.671	30.009	***
	(20.487)	(26.556)	
Product Portfolio			
Sale of unprocessed food during the year	8.6%	9.5%	
Specialize in 1 processed product	35.5%	44.6%	*
Make and sell beignets	39.5%	49.4%	*
Make and sell ready-to-eat meals	68.4%	58.3%	*
Make and sell other processed foods	66.4%	69.0%	
n	152	168	

Source: Authors' calculations. Test column presents t-tests for differences in means of continuous variables and Pearson chi squared tests for factor variables.

The sociodemographic characteristics of rural FAFH market vendors and urban FAFH market vendors are fairly similar on average. In comparing product profiles of rural and urban vendors, we find that specialization in one processed product is a bit more popular for rural vendors. Rural vendors are also slightly more likely than urban vendors to make and sell beignets. Urban vendors, on the other hand, are more likely to sell prepared, ready-to-eat meals.

Overall, our descriptive analysis indicates that there are major differences between the different tiers of cowpea and non-cowpea FAFH market vendors. Though the sociodemographic characteristics of vendors are moderately consistent across tiers, there are significant differences in the product portfolios of vendors, their business characteristics, and the characteristics of the market they operate in. The small and medium-scale cowpea processors seem to have more in common on average, whereas the large-scale processors are quite different in many regards. The cowpea processors that process the most cowpea, in value terms, are most reliant on family labor to support their businesses. These processors also tend to source their cowpea from sources outside the market they sell in and from wholesalers, whereas smaller processors rely more heavily on sourcing cowpea from the market they sell in and from retail vendors. Large processors also have a more diversified product portfolio than smaller processors on average.

We also find some differences across processors in rural and urban markets and differences in the rural and urban markets themselves. We find that urban markets tend to have a wider range variety of cowpea product types available, they are more often consumption markets, and they are more often permanent markets compared to rural markets. Rural processors tend to be more specialized than urban processors and they focus on a slightly different product mix of processed cowpea products than urban processors.

2.5.2 Decision to participate in and intensity of participation in processed cowpea products

Table 2.6 presents the coefficient estimates from the estimation of our hurdle model both with and without the IMR included as an explanatory variable. The IMR is not statistically significant in the model when it is included. Smith (2003) argues that the IMR is frequently not significant due to the double hurdle model's insufficient statistical power in estimating dependency, but that does not invalidate the use of double hurdle modeling techniques, just the estimation of dependency between stages. Regardless of the IMR's significance, the theoretical dependence between stages justifies the inclusion of the IMR. The significance and sign of the coefficients in the table are meaningful, however the coefficient values cannot be easily directly interpreted except for the second hurdle coefficients on the vendor's market tax rate and the price of cowpea in the market. Since these two explanatory variables are values included as natural logs, the coefficient estimates can be interpreted as the elasticity of the expected value of cowpea processed with respect to a 1% change in the independent variable. Therefore, cowpea vendors that pay 1% higher tax to the market processes 0.069% more cowpea on average. A 1% higher market cost of cowpea for cowpea processors is associated with processing 0.541% more cowpea in value terms on average.

Table 2.6: Coefficients from Double Hurdle Regression

	Hurdle 1: Probit		Hurdle 2 (no IMR): Lognormal		Hurdle 2 (IMR): Lognormal	
Region	**Coeff**	**BSE**	**Coeff**	**BSE**	**Coeff**	**BSE**
Dakar	0.574	(0.423)	1.009***	(0.241)	1.039***	(0.250)
Louga	-1.445**	(0.623)	-1.979***	(0.488)	-2.047***	(0.552)
Market Characteristics						
Market monitored by SIM	0.134	(0.243)	0.235*	(0.131)	0.239*	(0.133)
Rural market	0.741**	(0.325)	-0.013	(0.158)	0.008	(0.182)
Number of categories of cowpea products sold	-0.062	(0.105)	-0.07	(0.062)	-0.072	(0.062)
Price of cowpea (ln FCFA/kg)	0.239	(0.488)	0.541**	(0.233)	0.549**	(0.234)
Business Characteristics						
Market tax rate paid by vendor (ln FCFA/week)	-0.041	(0.047)	0.069***	(0.026)	0.069***	(0.026)
Operates in physical structure	0.341	(0.267)	-0.298**	(0.125)	-0.285**	(0.128)
Hours per week in this market	-0.001	(0.006)	0.006*	(0.004)	0.006*	(0.004)
Family labor (hours/week)	0.008	(0.008)	0.004***	(0.001)	0.004***	(0.001)
Has employees (non-family labor)	0.977	(0.624)	0.123	(0.203)	0.157	(0.256)
Vendor received financial aid at startup	0.066	(0.278)	-0.195	(0.163)	-0.192	(0.164)
Vendor sources some of their cowpea supply from this market	-	-	-0.491***	(0.166)	-0.483***	(0.164)
Vendor sources some of their cowpea supply from home production	-	-	0.505	(0.326)	0.504	(0.326)
Vendor sources some of their cowpea supply from villages	-	-	-0.126	(0.189)	-0.123	(0.189)
Vendor sources some of their cowpea supply from urban areas	-	-	0.22	(0.159)	0.216	(0.160)
Sells in all seasons	0.759	(0.472)	0.560**	(0.272)	0.588**	(0.290)
Number of years the seller has been in this market	0.038**	(0.015)	-	-	-	-
Vendor Sociodemographic Characteristics						
Attended some school	0.311	(0.260)	0.046	(0.122)	0.055	(0.126)
Has secondary occupation	0.237	(0.296)	0.008	(0.171)	0.020	(0.182)
Married	0.634**	(0.286)	0.115	(0.159)	0.132	(0.164)
Number of children	-0.124*	(0.071)	0.042	(0.033)	0.041	(0.034)
Product Portfolio Characteristics						
Sale of unprocessed food during the year	-0.451	(0.476)	0.082	(0.330)	0.066	(0.342)
Specialize in 1 processed product	1.225***	(0.356)	-0.205	(0.215)	-0.154	(0.283)
Make and sell beignets	2.139*	(1.351)	0.827***	(0.186)	0.892***	(0.288)
Make and sell ready-to-eat meals	2.954**	(1.252)	-0.068	(0.262)	0.035	(0.468)
Make and sell other processed foods	0.223	(0.329)	0.666***	(0.217)	0.673***	(0.216)
IMR from stage 1	-	-	-	-	0.128	(0.420)
Constant	-6.111**	(3.184)	3.703***	(1.704)	3.405*	(1.954)
n	*320*		*203*		*203*	
Replications	494		500		500	
Wald chi2	40.11		369.16		386.85	
Prob > chi2	0.0150		0.0000		0.0000	
Pseudo R2	0.435		-		-	
R-squared	-		0.597		0.602	
Adj R-squared	-		0.538		0.538	

Source: Authors calculations with bootstrapped standard errors (BSE).

To understand the marginal impact of our independent variables on the probability of processing cowpea and the value of cowpea processed, we calculate the Average Partial Effects (APEs) for the coefficients. Table 2.7 presents the APEs for the first and second hurdles. The APEs of each variable on *P(y>0)* can be interpreted as follows: $100 \times APE$ is the percentage point change in the probability of processing cowpea for a one-unit change in the independent variable. The APEs of each variable on *E(y|y>0)* are the additional value of cowpea processed in FCFA for a one-unit change in the explanatory variable given that a processor makes and sells cowpea products. The final column presents the unconditional APEs of a variable on *E(y)* which is the overall estimated impact of the variable on the expected value of cowpea processed, accounting for the probability impacts. All statistically significant effects of our market characteristics, business characteristics, vendor sociodemographic characteristics, and product portfolio characteristics have the same direction of impact on the probability of processing cowpea and the expected value of cowpea processed, i.e. there are no factors that make a processor less likely to process cowpea that also processors likely to process higher quantities cowpea, conditionally or unconditionally.

We find substantial and significant regional impacts for processors in Dakar and Louga, though we expected processors in Louga to be more likely to process cowpea and to process higher values of cowpea because this region is the top cowpea producing region. As cowpea is likely to be a more accessible input in these regions, we expected it to be more popular choice for processors. In future work, it would be worthwhile to further explore regional preferences for processed cowpea products to better understand why the largest cowpea producing region has a seemingly smaller cowpea processing sector than other regions in the country. The processors in Dakar process more cowpea on average than those in other areas, which is what we expected due to the high population density in the capital city of Dakar.

The only market characteristic that impacts a vendor's probability of processing cowpea is whether that market is rural, which makes a vendor 15.3 percentage points more likely to process cowpea. Being in a rural market, however, has no significant impact on the expected value of cowpea processed by a vendor. The market price of cowpea impacts the expected value processed as vendors in markets with a 1% higher price of cowpea are expected to process 3,899 FCFA more cowpea per week on average. The conditional impact is more pronounced. Conditional on being a cowpea processor, vendors in markets with a 1% higher price of cowpea are expected to process an additional 5,728 FCFA of cowpea per week. Vendors located in markets that are monitored by the SIM are not statistically more or less likely to process cowpea, however, the average partial effect on the unconditional expected value of cowpea processed is statistically significant, thus vendors in markets monitored by SIM are expected to process 1755

FCFA more cowpea per week than those in unmonitored markets.

In examining the business characteristics, a vendor's presence in the market for the full year increases the probability of processing cowpea by 15.7 percentage points compared to those who are only present in the market seasonally. Each additional year a vendor has been in the market increases the probability that they process cowpea by 0.8 percentage points. Vendors that have employees (non-family labor) for their business are 20.2 percentage points more likely to process cowpea. We also find that each additional hour of family labor dedicated to a business increases the conditional and unconditional expected value of cowpea processed by just under 44.9 and 42.3 FCFA per week respectively. These findings align with our expectations due to the labor intensity of processing cowpea (Cohen 1984, Gomez 2004). Additional experience and added labor can improve efficiency and productive capacity.

We hypothesized that cowpea processors operating in physical spaces may have larger processing capacity, and therefore higher expected values of cowpea processed, however, contrary to our expectations operating out of a physical structure reduces the expected amount processed by cowpea processors. The estimated impact of operating in a physical structure on the probability of processing cowpea is positive, but not significant at the 10%. In regard to input sourcing, we find that vendors that source at least some of their cowpea from the market in which they operate are less likely to process cowpea, in value terms, compared to those that do not source any cowpea from the market in which they operate. This suggests that the larger-scale operations are potentially more flexible in sourcing their cowpea from other locations, whereas smaller-scale operations may be more constrained to sourcing cowpea grain from local vendors in their market and thus, more subject to market availability.

Married vendors are 13.1 percentage points more likely to process cowpea, but each additional child a woman has reduces her likelihood of processing cowpea by 2.6 percentage points. This result is somewhat in line with expectations since previous findings suggest women are more likely to diversify into food processing or other non-farm employment to support their families (Awusabo-Asare & Tanle, 2008; Boateng, 2017; Diallo et al., 2023; Kpossilande et al., 2020).

We find that the product portfolios of vendors impact both the probability of processing cowpea, and the value processed per week. Three out of the five product portfolio characteristics have an impact on the probability of processing cowpea. Specializing in just one processed food product increases the probability of processing cowpea by 25.3%. Those who make and sell beignets are 44.2% more likely to process cowpea and those who make and sell ready-to-eat meals are 61.1% more likely to process cowpea. Cowpea is a key ingredient for both meals and popular snacks in the processed food sector in West Africa (Affrifah, 2022). In examining the impact of product portfolio characteristics on the expected value of cowpea processed, we find that making beignets has the largest impact with an increase in the conditional expected value of 9312 FCFA per week and an increase in the unconditional expected value of 9835 FCFA per week.

Table 2.7: Average Partial Effects from Double Hurdle Estimation

	APE on *P(y>0)*		APE on *E(y|y>0)*		APE on *E(y)*	
Regions	**Coeff**	**BSE**	**Coeff**	**BSE**	**Coeff**	**BSE**
Dakar	0.119	(0.078)	10844.870**	(4305.336)	7624.668***	(2107.631)
Louga	-0.299***	(0.108)	-21365.060**	(10175.290)	-15647.480***	(4331.297)
Market Characteristics						
Market monitored by SIM	0.028	(0.045)	2489.683	(1680.430)	1754.929*	(980.578)
Rural market	0.153***	(0.057)	86.862	(2389.445)	1532.694	(1446.218)
Number of categories of cowpea products sold	-0.013	(0.019)	-748.535	(782.838)	-571.127	(474.516)
Price of cowpea (ln FCFA/kg)	0.049	(0.089)	5728.162**	(2812.429)	3899.128**	(1722.178)
Business Characteristics						
Market tax rate paid by vendor (ln FCFA/week)	-0.009	(0.008)	716.617*	(389.478)	345.362*	(200.308)
Operates in physical structure	0.071	(0.048)	-2978.614*	(1704.228)	-1097.451	(1004.859)
Hours per week in this market	0.000	(0.001)	67.281	(53.241)	38.653	(25.992)
Family labor (hours/week)	0.002	(0.001)	44.928**	(21.367)	42.338**	(16.362)
Has employees (non-family labor)	0.202*	(0.110)	1643.458	(3447.183)	2933.587	(2094.335)
Vendor received financial aid at startup	0.014	(0.051)	-2005.212	(1675.625)	-1066.537	(1081.381)
Vendor sources some of their cowpea supply from this market	-	-	-5038.557**	(2497.075)	-3009.767***	(1137.936)
Vendor sources some of their cowpea supply from home production	-	-	5261.712	(4121.653)	3143.068	(2176.830)
Vendor sources some of their cowpea supply from villages	-	-	-1287.670	(2429.886)	-769.186	(1301.441)
Vendor sources some of their cowpea supply from urban areas	-	-	2257.254	(1787.796)	1348.364	(996.495)
Sells in all seasons	0.157*	(0.084)	6132.306	(4199.006)	5178.666**	(2221.536)
Number of years the seller has been in this market	0.008***	(0.003)	-	-	-	-
Vendor Sociodemographic Characteristics						
Attended some school	0.064	(0.046)	572.279	(1602.389)	962.457	(963.653)
Has secondary occupation	0.049	(0.053)	210.291	(2451.169)	599.341	(1466.154)
Married	0.131**	(0.052)	1379.041	(2126.061)	2090.411*	(1174.251)
Number of children	-0.026**	(0.013)	425.887	(458.631)	6.042	(252.333)

Table 2.7 (cont'd)

Product Portfolio Characteristics						
Sale of unprocessed food during the year	-0.093	(0.085)	689.372	(3872.159)	-488.116	(2285.666)
Specialize in 1 processed product	0.253***	(0.059)	-1611.642	(3285.302)	1484.756	(2002.023)
Make and sell beignets	0.442**	(0.201)	9312.739*	(4916.938)	9835.371***	(3386.224)
Make and sell ready-to-eat meals	0.611***	(0.193)	360.285	(6219.036)	6116.167	(4053.697)
Make and sell other processed foods	0.046	(0.060)	7025.209*	(3716.983)	4642.197***	(1781.458)

Source: Author's calculations with bootstrapped standard errors (500 replications)

Overall, we find evidence that there are some factors that contribute to both the probability of a vendor processing cowpea and the value of cowpea processed, but we also find that many factors only significantly contribute to one of these decisions. Thus, employing the double hurdle framework which allows for differences between the participation and intensity of participation decision is supported. The major factors that contribute positively towards the probability of processing cowpea as a FAFH market vendor are selling in a rural market (+15.3 percentage points), having employees (+20.2 percentage points), having more years of experience (+0.8 percentage points per year), being married (+13.1 percentage points), specializing in one processed product (+25.3 percentage points), and making beignets (+44.2 percentage points) or ready-to-eat meals (+61.1 percentage points). The product portfolio characteristics have the largest impact on the probability of processing cowpea. The key factor that statistically significantly reduce the probability of processing cowpea is being in Louga (-29.9 percentage points), the nation's top cowpea production region.

The major factors that increase the unconditional expected value of cowpea processed are selling in the capital region of Dakar, selling in a rural market, years of experience, selling year-round, selling specific types of products, and being located in a market with higher cowpea prices or a market that is monitored by the market information system (SIM) of the Senegalese Food Security Commission (CSA). Selling in a market in Louga and sourcing some cowpea from within the market a vendor is selling in both reduce the expected value processed.

2.5.3 Post-estimation

Table 2.8 presents the statistically significant differences in the characteristics of the most likely cowpea processors ($\geq 90^{th}$ percentile) and least likely cowpea processors ($\leq 10^{th}$ percentile). The most likely processors have an average predicted probability of processing cowpea of 0.999, whereas the processors predicted to be least likely to process cowpea have an average predicted probability of processing cowpea of only 0.022. All of the vendors in the group most likely to process cowpea do indeed process cowpea and all processors predicted to be least likely to process cowpea do not process cowpea in reality. Four fifths of the most likely to process cowpea are located in rural markets and markets monitored by the SIM compared to half of the least likely processors. The most likely processors are more likely to use family labor (57.1%) compared to the least likely processors (15.6%). Additionally, we find that nearly two-thirds of the most likely cowpea processors are operating out of physical structures compared to only one quarter of the least likely processors. One potential reason for this could be that cowpea are known to be quite vulnerable to pests like bruchids (Adomi et al. 2023) which can cause large losses, so operating within a physical structure may help vendors protect their cowpea supply from pests. This is somewhat in contrast with our findings, however, that operating in a physical structure is associated processing a lower value of cowpea. In future research, it would be worthwhile to explore the contrast that we see wherein the highest predicted processors frequently operate in physical structures yet operating out of a physical structure on average has a negative impact on the predicted value of cowpea processed.

Table 2.8: Predicted Most and Least Likely to Process Cowpea

	Most Likely to Process Cowpea	**Least Likely to Process Cowpea**	**Test**
Cowpea FAFH Market Vendor	100.00%	0.00%	***
Rural market	80.00%	53.10%	**
Market monitored by SIM	82.90%	50.00%	***
Physical Structure	62.90%	25.00%	***
Uses family labor	57.10%	15.60%	***
Vendor sells in this market in all seasons	100.00%	78.10%	***
Vendor has attended some school	68.60%	46.90%	*
	Mean (SD)	**Mean (SD)**	**Test**
Predicted Probability of Processing Cowpea	0.999	0.022	***
	(0.001)	(0.022)	
Years vendor has been selling in this market	13.486	7.906	***
	(6.705)	(6.616)	
Value of cowpea processed (FCFA/week)	19,671	0.000	***
	(15,431)	(0.000)	
n	35	32	

Source: Authors' calculations.

2.6 Conclusions

Cowpea is a nutritious legume that is high in protein and commonly processed for traditional dishes, meals, and snacks in West Africa (Affrifah et al., 2022). In this study, we explore the differences between cowpea processor-vendors in open-air markets in Senegal and their peers that process only non-cowpea food products by employing a unique survey dataset collected in 2021 by the market information system of the Commissariat a la Securite Alimentaire, Universite de Thies and Michigan State University. Using this survey data collected from over 300 processor-vendors across open-air markets in Senegal, we analyze the product portfolio decisions, specifically regarding the inclusion of processed cowpea products. We explore the factors that contribute to the FAFH processors choice to process cowpea and the amount of cowpea that they choose to process each day. The presence of non-cowpea processors in our dataset motivates the use of the double hurdle model for censored dependent variables. This model allows us to examine the expected participation level of those that currently participate, as well as those that do not currently participate in processing cowpea.

This model also allows different factors to contribute to the participation and intensity of participation decisions, which we find to be important. The first hurdle analyzes the probability that a FAFH market vendor processes cowpea. The second hurdle examines the amount of cowpea processed, conditional on processing cowpea. We also calculate the unconditional expected value of cowpea processed and we present and discuss the average partial effects of each of our explanatory variables on the probability of processing cowpea, the conditional expected value of cowpea processed, and the unconditional expected value of cowpea processed to understand how key regional, market, business, product, and sociodemographic variables impact the vendors choices.

Consistent with previous studies (Otoo et al., 2011; Allen et al., 2018), we find that women dominate FAFH market vending in Senegal. As such, the descriptive and empirical analysis focuses solely on women. Overall, our analysis suggests that there are differences not only between FAFH market vendors that process cowpea and those that do not, but there are also substantial differences between those that process smaller values of cowpea per week and those that process larger values on average. Non-cowpea processors are less likely to be married, to have attended school, and to employ family in their processing business. Those that do employ family labor use fewer hours per week on average than cowpea processors that use family labor. Though many factors have some impact on the predicted probability that a vendor processes cowpea, we find through our estimation procedure that the vendor’s product portfolio characteristics have the largest significant impacts. Specializing in one processed food product, for example, increases the probability of processing cowpea by 25 percentage points. Surprisingly, being located in the major cowpea production region, Louga, is associated with the largest significant decrease in the predicted probability of processing cowpea (-30 percentage points). In future work, it would be useful to further explore this relationship to understand why processors in open-air markets in Louga are less likely to process cowpea products when cowpea supply is expected to be relatively high in this region.

Our results suggest the existence of different types of cowpea processor-vendors in open air markets in Senegal. There are some vendors that are fairly small, processing less than 3000 FCFA of cowpea per week. These vendors spend less time in markets and have less support from employees or family labor than the larger cowpea processor-vendors. They frequently sell just one type of processed product, and most do not sell any unprocessed food items. Most of these vendors make and sell ready-to-eat meals. Some of these vendors sell beignets or other processed products in addition to or instead of ready-to-eat meals, but these other product types are less common for small-scale processor-vendors than for larger scale cowpea processor-vendors. More of the large-scale processors-vendors diversify, selling a variety of processed products, and a substantial number of them even sell unprocessed products. Additionally, smaller vendors more frequently source some of their cowpea from within the market in which they are selling and rely more on retailers, whereas larger cowpea processor-vendors often source at least some of their cowpea from wholesalers and are less likely to buy cowpea from the market in which they operate. More of the medium and large-scale processor-vendors sell in multiple markets, though this practice is still relatively uncommon, and most cowpea processor-vendors operate only in one market.

2.7 Policy Implications

The findings from this study are relevant to policy relating to the development of the processed food and FAFH sector in Senegal. This sector is an essential source of non-farm employment, especially for women (Allen et al., 2018). The larger cowpea processor-vendors in the markets are more likely to spend more time in the market each week, operate in the market year-round, and employ more family and hired labor than smaller processor-vendors. The cowpea processor-vendors that operate in all seasons process more cowpea per week than those that do not operate year-round. Those that do not operate year-round are typically non-operational in the rainy season, which coincides with low cowpea supply in markets. Of these seasonal vendors, around two-thirds participate in agriculture as a secondary activity, so they may be occupied with farm labor during the rainy season. Recent research in China finds that rural women are more likely to participate in non-farm employment when households have adopted mechanized farming strategies (Ma et al., 2024). Assuming women in Senegal would behave similarly, policies that increase the adoption of mechanized agricultural technologies could have positive spillover effects on small-scale women processors who could potentially grow their business substantially by participating in all seasons.

Investing in technologies that reduce spoilage, pest damage, and other post-harvest losses could drive increased stability in grain supply through all seasons, which could ease supply constraints on vendors who are currently unable to process cowpea in all seasons, thus also increasing the number of vendors who are able to operate their cowpea processing business year-round. These technologies may also ease storage constraints faced by processor-vendors. Widespread access to affordable and effective cowpea grain storage and protection solutions could allow processor-vendors to purchase grain when it is affordable and readily available to store it for use when prices are high or when cowpea is difficult to get.

Additionally, we find that the predicted probability of a FAFH market vendor processing cowpea is higher for vendors in rural markets, suggesting that processing cowpea is a popular and promising non-farm employment opportunity in rural areas. Researchers recently found evidence that when rural women diversify into non-farm employment activities in Senegal, household food security increases (Diallo et al., 2023). Policies that support the FAFH market vending sector could therefore not only improve women's employment outcomes but also contribute to increased food security for rural households.

Acknowledgements

This study was funded by the Bureau for Food Security of the United States Agency for International Development (USAID), under the Legume Research Systems Innovation Laboratory's Cooperative Agreement #7200AA18LE00003. Any opinions, findings, conclusions, or recommendations expressed here are those of the author alone.

REFERENCES

Adomi, A. A., Abdoulaye, T., Mohammed, A. B., Abdu, Z., & Musa, S. A. (2023). Impact of improved hermetic storage on food insecurity and poverty of smallholder cowpea farmers in Northwestern Nigeria. *Journal of Stored Products Research*, *100*, 102042.

Affrifah, N. S., Phillips, R. D., & Saalia, F. K. (2022). Cowpeas: Nutritional profile, processing methods and products—A review. *Legume Science*, *4*(3), e131.

Africapolis. (2015). *Country report: Senegal*. Africapolis. Retrieved from https://africapolis.org/en/country-report/Senegal

Albuquerque, T. G., Bragotto, A. P. A., & Costa, H. S. (2022). Processed Food: Nutrition, Safety, and Public Health. *International journal of environmental research and public health*, *19*(24), 16410. https://doi.org/10.3390/ijerph192416410

Alimi, B. A. (2016). Risk factors in street food practices in developing countries: A review. *Food Science and Human Wellness*, *5*(3), 141–148. https://doi.org/10.1016/j.fshw.2016.05.001

Allen, T. A., Heinrigs, P., & Heo, I. (2018). Agriculture, food and jobs in West Africa. *The West African Papers*. https://doi.org/10.1787/dc152bc0-en

Ashaley-Nikoi, J., & Abbey, E. (2023). Determinants of the level of informality amongst female street food vendors in sub-Saharan Africa: Evidence from two regions in Ghana. *Cities*, *138*, 104359. https://doi.org/10.1016/j.cities.2023.104359

Awusabo–Asare, K., & Tanle, A. (2008). Eking a living: Women entrepreneurship and poverty reduction strategies: The case of palm kernel oil processing in the Central Region of Ghana. *Norsk Geografisk Tidsskrift–Norwegian Journal of Geography*, *62*(3), 149–160. https://doi.org/10.1080/00291950802335525

Boateng, A. (2017). Contextualizing women's entrepreneurship in Africa. In *African Female Entrepreneurship* (pp. 3–33). https://doi.org/10.1007/978-3-319-65846-9_1

Bouafou, K. G. M., Beugré, G. F. C., & Amani, Y. C. (2021). Street Food around the World: A Review of the Literature. *Journal of Service Science and Management*, *14*(06), 557–575. https://doi.org/10.4236/jssm.2021.146035

Burke, W. (2009). Fitting and Interpreting Cragg's Tobit Alternative using Stata. *The Stata Journal*, *9*(4), 584–592. https://doi.org/10.1177/1536867x0900900405

Clark, G. (1997). *Onions are my husband: Survival and accumulation by West African market women*. University of Chicago Press.

Cohen, M. (1984). *The Urban Street Food Trade*. Equity Policy Center.

Cragg, J. G. (1971). Some Statistical Models for Limited Dependent Variables with Application to the Demand for Durable Goods. *Econometrica*, *39*(5), 829. https://doi.org/10.2307/1909582

Cudjoe, D. C., Balali, G. I., Titus, O. O., Osafo, R., & Taufiq, M. (2022). Food Safety in Sub-Sahara Africa, An insight into Ghana and Nigeria. *Environmental Health Insights*, *16*, 117863022211424. https://doi.org/10.1177/11786302221142484

Diagne, A., Smale, M., Theriault, V., & Wade, I. (2020). Quantifying the scale and scope of nutritious cowpea products in local markets of West Africa Research Protocole: Part I. In *Michigan State University College of Agriculture and Natural Resources*.

Diallo, T. M., Mazu, A. A., Araar, A., & Dieye, A. (2023). Women's employment in rural Senegal: what can we learn from non-farm diversification strategies? *Journal of Agribusiness in Developing and Emerging Economies*, *14*(1), 102–127. https://doi.org/10.1108/jadee-01-2022-0019

Engel, C., & Moffatt, P. (2014). dhreg, xtdhreg, and bootdhreg: Commands to implement double-hurdle regression. *The Stata Journal, 14*(4), 778–797.

Heckman, J. J. (1979). Sample selection bias as a specification error. *Econometrica*, *47*(1), 153. https://doi.org/10.2307/1912352

International Monetary Fund [IMF]. (2025). *GDP, current prices – Billions of US dollars* [Data file]. Retrieved from https://www.imf.org/external/datamapper/NGDPD@WEO/OEMDC/ADVEC/WEOWORLD/AFQ

Kpossilande, C. E., Honfoga, B. G., & Ferré, T. (2020). Economic potentials of artisanal food processing microenterprises in West Africa: case of "atta" production in Cotonou (Benin). *Agricultural and Food Economics*, *8*(1). https://doi.org/10.1186/s40100-020-00168-y

Ma, W., Zhou, X., Boansi, D., Horlu, G. S. A., & Owusu, V. (2024). Adoption and intensity of agricultural mechanization and their impact on non-farm employment of rural women. *World Development*, *173*, 106434. https://doi.org/10.1016/j.worlddev.2023.106434

Mahopo, T. C., Nesamvuni, C., Nesamvuni, A. E., De Bryun, M., Van Niekerk, J., & Ambikapathi, R. (2022). Operational characteristics of women street food vendors in rural South Africa. *Frontiers in Public Health*, *10*. https://doi.org/10.3389/fpubh.2022.849059

Mwangi, A., Hartog, A. D., Foeken, D., Riet, H. V., Mwadime, R. K. N., & Van Staveren, W. (2001). The ecology of street foods in Nairobi. *Ecology of Food and Nutrition*, *40*(5), 497–523. https://doi.org/10.1080/03670244.2001.9991664

Namugumya, B. S., & Muyanja, C. (2011). Contribution of street foods to the dietary needs of street food vendors in Kampala, Jinja and Masaka districts, Uganda. *Public Health Nutrition*, *15*(8), 1503–1511. https://doi.org/10.1017/s1368980011002710

Office of International Religious Freedom. (2022). *Report on International Religious Freedom: Senegal 2022*.

Oguntona, C. R. B., Razaq, M., & Akintola, T. T. (1998). Pattern of Dietary Intake and Consumption of Street Foods among Nigerian Students. *Nutrition and Health*, *12*(4), 247–256. https://doi.org/10.1177/026010609801200405

Okojie, P., & Isah, E. (2019). Food hygiene knowledge and practices of street food vendors in Benin City, Nigeria. *International Journal of Consumer Studies*, *43*(6), 528–535. https://doi.org/10.1111/ijcs.12538

Otoo, M., Fulton, J. R., Ibro, G., & Lowenberg-DeBoer, J. (2011). Women Entrepreneurship In West Africa: The Cowpea Street Food Sector in Niger and Ghana. *Journal of Developmental Entrepreneurship*, *16*(01), 37–63. https://doi.org/10.1142/s1084946711001732

Otoo, M., Ibro, G., Fulton, J. R., & Lowenberg-DeBoer, J. (2012). Micro-Entrepreneurship in Niger: factors affecting the success of women street food vendors. *Journal of African Business*, *13*(1), 16–28. https://doi.org/10.1080/15228916.2012.657937

Owoo, N. S., & Lambon-Quayefio, M. P. (2018). The Agro-Processing Industry and its Potential for Structural Transformation of the Ghanaian Economy. In R. S. Newfarmer, J. Page, & F. Tarp (Eds.), *Industries without Smokestacks: Industrialization in Africa Reconsidered*. Oxford University Press.

Posner, J. (1983). *Street Foods in Senegal*. Equity Policy Center.

Reardon, T., Liverpool-Tasie, L. S. O., & Minten, B. (2021). Quiet Revolution by SMEs in the midstream of value chains in developing regions: wholesale markets, wholesalers, logistics, and processing. *Food Security*, *13*(6), 1577–1594. https://doi.org/10.1007/s12571-021-01224-1

Reardon, T., Tschirley, D. L., Liverpool-Tasie, L. S. O., Awokuse, T. O., Fanzo, J., Minten, B., Vos, R., Dolislager, M., Sauer, C., Dhar, R., Vargas, C. M., Lartey, A., Raza, A., & Popkin, B. M. (2021). The processed food revolution in African food systems and the double burden of malnutrition. *Global Food Security*, *28*, 100466. https://doi.org/10.1016/j.gfs.2020.100466

Sauer, C., Reardon, T., Tschirley, D. L., Liverpool-Tasie, S., Awokuse, T. O., Alphonce, R., Ndyetabula, D., & Waized, B. (2021). Consumption of processed food & food away from home in big cities, small towns, and rural areas of Tanzania. *Agricultural Economics*, *52*(5), 749–770. https://doi.org/10.1111/agec.12652

Senegal 1000m Population Density. (2018). [Dataset]. WorldPop (www.worldpop.org - School of Geography and Environmental Science, University of Southampton; Department of Geography and Geosciences, University of Louisville; Departement de Geographie, Universite de Namur) and Center for International Earth Science Information Network (CIESIN), Columbia University. Global High Resolution Population Denominators Project - Funded by The Bill and Melinda Gates Foundation (OPP1134076). https://dx.doi.org/10.5258/SOTON/WP00675

Sethuraman, S. V. (1981). *The urban informal sector in developing countries: Employment, poverly and environment*. International Labour Organisation.

Sissoko, M., Theriault, V., & Smale, M. (2022). Beyond grain: the potential of cowpea in local markets of Mali. *Journal of Agribusiness in Developing and Emerging Economies*, *14*(2), 310–331. https://doi.org/10.1108/jadee-02-2022-0035

Smale, M., Thériault, V., Allen, A., & Sissoko, M. (2022). Is cowpea a ‘women’s crop’ in Mali? Implications for value chain development. *African Journal of Agricultural and Resource Economics*, *17*(2), 157–170. https://doi.org/10.53936/afjare.2022.17(2).11

Smale, M., Theriault, V., & Vroegindewey, R. (2020). Nutritional implications of dietary patterns in Mali. *African Journal of Agricultural and Resource Economics*, *15*(3), 177–193. https://afjare.org/nutritional-implications-of-dietary-patterns-in-mali/

Smith, M. U. (2003). On dependency in double-hurdle models. *Statistical Papers*, *44*(4), 581–595. https://doi.org/10.1007/bf02926011

Staatz, J. M., & Höllinger, F. (2016). West African food systems and changing consumer demands. *The West African Papers*. https://doi.org/10.1787/b165522b-en

Steyn, N. P., Mchiza, Z. J., Hill, J., Davids, Y. D., Venter, I., Hinrichsen, E., Opperman, M., Rumbelow, J., & Jacobs, P. (2013). Nutritional contribution of street foods to the diet of people in developing countries: a systematic review. *Public Health Nutrition*, *17*(6), 1363–1374. https://doi.org/10.1017/s1368980013001158

Tinker, I. (1999). Street foods in the 21 century. *Agriculture and Human Values*, *16*(3), 327–333.

Tobin, J. (1958). Liquidity preference as behavior towards risk. *The review of economic studies*, *25*(2), 65-86.

Toure, D., Herforth, A., Pelto, G. H., Neufeld, L. M., & Mbuya, M. N. N. (2021). An Emergent Framework of the Market Food Environment in Low- and Middle-Income Countries. *Current developments in nutrition*, *5*(4), nzab023. https://doi.org/10.1093/cdn/nzab023

University of California Cooperative Extension. (2020.). *Postharvest handling systems: Underground vegetables.* Vegetable Research & Information Center. https://vric.ucdavis.edu/postharvest/undergnd.htm

Usman, I., Afzaal, M., Imran, A., Saeed, F., Afzal, A., Ashfaq, I., Shah, Y. A., Islam, F., Azam, I., Tariq, I., Ateeq, H., Asghar, A., Farooq, R., Rasheed, A., Asif Shah, M. (2023). Recent updates and perspectives of plasma in food processing: a review. *International Journal of Food Properties*, *26*(1), 552–566. https://doi.org/10.1080/10942912.2023.2171052

Vuong, Q. (1989). Likelihood ratio tests for model selection and Non-Nested hypotheses. *Econometrica*, *57*(2), 307. https://doi.org/10.2307/1912557

Wooldridge, J. M. (2001). Corner solution outcomes and censored regression models. In *Econometric analysis of cross section and panel data* (1st ed.). MIT Press.

Wooldridge, J. M. (2009). *Hurdle and "Selection" Models [PowerPoint Slides].* https://legacy.iza.org/teaching/wooldridge-course-09/course_html/docs/slides_twopart_5_r1.pdf

World Bank. (2024, April 3). *The World Bank in Senegal*. Retrieved April 15, 2024, from https://www.worldbank.org/en/country/senegal/overview#1

World Bank, World Development Indicators (2025). *Population, total – Senegal, Nigeria* [Data file]. Retrieved https://data.worldbank.org/indicator/SP.POP.TOTL?locations=SN-NG

APPENDIX A: REGIONAL SAMPLING

Table 2.9: Regional Sampling Information

Region	Markets sampled in region
Dakar	14
Diourbel	6
Fatick	7
Kaffrine	3
Kaolack	7
Kédougou	3
Kolda	6
Louga	4
Matam	5
Saint-Louis	7
Sédhiou	6
Tambacounda	6
Thies	8
Ziguinchor	2
Total	84

Source: Authors' calculations.

APPENDIX B: TEST FOR POOLED VS RESTRICTED SAMPLE

Appendix B presents the Akaike's information criterion and Bayesian information criterion for the probit and lognormal hurdles with the pooled sample including men and women and the women only restricted sample. Lower values indicate a better fit, therefore across the board we find the model is best fit for the women only sample. This supports our theoretical exclusion of men. Due to the low number of observations, we cannot run regressions for the men only restricted sample.

Table 2.10: Test for Pooled vs Restricted Sample of Market Vendors

	Probit		Lognormal	
	All	**Women**	**All**	**Women**
Dakar	0.576	0.573	1.040***	1.038***
	(0.356)	(0.368)	(0.270)	(0.269)
Louga	-1.412***	-1.419***	-2.024***	-2.155***
	(0.411)	(0.421)	(0.446)	(0.438)
Market monitored by SIM	0.167	0.157	0.302**	0.307**
	(0.200)	(0.209)	(0.142)	(0.142)
Rural market	0.784***	0.750***	-0.031	-0.026
	(0.239)	(0.251)	(0.186)	(0.184)
Market tax (FCFA/week)	-0.031	-0.044	0.074***	0.073**
	(0.035)	(0.037)	(0.024)	(0.024)
Number of categories of cowpea products sold	-0.027	-0.055	-0.055	-0.045
	(0.084)	(0.088)	(0.059)	(0.060)
Cowpea price (FCFA)	0.128	0.263	0.427	0.359
	(0.376)	(0.39)	(0.274)	(0.275)
Vendor operates in formal structure	0.264	0.350	-0.329**	-0.345**
	(0.210)	(0.220)	(0.143)	(0.146)
Hours per week vendor is present in this market	-0.002	0.000	0.007**	0.008**
	(0.005)	(0.005)	(0.003)	(0.003)
Family labor (hours/week)	0.010**	0.008*	0.004**	0.004**
	(0.005)	(0.005)	(0.002)	(0.002)
Has employees (non-family labor)	0.945**	0.982**	0.038	0.141
	(0.353)	(0.400)	(0.235)	(0.240)
Vendor received financial aid at startup	-0.042	-0.072	0.061	0.077
	(0.266)	(0.271)	(0.188)	(0.186)
Vendor sells in this market in all seasons	0.822**	0.725**	0.413	0.419
	(0.330)	(0.342)	(0.314)	(0.306)
Years vendor has been selling in this market	0.031**	0.036**	-	-
	(0.014)	(0.015)		
Vendor has attended some school	0.303	0.289	-0.030	0.000
	(0.208)	(0.211)	(0.136)	(0.135)
Vendor has secondary occupation	0.331	0.261	-0.129	-0.092
	(0.226)	(0.235)	(0.165)	(0.163)
Married	0.578***	0.653***	0.199	0.219
	(0.241)	(0.250)	(0.173)	(0.174)
Number of children	-0.109*	-0.130**	0.050	0.045
	(0.058)	(0.061)	(0.036)	(0.036)
Sells at least one unprocessed food product	-0.579	-0.442	-0.129	0.007
	(0.360)	(0.379)	(0.165)	(0.260)

Table 2.10 (cont'd)

	Probit		Lognormal	
Specializes in 1 processed product	1.185***	1.210***	-0.289	-0.256
	(0.292)	(0.311)	(0.249)	(0.244)
Makes and sells beignets	1.958***	2.154***	0.860***	0.928***
	(0.328)	(0.372)	(0.266)	(0.266)
Makes and sells ready-to-eat meals	2.761***	2.970***	-0.020	-0.007
	(0.352)	(0.400)	(0.402)	(0.400)
Makes and sells other processed foods	0.172	0.220	0.735***	0.768***
	(0.275)	(0.286)	(0.189)	(0.189)
Vendor sources some of their cowpea supply from this market	-	-	-0.464***	-0.534***
			(0.168)	(0.170)
Vendor sources some of their cowpea supply from home production	-	-	0.437	0.553*
			(0.297)	(0.298)
Vendor sources some of their cowpea supply from villages	-	-	-0.176	-0.129
			(0.193)	(0.192)
Vendor sources some of their cowpea supply from urban areas	-	-	0.118	0.122
			(0.162)	(0.160)
Woman	1.462***		0.528	-
	(0.461)		(0.471)	
IMR	-	-	-0.058	0.137
			(0.395)	(0.384)
Intercept	-6.746**	-6.248**	3.995*	4.722**
	(2.588)	(2.657)	(2.188)	(2.110)
N	345	326	214	209
DF	24	23	28	27
LR Chi 2	203.82	187.28	-	-
Prob > chi2	0.000	0.000	-	-
Pseudo R2	0.445	0.440	-	-
F	-	-	8.67	9.39
Prob > F	-	-	0	0
R squared	-	-	0.5676	0.584
Adj R squared	-	-	0.502	0.521
AIC	304.282	286.3308	584.893	313.4735
BIC	400.370	377.2164	682.506	405.7186

Source: Authors' calculations.

APPENDIX C: COMPARING THE FIT OF TOBIT AND DOUBLE HURDLE SPECIFICATIONS

Table 2.11 below presents the regression results for the truncated regression for hurdle 2. Table 2.12 below presents the results from the simplified one-stage Tobit model. These two specifications were tested against the lognormal specification in the body of the paper using the Vuong (1989) statistic following Wooldridge (2009). Table 2.13 below presents the Vuong statistics comparing each pair of models to determine the best fit amongst the three options. The results show that the probit-truncated regression and probit-lognormal models are both significantly better fits than the Tobit model respectively. Additionally, in comparing the lognormal to the truncated specification for hurdle 2, we find that the lognormal specification is a significantly better fit.

Table 2.11: Truncated Regression for Hurdle 2

	Coefficient	BSE
Dakar	50331.99	13507.13
Louga	-254726.4	132117.3
Monitored by SIM	13406.33	8991.479
Rural market	12360.27	8713.109
Tax rate paid by vendor (ln FCFA/week)	3198.552	2008.076
Number of categories of cowpea products sold	1640.396	3897.007
Price of cowpea (ln FCFA/kg)	36041.89	15217.58
Vendor operates out of physical structure	-15541.42	8425.941
Hours per week in this market	350.4401	246.4251
Family labor (hours/week)	148.9232	75.60773
Has employees (non-family labor)	9387.271	13402.78
Vendor received financial assistance at startup	-16821.38	11356.27
Vendor sources some of their cowpea supply from this market	-14847.49	9110.112
Vendor sources some of their cowpea supply from home production	13086.38	17528.61
Vendor sources some of their cowpea supply from villages	-11260.85	10901.89
Vendor sources some of their cowpea supply from urban areas	6935.285	10173.26
Sells in all seasons	77794.25	30213.24
Years selling in this market	-1984.15	6778.433
Vendor has attended some school	8029.329	10415.7
Vendor has secondary occupation	792.4138	10620.08
Married	4451.01	2771.364
Number of Children	11943.39	13300.01
Sale of unprocessed products	-5448.593	16368.11
Specialize in 1 processed product	49842.39	13870.27
Make and sell beignets	6362.132	16210.22
Make and sell ready-to-eat meals	28309.99	13364.6
Make and sell other processed cowpea products	-434412.6	124367.6
Constant	50331.99	13507.13
Wald chi2(26)	47.49	
Prob > chi2	0.0062	
Replications	500	

Source: Authors' calculations with bootstrapped standard errors (BSE).

Table 2.12: Tobit for Model Comparison

	Coefficient	BSE
Dakar	9559.294***	3380.746
Louga	-9540.383**	3724.847
Monitored by SIM	3370.861*	1655.892
Rural Market	6488.401***	2150.323
Market tax rate paid by vendor (100 FCFA/week)	29.36315	379.6557
Number of categories of cowpea products sold	161.1958	863.5636
Price of cowpea (100 FCFA/kg)	7603.483	2868.433
Vendor operates out of physical structure	-382.3328	1756.425
Hours per week in this market	56.08185**	49.42993
Family labor (hours/week)	56.80722	25.36583
Has employees (non-family labor)	2796.872	2696.171
Vendor received financial assistance at startup	-3850.666**	1737.109
Vendor sources some of their cowpea supply from this market	6690.843***	2320.779
Vendor sources some of their cowpea supply from home production	1489.161	5562.75
Vendor sources some of their cowpea supply from villages	4738.295*	2786.146
Vendor sources some of their cowpea supply from urban areas	10524.08***	2395.822
Sells in all seasons	6507.991**	2730.926
Years selling in this market	178.2766	112.9262
Vendor has attended some school	821.1768	1481.703
Vendor has secondary occupation	4663.983*	2681.113
Married	3355.102	2072.512
Number of children	79.87268	378.088
Sale of unprocessed products	1143.467	3292.219
Specialize in 1 processed product	4033.343*	2416.938
Make and sell beignets	15780.75***	2319.362
Make and sell ready-to-eat meals	16837.58***	2793.93
Make and sell other processed cowpea products	3301.116	2542.538
Constant	-97524.39***	19614.95
n	320	
Uncensored	203	
Left-censored	117	
Replications	500	
Wald chi2 (df=28)	198.42	
Prob > chi2	0.0000	
Pseudo R2	0.0542	

Source: Authors' calculations with bootstrapped standard errors.

Table 2.13: Model Comparison Test

Test	Model Comparison	Test Statistic	p-value
Likelihood Ratio	Probit-Truncated Normal vs. Tobit	116.921	0.000
Vuong Test	Probit-Truncated Normal vs Probit-Lognormal	-0.190	0.000

Source: Authors' calculations.

CHAPTER 3. TECHNICAL EFFICIENCY OF GRAIN PROCESSORS IN URBAN SENEGAL

3.1 Introduction

Consumption of ready-to-eat and convenience foods has been increasing over the past few decades (Popkin, 2017). Key drivers of the increase in consumption include higher incomes, greater opportunity cost of time, and increased availability and affordability of food products (Kinsey, 1981; Reardon, Tschirley et al 2021). The growth of convenience foods is quite evident in high-income countries, but we are also seeing this trend in low-income countries in sub-Saharan Africa (SSA). Convenience foods are particularly important for urban consumers (Bricas p.171, 1985). Research on consumption of prepared and processed cereal dishes in SSA from the past 50 years has focused on four strands: (1) increased consumption of milled rice and wheat, (2) shift from manual home processing to purchasing pre-milled coarse grains, (3) increased consumption of food away from home, and (4) increased consumption of ultra-processed foods (Reardon, Tschirley et al., 2021).

Supply of processed food has increased in response to demand. Literature on the supply of processed foods in SSA can be categorized into three main strands: (1) imports of rice and wheat, (2) import of non-staple foods to be processed domestically, and (3) import of highly processed foods (Reardon, Tschirley et al., 2021). In the 1970's/80's, hammermills became widely available and adopted in SSA due to their ability to reduce domestic labor milling grains by hand. As a result, many small enterprises emerged processing grain flours. In recent years, large enterprises have cornered more of the market for first stage processed goods due to their ability to benefit from economies of scale (Reardon, Liverpool-Tasie et al., 2021). First stage processed goods refer to single-ingredient food products that have undergone some transformation to make them easier to consume or cook with, such as grains that have been milled into flour. Second stage processed goods refer to multi-ingredient food products or products that have undergone additional transformation beyond the first stage such as cooked grain dishes (Reardon, Tschirley et al., 2021). Second stage processors sold mostly unpackaged, highly processed products in the 80's, but have since evolved to also sell packaged products to compete with larger enterprises that are now entering the market and competing for market share (Reardon, Liverpool-Tasie et al., 2021).

With this growth in demand and supply of processed foods, it is essential to understand who the major actors in the industry are, what choices they make, and how performant they are. There are many farm level studies that have examined farmer efficiency, technological choices, organizational choices, and the factors that contribute to success, but these types of studies are not common in the food processing industry. Reardon, Tschirley et al. (2021) found that across sub-Saharan Africa, small and medium enterprises (SMEs) that make packaged processed foods and/or unpackaged convenience foods such as traditional street foods, are the primary producers of processed foods. A few studies have looked at the efficiency of food processors in Europe and Asia (Spain: Rapun Garate et al., 1996; the Czech Republic: Naglova & Pechrova, 2019; China: Fu, Sun, & Zhou, 2011) and in SSA in Nigeria (Abass et al. 2019; Obianefo et al., 2023). In Nigeria, Abass et al. (2019) found regional differences in efficiency scores of cassava processors in Nigeria. They also found that efficiency is impacted by enterprise size, interactions with other actors, the number of products, and whether the enterprise received training. Obianefo et al. (2023) found that there was a substantial technology gap between small scale rice milling enterprises in Anambra State, Nigeria that were part of a government program that provided training and subsidized equipment and the small-scale rice milling enterprises that were not part of this program. They also found that the technology gap was a contributing factor to the lower efficiencies of non-participants compared to participants. It is relevant to keep in mind that Nigeria has one of the highest GDPs on the African continent and a population 10 times larger than that of Senegal (International Monetary Fund, 2025; World Bank 2025), so while there may be similarities in the agri-food processing sector across SSA – it is also likely that there are major differences warranting research on food processing in SSA outside of Nigeria.

Since this area of the literature is relatively unexplored, our study provides new and valuable insights about the food processing SMEs. First, key characteristics of second-stage grain processing SMEs (i.e., street vendors and semi-industrial processors) in Senegal are examined. Second, the technical efficiencies of the street vendors and semi-industrial processors are estimated and then, the factors that impact their efficiency are analyzed and discussed.

The Senegalese Ministry of Agriculture and Rural Equipment defines: 1) industrial grain processors as companies equipped with high-capacity processing machines; 2) Semi-industrial processors as processing units represented by Economic Interest Groups (GIEs), Individual Enterprises, and Associations; and 3) Street vendors as vendors who process and sell grain products on street sides (Ministere de l'Agriculture et de l'Equipement Rural, 2019). The semi-industrial processors are relatively medium-scale, and more often formalized compared to the street vendors; some semi-industrial processors also make more packaged products to sell to retailers, in contrast to street vendors whose sole focus is selling directly to their customers (Ministere de l'Agriculture et de l'Equipement Rural, 2019).

There is some longstanding debate in the literature on how size affects efficiency (Lau & Yotopoulous, 1971). For informal enterprises, there is some evidence that smaller enterprises have higher labor productivity than larger enterprises (Islam & Amin, 2015). This contrasts previous findings that larger, informal enterprises are almost as efficient as their formal counterparts, but there is a sizeable productivity gap for smaller, informal enterprises (Benjamin & Mbaye, 2012). In Indonesia, evidence suggests that large scale shrimp traders have greater access to factor markets than small scale shrimp traders, which gives large enterprises a cost advantage and therefore higher levels of efficiency (Yi & Reardon 2015). The small number of large industrial firms that exist in Senegal prevents us from conducting meaningful statistical analysis for this population. A separate case study on the few large industrial processors may provide additional insights into the food processing sector of Senegal. In this study, we contribute to the size-productivity relationship discussion by estimating the efficiencies of small-scale street vendors and medium-scale semi-industrial processing enterprises in Senegal and exploring the factors that affect efficiency.

We also examine the use of capital-intensive processing techniques over those that are more labor intensive. We expect to see a large gap in technology adoption between street vendors and semi-industrial enterprises, with street vendors relying more on traditional, labor-intensive, manual processing techniques.

Being part of a cooperative or association of processors may improve access to resources, create opportunities for group purchasing discounts, or provide a variety of other benefits, however, the cooperatives/associations in SSA faces numerous challenges including funding constraints and literacy of membership, among others (Mamo et al., 2021). Findings regarding whether producer organizations successfully provide net benefits to their members are mixed, as there is evidence of some organizations providing more benefits than costs, whereas other organizations may face substantial challenges in providing sufficient benefits to the member base to outweigh the demands and costs associated with membership (Shiferaw, Hellin, & Muricho

2011). In this study we will explore organizational membership for street vendors and semi-industrial enterprises to explain which types of processors are members of organizations, and whether that impacts their efficiency.

Finally, in many low-income countries, women are heavily involved in the processing stage of agri-food value chains. In Senegal and Mali, second stage cowpea processing SMEs are mostly operated by women (see Chapter 2 and Sissoko et al., 2022). We examine whether women also dominate the street vending and/or semi-industrial food processing sectors in Senegal. It is beneficial to understand the factors affecting the performance of women-operated food processing SMEs, as they are key players in the grain value chains in Africa (Reardon, Liverpool-Tasie et al., 2021) and thus, the overall performance of food processing SMEs may be tied to women's welfare and employment.

To do so, we use a unique dataset collected in 2018 under the Agricultural Policy Support Program (PAPA) with information on 237 semi-industrial enterprises and 586 street vendors that participate in second-stage grain processing across the 14 regional capitals and 5 additional major urban centers in Senegal. Descriptive statistics are used to present key characteristics of SMEs. To examine the efficiency of second-stage processors in Senegal, we employ Stochastic Frontier Analysis (SFA). The technical efficiency scores of street vendors and semi-industrial enterprises are estimated separately and their determinants of inefficiency for both groups are examined and discussed.

3.2 The Senegalese Context

Our study focuses on small and medium sized second-stage grain processors across urban Senegal, a Sahelian country in West Africa. Per capita GDP in Senegal has grown 158% since the year 2000, up from $620 USD to $1600 (World Bank, 2022). It is expected that as incomes rise, households will devote more of their budget to convenience foods. The Senegalese diet is still heavily comprised of cereals. Annual per capita consumption of cereals is 237 kg including 73 kg of coarse grains like millet and sorghum, 39 kg of wheat, and 125 kg of rice (FAO, 2024).

Processing grain is very labor and time intensive. It takes more than one hour of tedious work to dehull two kilograms of millet, then, it still needs to be turned into flour and processed further for many dishes (Singh et al., 2024). It is thus clear why purchasing processed grain is desirable if one can afford to do so; the opportunity costs of processing the grain oneself are high. Dehulling the grain and grinding it into flour are considered first stage processing. Second stage processing of grain often involves incorporating water into grain flour and rolling the mixture into very small balls of dough, steam-cooking, and then potentially drying it (Chase-Wash, 2019). There are three primary sizes of granules created through this process. Thiakry is the name for the smallest (in diameter) product, followed by thiere, then finally arraw, the largest. These couscous-style products can be sold dried, where the consumer must finish preparing the product at home (e.g., add liquid and cook) or already prepared and ready for immediate consumption (Ministere de l'Agriculture et de l'Equipement Rural, 2019). Previous research has found that these processed grain products made with millet and sorghum have become more widely offered by grain processing SMEs, and particularly street vendors, since the early 2000's (Chase-Walsh, 2019; Reardon, Liverpool-Tasie et al., 2021).

In 2015, 97% of the food processing enterprises in Senegal were classified as small and informal and only 20 companies nationwide were considered large scale operations utilizing modern processing technology (Osinski & Sylla, 2020). Given that small enterprises still dominate the industry, it may be advantageous for them to join organizations to improve their access to bulk input or invest in a piece of technology together. In Senegal, common types of organizations include Economic Interest Groups (GIEs), unions, associations, and street traders' organizations (Greven, 2017). A GIE is a registered group of individuals or businesses that have come together to pool resources and knowledge, while facilitating easier access to markets and services (Senem Group, 2024). This could be a group of several unrelated processors, or members of a family who work together in a processing business and form their own GIE, which is the "smallest economic unit beyond self-employment" (Greven 2017, p.314). GIEs are registered enterprises and therefore, they are part of the formal economy. GIEs and Processor's Associations are both organization types that are legally recognized (ISRA/BAME, 2024)[2]. There are additional types of organizations such as interprofessional organizations and women's processing organizations (GPFs), but membership is not a legally recognized status. Semi-industrial enterprises are more frequently members of organizations that are associated with a legal status (Ministere de l'Agriculture et de l'Equipement Rural, 2019). These organizations provide a variety of different benefits to the enterprises comprising their membership, however, they also often require enterprises to participate in certain activities or pay membership fees. In

[2] Email communications with Senegalese Agricultural Research Institution - Bureau of Macroeconomic Analysis (ISRA-BAME) in 2024

this paper, we explore the common benefits and costs associated with being in a processor's organization.

3.3 Conceptual Model

The estimation of technical efficiency facilitates a deeper understanding of the productivity differences between enterprises and which factors contribute to these differences. Stochastic Frontier Analysis (SFA) was first introduced as a method for measuring productive inefficiencies by Aigner, Lovell, and Schmidt (1977) as well as Meeusen and van den Broeck (1977). SFA is a parametric estimation approach that builds upon traditional production function analysis by allowing for a composed error term that distinguishes between technical inefficiency and random noise, providing a greater degree of flexibility and nuance than pre-existing alternatives like non-parametric Data Envelopment Analysis (DEA), which attributes all deviations to inefficiency, or Ordinary Least Squares (OLS) which attributes all deviations to random, symmetric noise.

Let the production function for processor i with input vector x_i and output y_i be defined as

$$y_i = f(x_i, \beta) + v_i - u_i$$

where $f(x_i, \beta)$ is the optimal output level, u_i is a non-negative term that captures inefficiency, or how far below the optimum the enterprise is operating, v_i is a stochastic error term capturing production shocks, and β is a vector of parameters to be estimated. The technical efficiency (TE) score of processor i is then calculated as the ratio of the actual output, y_i, to the predicted optimal output, $f(x_i, \beta)$.

$$TE_i = y_i / f(x_i, \beta)$$

A score of $TE_i = 1$ suggests a processor is operating at full efficiency on their optimal frontier. A score of $0 < TE_i < 1$ indicates that a processor is operating below their best-practice frontier (Battese & Coelli, 1995). In addition to understanding how a processor's production compares to the optimal frontier, we want to understand if there are particular characteristics of processors that are associated with being more efficient given their inputs and technology. To achieve this, we model the heteroskedasticity of u_i, the technical inefficiency term, as a linear function of explanatory variables, z_i, that are hypothesized to affect the inefficiency of processing enterprises and the vector of parameters, δ, which can be estimated to analyze how the z_i variables affect TE.

$$u_i = g\ (z_i, \delta)$$

SFA has been used widely in studies in other industries, such as agricultural production (Amaza, Bila & Iheanacho, 2006; Theriault & Serra 2014) and manufacturing (Ajibefun and Daramola 2003; Tingum & Ofeh 2017), but is growing in popularity for studies related to agrifood processing (Naglova & Pechrova, 2019). Fu, Sun, and Zhou (2011) looked at technical efficiency of first stage processing of paddy rice and wheat flour in China and found that the technical efficiency was around 0.5 for both groups. Gatimbu and Ogada (2020) employed a stochastic metafrontier approach to look at the technology gaps and technical efficiency of small-scale tea processors in Kenya.

3.4 Data

We use the dataset collected under the Agricultural Policy Support Program (PAPA), a *Feed the Future* Initiative of the United States Agency for International Development (USAID) in Senegal. The project was a collaboration between the Senegalese Minister of Agriculture and Rural Equipment, Michigan State University (MSU), the International Food Policy Research Institute (IFPRI), and Africa Lead with support from the Senegalese Institute for Agricultural Research – Bureau for Macroeconomic Analysis (ISRA-BAME). The project surveyed food processors across 19 urban centers in Senegal, the 14 regional capitals as well as 5 additional large cities. The population of interest was food processing SMEs in urban Senegal. To construct the sample of street vendors, the 2013 Recensement General de la Population et de l'Habitat (RGPH) Census Districts for each of the 19 urban centers were identified and 125 Census Districts were randomly drawn using relative city weights. For the semi-industrial enterprises, a census was conducted in the 19 urban centers. The survey was administered in February and March of 2018. A total of 237 semi-industrial enterprises and 586 street vendors were surveyed. The dataset provides information on demographics, training, input accessibility and prices, business status and activities, production and sales, technology used, and contracts.

Descriptive statistics indicate that of the 237 semi-industrial processors, 8 are men and of the 586 street vendors, only 3 are men. These figures suggest that women dominate the small-scale grain processing sector in Senegal. This finding aligns with those in Chapter 2 of this dissertation and Sissoko et al. (2022), who found that the majority of cowpea processor-vendors in Senegalese and Malian markets were women. Based on these results, we limit the scope of our analyses to only women processors. Additionally, since the questions related to sales and input purchasing behaviors were broken down seasonally and that the analysis focuses on the peak season only due to lower recall time, processors that did not process grain products in the prior peak season or had incomplete information about their business activities for that season are excluded. After these adjustments, the final samples of processors for our analyses are composed of 552 street vendors and 200 semi-industrial processors.

3.5 Empirical Model

For the stochastic frontier analysis, we employ the Cobb-Douglas form of the production function, which is a simple yet flexible functional form that allows for straightforward interpretation of estimated coefficients and requires fewer parameters to be estimated compared to alternatives such as the translog production function. Following Kumbhakar and Lovell (2000), we begin with the Cobb-Douglas production function for processor *i*

$$\ln(y_i) = \beta_0 + \sum_{j=1}^{m} \beta_j \ln(x_{ji}) + v_i - u_i$$

where the technical inefficiency component of the error term is non-negative, $u_i \geq 0$, and we assume u_i and v_i are independently distributed such that $v_i \sim iid\ N(0, \sigma_v^2)$ and $u_i \sim N^+(0, \sigma_{u_i}^2)$. We simultaneously model the heteroskedasticity in the technical inefficiency term as a linear function of the hypothesized determinants of inefficiency z_i, we parameterize $\sigma_i^2 = \exp\ (z_i{}'\delta)$.

Let Φ( ) be the cumulative distribution function of the standard normal distribution, then the log likelihood function for the normal/half-normal stochastic frontier model is as follows:

$$\ln(L) = \sum_{i=1}^{N} \frac{1}{2} ln\left(\frac{2}{\pi}\right) - ln\ \sigma_S + ln\ \Phi\left(-\frac{\epsilon_i \lambda}{\sigma_S}\right) - \frac{\epsilon_i^2}{2\ \sigma_S^2}$$

$$\sigma_S^2 = \sigma_u^2 + \sigma_v^2$$

$$\gamma = \frac{\sigma_u^2}{\sigma_S^2}$$

$$\lambda = \frac{\sigma_u}{\sigma_v}$$

$$\epsilon_i = y_i - x_i\beta$$

To incorporate the heteroskedasticity in the technical inefficiency term, we replace σ_u with $\sigma_i^2 = \exp\,(z_i{}'\delta)$. The technical efficiency score is calculated as:

$$TE_i = E\{\exp\,(-u_i|\epsilon_i)\} = \left\{ \frac{1 - \Phi\left(\frac{\sigma_i^2 \sigma_v}{\sigma_S} - \frac{\epsilon_i \sigma_u^2 \sigma_S}{\sigma_S^2 \sigma_u \sigma_v}\right)}{1 - \Phi\left(-\frac{\epsilon_i \sigma_u^2 \sigma_S}{\sigma_S^2 \sigma_u \sigma_v}\right)} \right\} exp\left\{ \frac{\epsilon_i \sigma_u^2}{\sigma_S^2} + \frac{1}{2}\left(\frac{\sigma_u \sigma_v}{\sigma_S}\right)^2 \right\}$$

We estimate two separate stochastic frontier models - one for street vendors and one for semi-industrial processors - as we expect these two different types of processors are operating under different production frontiers. The descriptive findings in the results section showing the technological differences between the two types of enterprises justify this separation (Table 3.6).

The output variable, y_i is the total value of all second stage processed grain products sold by a processor *i* in FCFA per month. The vector x_i includes all of the factors of production: number of units of primary processing of equipment, number of units of secondary processing equipment, total number of labor days used per month, kilograms of raw grain inputs purchased in FCFA per month, kilograms of pre-processed grain inputs purchased in FCFA per month, monthly expenditure in FCFA for utilities (energy + water) and outsourced milling, a dummy variable if the processor rents out a production or sales space, and a dummy if the processor has a stove or furnace. For semi-industrial processors, we also include a dummy variable indicating if the processor has a refrigerator.

We face censoring in some of the independent variables, as not all enterprises use every factor of production. Since we must transform the variables by taking the natural logarithm for the Cobb-Douglas functional form, censoring will pose a problem. We explore the inclusion of dummy variables for the production factors that face censoring in addition to including the continuous versions of these variables transformed by *ln(x+1)* following the recommendation of Battese (1997). This approach is still commonly used in the literature today (Koppenberg, 2023). However, when we include indicator and level variables for the censored inputs in our model, we face issues generating feasible starting values for the SFA analysis. Therefore, we opt to keep the continuous variables and drop the indicators. Additionally, we test two other transformations of the censored continuous variables, *ln(x+0.01)* and the inverse hyperbolic sine transformation. The coefficient magnitudes differ slightly between models, but the directionality and significance do not change (see Appendix A for additional details).

We model the heteroskedasticity in the technical inefficiency of a processor *i* in the vector z_i, which is composed of variables hypothesized to impact a processors efficiency score, though they are not directly involved as productive factors in the production function. In this vector we include a dummy variable if the processor's main place of processing is their home, a dummy if the processor sells their products in a different place than they do the processing, a dummy if the processor employs shared or borrowed equipment in their processing, a dummy if the processor makes and/or sells non-grain processed food products, the natural log of the years of experience processing, a dummy if a processor makes both ready-to-eat and dried processed grain products, and the number of different processing techniques the business uses.

For semi-industrial vendors, we include a dummy variable if the processor is a member of any processor's organization, but this is left out of the street vendor model since street vendors are very rarely members of processor's organizations. Prior researchers found evidence that membership in an agricultural cooperative is endogenous to efficiency (Ahado et al., 2021; Ma et al., 2021; Neupane et al. 2022; Qu et al., 2020), thus we find it essential to consider the possibility that membership in a processor's organization is endogenous to the efficiency of processing enterprises. Following Bonfiglio et al. (2019), we address this potential endogeneity issue by employing the two-step instrumental variables estimator proposed in Karakaplan and Kutlu (2015). This estimator is a generalization of the commonly employed Battese and Coelli (1995) estimator. The Karakaplan and Kutlu estimator relaxes the assumption that v_i and u_i are independent by allowing them to be only conditionally independent given the observables in the model. Following this procedure, we instrument for membership in a processor's organization with the proportion of their 10 nearest neighbors in the dataset that are members of processor's organizations. The proportion of a processor's neighbors that are members of organizations should not directly impact the efficiency of a processing SME as they are not the recipients of any benefits of organizational membership, nor do they have any obligations to any organizations, either of which could impact their efficiency. However, previous research has shown that neighbor's membership in an organization can be an appropriate instrument for one's own membership as one's peers may encourage them to join, or one may see their peers benefit from membership (Ito et al. 2012; Lin et al., 2022; Ma & Abdulai, 2016; Zhang et al., 2020). The first-stage F statistic of our instrument is 11.37 with a p-value of 0.0000, providing support that our choice of instrument meets the relevance criteria as the F-statistic exceeds the rule-of-thumb minimum F-statistic of 10.

Let y_i be the natural log of the output in sales value, let x_{1i}be a vector of exogenous and endogenous variables of the production frontier, let $u_i \geq 0$ be the one-sided technical inefficiency term and let v_i be the two-sided random error term (Karakaplan & Kutlu, 2015).

$$y_i = x_{1i}'\beta + \ v_i - u_i$$

Then, let $Z_i = I_p \otimes z_i'$ where z_i a vector of exogenous instruments for the endogenous variables in the production function and I_p is the identity matrix. Also let ε_i be a two-sided error term (Karakaplan & Kutlu, 2015).

$$x_i = Z_i\delta + \varepsilon_i$$

The variance-covariance matrix of ε_i is denoted Ω and $\sigma_{vi}{}^2$is the variance of v_i. The correlation between $\widetilde{\varepsilon_i}$ and v_i is represented by ρ.

$$\begin{bmatrix} \widetilde{\varepsilon_i} \\ v_i \end{bmatrix} \equiv \begin{bmatrix} \sqrt{\Omega}\varepsilon_i \\ v_i \end{bmatrix} \sim \mathbf{N}\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} I_p & \sigma_{vi}\rho \\ \sigma_{vi}\rho' & \sigma_{vi}{}^2 \end{bmatrix} \right)$$

Then we allow $v_i$and $u_i$to be conditionally independent instead of requiring full independence (Karakaplan & Kutlu, 2015). Let x_{2i}be a vector of exogenous and endogenous variables that influence the inefficiency term. Then, let the inefficiency term depend on this vector as well as an observation specific random component $u_i{}^* \geq 0$ and $\sigma_{ui} = \sigma_u(x_{2i}; \varphi_u) > 0$ such that,

$$u_i = \sigma_{ui}\, u_i{}^*$$

In this model, u_i and v_i are conditionally independent given x_i and z_i. The log-likelihood function is,

$$\ln L(\theta) = \ln L_{y|x}(\theta) + lnL_x(\theta)$$

$$\ln L_{y|x}(\theta) = \sum_{i=1}^{n} \left(\frac{\ln\left(\frac{2}{\pi}\right) - \ln \sigma_i^2 - \left(\frac{e_i}{\sigma_i}\right)}{2} + \ln \Phi\left(\frac{-\lambda_i e_i}{\sigma_i}\right) \right)$$

$$\ln L_x(\theta) = \sum_{i=1}^{n} \left(\frac{-p \cdot \ln 2\pi - \ln(|\Omega|) - \varepsilon_i' \Omega^{-1} \varepsilon_i}{2} \right)$$

such that,

$$e_i = y_i - x_{1i}'\beta - \frac{\sigma_{wi}}{\sigma_{cw}} \eta'(x_i - Z_i\delta)$$

$$\varepsilon_i = x_i - Z_i\delta$$

$$\sigma_i^2 = \sigma_{wi}^2 + \sigma_{ui}^2$$

$$\lambda = \frac{\sigma_{ui}}{\sigma_{wi}}$$

Then, the efficiency estimator is,

$$E[\exp(-u_i)\,|e_i]^s = \left(\frac{1 - \Phi(\sigma_i^2 - \frac{\mu_i^*}{\sigma_i^*}}{1 - \Phi\left(-\frac{\mu_i^*}{\sigma_i^*}\right)} exp\left(-\mu_i^* + \frac{1}{2}\sigma_i^{*2}\right) \right)^s$$

where,

$$\mu_i^* = \frac{-e_i \sigma_{ui}^2}{\sigma_i^2}$$

$$\sigma_i^{*2} = \frac{\sigma_{wi}^2 \sigma_{ui}^2}{\sigma_i^2}$$

Then, a test for the need to correct for endogeneity can be conducted by testing the joint significance of the components of the endogeneity correction term (Karakaplan & Kutlu, 2015). Significance of individual components of the endogeneity correction term provide evidence of endogeneity of individual variables. In our case, we are only examining one hypothesized endogenous variable, membership in a processor's organization, therefore the significance of the coefficient on the correction term for membership in a processor's organization is a sufficient test for the need for the endogeneity correction.

All models are estimated using maximum likelihood techniques in StataBE 18.5. Since the sample of street vendors was stratified by city, we cluster the standard errors at the city level for the estimation of the street vendors' frontier. For one city, there was only one processor sampled so the processor is clustered with the next nearest city, leaving us with 18 city clusters. By contrast, the population of semi-industrial processors was identified and then surveyed, therefore, we do not need to adjust for sampling procedures in the standard errors for the semi-industrialists' frontier. Instead, we include control variables for the largest cities in the dataset, Dakar, Thies, Kaolack, and Mbour, which are each major population centers (Africapolis, 2015).

3.6 Results

3.6.1 Key characteristics of SMEs

Table 3.1: Demographics of Women's 2nd Stage Grain Processing SMEs in Urban Senegal

	Processor Type	
	Semi-Industrial	**Street Vendor**
Age (years)	53.6 (11.3)	48.3 (11.9)
Marital Status		
Single	4 (2.0%)	19 (3.4%)
Married	155 (77.5%)	422 (76.4%)
Divorced	11 (5.5%)	10 (1.8%)
Widowed	30 (15.0%)	101 (18.3%)
Literacy level		
Unable to read or write	84 (42.0%)	456 (82.6%)
Can read in one language	33 (16.5%)	41 (7.4%)
Can read and write in one language	83 (41.5%)	55 (10.0%)
n	200	552

Source: Authors' calculations using PAPA 2018 data. For continuous variables, mean values are given with standard deviations in parentheses. For indicator variables, frequency is given with the percentage in parentheses.

Table 3.1 (above) builds a demographic profile of the women who operate second stage grain processing enterprises in urban Senegal. We find that the average age of the women processors is around 50 years old. Just over 75% of the women processors are married in both the semi-industrial group and the group of street vendors. We also find the semi-industrial women processors are on average more literate than the street vendors. While 58% of semi-industrial processors are able to read and/or write, only 17.4% of street vendors can read and/or write.

In Table 3.2, we present details about the business activities of women's second stage grain processing enterprises. We find that semi-industrial processors make more than 4 different types of processed grain products on average, compared to less than 2 for street vendors. Despite this difference, the number of processing activities semi-industrialists use to make their products in is not much greater than the number of processing activities used by street vendors. This indicate that the semi-industrialists are making different products that share some processing techniques. A high proportion of street vendors (88.2%) and semi-industrial processors (70%) process food for their business at home. Additionally, we find that 43% of semi-industrial processors and 41.7% of street vendors sell their products somewhere other than where they process them.

Semi-industrial processors sell on average more than three times the value per month that street vendors, with average monthly sales of processed grain products in the peak season around 190,000 FCFA compared to around 60,300 FCFA. Millet is the most popularly processed grain by far with 97% of semi-industrial processors and ~95% of street vendors processing the grain. Maize is the second most popular with ~36% of semi-industrialists and 15% of street vendors preparing maize-based products. While 93.5% of street vendors make ready-to-eat food products, only 17.4% of them make any dry products. In contrast, 74.5% of the semi-industrial processors make dried grain products and 47.5% make ready-to-eat grain products.

Few processors sell unprocessed grains or non-grain food products. The processors that are engaged in non-grain-processing activities are often processing these other foods such as fruits and vegetables or legumes. Semi-industrial enterprises generally engage in more post-production activities than street vendors. About 56% of the semi-industrial processors package dried products in plastic bags and a combined 11% package ready-to-eat products in plastic bags or boxes. A third of semi-industrial processors participate in product labeling and just over a quarter of these businesses deliver their products. In comparison, only 9.2% of street vendors package their ready-to-eat products in plastic bags and less than 5% of street vendors participate in each of the other activities respectively. Second-stage grain processing SMEs rely heavily on direct-to-consumer sales with over 99% of vendors selling through this channel. Semi-industrial processors are much more likely than street vendors to sell through other sales channels in addition to selling directly to their consumers. About 45% of the semi-industrial enterprises sell to retailers and even 4% of them sell to supermarkets. By packaging, labeling and potentially

Table 3.2: Business Profiles of Women's 2nd Stage Grain Processing SMEs in Urban Senegal

	Processor Type	
	Semi-Industrial	**Street Vendor**
Grain Processing Activities		
Processed grain sales in peak season (FCFA/month)	190,030 (319,116)	60,274 (76,049)
Years of grain processing experience	9.963 (7.356)	11.930 (9.906)
Number of processed grain products made	4.090 (2.959)	1.772 (1.236)
Number of cereals processed in peak season	2.305 (0.875)	1.895 (0.599)
Number of processes business uses for all products	4.885 (2.262)	4.096 (1.734)
Conduct processing activities in home	140 (70.0%)	487 (88.2%)
Sell products somewhere other than place of processing	86 (43.0%)	230 (41.7%)
Processes millet	194 (97.0%)	524 (94.9%)
Processes sorghum	10 (5.0%)	8 (1.4%)
Processes maize	71 (35.5%)	80 (14.5%)
Processes rice	31 (15.5%)	17 (3.1%)
Processes fonio	13 (6.5%)	2 (0.4%)
Makes and sells dry processed grain products	149 (74.5%)	96 (17.4%)
Makes and sells ready-to-eat processed grain products	95 (47.5%)	516 (93.5%)
Makes and sells both dry and ready-to-eat processed grain products	44 (22.0%)	60 (10.9%)
Other Activities		
Sells raw grain	7 (3.5%)	2 (0.4%)
Sells fruits and vegetables	14 (7.0%)	24 (4.3%)
Sells legumes	11 (5.5%)	14 (2.5%)
Sells other agrifood products	4 (2.0%)	5 (0.9%)
Processes fruits and vegetables	32 (16.0%)	3 (0.5%)
Processes legumes	25 (12.5%)	24 (4.3%)
Processes other agrifood products	10 (5.0%)	7 (1.3%)
Refrigeration of ready-to-eat products	4 (2.0%)	20 (3.6%)
Packaging ready-to-eat products in plastic bags	14 (7.0%)	51 (9.2%)
Packaging ready-to-eat products in plastic boxes	8 (4.0%)	2 (0.4%)
Packaging dried products in plastic bags	112 (56.0%)	13 (2.4%)
Labeling	64 (32.0%)	2 (0.4%)
Delivery	52 (26.0%)	25 (4.5%)
Sells directly to consumers	198 (99.0%)	550 (99.6%)
Sells to retailers	90 (45.0%)	46 (8.3%)
Sells to supermarkets	8 (4.0%)	0 (0.0%)
Finances		
Proportion of working capital needs in previous month covered by business revenue	0.937 (0.173)	0.936 (0.177)
Used own money to start business	93 (46.5%)	272 (49.3%)
Used loan money to start business	75 (37.5%)	151 (27.4%)
Used gifted money to start business	85 (42.5%)	202 (36.6%)
Used gifted/loaned money from family/friends to start business	51 (25.5%)	209 (37.9%)
n	200	552

Source: Authors' calculations using PAPA 2018 data. For continuous variables, mean values are given with standard deviations in parentheses. For indicator variables, frequency is given with the percentage in parentheses.

delivering their products, semi-industrial processors may more easily sell their products through indirect sales channels. Packaging dried products, labeling, and delivery are all positively correlated with retail sales with correlation coefficients of 0.51, 0.31 and 0.41 respectively. The non-use of refrigeration, packaging, and labeling and the non-participation in delivery activities is negatively correlated with use of retail sales channels with a correlation coefficient of -0.38.

Despite substantial differences in the business activities of street vendors and semi-industrial grain processors, the financing situation looks much more similar between the two groups. Both groups cover, on average, 94% of their monthly working capital needs with their business revenues. The major difference between the groups when it comes to financing is that more semi-industrial processors were able to obtain loans or gift funding from sources outside of family and friends to start their businesses, whereas street vendors more frequently rely on gift funds and loans from their friends and family.

Table 3.3 presents information about the formal and informal networks for second stage grain processors in urban Senegal. The government and NGOs are primary sources of training for processors and while 57.5% of the semi-industrial processors have received some type of training, less than 5% of the street vendors have received any training. It is relevant to note, however, that we do not have information on trainings from NGOs that were attended more than one year before the data was collected. The government trainings at startup can be particularly intensive and provide support through the critical early stages of enterprise development until the business can function on its own (Ministre de l'Agriculture et de l'Equipment Rural, 2020). A total of 58 of the semi-industrial processors have benefitted from this unique opportunity (29%), whereas only 13 of the street vendors were trained in this way (2.4%). Across all training types and overall, the rate of training is more than 10x higher for semi-industrial processors than for street vendors.

Semi-industrial processors are also substantially more likely to be part of processors organizations. About 42.5% of semi-industrialists are in organizations compared to 3.1% of street vendors. These organizations range in formality, benefits, and costs. GIEs and Associations are more formal, as they have legal statuses. They are also the most popular types of organizations of which second stage grain processing SMEs are members.

Table 3.3: Formal and Informal Professional Networks of Women's 2nd Stage Grain Processing SMEs in Urban Senegal

	Processor Type	
	Semi-Industrial	**Street Vendor**
Has ever received training from the government or an NGO	115 (57.5%)	26 (4.7%)
Has received training from an NGO in the past 12 months	75 (37.5%)	17 (3.1%)
Received training from the government at/just before startup	58 (29.0%)	13 (2.4%)
Has received training from the government after startup	42 (21.0%)	7 (1.3%)
Member of any type of processor's organization	85 (42.5%)	17 (3.1%)
Member of a GIE	27 (13.5%)	6 (1.1%)
Member of an Association of processors	26 (13.0%)	6 (1.1%)
Member of a Cooperative of processors	13 (6.5%)	1 (0.2%)
Member of a GPF	10 (5.0%)	4 (0.7%)
Member of an interprofessional organization including processors	9 (4.5%)	0 (0.0%)
Member of another type of processor's organization	11 (5.5%)	0 (0.0%)
Shares information with other enterprises in same locality	17 (8.5%)	46 (8.3%)
Share labor or subcontracting services with other enterprises in the same locality	12 (6.0%)	36 (6.5%)
Borrows equipment or shares with other enterprises in same locality	52 (26.0%)	113 (20.5%)
Registered at startup	87 (43.5%)	6 (1.1%)
Registered in 2018	126 (63.0%)	8 (1.5%)
n	200	552

Source: Authors' calculations using PAPA 2018 data. Frequency is given with the percentage in parentheses.

Though it is clear from the training and organizational membership statistics that street vendors are not well connected to the more formal or more established professional networks in processing, we do find that many street vendors establish informal networks with peers in their locality. Interestingly, we see that semi-industrial processors are involved with informal networks in their locality at similar rates to street vendors. This suggests that formal professional networks serve as a complement to informal networks, which may still be integral to some processors who either benefit from both informal and formal networks or still rely on informal networks even when their access to formal networks increases. It is somewhat common for processing enterprises to use borrowed equipment or share equipment with others in their locality as 26% of semi-industrial processors and 20.5% of street vendors borrow or share equipment. Sharing information with peers in the same locality is less common 8.5% of semi-industrialists and 8.3% of street vendors share information. The least common informal networking activity is sharing labor or subcontracting services as only 6% of semi-industrial processors and 6.5% of street vendors do such. Additionally, a very small proportion of street vendors are registered, whereas more than half of the semi-industrial processors are registered.

Table 3.4: Organizational Advantages and Obligations for Members of Processing Organizations

	Processor Type	
	Semi-Industrial	**Street Vendor**
Years in organization	7.6 (6.5)	7.0 (6.1)
Processor is a board member of the organization	59 (69.4%)	6 (35.3%)
Obligations of Organizational Membership		
Membership fees	67 (78.8%)	12 (70.6%)
Contributions	64 (75.3%)	6 (35.3%)
Participation in meetings	56 (65.9%)	11 (64.7%)
Fulfilling organizational commitments	53 (62.4%)	11 (64.7%)
Advantages of Organizational Membership		
Consulting on processing technology	70 (82.4%)	9 (52.9%)
Price advice	42 (49.4%)	5 (29.4%)
Product quality control	33 (38.8%)	1 (5.9%)
Acquisition of packaging	31 (36.5%)	1 (5.9%)
Group input purchasing	19 (22.4%)	1 (5.9%)
Facilitation of access to credit	31 (36.5%)	7 (41.2%)
n	85	17

Source: Authors' calculations using PAPA 2018 data. For continuous variables, mean values are given with standard deviations in parentheses. For indicator variables, frequency is given with the percentage in parentheses.

Table 3.4 (above) examines the benefits and costs of membership in a processor's organization more closely. For this analysis, we are only looking at the processors who are part of an organization, i.e. 85 semi-industrial vendors and 17 street vendors. Semi-industrial processors have been members of their respective organization for an average of 7.6 years and street vendors have been members for an average of 7.0 years. While nearly 70% of semi-industrial processors are members of the board of their organization, only around 35% of street vendors are members of the board of their organization. Obligations of membership are similar in the organizations that street vendors and semi-industrial processors are a part of. Most organizations require the processors to pay membership fees. Many also require that members participate in organizational meetings or meet various other organizational commitments. The most commonly reported advantage of organizational membership is consulting on processing technology. The next most commonly reported advantage from semi-industrial processors who are members of organizations is pricing advice, but for street vendors the next most commonly reported advantage is facilitation of access to credit.

Table 3.5 explores the use of inputs and labor and average monthly expenses for women's second stage grain processing enterprises. Overall, semi-industrial processors use an average of around 2,391 kg of grain inputs per month in peak season, whereas street vendors use only an average of 356kg. All processors in both the semi-industrial and street vendor categories use some raw grain inputs, but only 40.5% of semi-industrial processors and 27.7% of street vendors use processed grain inputs. Few street vendors rent a space for processing or selling (2.5%). Semi-industrial processors are also more likely to rent a space to begin with (20%). The majority of both street vendors and semi-industrial processors outsource some grain milling, costing around 25,668 FCFA per month for semi-industrialists and 14,382 FCFA per month for street vendors. About 30% of semi-industrial processors and 25.5% of street vendors use additional labor in their business. For street vendors, the more common type of labor employed is family labor, whereas for semi-industrial enterprises it is more common to employ non-family labor.

Table 3.5: Inputs, Labor, and Expenses for Women's 2nd Stage Grain Processing SMEs

	Processor Type	
	Semi-Industrial	**Street Vendor**
Total grain inputs per month in peak season (kg)	2,391 (6,227)	356 (402)
Uses raw grain inputs	200 (100.0%)	552 (100.0%)
Raw grain inputs per month in peak season (kg)	2,154 (6,099)	340 (399)
Uses processed grain inputs	81 (40.5%)	153 (27.7%)
Processed grain inputs in peak season (kg)	958 (3,079)	100 (180)
Has monthly water expense	105 (52.5%)	177 (32.1%)
Monthly water expense (FCFA)	8,728 (17,846)	4,143 (5,427)
Has monthly energy expenses	198 (99.0%)	541 (98.0%)
Monthly energy expense (FCFA)	37,419 (48,688)	22,520 (32,333)
Rents a space for processing or sales	40 (20.0%)	14 (2.5%)
Monthly rent for processing/sales space (FCFA)	56,145 (37,267)	16,950 (22,739)
Has monthly outsourced milling expense	159 (79.5%)	504 (91.3%)
Monthly outsourced milling expense (FCFA)	25,668 (63,486)	14,382 (16,003)
Has monthly packaging expense	92 (46.0%)	260 (47.1%)
Monthly packaging expense (FCFA)	27,115 (42,686)	9,594 (11,548)
Employs any type of labor	60 (30.0%)	141 (25.5%)
Employs family labor	26 (13.0%)	126 (22.8%)
Employs non-family labor	43 (21.5%)	26 (4.7%)
Total labor days per month	23.2 (15.0)	24.7 (13.4)
n	200	552

Source: Authors' calculations using PAPA 2018 data. For continuous variables, mean values are given with standard deviations in parentheses. For indicator variables, frequency is given with the percentage in parentheses.

In Table 3.6, we present the information on the equipment used by the enterprise and the processing activities they conduct to create their products. Most enterprises have both stage 1 and stage 2 processing equipment. Semi-industrial processors that have first stage processing equipment have on average 13.3 units compared to only 3.3 units on average for street vendors that have first stage equipment. The gap between the average number of units of second stage equipment for semi-industrial processors and street vendors is smaller than the gap for first stage equipment. Semi-industrial processors and street vendors that use second stage processing equipment have on average 5.2 and 2.2 units of equipment respectively. 40% of the semi-industrial processors use a stove and/or furnace for their processing compared to 46.2% of the street vendors. The refrigerator use rate is higher for semi-industrial processors (12%) than street vendors (5.4%).

Table 3.6: Technology Used by Women's 2nd Stage Grain Processing SMEs in Urban Senegal

	Processor Type	
	Semi-Industrial	**Street Vendor**
Use stage 1 processing equipment	190 (95.0%)	514 (93.1%)
Number of units of stage 1 processing equipment	13.3 (16.6)	3.3 (2.0)
Use stage 2 processing equipment	194 (97.0%)	525 (95.1%)
Number of units of stage 2 processing equipment	5.2 (9.6)	2.2 (1.4)
Use stove and/or furnace	80 (40.0%)	255 (46.2%)
Number of stoves and/or furnaces	2.0 (1.2)	1.3 (0.5)
Use refrigerator(s)	24 (12.0%)	30 (5.4%)
Mechanical parboiling process for ready-to-eat products	3.1%	1.2%
Manual parboiling process for ready-to-eat products	96.9%	98.8%
Mechanical parboiling process for dried products	7.0%	11.3%
Manual parboiling process for dried products	93.0%	88.7%
Mechanical de-clumping process for ready-to-eat products	1.5%	1.2%
Manual de-clumping process for ready-to-eat products	98.5%	98.8%
Mechanical de-clumping process for dried products	5.8%	8.8%
Manual de-clumping process for dried products	94.2%	91.2%
Mechanical sifting for ready-to-eat products	1.3%	1.7%
Manual sifting for ready-to-eat products	98.7%	98.3%
Mechanical sifting for dried products	4.8%	9.0%
Manual sifting for dried products	95.2%	88.5%
Mechanical hydration/rolling for ready-to-eat products	1.7%	0.0%
Manual hydration/rolling for ready-to-eat products	98.3%	100.0%
Mechanical hydration/rolling for dried products	4.2%	1.7%
Manual hydration/rolling process for dried products	95.8%	98.3%
Mechanical drying process for dried products	9.6%	0.0%
Manual drying process for dried products	90.4%	100.0%
Mechanical packaging process for ready-to-eat products	2.5%	0.8%
Semi-mechanical packaging process for ready-to-eat products	23.8%	0.3%
Manual packaging process for ready-to-eat products	61.3%	98.9%
Mechanical packaging process for dried products	7.5%	3.6%
Semi-mechanical packaging process for dried products	53.1%	10.9%
Manual packaging process for dried products	39.5%	85.5%
n	200	552

Source: Authors' calculations using PAPA 2018 data. For continuous variables, mean values are given with standard deviations in parentheses. For indicator variables, frequency is given with the percentage in parentheses.

In examining the various types of processing activities enterprises are engaging in, we see that rates of mechanization are low across the board for all processes and all processor types.

Around 75% of the semi-industrial enterprises make any dry products and around 48% make any ready-to-eat products. For street vendors, around 17% make any dry products and 94% make ready-to-eat products. The processing activities that an enterprise participates in will depend on the types of products made. Table 3.6 shows the percentage of enterprises, within each processor type and overall, using mechanical vs manual technologies for each processing activity when making ready-to-eat or dried products. The rates of use of mechanical processes are higher for dried products than for ready-to-eat products. For example, 7% of semi-industrial enterprises who parboil during the making of dry products use mechanical technology compared to only 3.1% who parboil during the making of ready-to-eat products.

3.6.2 Stochastic Frontier Analysis

Table 3.7 presents the estimation results for both SFA models: the model for street vendors and the model for semi-industrial processors including the endogeneity correction. Recall that we use the proportion of a semi-industrialist's 10 nearest neighbors that are members of processor's organizations as an instrument in the correction for endogeneity of a processor's own membership. Although the endogeneity correction term is not significant, we choose to proceed with this version of the model that incorporates the correction, due to the strong evidence in the literature supporting the need for the correction (Ahado et al., 2021; Ma et al., 2021; Neupane et al. 2022; Qu et al., 2020). Results from the model without the endogeneity correction can be found in Appendix C. If we omit the endogeneity correction, the findings are not substantially impacted.

Since we follow the Cobb-Douglas functional form for our production function, the estimated coefficients can be interpreted as elasticities. This means a 1% increase in raw grain inputs per month (in kilograms) is associated with a 0.240% increase in sales for street vendors and a 0.228% increase in sales for semi-industrial processors. Increasing processed grain inputs by 1% is associated with a 0.114% increase in sales for street vendors and a 0.082% increase for semi-industrial processors. The impacts of increasing grain inputs are predicted to be similar for semi-industrial enterprises and street vendors.

Table 3.7: Stochastic Frontier Analysis Estimation Results

	Model 1: Street Vendors	Model 2: Semi-Industrial
Production Function Parameters		
Raw grain inputs in *ln(kg/month)*	0.240 ***	0.228 ***
	(0.049)	(0.039)
Processed grain inputs in *ln(kg/month)*	0.114 ***	0.082 **
	(0.032)	(0.028)
Utility costs in *ln(FCFA/month)*	0.133 ***	0.059
	(0.031)	(0.055)
Cost of outsourced milling in *ln(FCFA/month)*	-0.014	-0.023
	(0.027)	(0.018)
Number of labor days per month *(ln)*	0.053 **	0.045
	(0.023)	(0.055)
Number of units of first stage processing equipment *(ln)*	0.392 ***	0.060
	(0.079)	(0.085)
Number of units of second stage processing equipment *(ln)*	0.169 *	0.334 *
	-(0.101)	(0.132)
Uses stove and/or furnace	-0.152	0.141
	(0.099)	(0.165)
Uses refrigerator	-	0.647 *
	-	(0.259)
Rents processing or selling space	-	0.076
	-	(0.189)
Intercept	7.892 ***	9.079 ***
	(0.440)	(0.565)
Stochastic Error		
Intercept	-0.749 ***	-0.402 *
	(0.289)	(0.174)
Technical Inefficiency		
Grain processing experience *ln(years)*	-0.292	-0.046
	(0.178)	(0.401)
Number of processes used in production	0.093	0.028
	(0.089)	(0.112)
Shares or borrows some equipment	0.631 **	1.015
	(0.271)	(0.680)
Also processes non-grain foods	1.293 **	1.012
	(0.601)	(0.843)
Processed in home	0.971 *	0.874
	(0.567)	(0.768)
Sells in location other than processing location	-0.812	2.060 **
	(0.527)	(0.755)
Makes dry and ready-to-eat products	-2.949 *	-0.572
	(1.636)	(0.577)
Member of processor’s organization	-	-1.157 *
	-	(0.929)
Sell processed products to retailers	-	-2.100 **
	-	(0.807)
Intercept	-1.089	-1.609
	(0.876)	(1.695)
Endogeneity Correction Term	-	-0.075
	-	(0.409)
n	552	200
Clusters used in std. err. calculation	Yes (18 cities)	No
Control variables for major cities	No	Yes
Wald chi 2	334.07	94.96
Degrees of freedom	8	10
Prob > chi2	0.000	0.000

*Source: Authors' calculations using PAPA 2018 data. The control variables for major cities include Dakar, Thies, Mbour, and Kaolack; *** p<0.01, ** p<0.05, * p<0.10.*

For street vendors, increasing utility expenditure by 1% is associated with a 0.133% increase in the value of processed grain products sold. Increasing the use of labor days by 1% is associated with a 0.053% increase in sales value. Increasing the quantity of first stage processing equipment by 1% is associated with a 0.392% increase in sales and a 1% increase in the quantity of second stage processing equipment is associated with a more modest 0.169% increase in sales.

For semi-industrial enterprises, the use of a refrigerator is associated with 64.7% higher sales. Spending 1% more on outsourced milling does not significantly increase or decrease expected sales. Increasing the quantity of first stage processing equipment does not have a statistically significant impact, but increasing the quantity of second stage processing equipment by 1% is associated with a 0.334% increase in sales. This aligns with the focus of our analysis on second-stage processors, as these processors rely more heavily on second stage processing equipment, using first stage processing equipment generally only to transform raw grain inputs in preparation for further processing.

In examining the estimated coefficients on the variables in the technical inefficiency term we can interpret the sign and significance. As we are estimating the factors that affect inefficiency, a positive coefficient is associated with an increase in inefficiency. In Table 3.7 we can see that there are several factors associated with increasing inefficiency of street vendors: Sharing or borrowing equipment, processing non-grain foods in addition to grains, and conducting one's processing activities in one's own home. We also find that street vendors who make both dry and ready-to-eat products are more efficient than their counterparts that only make dry or only make ready-to-eat products. There are a few potential reasons we may see this result. Processors who make both product types may benefit from economies of scale if they produce ready-to-eat and dried products using the same grain(s) and the same or similar processing steps. These processors could also be more efficient because they are more flexible. For example, they can sell both dried couscous as well as a ready-to-eat, steamed couscous dish. This could draw in a wider variety of customers by including both those who want to consume on the spot and those who want to purchase convenience food to take home. It could also increase transaction size for customers who can purchase a snack or meal to eat on the spot as well as convenience food to take home from the same vendor. Comparing two of the factors that influence the efficiency of street vendors, we see that those who diversify and make both dry and ready-to-eat second stage processed grain products have higher efficiency scores than those who specialize in only dry or ready-to-eat grain products, whereas those who diversify to process non-grain products have lower efficiency scores than those who specialize in only grain products. Given that we are only examining sales of processed grain products, we cannot speak to the efficiency of these street vendors related to the non-grain products they are selling or their overall sales for their enterprise compared to grain-only processing enterprises.

For semi-industrial enterprises, the only statistically significant increase in inefficiency is associated with selling in a location other than where one processes the grain. By having to move the finished product to sell it, processors may face substantial transportation costs. Both selling to retailers and being a member of a processor's organization have positive and statistically significant effects on a processor's estimated technical efficiency score. Both of these factors involve interactions with other players in the processed grain value chain who can increase a vendor's opportunity set in some way. These opportunities vary substantially, however, from pooling and forming a GIE of resources to introduction to an entirely new customer base through retail distribution.

Table 3.8: TE Scores for Semi Industrial Processors and Street Vendors

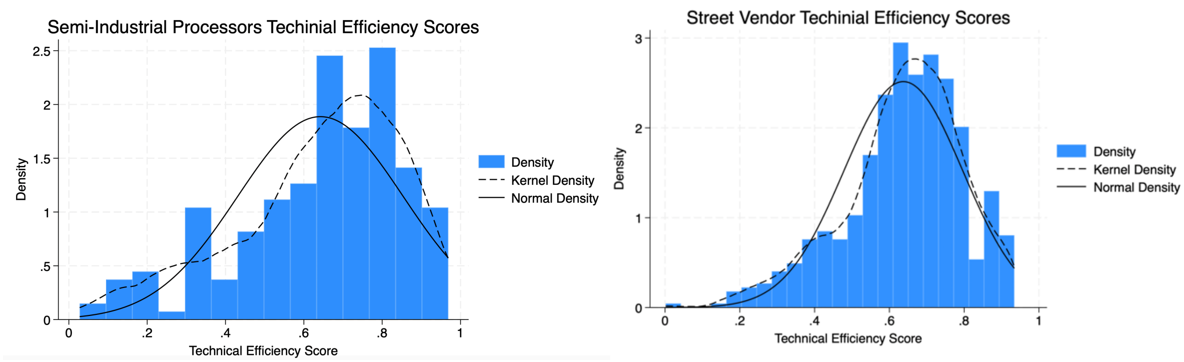
	Processor Type	
	Street Vendors	**Semi-Industrials**
Percentile	TE Score	TE Score
1%	0.204	0.096
5%	0.332	0.202
10%	0.408	0.320
25%	0.551	0.533
50%	0.654	0.679
75%	0.748	0.806
90%	0.823	0.871
95%	0.877	0.933
99%	0.920	0.964
Mean	0.637	0.642
Std. Dev.	0.159	0.211
Min	0.002	0.028
Max	0.934	0.969
n	552	200

Source: Authors' calculations using PAPA 2018 data.

Table 3.8 presents the estimated Technical Efficiency (TE) scores for the semi-industrial processors and street vendors. The mean efficiency of semi-industrial processors is 0.642 and the mean efficiency of street vendors is 0.637. The results in Table 8 show that on average, street vendors and semi-industrial enterprises are equally as close to their own optimal frontiers. Note that we must be cautious in comparing TE scores between the two groups as they are not directly comparable since they have different optimal frontiers. In future research, we would like to explore Meta-Frontier Analysis (MFA) which would allow us to estimate an encompassing best practice frontier across processors to generate directly TE scores that are directly comparable across groups, but unfortunately our data was not suitable for this type of analysis. See Appendix B for more information.

Though we cannot compare the TE scores across processor types directly because they are sampled from different populations, we can draw some insights from comparing the distribution of TE scores for street vendors and semi-industrial. Figure 3.1 shows histograms of the TE scores of street vendors and semi-industrial processors, along with the plot of the kernel density and the normal density. We can see visually that neither group is perfectly normally distributed, but they are both relatively normal. Both group's peaks are slightly to the right of the peak of the normal distribution and both distributions are slightly more concentrated around the mean than the normal distribution, making the peak a bit taller.

Figure 3.1: Technical Efficiency Score Distributions



Source: Authors' calculations using PAPA 2018 data.

We seek to further explore differences in TE scores between different sub-groups of street vendors and semi-industrial processors. As the TE scores are not normally distributed, we must use an alternative to a t-test. We employ the Mann-Whitney test which is a non-parametric test that assigns a rank to each TE score for processor and then sums across the sub-group of semi-industrial processors or street vendors, respectively, to test for systematic differences in the distribution instead of testing differences in the mean.

First, to further examine the impacts of membership in a processor's organization, we compare the distribution of TE scores of semi-industrial firms that are members of processors organizations to the scores of those that are not members. The mean TE score for the 115 non-member semi-industrial enterprises is 0.565 ± (0.217) and the rank sum is 9,144. The mean score for the 85 member semi-industrial processors is 0.747 ± (0.151) and the rank sum is 10,956. The null hypothesis that the ranks of the TE score distributions of member and non-member semi-industrial vendors are equal is rejected at the 1% significance level, indicating that member semi-industrial processors tend to have higher TE scores than non-member semi-industrial processors.

Next, we look at the difference in efficiency of street vendors and semi-industrial enterprises that share or borrow equipment versus those that do not. For semi-industrial processors, the mean TE score for the 52 processors who share or borrow equipment is is 0.617 ± (0.190) compared to the mean score for the 148 with no training at startup, 0.651 ± (0.218). The Mann-Whitney test fails to reject the null hypothesis; thus we find no statistically significant evidence that the distribution of efficiency scores for semi-industrial enterprises that share equipment is different than the distribution of efficiency scores for those that do not share. For the street vendors, 439 do not share or borrow equipment and their mean TE score is 0.647 ± (0.148) compared to the 113 street vendors that do share or borrow equipment and have an average TE score of 0.599 ± (0.192). The Mann-Whitney test rejects the null hypothesis at the 5% level, suggesting that there is a difference in the distribution of TE scores for street vendors who share equipment and those who do not. Those who do not share equipment have higher efficiency on average.

To further examine how the processing and sales locations impact TE scores, we look at the Mann-Whitney tests for those that process at home versus those that do not, as well as for those enterprises that process and sell in only one location versus those that sell in a location other than where they process. The mean TE score of the 140 semi-industrial enterprises that process at home is 0.591 ± (0.209) and the rank sum is 8151. The mean score of the enterprises that do not process at home is 0.761 ± (0.166) and the rank sum is 11,949. The Mann-Whitney test rejects the null hypothesis at the 1% level, suggesting that non-home processors tend to have higher efficiency scores. The 65 street vendors that process outside their home have a mean TE score of 0.749 ± (0.126) and a rank sum of 25,960. The 487 street vendors that process in their home have an average TE score of 0.622 ± (0.157) and a rank sum of 126,668. The null hypothesis that the distributions of the two groups are the same is rejected at the 1% significance level.

The 86 semi-industrial firms that sell in a location other than where they process have an average TE score of 0.590 ± (0.230) and a rank sum of 7,539. The 114 semi-industrial enterprises that process and sell in the same location have an average TE score of 0.682 ± (0.188) and a rank sum of 12,561. The Mann-Whitney test rejects the null hypothesis at the 1% significance level, suggesting differences in the score distribution of those that process and sell in the same location and those that sell in a different location to where they process. For street vendors, the efficiency score of the 230 enterprises that sell in a location other than where they process is 0.705 ± (0.123) with a rank sum of 80,276. The efficiency of the 322 that process and sell in the same place is 0.589 ± (0.164) and the rank sum is 72,352. The Mann-Whitney test reveals that the null hypothesis is rejected at the 1% level. These findings suggest that for street vendors, selling in a location other than the processing location is associated with a higher TE score, but for semi-industrial firms, co-locating processing and sales operations is associated with higher TE scores.

3.7 Policy Implications

Our analysis of technical efficiency and drivers of inefficiency for street vendors and semi-industrial processors that make second stage processed grain products reveals key insights. First, our findings support the existing literature that women owned and operated SMEs dominate the processed food sector. This continues to be an important consideration for policymakers hoping to bolster the food processing sector. Additionally, policymakers seeking to support women's employment opportunities could design policies to support grain processing SMEs. We find that there is a larger concentration of highly efficient semi-industrial processors than street vendors, which suggests that even though there are fewer actors in this space, supporting the semi-industrial processors could be an effective way to boost sustainable growth of the processed food sector.

Our finding that sharing and/or borrowing equipment is a significant factor in reducing efficiency for street vendors suggests that improving access and affordability of key grain processing technologies could improve the efficiency of women's small-scale grain processing enterprises by allowing more of these women to own their own equipment. When sharing or borrowing equipment, each processor is constrained to only doing the processing activities that require that piece of equipment when that piece of equipment is in their possession. This could lead to lower efficiency by reducing total processing capacity per month for an enterprise or causing bottlenecks because they are unable to move to the next processing stage until they gain access to the equipment they need. The finding that few processors, even semi-industrial processors, have access to mechanical or semi-mechanical equipment also suggests that the low level of mechanization for food processing SMEs in general could be limiting their growth and ability to scale up their operations. Anticipated barriers to mechanization include electrification and access to credit, but these would be worth exploring in future analyses.

The finding that membership in a processor's organization significantly reduces technical inefficiency of semi-industrial second stage grain processors is substantial because it indicates that these membership in organization may have associated costs, but the benefits are likely to outweigh the costs of membership in by expanding an enterprise's productive capacity (measured as the value of processed products sold). The most direct policy implication one may draw from this is that increasing access to processor's organizations is a promising way to improve efficiency of semi-industrial processors, and potentially street vendors – though current street vendor participation rates in these organizations are too low to reliably estimate the impacts of membership using available data. We find that the most common benefits associated with membership in a processors organization for semi-industrial enterprises include advice on processing technologies and pricing. In future research, it would be worth exploring whether or not technological consulting and pricing advice received outside of processor's organizational membership is a contributing factor to reducing inefficiency through increased adoption of technologies and better pricing strategies respectively. If so, initiatives to provide these insights to farmers could potentially help bridge the gap and improve efficiency of enterprises that are not members of processors organizations.

We also recognize that there is a relatively strong sub-group of semi-industrial second stage grain processors that are engaging in post-processing value addition activities such as packaging, labeling and delivery. Many of these processors are the ones who are engaging in retail sales of dried second stage processed grain products. Our analysis finds that selling through retail channels is a statistically significant factor driving higher technical efficiency scores for semi-industrial processors, therefore this segment of the processing industry may warrant further research exploring post-second-stage processing value addition activities.

3.8 Conclusions

Over the past few decades, the demand and supply of processed foods have grown substantially across SSA. This expansion has increased the sector's importance in promoting food security and created employment opportunities, especially for women. Little is known about who the suppliers of processed foods are in West Africa. In this study, we explore the characteristics of second-stage grain processing SMEs in urban Senegal to understand who the processors are, and how efficient they are. Using data from the 2018 Agricultural Policy Support Program (PAPA), we explore the profiles and business practices of street vendors and semi-industrial processors that make second stage processed grain products across 19 major cities in Senegal. We restrict our focus to women processors, since they almost exclusively process in both groups, resulting in a sample of 552 street vendors and 200 semi-industrial grain processors.

We find that the average semi-industrial processor sells three times more than the average street vendor. We also find that millet is the most widely processed grain with 97% of semi-industrial processors and 95% of street vendors processing millet products. The majority of street vendors are focused on making ready-to-eat processed grain products (94%) and few make ready-to-eat grain products (17%). In contrast, just under half of the semi-industrial enterprises make any ready-to-eat products while nearly 75% make any dry products. Some semi-industrial processors engage in post-processing activities like packaging, labeling, and delivery of their goods, but few street vendors are engaged in these activities. Semi-industrial enterprises are also more likely to sell to retailers than street vendors, though all processors are reliant on direct-to-consumer sales for at least some of their business. There are a few semi-industrial processors who have gotten their products into supermarkets, but this is uncommon.

We find that street vendors are less likely than semi-industrial enterprises to be engaged with formal professional networks such as processor's organizations or NGOs that may provide training, but both groups are networking informally with other processors in their area to share equipment, and to a lesser extent, information and services. Street vendors, on average, have less equipment than semi-industrial processors and though it is uncommon for any processors to have mechanical or semi-mechanical processing technologies, ownership of these types of technologies is more common for semi-industrial processors than street vendors.

To understand how efficient urban grain processing SMEs are in Senegal, we estimate two stochastic frontier models, one for semi-industrial processors and one for street vendors. The stochastic frontier model decomposes the error component in the estimation of a production frontier to allow for technical inefficiency of the enterprise that is non-random. We are able to model this inefficiency as a function of enterprise characteristics to explore the factors that drive processors to greater inefficiency. For street vendors, we find that processing in one's own home, processing non-grain foods, and sharing or borrowing equipment are all factors that decrease efficiency. On the other hand, estimated efficiency is higher for street vendors that make both dry and ready-to-eat processed grain products. For semi-industrial enterprises, we find that those who sell their products in a location other than where they do their processing are more inefficient. This could be due to the added complexity or costs of transporting finished products. Semi-industrial enterprises that are members of processor's organizations or that sell through retail channels are more efficient than their counterparts. The average technical efficiency scores of street vendors (0.637 ± 0.159) and semi-industrial enterprises (0.642 ± 0.211) are similar. Although we cannot directly compare them, we can say that compared to their own respective potential production frontier, street vendors and semi-industrial firms achieve similar levels of efficiency on average.

Acknowledgements

This research was made possible by the United States Agency for International Development (USAID) through funding to the Feed the Future Innovation Lab for Food Security Policy Research, Capacity and Influence (PRCI) under grant 7200AA19LE000001. Any opinions, findings, conclusions, or recommendations expressed here are those of the author alone.

REFERENCES

Abass, A., Olarinde, L., Okoruwa, V., Amaza, P., Awoyale, W., Alabi, T., & Ndavi, M. (2019). Drivers of technical efficiency in cassava processing in Nigeria: Implications for a commercializing food sector. *Tropicultura*. DOI: 10.25518/2295-8010.573.

Africapolis. (2015). *Country report: Senegal*. Africapolis. Retrieved from https://africapolis.org/en/country-report/Senegal

Ahado, S., Hejkrlík, J., Enkhtur, A., Tseren, T., & Ratinger, T. (2021). Does cooperative membership impact the yield and efficiency of smallholder farmers? Evidence from potato farmers in Mongolia. *China Agricultural Economic Review*, *13*(4), 736-755. DOI: 10.1108/CAER-01-2021-0013

Aigner, D., Lovell, C. A. K., & Schmidt, P. (1977). Formulation And Estimation Of Stochastic Frontier Production Function Models. *Journal of Econometrics*, *6*, 21–37.

Ajibefun, I. A., & Daramola, A. G. (2003). Determinants of technical and allocative efficiency of micro-enterprises: Firm-level evidence from Nigeria. *African Development Review*, *15*(2–3), 353–395. https://doi.org/10.1111/j.1467-8268.2003.00077.x

Amaza, P. S., Bila, Y., & Iheanacho, A. C. (2006). Identification of Factors that Influence Technical Efficiency of Food Crop Production in West Africa: Empirical Evidence from Borno State, Nigeria. In *Journal of Agriculture and Rural Development in the Tropics and Subtropics* (Vol. 107, Issue 2).

Battese, G. E., & Coelli, T. J. (1995). A model for technical inefficiency effects in a stochastic frontier production function for panel data. *Empirical Economics*, *20*(2), 325–332. https://doi.org/10.1007/bf01205442

Battese, G. E. (1997). A Note On The Estimation Of Cobb-Douglas Production Functions When Some Explanatory Variables Have Zero Values. *Journal of Agricultural Economics*, *48*(1–3), 250–252. https://doi.org/10.1111/j.1477-9552.1997.tb01149.x

Benjamin, N. C., & Mbaye, A. A. (2012). The Informal Sector, Productivity, and Enforcement in West Africa: A Firm-level analysis. *Review of Development Economics*, *16*(4), 664–680. https://doi.org/10.1111/rode.12010

Bonfiglio, A., Henke, R., Pierangeli, F., & D'Andrea, M. R. P. (2019). Effects of redistributing policy support on farmers' technical efficiency. *Agricultural Economics*, *51*(2), 305–320. https://doi.org/10.1111/agec.12556

Bricas, A., Courade, G., Coussy, J., Hugon, P., & Muchnik, J. (1985). *Nourrir les villes en Afrique sub-saharienne*. L'Harmattan.

Chase-Walsh, S. V. (2019). *Willingness to Pay for Processed Grains in Dakar, Senegal: An Analysis Using Discrete Choice Experiments*. Michigan State University. Agricultural, Food, and Resource Economics.

FAO. 2024. Cereal supply and demand balances for sub-Saharan African countries – Situation as of June 2024. Rome. https://doi.org/10.4060/cd1405en

Farrell, M. J. (1957). The Measurement of Productive Efficiency. In *Journal of the Royal Statistical Society. Series A (General)* (Vol. 120, Issue 3). https://www.jstor.org/stable/2343100

Fu, W. G., Sun, S., & Zhou, Z. Y. (2011). Technical efficiency of food processing in China: The case of flour and rice processing. *China Agricultural Economic Review*, *3*(3), 321–334. https://doi.org/10.1108/17561371111165761

Gatimbu, K. K., & Ogada, M. J. (2020). Technical efficiency of the small-scale tea processors in Kenya: a stochastic metafrontier approach. *African Journal of Economic and Management Studies*, *11*(4), 653–667. https://doi.org/10.1108/ajems-10-2018-0303

Gaye, I., Thiam, A., & Sall, N. (2003). Etude de marché des produits transformés du mil et du sorgho: Initiative pour le developpement des mils et sorghos en Afrique de l'Ouest et du Centre, Un pilotage par l'aval. *Dakar: Comité National de Concertation du Sénégal.*

Greven, T. (2017). Organizing the informal economy in Senegal. In *Springer eBooks* (pp. 303–322). https://doi.org/10.1007/978-981-10-5756-4_12

Islam, A. M., & Amin, M. (2023). The gender labor productivity gap across informal firms. *World Development*, *167*, 106229. https://doi.org/10.1016/j.worlddev.2023.106229

Ito, J., Bao, Z., & Su, Q. (2012). Distributional effects of agricultural cooperatives in China: Exclusion of smallholders and potential gains on participation. *Food Policy*, *37*(6), 700–709. https://doi.org/10.1016/j.foodpol.2012.07.009

Karakaplan, Mustafa U. and Kutlu, Levent. (2015). Handling Endogeneity in Stochastic Frontier *Economics Bulletin.* http://dx.doi.org/10.2139/ssrn.2607276

Kinsey, J. (1981). *Food Away From Home Expenditures by Source of Household Income* [Paper]. American Agricultural Economics Association Summer Meetings, Clemson University, Clemson, South Carolina.

Koppenberg, M. (2023). Markups, organic agriculture and downstream concentration at the example of European dairy farmers. *Agricultural Economics*, *54*(2), 161–178. https://doi.org/10.1111/agec.12762

Kumbhakar, S. C. (1987). The specification of technical and allocative inefficiency in stochastic production and profit frontiers. *Journal of Econometrics*, *34*(3), 335–348. https://doi.org/10.1016/0304-4076(87)90016-9

Kumbhakar, S. C., Ghosh, S., & McGuckin, J. T. (1991). A Generalized Production Frontier Approach for Estimating Determinants of Inefficiency in U.S. Dairy Farms. *Journal of Business & Economic Statistics*, *9*(3), 279. https://doi.org/10.2307/1391292

Kumbhakar, S., & Lovell, C. A. (2000). *Stochastic Frontier Analysis*. Cambridge University Press. https://doi.org/https://doi.org/10.1017/CBO9781139174411

Lin, B., Wang, X., Jin, S., Yang, W., & Li, H. (2021). Impacts of cooperative membership on rice productivity: Evidence from China. *World Development*, *150*, 105669. https://doi.org/10.1016/j.worlddev.2021.105669

Ma, W., & Abdulai, A. (2016). Does cooperative membership improve household welfare? Evidence from apple farmers in China. *Food Policy*, *58*, 94–102. https://doi.org/10.1016/j.foodpol.2015.12.002

Ma, W., Zheng, H., Zhu, Y., & Qi, J. (2021). Effects of cooperative membership on financial performance of banana farmers in China: A heterogeneous analysis. *Annals of Public and Co-operative Economy*, *93*(1), 5–27. https://doi.org/10.1111/apce.12326

Macauley, H. (2015). *Cereal Crops: Rice, Maize, Millet, Sorghum, Wheat* [Background Paper]. Feeding Africa, Abdou Diouf International Conference Center, Dakar, Senegal.

Mamo, Y. A., Haji, J., Legesse, B., & Sassi, M. (2021). Challenges of agricultural cooperatives and their impact on profitability of potato growers in eastern Ethiopia. *Review of Agricultural and Applied Economics, 24*(2), 62–77. https://doi.org/10.15414/raae.2021.24.02.62-77

Meeusen, W., & van Den Broeck, J. (1977). Efficiency Estimation from Cobb-Douglas Production Functions with Composed Error. *International Economic Review*, *18*(2), 435. https://doi.org/10.2307/2525757

Ministre de l'Agriculture et de l'Equipement Rural. (2020). Rapport de recherche – Structure, Comportement, et Performance de la transformation des cereals seches au Senegal. *Feed the Future Senegal Projet d'Appui aux Politiques Agricoles.*

Náglová, Z., & Pechrová, M. Š. (2019). Subsidies and technical efficiency of Czech food processing industry. *Agricultural Economics (Czech Republic)*, *65*(4), 151–159. https://doi.org/10.17221/234/2018-AGRICECON

Neupane, H., Paudel, K. P., Adhikari, M., & He, Q. (2022). Impact of cooperative membership on production efficiency of smallholder goat farmers in Nepal. *Annals of Public and Co-operative Economy*, *93*(2), 337–356. https://doi.org/10.1111/apce.12371

Obianefo, C. A., Ezeano, I. C., Isibor, C. A., & Ahaneku, C. E. (2023). Technology gap Efficiency of Small-Scale rice processors in Anambra State, Nigeria. *Sustainability*, *15*(6), 4840. https://doi.org/10.3390/su15064840

Osinski, J., & Sylla, F. (2020). *Senegal Food Processing Ingredients 2020* [Report] USDA Foreign Agriculture Service.

Popkin, B. M. (2017). Relationship between shifts in food system dynamics and acceleration of the global nutrition transition. *Nutrition Reviews*, *75*(2), 73–82. https://doi.org/10.1093/nutrit/nuw064

Qu, R., Wu, Y., Chen, J., Jones, G. D., Li, W., Jin, S., Chang, Q., Cao, Y., Yang, G., Li, Z., & Frewer, L. J. (2020). Effects of Agricultural Cooperative Society on Farmers' Technical Efficiency: Evidence from Stochastic Frontier Analysis. *Sustainability*, *12*(19), 8194. https://doi.org/10.3390/su12198194

Rapun Garate, M., Iraizoz Apezteguia, B., Olmeda Fernandez, M., & Sanchez Garcia, M. (1996). [Productive structure and trade policy of food and agriculture industry of Navarra [Spain]]. *Serie Investigacion y Desarrollo Agrarios-Gobierno de Navarra (Espana)*, (1).

Reardon, T., Thiombiano, T., & Delgado, C. (1989). The importance of non traditional cereals in the consumption by rich and poor people in Ouagadougou. *Economie Rurale (France)*, 9–14.

Reardon, T., Liverpool-Tasie, L. S. O., & Minten, B. (2021). Quiet Revolution by SMEs in the midstream of value chains in developing regions: wholesale markets, wholesalers, logistics, and processing. *Food Security*, *13*(6), 1577–1594. https://doi.org/10.1007/s12571-021-01224-1

Reardon, T., Tschirley, D., Liverpool-Tasie, L. S. O., Awokuse, T., Fanzo, J., Minten, B., Vos, R., Dolislager, M., Sauer, C., Dhar, R., Vargas, C., Lartey, A., Raza, A., & Popkin, B. M. (2021). The processed food revolution in African food systems and the double burden of malnutrition. *Global Food Security*, *28*. https://doi.org/10.1016/j.gfs.2020.100466

Rudinskaya, T., & Kuzmenko, E. (2019). Investments, technical change and efficiency: Empirical evidence from Czech food processing. *AGRIS Online Papers in Economics and Informatics*, *11*(4), 93–103. https://doi.org/10.7160/aol.2019.110409

Senegal English Media Group. (2024) *For the Establishment of an Economic Interest Group*

(GIE). April 25. https://senemgroup.com/for-the-establishment-of-an-economic-interest-group-gie/

Shiferaw, B., Hellin, J., & Muricho, G. (2016). Markets access and agricultural productivity growth in developing countries: challenges and opportunities for producer organizations. In *Edward Elgar Publishing eBooks*. https://doi.org/10.4337/9781784719388.00013

Singh, S. M., T, J. J., & Rao, P. S. (2024). Technological advancements in millet dehulling and polishing process: An insight into pretreatment methods, machineries and impact on nutritional quality. *Grain & Oil Science and Technology*, *7*(3), 186–195. https://doi.org/10.1016/j.gaost.2024.05.007

Sissoko, M., Theriault, V., & Smale, M. (2022). Beyond grain: the potential of cowpea in local markets of Mali. *Journal of Agribusiness in Developing and Emerging Economies*, *14*(2), 310–331. https://doi.org/10.1108/jadee-02-2022-0035

Theriault, V., & Serra, R. (2014). Institutional Environment and Technical Efficiency: A Stochastic Frontier Analysis of Cotton Producers in West Africa. *Journal of Agricultural Economics*, *65*(2), 383–405. https://doi.org/10.1111/1477-9552.12049

Timmer, C. P. (1971). Using a Probabilistic Frontier Production Function to Measure Technical Efficiency. *Journal of Political Economy*, *79*(4), 776–794. https://doi.org/10.1086/259787

Tingum, E. N., & Ofeh, M. A. (2017). Technical Efficiency of Manufacturing Enterprises in Cameroon: Sources and Determinants. *International Journal of Financial Research*, *8*(3), 172. https://doi.org/10.5430/ijfr.v8n3p172

World Bank, World Development Indicators (2022). *GDP per capita (current US$) – Senegal.* [Data file]. Retrieved from https://data.worldbank.org/indicator/NY.GDP.PCAP.CD?locations=SN

Yi, D., & Reardon, T. (2015). Allocative Efficiency of Agrifood Traders: Shrimp Traders in Indonesia. Bulletin of Indonesian Economic Studies, 51(3), 405-423. https://doi.org/10.1080/00074918.2015.1107676

Zhang, S., Sun, Z., Ma, W., & Valentinov, V. (2019). The effect of cooperative membership on agricultural technology adoption in Sichuan, China. *China Economic Review*, *62*, 101334. https://doi.org/10.1016/j.chieco.2019.101334

APPENDIX A: INDEPENDENT VARIABLE TRANSFORMATION COMPARISONS

Table 3.9: Comparing Results from Stochastic Frontier Analysis Models

	Street Vendors			Semi-Industrial		
Model: f(x) =	***ln(x+1)***	***ln(x+.01)***	***arcsin(x)***	***ln(x+1)***	***ln(x+.01)***	***arcsin(x)***
Production Function Parameters						
Raw grain inputs *f(kg/month)*	0.240 *** (0.049)	0.122 *** (0.037)	0.209 *** (0.048)	0.228 *** (0.039)	0.123 *** (0.029)	0.242 *** (0.040)
Processed grain inputs *f(kg/month)*	0.114 *** (0.032)	0.104 *** (0.029)	0.093 *** (0.026)	0.082 ** (0.028)	0.091 *** (0.029)	0.093 *** (0.028)
Utility costs *f(FCFA/month)*	0.133 *** (0.031)	0.165 *** (0.035)	0.142 *** (0.032)	0.059 (0.055)	0.096* (0.055)	0.055 (0.056)
Cost of outsourced milling *f(FCFA/month)*	-0.014 (0.027)	-0.012 (0.019)	-0.015 (0.026)	-0.023 (0.018)	-0.021 (0.013)	-0.033 * (0.018)
Number of labor days per month *f(days/month)*	0.053 ** (0.023)	0.031 *** (0.010)	0.047 ** (0.020)	0.045 (0.055)	0.018 (0.023)	0.026 (0.048)
Number of units of first stage processing equipment *f(units)*	0.392 *** (0.079)	0.106 *** (0.027)	0.320 *** (0.061)	0.060 (0.085)	0.025 (0.045)	0.104 (0.074)
Number of units of second stage processing equipment *f(units)*	0.169 * (0.101)	0.038 (0.036)	0.131 * (0.079)	0.334 * (0.132)	0.139 *** (0.064)	0.303 *** (0.109)
Uses stove and/or furnace	-0.152 (0.099)	-0.14 (0.097)	-0.15 (0.099)	0.141 (0.165)	0.155 (0.163)	0.12 (0.155)
Uses refrigerator	- -	- -	- -	0.647 * (0.259)	0.625 ** (0.272)	0.736 *** (0.247)
Rents processing or selling space	- -	- -	- -	0.076 (0.189)	0.164 (0.194)	0.199 (0.210)
Intercept	7.892 *** (0.440)	8.939 *** (0.497)	7.718 *** (0.473)	9.079 *** (0.565)	9.903 *** (0.557)	8.691 *** (0.624)
Stochastic Error (ln sig2v)						
Intercept	-0.749 *** (0.289)	-0.625 ** (0.263)	-0.730 ** (0.284)	-0.402 * (0.174)	-0.360 ** (0.157)	-0.390 ** (0.169)
Technical Inefficiency (ln sig2u)						
Grain Processing Experience *f(years)*	-0.292 (0.178)	-0.339 * (0.186)	-0.305 * (0.183)	-0.046 (0.401)	-0.129 (0.304)	-0.071 (0.388)
Number of processes used in production	0.093 (0.089)	0.03 (0.090)	0.093 (0.090)	0.028 (0.112)	0.014 (0.103)	0.027 (0.110)
Shares or borrows some equipment	0.631 ** (0.271)	0.555 *** (0.208)	0.643 ** (0.267)	1.015 (0.680)	1.097* (0.655)	1.020 (0.671)
Also processes non-grain foods	1.293 ** (0.601)	1.279 ** (0.621)	1.286 ** (0.595)	1.012 (0.843)	0.765 (0.678)	0.980 (0.792)
Processed in home	0.971 * (0.567)	1.208 * (0.720)	0.986 * (0.571)	0.874 (0.768)	0.806 (0.693)	0.853 (0.746)
Sells in location other than processing location	-0.812 (0.527)	-0.873 (0.590)	-0.81 (0.523)	2.060 ** (0.755)	1.978 *** (0.594)	2.018 *** (0.706)
Makes dry and ready-to-eat products	-2.949 * (1.636)	-3.425 * (2.016)	-2.969 * (1.627)	-0.572 (0.577)	-0.551 (0.549)	-0.579 (0.573)
GIE or Association Member	- -	- -	- -	-1.573 (1.820)	-1.107 (0.998)	-1.490 (1.591)
Intercept	-1.089 (0.876)	-0.806 (0.921)	-1.066 (0.867)	-1.609 (1.695)	-1.055 (1.218)	-1.475 (1.579)
Endogeneity Correction Term	- -	- -	- -	-0.075 (0.409)	0.095 (0.330)	-0.049 (0.388)
n	552	552	552	200	200	200

*Source: Authors' calculations using PAPA 2018 data; *** p<0.01, ** p<0.05, * p<0.10.*

APPENDIX B: META FRONTIER EXPLORATION

In addition to the SFA models, we explore Metafrontier Analysis (MFA), proposed in Battese and Rao (2002). Through MFA, different sub-groups within a larger group are assumed to have the same potential technologies accessible but may have different production frontiers. A stochastic metafrontier is an enveloping frontier that encompasses all the different sub-group frontiers into a "best practice" frontier. Several meaningful statistics can be calculated after conducting a MFA including the ratio of an enterprise's expected output from the sub-group SFA to the enterprise's expected output from the full group MFA called the Technology Gap Ratio and the ratio of an enterprise's TE score from the sub-group SFA to the enterprise's TE score from the full group MFA. This normalizes the TE scores within the broader group, allowing for comparison in efficiency between subgroups with different technologies or between a subgroup and the broader group.

Table 3.10: Divisions Explored Econometrically for Meta Frontier Analysis

	Processor Type	
	Semi-Industrial	**Street Vendor**
Sales greater than 40,000/month	145 (72.5%)	257 (46.6%)
Sales less than or equal to 40,000 FCFA/month	55 (27.5%)	295 (53.4%)
More than 5 processes	109 (54.5%)	56 (10.1%)
5 or fewer processes	91 (45.5%)	496 (89.9%)
Less than half of sales from dry products	55 (27.5%)	489 (88.6%)
Half of sales or more from dry products	145 (72.5%)	63 (11.4%)
Do not purchase processed grain	119 (59.5%)	399 (72.3%)
Purchase processed grain	81 (40.5%)	153 (27.7%)
n	200	552

Source: Authors' calculations using PAPA 2018 data

In our exploration of a MFA for the second stage grain processing industry in urban Senegal, we find consistently that our data is insufficient to estimate a metafrontier. We explored a variety of sub-group divisions, testing MFA models for each of the groupings showing in the above table and exploring many other possibilities descriptively. We found that our samples of street vendors and semi-industrial processors are too small and homogenous for the estimation of a metafrontier with sub-groups, leading to convergence issues at different points in the estimation process. This is an area for future research to revisit.

APPENDIX C: RESULTS OF MODEL WITHOUT ENDOGENEITY CORRECTION

Table 3.11: Results for Semi Industrial Firms with and without Endogeneity Correction

	Model 1: No Correction	Model 2: Correction
Production Function Parameters		
Raw grain inputs in *ln(kg/month)*	0.227 ***	0.228 ***
	(0.039)	(0.039)
Processed grain inputs in *ln(kg/month)*	0.082 ***	0.082 **
	(0.028)	(0.028)
Utility costs in *ln(FCFA/month)*	0.060	0.059
	(0.055)	(0.055)
Cost of outsourced milling in *ln(FCFA/month)*	-0.024	-0.023
	(0.018)	(0.018)
Number of labor days per month *(ln)*	0.043	0.045
	(0.054)	(0.055)
Number of units of first stage processing equipment *(ln)*	0.064	0.060
	(0.082)	(0.085)
Number of units of second stage processing equipment *(ln)*	0.329 **	0.334 *
	(0.128)	(0.132)
Uses stove and/or furnace	0.153	0.141
	(0.152)	(0.165)
Uses refrigerator	0.635**	0.647 *
	(0.247)	(0.259)
Rents processing or selling space	0.081	0.076
	(0.187)	(0.189)
Intercept	9.095 ***	9.079 ***
	(0.548)	(0.565)
Stochastic Error		
Intercept	-0.414 ***	-0.402 *
	(0.155)	(0.174)
Technical Inefficiency		
Grain processing experience *ln(years)*	-0.073	-0.046
	(0.362)	(0.401)
Number of processes used in production	0.023	0.028
	(0.107)	(0.112)
Shares or borrows some equipment	0.994	1.015
	(0.647)	(0.680)
Also processes non-grain foods	0.947	1.012
	(0.702)	(0.843)
Processed in home	0.861	0.874
	(0.720)	(0.768)
Sells in location other than processing location	2.014***	2.060 **
	(0.624)	(0.755)
Makes dry and ready-to-eat products	-0.570	-0.572
	(0.576)	(0.577)
Member of processor’s organization	-1.312*	-1.573
	(0.775)	(1.820)
Sell processed products to retailers	-2.100	-2.100 **
	(0.801)	(0.807)
Intercept	-1.493	-1.609
	(1.409)	(1.695)
Endogeneity Correction Term	-	-0.075
	-	(0.409)
n	200	200
Control variables for major cities	Yes	Yes
Wald chi 2	94.60	94.96
Degrees of freedom	10	10
Prob > chi2	0.000	0.000

*Source: Authors' calculations using PAPA 2018 data. The control variables for major cities include Dakar, Thies, Mbour, and Kaolack; *** p<0.01, ** p<0.05, * p<0.10.*