FROM CHICKENS TO PERSISTENT POVERTY: THREE ESSAYS ON DYNAMIC BEHAVIOR

By

Samantha Lucía Padilla

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ABSTRACT

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My dissertation research applies dynamic optimization and panel-data methods to study household welfare in the United States and broiler poultry farms in Nigeria. The first chapter examines if persistent poverty among subpopulations in the United States can be explained by a poverty trap. Using panel data spanning over 40 years (1969-2017), we employ the most current nonparametric, semiparametric, and parametric estimation methods to test for a poverty trap and conditional convergence. Our results consistently find that there is no multiple equilibrium poverty trap in the United States generally, nor among female and black headed households. We find a single stable equilibrium that varies by the race and gender of the household head but is always above the U.S Census poverty line. Although there is no evidence of a poverty trap, there is evidence of persistent poverty among female and black headed households and systematic differences in incomes across racial lines. We consistently observe black-headed households converging to significantly lower equilibrium than white-headed households. While conditional convergence for African Americans is robust to the choice of method or time period, for female headed households the income gap is shrinking, consistent with improvements in the gender wage gap. Existing programs and policies have been ineffective in eliminating (or significantly reducing) the racial income gap at all education levels and occupations. This systematic discrimination needs to be addressed through labor and education reforms.

Chapters 2 and 3 focus on optimal decisions of commercial poultry farms in Nigeria using a discrete time and space dynamic programming (DP) algorithm, disaggregated by firm size. In Chapter 2, we explore the profitability of commercial farms facing rising input costs and increasing energy needs due to the adoption of climate mitigating technologies.

Using a cross-sectional dataset and a one-year weekly panel of farm inputs and prices, we employ a dynamic programming model to determine the source of economies of scale among commercial poultry farms. In the presence of high feed costs and increased energy needs, the optimal strategy for medium sized farms is to sell and exit the industry. However, it remains profitable for large firms to stay in the sector. The findings are robust to various alternative model assumptions and specifications. They indicate that broiler farms need larger flock sizes to withstand negative input price shocks and expand energy consumption in the face of volatile and hotter temperatures. The sensitivity of the poultry industry to changes in feed prices is a major threat to the growth and survival of farms and highlight the importance of developing risk management mechanisms to counteract the effects of unstable prices.

Chapter 3 examines the effect of electricity supply fluctuations on poultry farmer storage and freezer investment decisions. We combine a replacement and storage model to derive optimal storage rules. Then, we use expected cash flows from the model to derive freezer investment rules under uncertainty, due to fluctuating electricity supply and stochastic broiler and diesel prices. We find evidence that poultry farmers would use the storage option to take advantage of arbitrage opportunities and price premiums, but poor electricity supply hinders this. Despite positive gains from storage, freezer investments are not an optimal strategy due to high freezer costs and the need for generator use to complement poor electricity supply. The findings of this research (and its implications) are applicable across developing countries in Africa and Latin America that face scarce electricity supply and are in the process of expanding commercialized agricultural value chains as a way to increase farm incomes and stimulate economic growth.

Para mi mamá, María Eleonora Pavón Larios.
Mi más grande amor e inspiración.

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CHAPTER 1

PERSISTENT POVERTY IN THE UNITED STATES: MULTIPLE EQUILIBRIUM POVERTY TRAPS OR CONDITIONAL CONVERGENCE?

1.1 Introduction

Is the American Dream rapidly becoming the American Illusion? This question posed by Philip Alston (describing the reality of 40 million individuals living in poverty) echoes the current sentiment of many in America. However, this is not the first time the United States of America (USA) has experienced a need to address national poverty. Many components of the current welfare system (SNAP, Medicare, and Medicaid) were first introduced in the 1960s to counteract the then high poverty rate of 26%. Since then, the United States has been successful in reducing the average poverty rate in the country from the high 26% in 1960 (Wimer et al., 2013) to 12.3% in 2017.

Although the average poverty rate has improved, certain households in the United States today experience poverty at levels somewhat comparable to those in developing countries (Deaton, 2018). Particularly vulnerable populations include black and female headed households (Gottschalk, 1997; Snyder and McLaughlin, 2004). In 2017, the poverty rate of female headed households with children was five times higher than male headed households at 27% compared to 9% (Table 1.1). Similarly, 23% of black-headed households were in poverty, compared to only 8% of white-headed households (Table 1.2).[1] Examining persistence, we find that 18% and 22% of female and black headed households, respectively, that were poor in 2017 had been in poverty for five to ten previous consecutive waves of data (Table 1.3). These concerning statistics indicate a potential structural nature to poverty in the United States. Structural poverty refers to a deep rooted, persistent poverty due to market failures; where the poor are excluded from opportunities that could enable them grow

[1]These statistics were computed using the Panel Study of Income Dynamics (PSID) and were adjusted using sampling weights.

out of poverty.

This study explores the extent to which the poverty situation of black and female headed households in the United States is an indication of a poverty trap. This could be a "multiple equilibrium" poverty trap (Carter and Barrett, 2006) or conditional convergence into poverty. The former occurs when there is a bifurcated income path, with at least two stable equilibria and at least one the equilibria is below the poverty line, while the latter refers to when individuals with particular "permanent traits" converge to a single low equilibrium below the poverty line (Barrett and Carter, 2013).

Thus far, the poverty trap framework has largely been applied in developing countries; where multiple market failures (e.g credit and insurance) prevent some from being able to take advantage of productivity or welfare enhancing opportunities. This framework is relevant for exploring poverty in the US since particular features of the U.S. economy (such as exclusion of female and minority headed households from credit markets (Rao and Malapit, 2015; Cole and Mehran, 2011; Blanchflower, Levine, and D. J. Zimmerman, 2003)) could potentially influence structural nature of poverty, similar to the situation in a developing country. Furthermore, the large gaps between the incomes of blacks and whites have barely changed in the last 30 years. The distribution of wealth in the United States is concentrated in the top 1% of the population, and real wages today have the same purchasing power they did 40 years ago (Kochhar and Cilluffo, 2017; Shambaugh, Nunn, and Anderson, 2019).

If subpopulations in the U.S. are structurally poor as opposed to stochastically poor,[2] this has significant policy implications as different programs are necessary for addressing poverty traps versus stochastic poverty. Evidence of structural poverty among certain subpopulations could explain why current welfare efforts have not been successful in alleviating poverty for such groups. On the other hand, evidence of conditional convergence would highlight the existence of systematic barriers facing certain groups in the United States. If the purpose of the welfare state is to aid the most vulnerable individuals, the presence of either limits

[2]Stochastic poverty refers to individuals that experience poverty after a income shock, but are expected to return to a non-poor status given the assets at their disposal (Carter and Barrett, 2006).

the effectiveness of existing programs since they fail to address the mechanisms (market and institutional failures) driving structural poverty.

This study makes two main contributions to the development literature. To the best of our knowledge, this is the first study to apply the poverty trap theory in a developed country using a rich dataset that covers up to six generations of families over several decades. The only other study that uses a long-term panel to study poverty traps is Arunachalam and Shenoy (2017) in the context of India.

Our second contribution is methodological. In the past, most studies on poverty traps have largely focused on nonparametric and parametric methods to test for the existence of poverty traps. Both approaches have their limitations in identifying a poverty tap (Barrett and Carter, 2013) and we improve on several of these methods while confirming that our results are robust across various empirical methods. For example, results from nonparametric estimations are sensitive to the choice of bandwidth[3] (Seifert and Gasser, 2004; Rice, 1984), are prone to overfitting, and do not allow for the inclusion of additional covariates as controls nor the removal of time-invariant heterogeneity. While parametric estimations are less prone to overfitting and allow for control for observables and heterogeneity, this comes at the cost of imposing a functional form on the relationship between the dependent variable (current income) and the regressor of interest (lagged income), making it difficult to identify the s-shape curve indicative of a poverty trap. This study improves on both of these approaches and employs more flexible estimation strategies, such as a novel test developed by (Arunachalam and Shenoy, 2017) that relies on changes in the probability of negative income growth instead of a graphical analysis sensitive to fit issues. For our parametric test, rather than relying on commonly used estimators, we implement Monte Carlo simulations to compare the performance of the Arellano-Bond GMM estimator given different specifications[4] and to

[3] In the context of nonparametric estimations, a bandwidth is the parameter h that controls the degree of smoothing.

[4] Difference and system GMM have been widely used as the parametric, direct test in poverty trap studies, but they are highly sensitive to the number of instruments and due to its complex techniques, can easily lead to invalid estimates (Roodman 2009). We simulate varying the number of lags to be used of instruments, two-step vs. one step estimation, and first difference vs. orthogonal deviations.

alternate estimators (OLS, FE).[5] Although the Arellano and Bond estimator is sensitive to specifications, it deals with heterogeneity in ways other methods used in this study cannot.

For our nonparametric estimations, we use the bootstrap aggregating algorithm to estimate a predicted local polynomial regression (nonparametric) and use the generalized cross validation (GCV) criterion to predict the optimal bandwidth. By randomly drawing bootstrap samples from the data set, fitting a local polynomial regression in each bootstrap, and averaging over all the samples, we avoid overfitting the data. Lastly, we use a penalized smoothing spline (semi-nonparametric) to combine the strengths of the parametric and non-parametric methods (Naschold, 2013; Dillon and Quiñones, 2016). Using this suite of methods not only improves on previous papers but confirms the robustness of our findings.

Our results indicate that there is no multiple equilibrium poverty trap in the United States generally, nor among female and black headed households. We find a single stable equilibrium that varies by the race and gender of the household head but is always above the U.S Census poverty line. These results are consistent across estimation methods and time periods. However, we find strong evidence of conditional convergence across subpopulations in the United States. We consistently observe black-headed households converging to significantly lower equilibrium than white-headed households. We also find some evidence of a gap between female and male headed households. While conditional convergence for blacks is robust to the choice of method or time period, for female headed households the income gap is shrinking, consistent with improvements in the gender wage gap (Bernhardt, Morris, and Handcock, 1995; Francine D Blau, 2016), increases in labor force participation over the past decades (Lawrence M. Kahn and Francine D Blau, 2005; Weiner, 2016), and share of women working in professional occupations (Goldin, 2006).

Lack of evidence in support of a poverty trap in the United States suggests that while there are some mechanisms driving persistent poverty, there are opportunities to escape poverty. However, conditional convergence at significantly different (and lower) levels for

[5] The Arellano and Bond (1991) estimator was designed for large N-small T.

black headed households indicate that there are systematic restrictions and challenges faced by black headed households that prevent them from achieving the same living standards attainable by other subpopulations, which is still a major cause for concern.

1.2 Poverty Trap Framework

A poverty trap is defined as "poverty that is self-reinforcing due to equilibrium behaviors which perpetuate low standards of living" (Azariadis and Stachurski, 2005; Barrett, Garg, and McBride, 2016). This theory is derived from the macroeconomics growth literature and challenges the traditional convergence hypothesis where income differences between two economic actors endowed with different initial conditions and facing disparities in standards of living should diminish over time and eventually disappear (Mookherjee and Ray, 2001).

The microeconomic poverty trap literature has almost exclusively focused on households in developing countries because of the prevalence of extreme and persistent poverty. A trap is explained by market failures (mechanisms) that prevent economic agents from being able to take advantage of opportunities to improve their welfare and exit poverty, even when safety net programs, interventions, and foreign aid exist. The multiple financial market failures (MFMF) poverty trap is the most widely studied in empirical work since many of the issues in developing countries stem from financial constraints (Carter and Barrett, 2006; Barrett and Carter, 2013; Dutta, 2015). Restricted access to the credit market and the income and wealth disparities in the United States make the poverty trap framework applicable to explore persistent poverty. Rao and Malapit (2015) find that female single parent households of color are more likely to be unbanked (no saving or checking account) or underbanked (underuse of formal sector financial institutions for institutions like fringe banks). In the U.S. context, lack of use of formal saving establishments also affects a head's ability to access credit necessary to make asset investments. Differences in access to credit also exist between female and male business owners; using data from the Surveys of Small Business Finances, Cole and Mehran (2011) find female owners are more likely to be discouraged to apply for credit than male business owners. On the other hand, black business owners are twice more likely to be denied credit than white owners (Blanchflower, Levine, and D. J. Zimmerman, 2003).

While the majority of poverty trap studies in developing countries have focused on asset poverty, partly due to the challenges associated with good income data (Carter and Barrett, 2006), we use income data following Arunachalam and Shenoy (2017), Antman and McKenzie (2007), and the argument that poverty trap results are sensitive to how asset data is used and aggregated (McKay and Perge, 2013). Furthermore, using income variables in this context is appropriate since individuals in the U.S. mostly engage in jobs with well-defined dollar wages, as opposed to households in developing countries that depend on agriculture and/or a highly informal economy to earn a living. In the United States, income and wages are very well documented compared to developing countries, even for jobs that might be considered informal in developing countries.

1.3 Data Source: Panel Study of Income Dynamics (PSID)

This study uses the family and individual files from the Panel Study of Income Dynamics (PSID), the longest longitudinal, intergenerational household survey in the United States. The data has been collected for almost 50 years. About 75,000 people have participated, and as many as six generations within a sample family are represented. From 1968-1996, respondents were interviewed every year, but starting in 1997 the survey was conducted biannually. The unusual switch from annual to biannual data collection makes parametric estimation over the complete period difficult; therefore, we only focus on data collected every other year since 1969. Participants receive approximately $1 per minute of the interview.

The PSID was created from two independent samples: an oversample of 1,872 low-income families from the Survey of Economic Opportunity (SEO) and a representative sample of 2,930 families from the Survey Research Center (SRC) at the University of Michigan. The dataset continues to grow as the number of "sample" people, individuals from PSID families and everyone born and adopted by a sample person, increases. The split-off families of children from PSID original families are also interviewed, further increasing the size of the dataset. The PSID data is organized into five different data files: family file, cross-year individual file, birth history file, marriage history file and parent identification file. In this study we focus on the head of household, regardless of whether the family is a split-off or not. Most detailed information about the head of household is contained in the family file (McGonagle and Schoeni, 2006).

Over the years, the PSID has been updated to maintain its representativeness. In 1997, a sample of 511 immigrant families composed of individuals who moved to the United States post-1968 was added to the core survey. Likewise, different supplements have been created: The Child Development Supplement (since 1997), the Transition into Adulthood Supplement (since 2005), the Disability and Use of Time Supplement (since 2009) and more recently in 2014, the Well-being and Daily Life Supplement, the first supplement using the internet as the primary method of data collection.

Every wave of the PSID has asked respondents about sources of income of the head and spouse in the past period; if the wave year equals t, all the income variables refer to income in time $t-1$. We use the PSID constructed total family income variable defined as the sum of all sources of labor income of the head and wife from wages, profits from businesses, dividends, royalties cash flows from asset holdings (i.e. stocks, bonds, savings accounts), as well as transfer income.[6] All our income variables are converted to 2018 dollars using personal consumption expenditures (PCE) price index.[7]

Our unit of study is the household, but we focus on the characteristics of the head of household such as education, age, marital status, race and sex (Table 1.4). In this data set, headship is self-reported and not based on income measures. Past poverty traps studies have also included household head characteristics in the parametric estimations (Liverpool-Tasie and Winter-Nelson, 2011; A. R. Quisumbing and Baulch, 2013).

[6] Transfer income includes both private and public sources of income such as social security, welfare, income from settlements, inheritances, and loans from family members.

[7] The price index data was extracted from the Federal Reserve Economic Data.

1.3.1 Household Attrition

The attrition rate over the study periods is very high (Table 1.5). We test whether attrition is random using two approaches. First, following Baulch and A. Quisumbing (2011), we estimate a probit model with the attrition indicator as the dependent variable and the regressors are baseline wave (1969, 1981, 1997, or 2001) variables believed to predict the attrition. The results for this estimation are displayed in Table 1.6. The pseudo-R squared suggests the covariates included explain between 6%-58% of panel attrition in the years selected. In most of the periods evaluated, we find that age of the household, widow status, sex of the household head, veteran status, and race are significant predictors of attrition. Second, we perform the Becketti et al. (1988) (BGLW) test by regressing log income in 2017 on the baseline wave household variables, the attrition indicator variable, and the attrition indicator interacted with the other explanatory variables. We reject the null hypothesis that attrition is random based on the large Chi-squared statistic and significance at the 1% level ($p < 0.001$).

The results from both tests confirm that attrition is non-random and should be addressed with the use of inverse probability weights. These weights were computed in combination with the PSID sample weights (Wooldridge, 2010):

$$IPW_{i,T} = w_i \prod_{t=2}^{T} \frac{1}{\hat{p_{i,t}}} \tag{1.1}$$

where i indexes units of observations, $t = 1 \ldots T$ refers to the year, w_i corresponds to the PSID sampling weight, and $\hat{p_{i,t}}$ is the probability of being re-interviewed in round t.

1.4 Estimation Strategies

Many articles have recognized the difficulties of finding nonconvexities in the relationship between current and lagged income. Parametric results deal with heterogeneity at the expense of imposing a functional form, while nonparametric methods allow for no controls, are sensitive to specifications, and tend to overfit the data Naschold (2013) and Seifert and Gasser (2004). To confirm the robustness of our findings and complement the limitations of each of the methods, we use four different estimation strategies that improve both parametric and nonparametric methods and are more flexible. We begin with the (Arunachalam and Shenoy, 2017) test for poverty traps based on negative income growth, followed by a kernel-weighted local polynomial regression with bootstrap aggregation, a parametric model estimated using Generalized Method of Moments (GMM), and a penalized cubic spline regression. In this section, we discuss each of the methods and how they can be used to identify a poverty trap.

1.4.1 Arunachalam-Shenoy Test

Arunachalam and Shenoy (2017) argue that in the presence of a poverty trap, the probability of negative income growth decreases at income levels around the unstable equilibrium between the low and high steady states. Panels A and B in Figure 1.1 illustrate the intuition behind the test; for households with a single convergence point, the probability of negative income growth is always increasing in income (Panel A). Households above the steady state are always expected to experience a higher probability of negative income growth than poorer households because they are being pulled towards the single equilibrium. However, in the case of a poverty trap (Panel B) multiple equilibria cause the probability of negative income growth to decrease within a certain range above the unstable equilibrium. If the richer household is below the high steady state and within the high basin of attraction, the probability of negative growth decreases, a clear difference from the single convergence case.

The A-S test consists of first selecting a range of time and creating an indicator variable for negative income growth over that period. Next, outliers in the initial year are discarded and the initial year is split into 10 bins. Then, the mean of the indicator and standard error is computed by regressing the indicator for negative income growth on a set of bin dummies. Finally, we use a standard a t-statistic to test for differences in means. A significant positive difference in means between two successive bins (bins j and $j+1$), indicative of a decline in the probability of negative income growth, is evidence of a poverty trap.

A limitation of this test relates to the choice of bins. Arunachalam and Shenoy (2017) do not justify their choice of 10 bins or discuss how different number of bins could potentially affect the test's effectiveness in detecting a trap. Partitioning the data into too few bins fails to accurately display the distribution of income and selecting too many bins can affect the tests ability of properly identifying real changes in the probability of income growth. We confirm the robustness of our findings to several choices of the number of bins.[8]

1.4.2 Parametric Estimations

A typical parametric approach to poverty trap identification looks at the relationship between current income and some polynomial expansion of lagged income, controlling for various household and location characteristics expected to be correlated with income. However, it does not test the ability of an estimator $\hat{\beta}$ to predict the true β. We improve on this using a Monte Carlo simulation that replicates the most essential characteristics of the data generating process.[9] This additional step is vital to panel studies with high rates of attrition and autocorrelation (as is present in the PSID data set) and given the sensitivity of the Arellano and Bond estimator to different specifications.

The parametric model used is specified as a third order polynomial function of its lagged value following Jalan and Ravallion (2002):

$$y_{i,t} = \beta_0 + \sum_{p=1}^{3} \beta_p (y_{i,t-1})^p + \gamma X_{i,t} + c_i + \epsilon_{i,t} \quad (t = 2, \ldots, T) \tag{1.2}$$

where i indexes the household and t indexes the year; $y_{i,t}$ corresponds to log income of the household in time t, $y_{i,t-1}$ is lagged log income, $X_{i,t}$ is a vector of household characteristics that potentially influence the effect of the of lagged income on the dependent income variable, and c_i denotes the time-invariant fixed effect. The vector $X_{i,t}$ includes age of the head, squared age of head, educational attainment level, geographic location of the household (at the region[10] level), marital status, and race. By using a parametric method, we are able to

[8] The coefficient plots of 15 and 20 bins are in the appendix.

[9] See Appendix 1C for a more detailed description of the Monte Carlo simulation.

[10] There are 6 different regions in the PSID: Northeast, North Central, South, West, Alaska/Hawaii, and Foreign Country.

account for observed and unobserved, time-invariant heterogeneity; a benefit over all other estimation methods in this study. Lastly, for all the parametric estimations, we use inverse probability weights to account for attrition.

Our parameters of interest are the coefficients on the lagged dependent variable, the squared, and the cubic lagged dependent variable: $\beta_1, \beta_2,$ and β_3, as well as the visual representation of the relationship between lagged and current income. In this estimation procedure, evidence of a poverty trap is a significant relationship between predicted log income and the lagged income terms, as well as an s-shaped curve that intersects the 45-degree line from a level below the U.S. poverty line.

Results from 1,000 Monte Carlo simulations confirm that fixed effects and the Arellano and Bond estimator (two-step estimation with the Windmeijer correction and limited lags as instruments) perform best in a large panel with attrition (Appendix 1C). Usually, the lagged depended variable will be correlated with the fixed effect in the error term resulting in dynamic panel bias (Nickell, 1981), but the bias becomes insignificant with a large T (Roodman, 2006).

1.4.3 Nonparametric Estimation

For the nonparametric estimation, we use a kernel-weighted local polynomial regression, an extension of the local linear regression, to estimate the relationship between current and past values of income. Local polynomial regressions help reduce bias in the interior of the income distribution Naschold (2013), but are still sensitive to overfitting and the choice of bandwidth. We complement the standard nonparametric analysis used in the poverty trap literature with bootstrap aggregating, a machine learning algorithm that can reduce variance, improve unstable procedures and overfitting (Breiman, 1996). The method, also called bagging, generates multiple versions of a predictor variable by making bootstrap samples with replacement from the original dataset (referred to as the “training set”). Then, a model is fitted using each bootstrap sample and combined by averaging the fitted values of all samples. Evidence of a poverty trap would be the s-shaped curve of the aggregated fitted line.

Our model to test for the existence of a poverty trap estimates:

$$Y_{it+1} = m(Y_{it}) + \sigma^2(Y_{it})\epsilon_{it} \tag{1.3}$$

where Y_{it} is real per capita total family income, and $m(.)$ and $\sigma^2(.)$ are the mean and variance functions, respectively. The goal is to estimate the expected value of Y_{it+1} conditional on $Y_{it} = y_{0t}$ without assuming a functional form for $m(.)$ and $\sigma^2(.)$:

$$m(y_{0t}) = E(Y_{it+1}|Y_{it} = y_{0t}) \tag{1.4}$$

The local polynomial estimator of m at a point y_{0t} is based on the polynomial approximation of $m(Y_{it})$ near y_{0t} by minimizing the regression problem weighted by the kernel function K:

$$\sum_{i=1}^{N} \Big(Y_{it+1} - \sum_{j=0}^{p} \beta_j (Y_{it} - y_{0t})^j\Big)^2 \ K(\frac{Y_{it} - y_{0t}}{h}) \tag{1.5}$$

with respect to $\beta_0,\ \beta_1,\ \ldots \beta_p$ and where h is the smoothing parameter (bandwidth). Thus, the local polynomial regression is a weighted regression using data centered around y_{0t} (Seifert and Gasser, 2004).

We use degree $p = 3$, a bandwidth minimizes the generalized cross validation (GCV) criterion (Loader, 1999), and the asymptotically optimal Epanechnikov kernel weight function (Seifert and Gasser, 2004). To identify a multiple equilibrium poverty trap, the smoothing plot must have a bifurcated income path, with at least two stable equilibria, with at least one below the poverty line, and an unstable one in between. The dynamic, unstable threshold is referred to as the Micawber threshold[11] (F. J. Zimmerman and Carter, 2003).

[11] Lipton (1993) defines the Micawber threshold as "an initial wealth level below which agents adopt the defensive portfolio strategy and are never able to lift themselves up by their Victorian bootstraps to a higher living standard".

1.4.4 Semiparametric Estimations

The most widely used semiparametric regression models are partially linear and single index models (Libois and Verardi, 2013). In this paper we focus on partially linear models (PLM) for their flexibility and easier computability compared to other models (Liang, Mammitzsch, and Steinebach, 2006). Specifically, we estimate penalized cubic spline regressions (semi nonparametric) because of their flexibility and robustness to the choice of knots.

Splines, defined as piecewise polynomials joined together to make a single smooth curve, estimate the regression function f:

$$E\left(y|x\right) = f\left(x\right) \tag{1.6}$$

However, splines introduce the use of local basis functions h_m such that f is:

$$f\left(x\right) = \sum_{m=1}^{M} \beta_m h_m\left(x\right) \tag{1.7}$$

Using this approach makes the estimation of the regression function more flexible by ensuring that a given observation only affects the nearby fit, not the fit of the entire line (Breheny 2015). When using splines, the data is first partitioned into $K+1$ intervals by choosing K points called "knots" (Breheny 2015). The basis functions are joined with the knots and the regression model is then a piecewise continuous function. There are several types of splines, from spline regressions, to smoothing splines. Spline regressions suffer from sensitivity to the choice and the position of the knots. Selecting a non-optimal number of knots can lead to an amount of smoothing that under or overfits the data (Griggs 2013). These regressions are not completely nonparametric since the number of knots is a parametric choice and greatly affect the fit. Penalized splines, from the class of smoothing splines, mitigate this issue by "solving for the function f that minimizes the objective function below, a penalized version of the least squares objective" (Breheny 2015):

$$\sum_{i=1}^{n} \{y_i - f(x_i;\beta)\}^2 + \lambda \int \{f''(u)\}^2 \, du \tag{1.8}$$

The first portion of equation (1.8) is the MSE, that captures the fit to the data, while the second term penalizes curvature through the smoothing parameter λ to prevent overfitting. We estimate λ via the GCV criterion method. The identification of a poverty trap using this method is similar to the nonparametric method: a graphical representation of the relationship between income in time t and $t - x$. A non-convex, S-shaped, income dynamic path with two stable equilibrium (one necessarily below the poverty line) would be evidence of a poverty trap.

1.5 Detecting a Poverty Trap

1.5.1 Arunachalam and Shenoy (2017) Test

We find no evidence in favor of a poverty trap among all households or for female-headed households and black headed households. All the differences in means are insignificant or reveal a significant negative difference in income (coefficient tables in Appendix 1A).

Figures 1.2-1.13 display the coefficient plots from the regression of the indicator variable on bin fixed effects for incomes in 1969-2017, 1981-2017, 1997-2017, 2001-2016 for each of the samples. These years were selected because 1969 and 1997 are both periods of economic growth, while 1981 and 2001 are a recession year. In addition, 1997 and 2001 are far enough from the final year 2017 that incomes would converge to their true states and allow for larger samples due to smaller attrition rates.

The plots graphically demonstrate that decreases in probability of negative income growth from one bin to the next (as income increases) are not significant for the US generally and among the different subsamples. These results are robust to the different initial years. There is more variance in the coefficient plots of female and black headed households, but this is primarily due to smaller sample sizes compared to the sample of all households. Our results are consistent when we partition initial income into 15 bins (coefficient plots in Appendix 1D).

1.5.2 Nonparametric Estimation Results

We generate 1,000 training sets (bootstrap samples) with replacement and for each of the training sets, we fit a kernel-weighted local polynomial regression line. By generating multiple sets, we are able to get a closer approximation of the income curve by averaging over all fitted lines. We plot the fitted values from the first 10 sets (blue lines) and the average over the output from all training sets (red line). We include the 45-degree line and a crossing of this line from above indicates a stable equilibrium. We do not find evidence of multiple equilibria in the total sample nor in both subsamples of female and black headed households.

The results from the total sample suggest a single, stable equilibrium between $37,000-$40,000 for the four periods (Figures 1.14-1.17). All equilibria are higher than the official U.S. poverty income level of $12,490, confirming the results from the Arunachalam and Shenoy test. For the period 1969-2017, the curvature of the curve prior to crossing the 45-degree line indicates that incomes are rapidly increasing for households with the lowest incomes in 1969. As the curve crosses the reference line, the fitted line flattens. A similar trend occurs in 1981-2017 and 1997-2017.

For female headed households, there is a single convergence point at $40,000 from 1981-2017 and $35,000 for both 1997-2017 and 2001-2017 periods (Figures 1.18-1.20). A potential reason why we observe convergence at different levels could be the result of female earnings experiencing a steady increase in the 1980s (the female-to-male earnings ratio steadily increasing) and not in the 1990s (Francine D. Blau and Lawrence M. Kahn, 2007).

For black headed households, the equilibria are at $29,000 from 1981-2017 $35,000 from 1997-2017 and $30,000 for 2001-2017 (Figures 1.21-1.23).[12] In addition, the slope of the fitted line appears to be much flatter than the curve of the total sample. For the case of

[12] The period 1969-2017 is omitted for the subsamples because of the lack of observations. The total sample from 1969-2017 has about 300 observations, and the subsamples are much smaller.

black headed households, we can attribute the variation in convergence levels at the different periods to the economic strength of the initial year. Both 1981 and 2001 are years in which an economic recession occurred, whereas 1997 was a year of economic growth. The single equilibria for 1981-2017 and 2001-2017 are lower than for 1997-2017.

1.5.3 Parametric Estimation Results

The fixed effects estimation results for the total sample, the sample of female heads, and the sample of black-headed households are displayed in Table 1.10. The coefficients on the on lagged income and lagged income squared are statistically significant in the three samples, suggesting the relationship between these two variables is nonlinear. However, the coefficient on lagged income cubed is not statistically significant at the 5% level for the total sample and not significant for black headed households. In addition, the sign of coefficient on log income (conditional on controlling for squared and cubed lagged income) should be positive for the required s-shape curve of a poverty trap (Liverpool-Tasie and Winter-Nelson, 2011). We plot the fitted values against lagged income for each of the samples and find no evidence of an S-shaped curve (Figures 1.24-1.26). The results indicate the relationship between income and its lagged value is somewhat nonlinear, but it is not nonconvex (a necessary condition for poverty trap) and converges to $28,000 for female headed households and $32,000 for black headed households as indicated by the intersection of the fitted value with the 45 degree line. Household characteristics such as marital status, education level and age are significant determinants of total household income. Surprisingly, only some races (not including black) are significant in the fixed effects estimations.

The Arellano-Bond estimation results are reported in Tables 1.11-1.13. In the total sample (Table 1.11, Column 1), the sample of female heads (Table 1.12, Column 1), and the sample of black headed households (Table 1.13, Column 1) we use lags 1-3 as instruments, following the results from the Monte Carlo simulations in Appendix 1C. The coefficients on the three income variables are not significant and differ in magnitude to the fixed effects results. We use orthogonal deviations instead of first differencing to account for the gaps in our panel and increase sample size. However, we fail to reject the AR(2) test for no autocorrelation and therefore proceed to estimate column (2) using third lags as instruments. For columns (2) and (3) we limit the number of lags to be used as instruments since the results are sensitive to the number of instruments and so are the tests of over identifying restrictions. We find the coefficients on the income covariates are not significant across the different samples, and therefore rely on the fixed effects estimations.

1.5.4 Semi-parametric Estimation Results

The penalized smoothing spline plots from the semiparametric analysis are presented in Figures 1.27-1.35. They confirm the results of no poverty trap in the total sample of households (Figures 1.27-1.29), female headed households (Figures 1.30-1.32), and black headed households (Figures 1.33-1.35). In each case, we find evidence of convergence to single equilibrium and the single stable equilibrium for the different populations are in a similar range to the nonparametric crossings and the plot of fitted values predictions from the fixed effects estimations.

1.6 Conditional Convergence

Despite the lack of evidence of a poverty trap in the United States, we find support for conditional convergence: the idea that individuals with similar intrinsic characteristics tend to converge to similar incomes and living standards (Carter and Barrett 2006). Conditional convergence implies a household of certain group will converge to a steady state, regardless of their initial income (Arunachalam and Shenoy 2017).

We test for convergence following Arunachalam and Shenoy (2017). The test consists of regressing income growth on initial income for each of the groups and computing the steady states $\hat{y}_{ss}^H$ as the ratio of the intercept to the slope:

$$\hat{y}_{ss}^H = -\frac{\hat{\beta}_0^H}{\hat{\beta}_1^H} \quad for\ H = W,\ B \tag{1.9}$$

Then, the Jacobian of the steady state is used to compute a consistent estimator for the variance of the steady state, $\hat{v}_{ss}^{H}$. The testing statistic is then:

$$\hat{\kappa} = \frac{\hat{y}_{ss}^{W} - \hat{y}_{ss}^{B}}{\sqrt{\hat{v}_{ss}^{W} + \hat{v}_{ss}^{B}}} \tag{1.10}$$

The null hypothesis that the steady state of white-headed households is no higher than black-headed households is rejected at the 5% level if $\hat{\kappa} > \Phi^{-1}(0.95)$.

For all years considered (1981-2017, 1997-2017, 2001-2017),[13] we find a significant gap between the steady state of black and white-headed households. Between 1981 and 2017, white headed households converge to an income 61% higher than their black counterparts. The gap diminishes to 27%, between 1997-2017 but then increases to 36% between 2001-2017 (Table 1.14). The increase is primarily due to a decline in the steady states of both white and black-headed households from 2001 to 2017; a possible explanation for this could be the 2000-2001 recession (FRED, 2018). Our results are consistent with the findings of Chetty, Hendren, Kline, et al. (2014), Mazumder (2014), and Bhattacharya and Mazumder (2011) that show upward income mobility is lower for African American communities compared to white Americans. Lastly, using nonparametric plots, we find evidence that black-headed households converge to significantly lower per capita income levels than white headed households, consistent with the Arunachalam and Shenoy convergence test. For example, Figure 1.36 shows that the difference in per capita income between the two groups is approximately \$11,000 in 1981-2017. In a more recent period (2001-2017), the difference shrinks to \$6,000 (Figure 1.38).

We also find differences in income persist across occupations, with white headed households on average having higher per capita labor incomes than black headed households for the same occupations. Our findings are consistent theories with results from labor economics (Chetty, Hendren, Jones, et al., 2018; Mandel and Semyonov, 2016; Bertrand and Mullainathan, 2004),

[13] We omit years 1969-2017 because there are only 70 black-headed households that remain in the sample over that period.

sociology (Conley, 2010; Oliver and Shapiro, 2001) and criminal justice (Pager, 2003) that demonstrate evidence of discrimination and disparities in wealth and income between black and white households. Using an intergenerational dataset, Chetty, Hendren, Jones, et al. (2018) finds that conditional on parent's income, the black-white income gap of children is driven by differences in wages and employment rates between black and white men. Mandel and Semyonov (2016) argue that the racial pay gap is the result of economic discrimination and income inequality. Pager (2003) uses an experimental audit approach and finds the effect of a criminal record is 40% larger for African Americans than for whites.

One factor that can potentially worsen conditional convergence between white and black households could be the differences in the educational opportunities available to white and black students, although the income/wage gap prevails at all education levels (Conley, 2010). For example in 2014, Department of Education Office of Civil Rights released a letter acknowledging how racial disparities in access to "rigorous courses, academic programs, and extracurricular activities; stable workforces of effective teachers, leaders, and support staff; safe and appropriate school buildings and facilities; and modern technology and high-quality instructional materials" negatively affect the education of non-white students. The effect of these educational disparities manifest at the college level as well: in 2013 African Americans constituted 15% of the total undergraduate school enrollment in degree granting institutions while white students made up 60% (Musu-Gillette et al., 2016). African Americans also have a higher dropout rate (6.5%) than white college students (4.3%) (NCES, 2017). This occurs alongside substantial evidence that demonstrates that higher education translates to better wages. Between 1963 and 1989, Juhn, Murphy, and Pierce (1993) found real average weekly wages for the least skilled workers declined by 5% and the wages of the most skilled workers rose by 40%. More recently, the U.S. Census workers earnings data in 2016 show mean earnings of college graduates are 93% higher than individuals with only a high school degree. Thus, if a higher proportion African-Americans are not obtaining a college degree, their incomes converge to a lower equilibrium than those of white counterparts. There is some evidence in the PSID that over time, white headed households that were poor in the initial year, were more likely to obtain higher education. From 2001-2017 (period with least attrition), we find that 6% (4%) of white headed households that were poor in 2001 and had high school degree had obtained a college degree (advanced degree) by 2017, compared to only 2% (0.8%) of black headed households (Table 1.15). While transition frequencies are not an indication of an educational system in which African-Americans are discriminated against or addresses the systematic racism that drives income disparities, it suggest that at the lowest income levels, there are differences in educational attainments between white and black headed household that should be explored further.

For female headed households, we only find a significant gap between steady states of 10% between 1997-2017. A reason for the lack of conditional convergence could be the shrinking gender wage gap and women entering male-dominated professions (that tend to be higher paying careers) in the last decades (Francine D Blau and Lawrence M Kahn, 2000; Francine D. Blau, 2012; Goldin, 2006). For example, in 1981, only 0.10% of female heads in the PSID sample reported "engineer" as an occupation, compared to 32% in 2001.

1.7 Conclusion

This paper investigates whether the persistent poverty observed among female and black headed households in the United States is an indication of a poverty trap. Looking at household income over multiple periods, we used a suite of empirical methods, for robustness and consistency with past literature. We improve both parametric and nonparametric methods using Monte Carlo simulations and boostrap aggregating, a machine learning algorithm. Our findings demonstrate there is no evidence of nonconvexities in relationship between current income (2017) and an initial level of income (1969, 1981, 1997, 2001). This indicates that there is no poverty trap in the United States. However, we find strong evidence of conditional convergence for black-headed households.

Multiple empirical methods evaluated across different time periods consistently reveal a systematic difference between black and white headed households. White headed households converge to incomes higher than black, irrespective of the time period considered. The steady state gap was 60% higher for white headed households compared to black between 1981-2017. This difference in convergence levels then decreased to 27% from 1997-2017 and increased again to 36% from 2001-2017. We attribute this increase to a decrease in the steady state of white and black heads as a results of a 2000-2001 recession. Our conditional convergence results are consistent with income mobility studies and findings in the areas of labor economics, sociology, and criminal justice that suggest long-standing patterns of discrimination against African Americans.

We believe that conditional convergence could be the result of labor market and economic discrimination, potentially worsened by differences in educational opportunities available to black and white students. Transition frequencies demonstrate that 10% of white headed households in poverty with a high school increased their educational attainment, compared to 3% of poor black headed households. While this is not enough evidence to conclude the education system in the United States disfavors African-Americans, it is not inconsistent with system disparities identified in recent years.

The findings of this paper have key policy implications. Although there is no evidence of a poverty trap, there is evidence of persistent poverty among female and black headed households and systematic differences in incomes across racial lines. Existing programs and policies have been ineffective in eliminating (or significantly reducing) the racial income gap at all education levels and occupations. This systematic discrimination needs to be addressed. One potential mechanism is through labor and education reforms. For example, programs that monitor business payroll practices should exist in communities with a diverse labor force. However, further research is needed to better understand the mechanisms that are driving the observed conditional convergence to identify the necessary policies to reduce the racial income gap. Lessons from the apparent improvement in gender wage gap could be useful. Some observable factors that have reduce the gender earnings gap are the educational advances of women (Goldin, Katz, and Kuziemko, 2006). In 2017, 72% of women with a bachelor's degree participated in the labor force, compared to only 28% of African-Americans (Brundage, 2017). A few avenues for future work include the study of the systematic reasons driving conditional convergence and the study of poverty among other minority groups in the United States with primary collected datasets and alternative empirical approaches, such as experiments.

APPENDICES

APPENDIX 1A: Tables

Table 1.1: Weighted Poverty Rates of Female and Male Headed Households (%)

	Female		Male	
Year	Without Children	With Children	Without Children	With Children
1969	22.26	31.68	8.96	6.66
1971	22.82	29.03	8.55	6.29
1973	18.59	24.34	5.63	4.82
1975	18.02	23.63	6.01	3.68
1977	18.2	28.18	4.89	4.45
1979	17.19	30.04	4.98	3.13
1981	17.85	29.86	5.17	4.8
1983	17.45	36.83	6.42	6.69
1985	17.12	36.3	6.11	5.13
1987	16.6	35.64	5.89	5.59
1989	16.23	31.82	6.01	5.23
1991	18.15	33.43	5.72	7.52
1993	16.07	40.38	7.49	6.8
1995	17.76	35.09	7.76	5.25
1997	20.79	40.97	9.46	17.53
1999	15.53	30.94	5.67	5.29
2001	12.21	27.4	5.33	4.91
2003	13.97	27.93	6.04	5.64
2005	15	26.34	6.4	5.6
2007	15.28	30.85	7.19	5.82
2009	15.04	28.54	7.54	6.01
2011	16.36	29.58	7.72	8.23
2013	16.11	32.24	8.51	7.01
2015	16.59	29.48	9.12	7.13
2017	16.39	27.16	7.94	5.35

Table 1.2: Weighted Poverty Rates of White and Black Headed Households (%)

	White		Black	
Year	Without Children	With Children	Without Children	With Children
1969	11.66	6.31	29.14	33.11
1971	11.97	6.2	27.16	33.5
1973	8.87	4.55	21.77	29.4
1975	8.49	4.03	24.29	27.66
1977	8.22	5.61	22.85	30.31
1979	7.99	4.68	20.51	30.03
1981	8	7.05	24.68	29.18
1983	8.29	9.44	28.82	37.35
1985	7.89	7.68	29.53	38.42
1987	7.82	8.59	25.82	37.15
1989	7.53	7.65	25.45	34.06
1991	8.23	8.73	25.76	36.12
1993	8.27	9.43	26.39	37.82
1995	8.95	8.1	27.23	32.86
1997	8.48	7.54	29.44	39.24
1999	7.32	5.9	23.06	26.89
2001	6.31	5.62	18.43	20.17
2003	7.07	6.22	19.75	26.71
2005	7.45	7.66	20.49	25.05
2007	8.15	8.18	19.61	29.7
2009	7.57	8.2	24.37	26.89
2011	8.11	9.88	24.42	26.53
2013	8.42	9.56	24.41	29.33
2015	8.99	9.03	24.31	29.06
2017	8.67	8.07	21.8	23.11

Table 1.3: Weighted Persistence of Poverty among Households in the United States

	Female Heads		Male Heads		White Heads		Black Heads	
Children	No	Yes	No	Yes	No	Yes	No	Yes
Poor in 2017	0.45	0.33	0.46	0.49	0.46	0.47	0.37	0.31
Poor in 2017 and 2015	0.15	0.16	0.16	0.26	0.19	0.23	0.11	0.14
Poor in 2017-2013	0.11	0.12	0.13	0.05	0.12	0.1	0.11	0.1
Poor in 2017-2011	0.07	0.15	0.1	0.04	0.05	0.06	0.11	0.15
Poor for 5-10 waves of data	0.18	0.18	0.13	0.14	0.17	0.13	0.21	0.22
Poor for $\geq$10 waves	0.04	0.06	0.03	0.03	0.01	0.01	0.09	0.07

Table 1.4: Summary Statistics

VARIABLES	(1) 1969-2017 Mean	(2) 1969-2017 Std. Dev.	(3) 1981-2017 Mean	(4) 1981-2017 Std. Dev.	(5) 1997-2017 Mean	(6) 1997-2017 Std. Dev.
Age of head	43.89	16.38	44.19	16.31	44.84	16.08
Number of children	0.97	1.3	0.9	1.2	0.85	1.18
Sex of head	0.69	0.46	0.68	0.47	0.68	0.47
Log income	10.59	0.81	10.62	0.82	10.68	0.8
Married	0.55	0.5	0.54	0.5	0.53	0.5
Single	0.18	0.39	0.2	0.4	0.22	0.41
Widowed	0.08	0.28	0.08	0.27	0.06	0.24
Divorced	0.12	0.33	0.13	0.33	0.13	0.34
Separated	0.06	0.24	0.06	0.24	0.05	0.23
Northeast	0.14	0.35	0.14	0.35	0.13	0.34
North Central	0.24	0.43	0.24	0.43	0.25	0.43
South	0.44	0.5	0.44	0.5	0.43	0.5
West	0.17	0.38	0.18	0.38	0.18	0.38
Less than HS Degree	0.27	0.44	0.23	0.42	0.17	0.37
HS Degree	0.54	0.5	0.56	0.5	0.58	0.49
College Degree	0.12	0.33	0.13	0.34	0.15	0.36
Advanced Degree	0.07	0.26	0.08	0.28	0.1	0.3
White	0.6	0.49	0.6	0.49	0.59	0.49
Black	0.35	0.48	0.35	0.48	0.35	0.48
American Indian	0.01	0.11	0.01	0.09	0.01	0.08
Asian	0.01	0.09	0.01	0.1	0.01	0.12
Native Hawaiian	0.02	0.12	0.02	0.13	0.01	0.12
Other	0.02	0.13	0.02	0.13	0.03	0.16

Table 1.5: Attrition Rates of Household Heads

	1969-2017		1981-2017		1997-2017		2001-2017	
	Freq.	Att. Rate	Freq.	Att. Rate	Freq.	Att. Rate	Freq.	Att. Rate
Attrition % (Freq. = households remaining)	336	92%	1,236	81.60%	2,668	60.80%	3,181	57%

Table 1.6: Attrition Probit Results

VARIABLES	(1) 1969-2017	(2) 1981-2017	(3) 1997-2017	(4) 2001-2017
Age of Household Head	0.0509***	0.0394***	0.0169***	0.00898***
	(-0.0067)	(-0.00189)	(-0.00136)	(-0.00143)
Black	-0.093	0.123**	-0.257***	-0.199***
	(-0.136)	(-0.0494)	(-0.054)	(-0.0463)
American Indian	-0.402	0.645***	0.0481	0.0409
	(-0.256)	(-0.155)	(-0.223)	(-0.162)
Asian	-	-	0.0229	0.137
			(-0.272)	(-0.182)
Native Hawaiian	-	-	-0.07	-0.427***
			(-0.229)	(-0.0832)
Single	0.154	-0.199**	-0.0888	-0.174**
	(-0.215)	(-0.0813)	(-0.0633)	(-0.0732)
Widowed	0.22	0.292*	0.520***	0.605***
	(-0.412)	(-0.15)	(-0.0958)	(-0.0978)
Divorced	0.307	-0.241***	-0.027	0.0714
	(-0.369)	(-0.0902)	(-0.0826)	(-0.0707)
Separated	0.19	-0.0904	0.0991	0.126
	(-0.288)	(-0.1)	(-0.081)	(-0.0794)
Region: North Central	-0.114	-0.159**	-0.182***	-0.116***
	(-0.121)	(-0.0663)	(-0.0647)	(-0.0383)
Region: South	0.118	0.113*	-0.0379	-0.0739*
	(-0.129)	(-0.064)	(-0.0566)	(-0.0394)
Region: West	-0.192	-0.041	-0.122*	-0.0522
	(-0.152)	(-0.0742)	(-0.0739)	(-0.036)
Region: Alaska/Hawaii	-	-	0.145	0.447***
			(-0.582)	(-0.0954)
Region: Foreign Country	-	0.17	0.410***	-0.0668**
		(-0.386)	(-0.0558)	(-0.0289)
Log Income	-0.142	-0.0808**	0.0038	-0.00021
	(-0.0999)	(-0.0363)	(-0.026)	(-0.0325)
Own/Rent (0/1)	0.0314	0.0423***	0.0152	0.0269***
	(-0.0256)	(-0.0123)	(-0.00965)	(-0.00878)

Table 1.6: (cont'd)

VARIABLES	(1) 1969-2017	(2) 1981-2017	(3) 1997-2017	(4) 2001-2017
Sex of Household Head	0.106	0.267***	0.255***	0.267***
	(-0.23)	(-0.0716)	(-0.0765)	(-0.0695)
People in Family Unit	-0.0687***	-0.0703***	0.0158	0.0161
	(-0.0262)	(-0.015)	(-0.0189)	(-0.0171)
Head's Educ: HS	-0.123	-0.202***	-0.0563	-0.0265
	(-0.114)	(-0.0521)	(-0.0506)	(-0.0449)
Head's Educ: College	-0.0563	-0.276***	0.0291	0.147**
	(-0.176)	(-0.0817)	(-0.0684)	(-0.0691)
Head's Educ: Ad. Degree	0.0427	-0.282**	0.0441	0.12
	(-0.272)	(-0.121)	(-0.0989)	(-0.0969)
Length of Survey (min)	0.000313	-0.00055	-0.00204	-0.00181**
	(-0.00241)	(-0.00233)	(-0.00129)	(-0.0008)
Number of Calls	0.0199	0.0180**	0.00646**	0.00416*
	(-0.0218)	(-0.00874)	(-0.00327)	(-0.00233)
Veteran Status	0.00717	0.0237*	0.0369**	0.0344**
	(-0.024)	(-0.0134)	(-0.0145)	(-0.0144)
Might Move (0/1)	-0.0202	-0.0297**	-0.00552	0.00916
	(-0.0249)	(-0.0121)	(-0.0117)	(-0.0106)
Age Squared	-0.00877***	0.00196***	0.00179***	
	(-0.00081)		(-0.00028)	(-0.00016)
Constant	3.460***	0.254	-0.964***	-0.845**
	(-1.117)	(-0.43)	(-0.327)	(-0.39)
Pseudo R-squared	0.58	0.14	0.07	0.06

Table 1.7: T-Test for Negative Income Growth for All Households (Bins=10)

	1969-2017		1981-2017		1997-2015		2001-2017	
	Coef.	t	Coef.	t	Coef.	t	Coef.	t
Bin 1 - Bin 2	-	-	-0.07	-1.18	-			
			(0.06)					
Bin 2 - Bin 3	-	-	0.07	1.11	-0.02	-1.40		
			(0.06)		(0.02)			
Bin 3 - Bin 4	-		-0.12	-2.01	-0.27	-3.69	-0.11	-1.65
			(0.06)		(0.07)		(0.07)	
Bin 4 - Bin 5	0.045	0.32	-0.10	-1.18	-0.01	-0.19	-0.14	-1.74
	(0.14)		(0.09)		(0.09)		(0.08)	
Bin 5 - Bin 6	-0.16	-1.54	-0.06	-0.76	-0.05	-0.90	-0.16	-2.68
	(0.11)		(0.08)		(0.06)		(0.06)	
Bin 6 - Bin 7	-0.25	-2.29	-0.11	-1.70	-0.06	-1.29	-0.05	-0.98
	(0.11)		(0.07)		(0.05)		(0.05)	
Bin 7 - Bin 8	-0.017	-0.19	-0.11	-1.85	-0.009	-0.23	-0.02	-0.61
	(0.09)		(0.06)		(0.04)		(0.04)	
Bin 8 - Bin 9	-0.23	-2.75	-0.13	-2.58	-0.18	-4.70	-0.08	-2.14
	(0.08)		(0.05)		(0.03)		(0.03)	
Bin 9 - Bin 10	-0.17	-1.72	-0.22	-4.44	-0.21	-5.46	-0.20	-5.81
	(0.10)		(0.05)		(0.04)		(0.03)	

Note: Robust standard errors in parenthesis

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

Table 1.8: T-Test for Negative Income Growth Female-Headed Households (Bins=10)

	1969-2017		1981-2017		1997-2015		2001-2017	
	Coef.	t	Coef.	t	Coef.	t	Coef.	t
Bin 1 - Bin 2	-	-	-		-0.01	-1.25	-	
					(0.01)			
Bin 2 - Bin 3	-	-			0.008	0.60	-0.04	-1.39
					(0.01)		(0.03)	
Bin 3 - Bin 4	-0.17	-1.03	-0.11	-1.57	-0.36	-3.95	-0.09	-1.08
	(0.16)		(0.07)		(0.07)		(0.09)	
Bin 4 - Bin 5	0.14	0.85	-0.13	-1.19	0.07	0.61	-0.19	-1.83
	(0.17)		(0.10)		(0.09)		(0.10)	
Bin 5 - Bin 6	-0.23	-1.52	-0.06	-0.58	-0.16	-1.87	-0.20	-2.33
	(0.15)		(0.11)		(0.11)		(0.08)	
Bin 6 - Bin 7	-0.20	-0.94	-0.13	-1.37	0.01	0.14	-0.06	-0.93
	(0.22)		(0.09)		(0.08)		(0.07)	
Bin 7 - Bin 8	-0.06	-0.28	-0.25	-2.34	-0.06	-0.78	0.02	0.31
	(0.23)		(0.10)		(0.08)		(0.07)	
Bin 8 - Bin 9	0.03	0.11	0.04	0.25	-0.16	-1.73	-0.01	-0.14
	(0.31)		(0.16)		(0.09)		(0.08)	
Bin 9 - Bin 10	0.49	1.89	0.14	0.51	-0.23	-2.14	-0.33	-4.40
	(0.26)		(0.28)		(0.10)		(0.08)	

Note: Robust standard errors in parenthesis

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

Table 1.9: T-Test for Negative Income Growth Black-Headed Households (Bins=10)

	1969-2017		1981-2017		1997-2015		2001-2017	
	Coef.	t	Coef.	t	Coef.	t	Coef.	t
Bin 1 - Bin 2	-		-		-0.01	-1.25	-	
					(0.01)			
Bin 2 - Bin 3	-		-		0.008	0.60	-0.04	-1.39
					(0.01)		(0.03)	
Bin 3 - Bin 4	-		-0.11	-1.57	-0.36	-3.95	-0.09	-1.08
			(0.07)		(0.07)		(0.09)	
Bin 4 - Bin 5	0.14	0.85	-0.13	-1.19	0.07	0.61	-0.19	-1.83
	(0.17)		(0.10)		(0.09)		(0.10)	
Bin 5 - Bin 6	-0.23	-1.52	-0.06	-0.58	-0.16	-1.87	-0.20	-2.33
	(0.15)		(0.11)		(0.11)		(0.08)	
Bin 6 - Bin 7	-0.20	-0.94	-0.13	-1.37	0.01	0.14	-0.06	-0.93
	(0.22)		(0.09)		(0.08)		(0.07)	
Bin 7 - Bin 8	-0.06	-0.28	-0.25	-2.34	-0.06	-0.78	0.02	0.31
	(0.23)		(0.10)		(0.08)		(0.07)	
Bin 8 - Bin 9	0.03	0.11	0.04	0.25	-0.16	-1.73	-0.01	-0.14
	(0.31)		(0.16)		(0.09)		(0.08)	
Bin 9 - Bin 10	0.49	1.89	0.14	0.51	-0.23	-2.14	-0.33	-4.40
	(0.26)		(0.28)		(0.10)		(0.08)	

Note: Robust standard errors in parenthesis

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

Table 1.10: Fixed Effects Estimations

VARIABLES	(1) Total Sample	(2) Female Heads	(3) Black Heads
Lagged Log Income	-2.736**	-7.825***	-3.029*
	(1.280)	(2.032)	(1.759)
Squared Lagged Log Income	0.251**	0.783***	0.292*
	(0.124)	(0.203)	(0.174)
Cubed Lagged Log Income	-0.00686*	-0.0253***	-0.00870
	(0.00402)	(0.00676)	(0.00574)
Age of Head	0.0392***	0.0458***	0.0436***
	(0.00266)	(0.00533)	(0.00477)
Squared Age of Head	-0.000417***	-0.000460***	-0.000484***
	(1.56e-05)	(3.06e-05)	(3.57e-05)
Number of people in household	0.0626***	0.107***	0.0664***
	(0.00361)	(0.00710)	(0.00595)
Children (0/1)	-0.0995***	-0.118***	-0.0791***
	(0.00839)	(0.0181)	(0.0153)
Single	-0.315***	-0.126*	-0.360***
	(0.0185)	(0.0659)	(0.0300)
Widowed	-0.110***	-0.0264	-0.204***
	(0.0276)	(0.0717)	(0.0440)
Divorced	-0.244***	-0.108*	-0.306***
	(0.0158)	(0.0631)	(0.0289)
Separated	-0.242***	-0.133**	-0.326***
	(0.0189)	(0.0634)	(0.0294)
Black	-0.0257	-0.128*	-
	(0.0480)	(0.0741)	
American Indian	-0.0225	-0.158	-
	(0.0402)	(0.126)	
Asian	0.141*	0.196**	-
	(0.0795)	(0.0920)	
Native Hawaiian	-0.0557*	-0.00975	-
	(0.0293)	(0.0625)	

Table 1.10: (cont'd)

VARIABLES	(1) Total Sample	(2) Female Heads	(3) Black Heads
North Central	-0.0183	-0.0857	-0.137*
	(0.0369)	(0.0761)	(0.0829)
South	-0.0332	-0.0973	-0.123*
	(0.0314)	(0.0650)	(0.0653)
West	0.0100	-0.0143	-0.0791
	(0.0388)	(0.0884)	(0.0842)
Hawaii/Alaska	0.0743	0.212	0.0847
	(0.0942)	(0.133)	(0.329)
Foreign Country	-0.272***	-0.293**	-0.259***
	(0.0691)	(0.146)	(0.100)
H.S. Degree	0.0286	0.0328	0.0823***
	(0.0198)	(0.0444)	(0.0284)
College Degree	0.142***	0.157***	0.210***
	(0.0257)	(0.0577)	(0.0482)
Advanced Degree	0.206***	0.301***	0.379***
	(0.0297)	(0.0615)	(0.0526)
Sex of Household Head	0.140***	-	0.101
	(0.0379)	-	(0.0627)
Constant	18.54***	34.38***	19.06***
	(4.369)	(6.749)	(5.885)
Observations	56,545	17,981	21,542
R-squared	0.224	0.186	0.196
Number of UniqueID	8,104	3,177	3,337
Individual FE	YES	YES	YES
Year FE	YES	YES	YES

Note: Robust standard errors in parenthesis

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

Table 1.11: Arellano and Bond Estimations for the Total Sample

VARIABLES	(1)	(2)	(3)
Lagged Log Income	4.001	11.47	2.450
	(8.234)	(9.781)	(6.702)
Squared Lagged Log Income	-0.380	-1.064	-0.199
	(0.804)	(0.947)	(0.645)
Cubed Lagged Log Income	0.0126	0.0339	0.00632
	(0.0260)	(0.0304)	(0.0206)
Age of Head	0.0441***	0.0380***	0.0369***
	(0.00454)	(0.00604)	(0.00535)
Squared Age of Head	-0.000439***	-0.000343***	-0.000347***
	(3.74e-05)	(4.91e-05)	(4.04e-05)
Number of people in household	0.0623***	0.0644***	0.0642***
	(0.00631)	(0.00850)	(0.00717)
Children	-0.124***	-0.0981***	-0.100***
	(0.0117)	(0.0120)	(0.0111)
Single	-0.397***	-0.123	-0.175*
	(0.0555)	(0.102)	(0.0926)
Widowed	-0.248***	-0.325***	-0.270***
	(0.0798)	(0.0927)	(0.0963)
Divorced	-0.269***	-0.111	-0.141**
	(0.0389)	(0.0736)	(0.0659)
Separated	-0.213***	-0.342***	-0.293***
	(0.0373)	(0.0798)	(0.0694)
Black	-0.00422	-0.0125	-0.000513
	(0.109)	(0.0974)	(0.0911)
American Indian	-0.0167	-0.0134	-0.0189
	(0.0348)	(0.0415)	(0.0440)
Asian	0.0565	0.0730	0.110
	(0.0910)	(0.0750)	(0.0949)
Native Hawaiian	-0.0522	-0.0173	-0.0437
	(0.0410)	(0.0358)	(0.0359)

Table 1.11: (cont'd)

VARIABLES	(1)	(2)	(3)
North Central	0.0568	0.125	0.121
	(0.107)	(0.167)	(0.145)
South	0.0154	-0.0712	-0.0349
	(0.0922)	(0.122)	(0.109)
West	0.0939	-0.0232	0.0109
	(0.104)	(0.129)	(0.131)
Hawaii/Alaska	0.0928	-0.0516	-0.186
	(0.144)	(0.265)	(0.273)
Foreign Country	-0.152	-0.0663	0.0371
	(0.107)	(0.218)	(0.214)
H.S. Degree	-0.0469	-0.0281	0.0436
	(0.0747)	(0.0654)	(0.0633)
College Degree	0.0768	-0.0214	0.111
	(0.111)	(0.112)	(0.103)
Advanced Degree	0.0768	-0.0348	0.136
	(0.129)	(0.132)	(0.120)
Observations	48,368	48,368	48,368
Number of Unique IDs	6,908	6,908	6,908
Lag Limits	1-3	3-4	3-5

Note: Robust standard errors in parenthesis

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

Table 1.12: Arellano and Bond Estimations (Female Headed Households)

VARIABLES	(1)	(2)	(3)
Lagged Log Income	-6.924	-13.49	-10.31
	(7.322)	(9.486)	(8.065)
Squared Lagged Log Income	0.724	1.349	1.045
	(0.720)	(0.934)	(0.792)
Cubed Lagged Log Income	-0.0242	-0.0436	-0.0341
	(0.0235)	(0.0305)	(0.0258)
Age of Head	0.0540***	0.0390***	0.0408***
	(0.00690)	(0.00803)	(0.00817)
Squared Age of Head	-0.000501***	-0.000381***	-0.000413***
	(5.00e-05)	(5.50e-05)	(5.14e-05)
Number of people in household	0.130***	0.130***	0.131***
	(0.0108)	(0.0113)	(0.0107)
Children	-0.131***	-0.132***	-0.142***
	(0.0255)	(0.0248)	(0.0249)
Single	-0.196	-0.303	-0.268
	(0.192)	(0.311)	(0.252)
Widowed	-0.0928	-0.0471	-0.133
	(0.198)	(0.317)	(0.249)
Divorced	-0.282	-0.304	-0.261
	(0.175)	(0.296)	(0.224)
Separated	-0.305*	-0.376	-0.361
	(0.173)	(0.290)	(0.230)
Black	-0.310***	-0.290***	-0.298***
	(0.0934)	(0.101)	(0.102)
American Indian	-0.165	-0.147	-0.104
	(0.180)	(0.189)	(0.170)
Asian	0.133	0.120	0.0986
	(0.0936)	(0.0843)	(0.0912)
Native Hawaiian	0.00848	0.0417	0.0285
	(0.0844)	(0.0681)	(0.0754)

Table 1.12: (cont'd)

VARIABLES	(1)	(2)	(3)
North Central	0.125	-0.141	-0.0890
	(0.159)	(0.176)	(0.147)
South	0.133	-0.0512	-0.00506
	(0.124)	(0.129)	(0.0914)
West	0.124	0.0999	0.0699
	(0.162)	(0.151)	(0.134)
Hawaii/Alaska	0.282	0.218	0.265*
	(0.184)	(0.186)	(0.147)
Foreign Country	-0.153	0.0167	0.0118
	(0.151)	(0.132)	(0.117)
H.S. Degree	-0.0264	-0.115	-0.125
	(0.118)	(0.124)	(0.114)
College Degree	-0.0337	-0.0946	-0.110
	(0.160)	(0.169)	(0.146)
Advanced Degree	-0.112	-0.117	-0.0754
	(0.182)	(0.184)	(0.157)
Observations	14,781	14,781	14,781
Number of Unique ID	2,585	2,585	2,585
Lag Limits	1-3	3-4	3-5

Note: Robust standard errors in parenthesis

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

Table 1.13: Arellano and Bond Estimations (Black Headed Households)

VARIABLES	(1)	(2)	(3)
Lagged Log Income	-1.289	-7.942	-11.92
	(9.578)	(11.67)	(9.694)
Squared Lagged Log Income	0.0862	0.805	1.157
	(0.951)	(1.159)	(0.966)
Cubed Lagged Log Income	-0.000786	-0.0262	-0.0364
	(0.0313)	(0.0382)	(0.0319)
Age of Head	0.0513***	0.0416***	0.0503***
	(0.00875)	(0.00932)	(0.00834)
Squared Age of Head	-0.000510***	-0.000426***	-0.000475***
	(6.89e-05)	(7.98e-05)	(7.04e-05)
Number of people in household	0.0689***	0.0699***	0.0767***
	(0.0120)	(0.0125)	(0.0126)
Children	-0.0884***	-0.0891***	-0.0866***
	(0.0305)	(0.0253)	(0.0259)
Single	-0.429***	-0.366**	-0.262*
	(0.105)	(0.157)	(0.137)
Widowed	-0.362**	-0.338*	-0.362**
	(0.163)	(0.193)	(0.171)
Divorced	-0.301***	-0.301**	-0.289***
	(0.0919)	(0.127)	(0.109)
Separated	-0.303***	-0.380***	-0.321***
	(0.0881)	(0.137)	(0.117)

Table 1.13: (cont'd)

VARIABLES	(1)	(2)	(3)
North Central	0.207	-0.0413	-0.121
	(0.311)	(0.364)	(0.270)
South	0.468*	0.199	0.0407
	(0.270)	(0.308)	(0.238)
West	0.754**	0.258	0.192
	(0.320)	(0.383)	(0.341)
Hawaii/Alaska	1.219*	0.765**	0.326
	(0.698)	(0.385)	(0.765)
Foreign Country	0.590*	-0.0978	-0.0444
	(0.327)	(0.485)	(0.321)
Sex of Household Head	0.124	0.0635	0.103
	(0.133)	(0.145)	(0.134)
H.S. Degree	0.203**	0.109	0.112
	(0.0963)	(0.114)	(0.110)
College Degree	0.750***	0.384*	0.489**
	(0.243)	(0.232)	(0.205)
Advanced Degree	0.712***	0.418*	0.489**
	(0.240)	(0.239)	(0.194)
Observations	18,166	18,166	18,166
Number of Unique ID	2,852	2,852	2,852
Lag Limits	1-3	3-4	3-5

Note: Robust standard errors in parenthesis

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

Table 1.14: Gaps between steady states (%)

Households:	1981-2017	1997-2017	2001-2017
White- Black	61%***	27%***	36%***
Male- Female	11%	10%**	2%

Table 1.15: Education Transitions of Households in Poverty in 2001

Black Headed Households

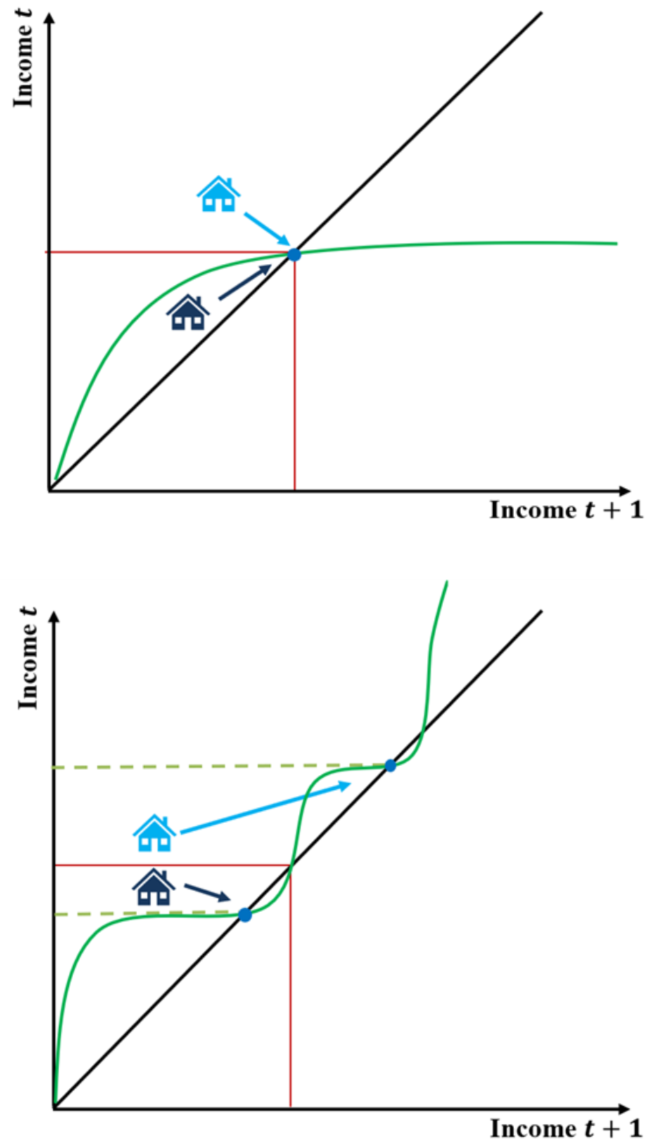
	Less than HS	HS Degree	College Degree	Advanced	Total
Less than HS	65.85	34.15	0	0	100
HS	0	96.69	2.48	0.83	100
College Degree	0	0	60	40	100

White Headed Households

	Less than HS	HS Degree	College Degree	Advanced	Total
Less than HS	56.25	34.38	6.25	3.13	100
HS	0	89.58	6.25	4.17	100
College Degree	0	0	54.55	45.45	100
Advanced Degree	0	0	0	100	100

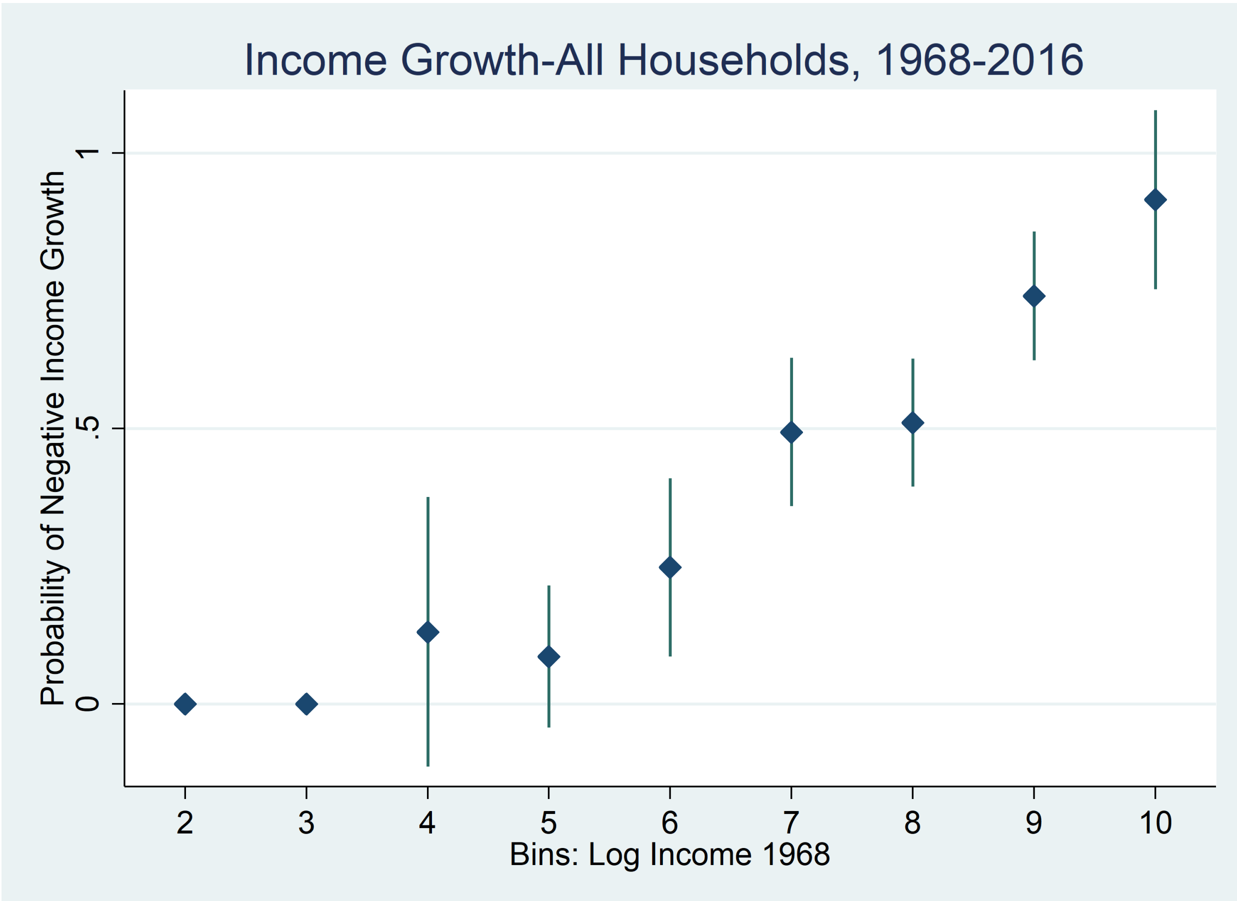
APPENDIX 1B: Figures

Figure 1.1: Representation of the Arunachalam and Shenoy (2017) Test



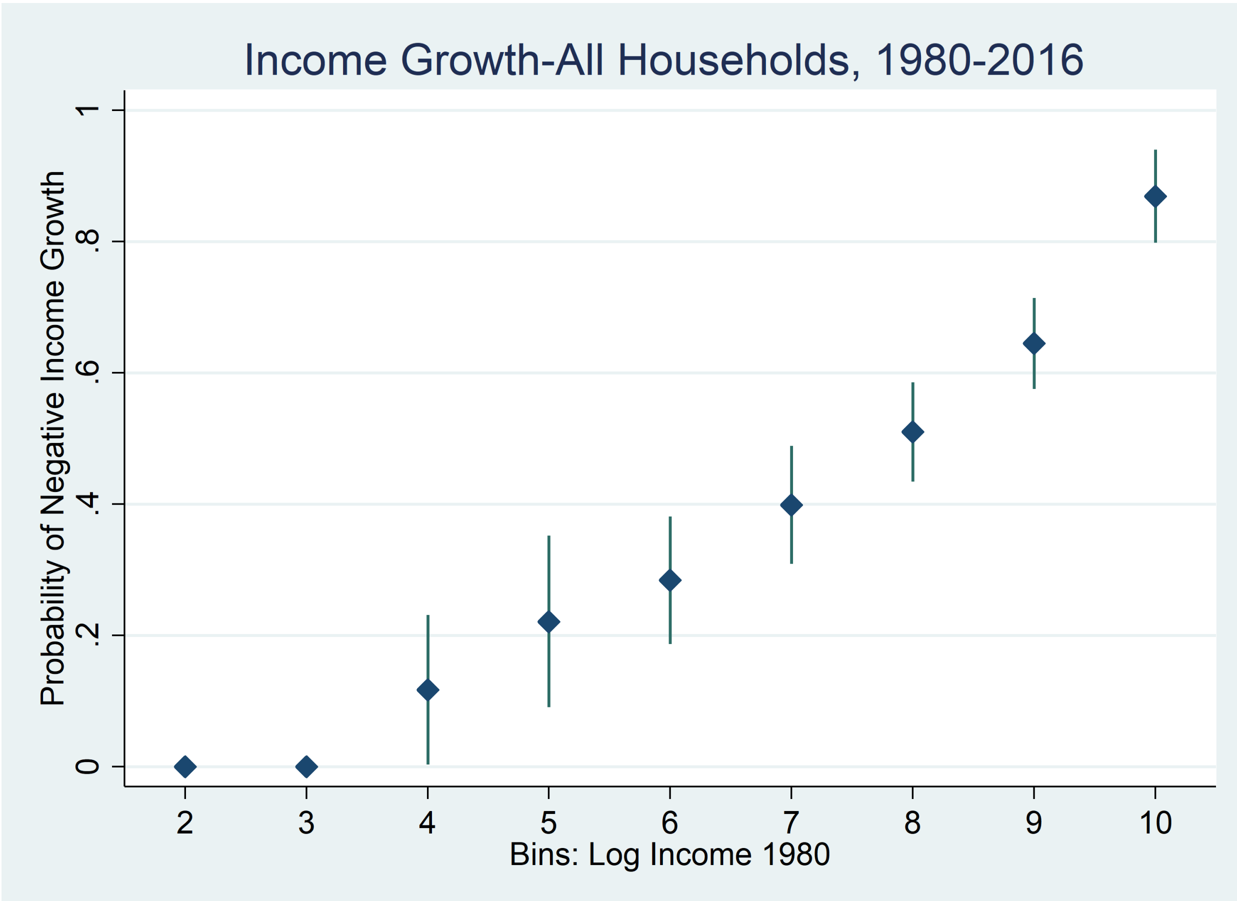
Panel A (top) is the case with a single converging equilibrium, under which the probability of negative income growth is always increasing in income because richer households (light blue) are being push back to the single steady state. On the other hand, Panel B (bottom) displays the case of a poverty trap: after a threshold (red line) the probability of negative income growth decreases. The light blue household has a lower probability of negative growth, than the dark blue (poorer) house. This graph is an adaptation of Arunachalam and Shenoy (2017). The arrows in both panels indicate where each of the households is converging.

Figure 1.2: Coefficient Plot for the Total Sample of Households, 1968-2016



Coefficient plot for the total sample of households. We observe an upward trend, but no decline in the probability of negative income growth from one income bin to the next. This is indicative of no poverty trap in the period specified.

Figure 1.3: Coefficient Plot for the Total Sample of Households, 1980-2016



The plot confirms graphically the no poverty trap result.

Figure 1.4: Coefficient Plot for the Total Sample of Households, 1996-2016

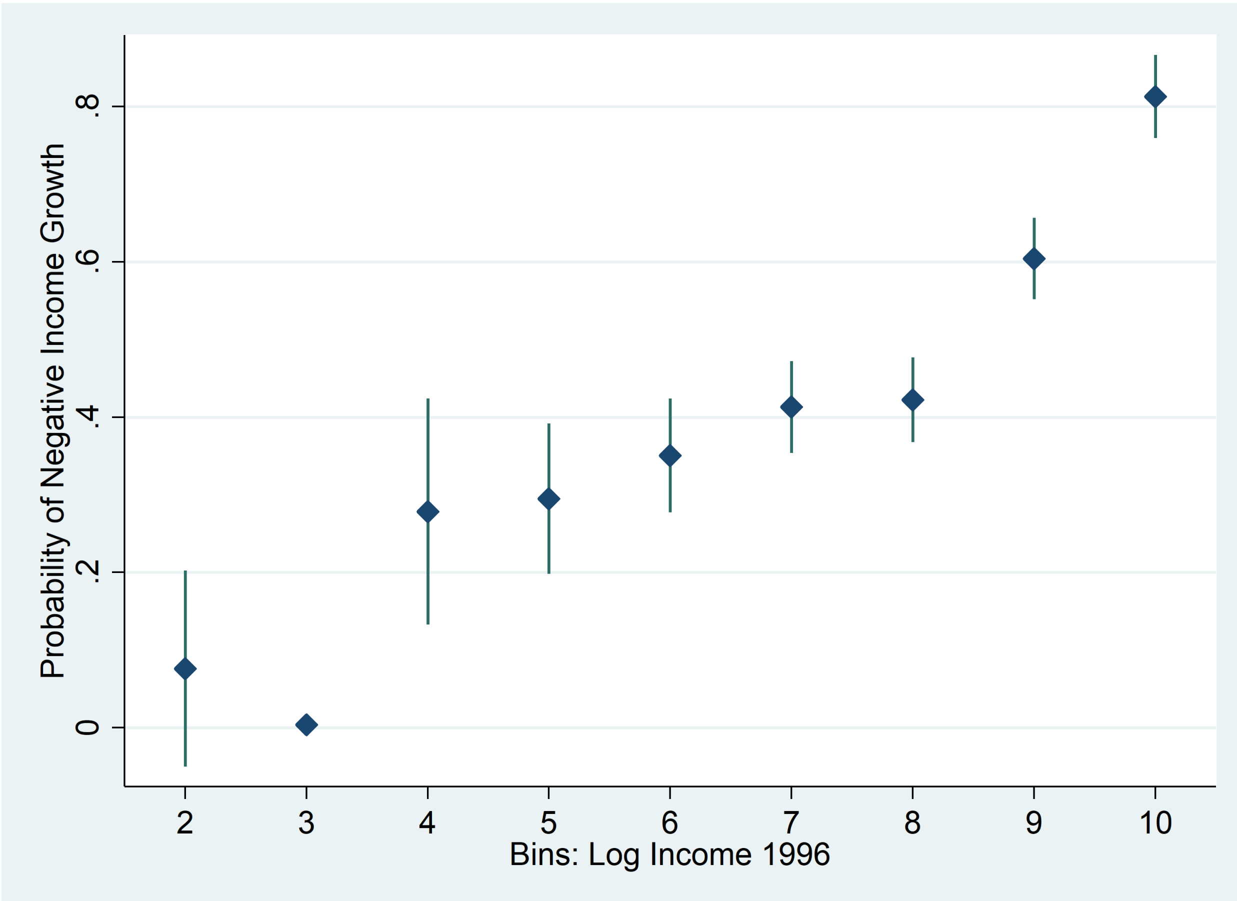


Figure 1.5: Coefficient Plot for the Total Sample of Households, 2000-2016

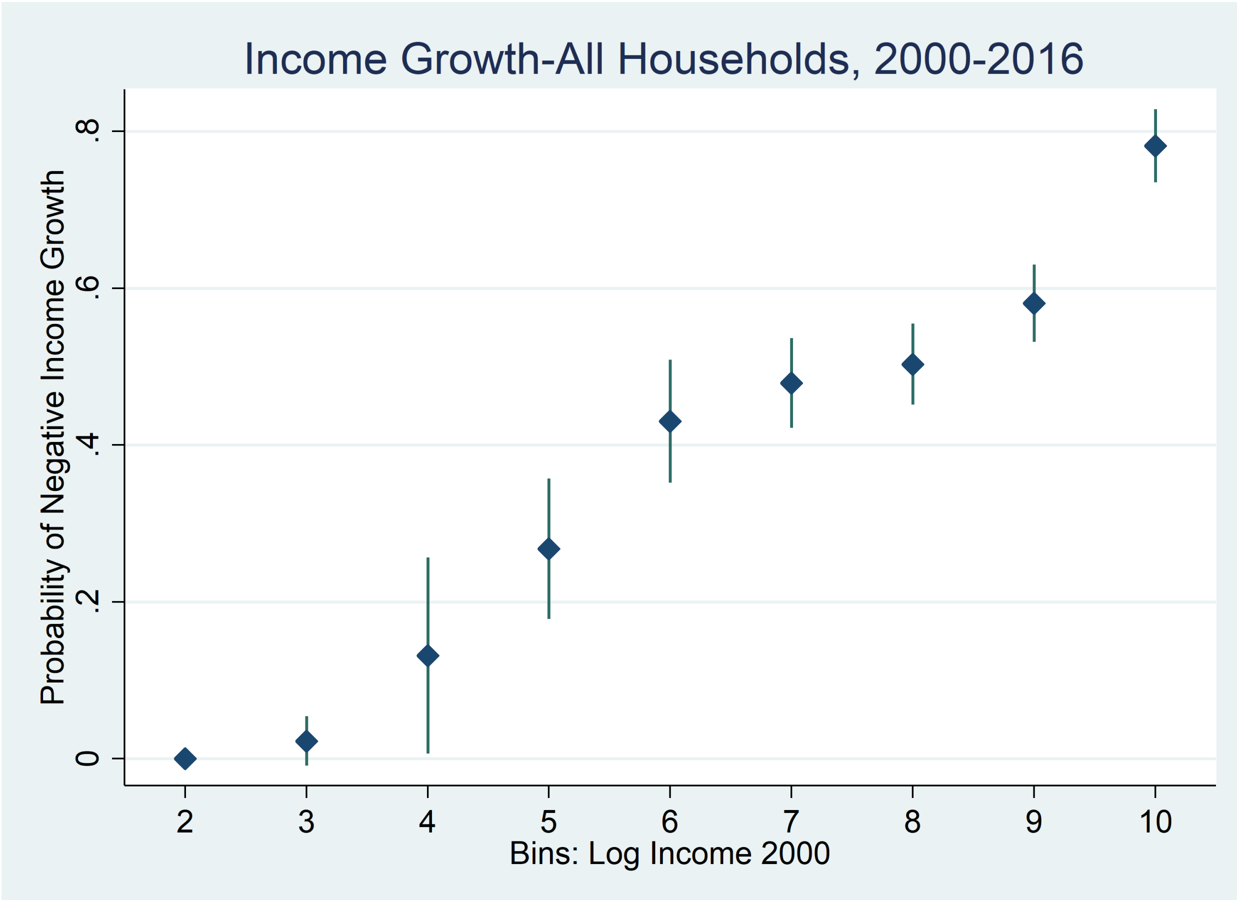
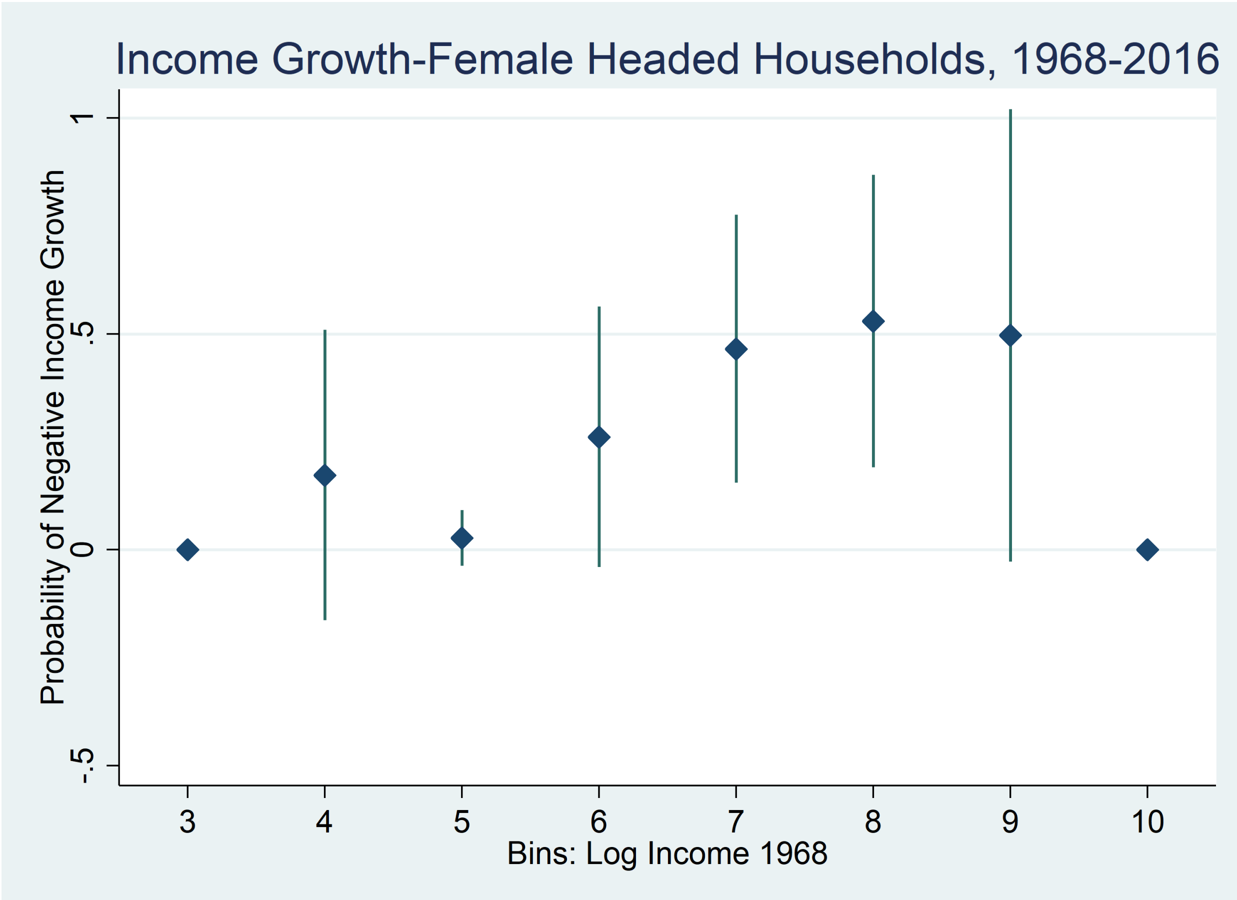


Figure 1.6: Coefficient Plot for Female Headed Households, 1968-2016



The coefficient estimates have more variability compared to the total sample and larger confidence intervals. There is no significant decline in the probability of negative income growth. A probability of zero indicates there were not enough observations in the bins and thus, omitted from the estimation.

Figure 1.7: Coefficient Plot for Female Headed Households, 1980-2016

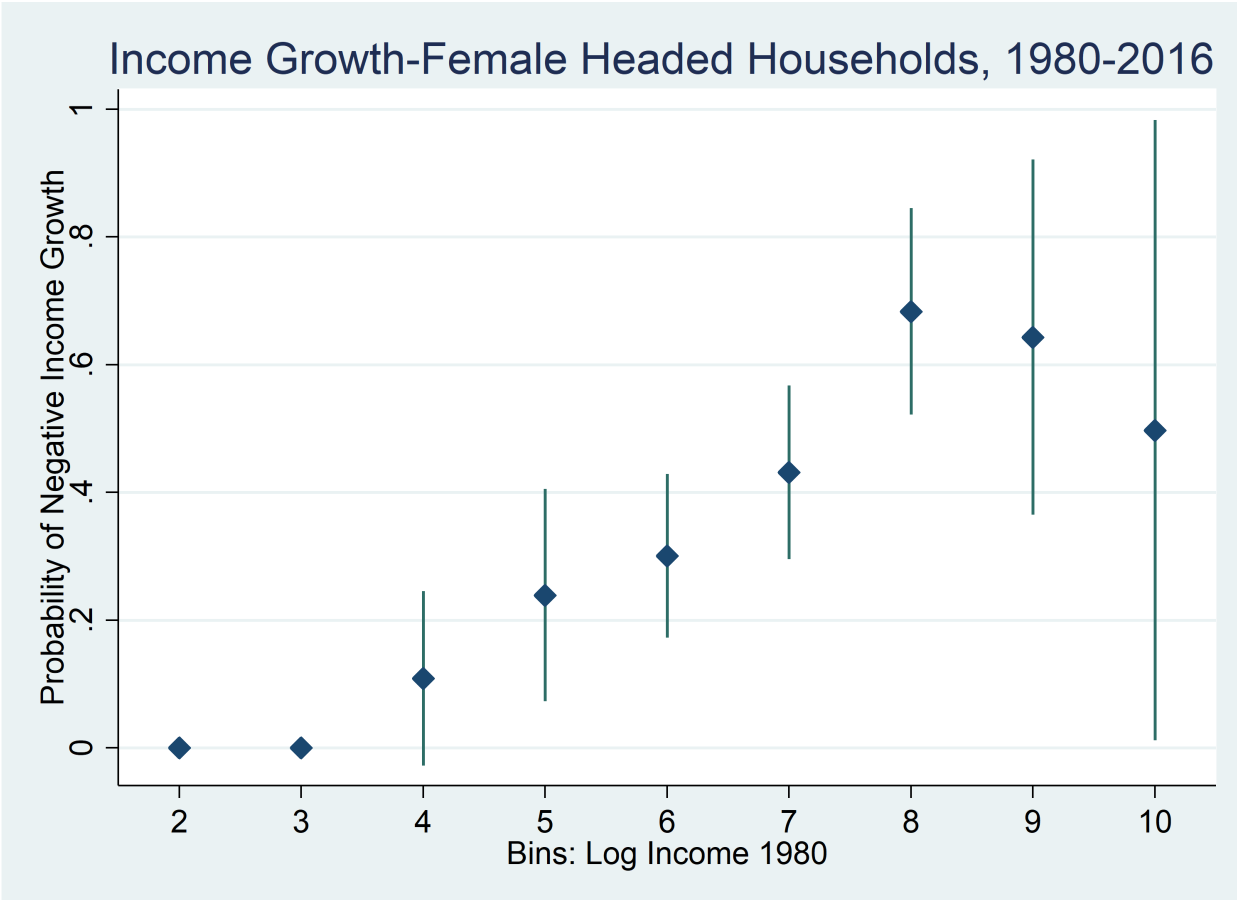


Figure 1.8: Coefficient Plot for Female Headed Households, 1996-2016

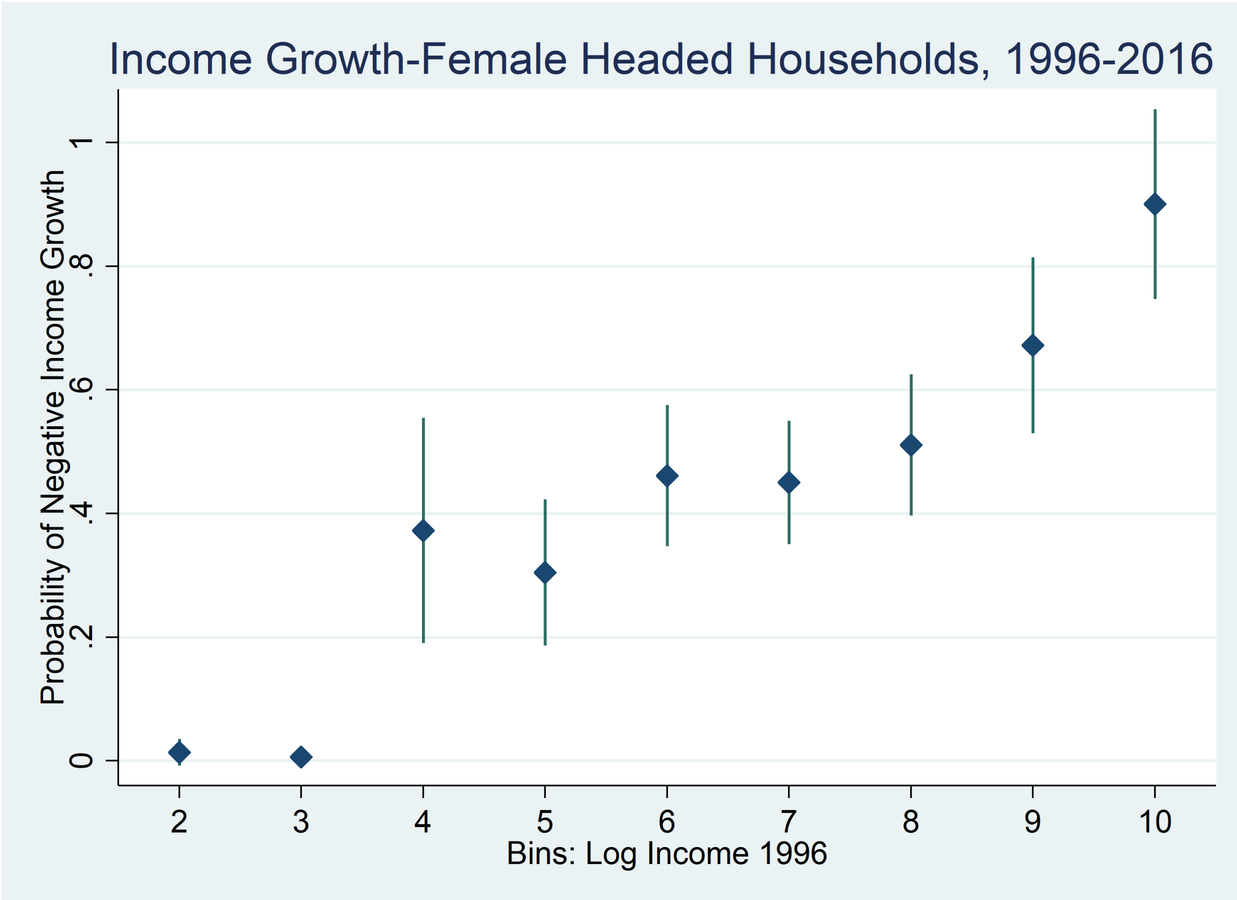
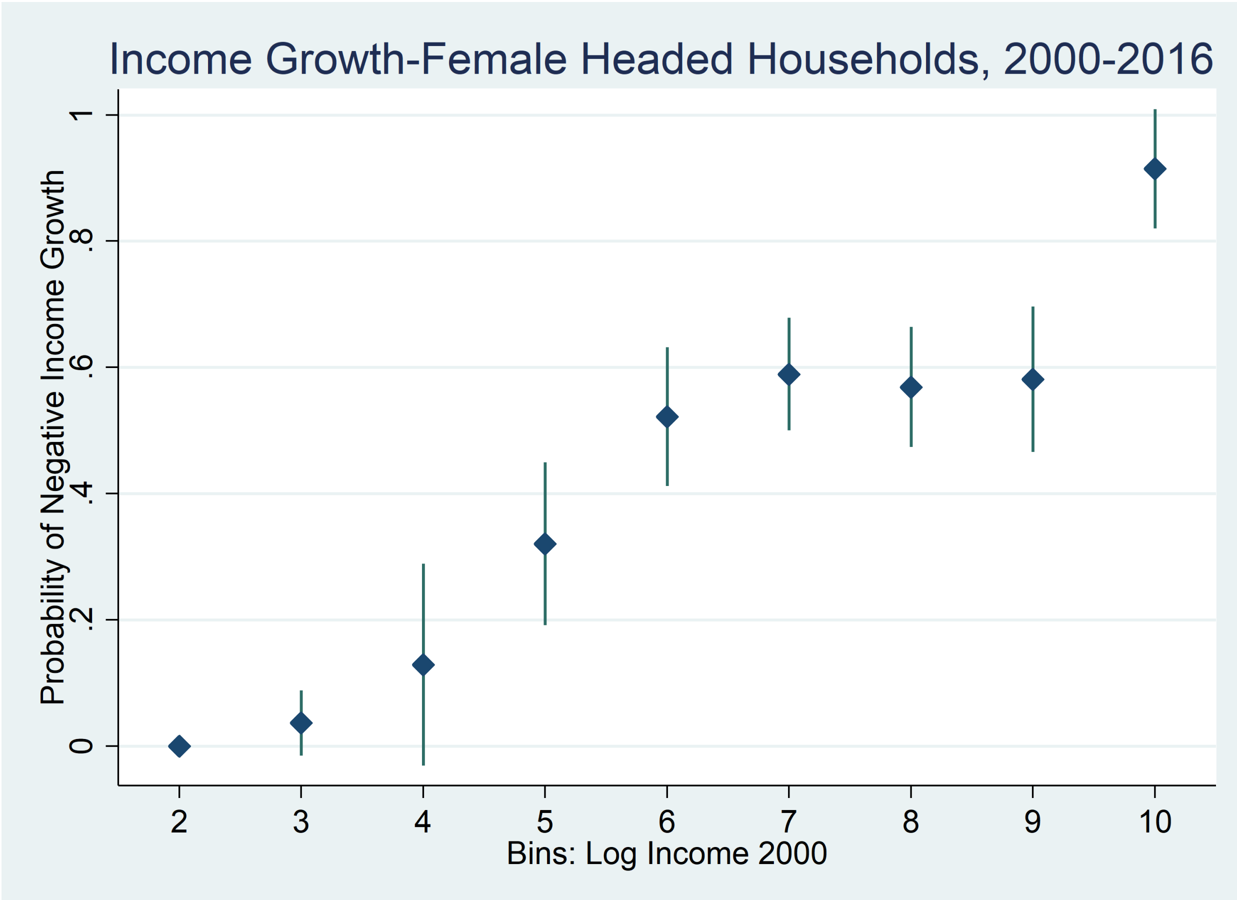


Figure 1.9: Coefficient Plot for Female Headed Households, 2000-2016



The coefficients have smaller confidence intervals because of the increase of female headship in more recent years.

Figure 1.10: Coefficient Plot for Black Headed Households, 1968-2016

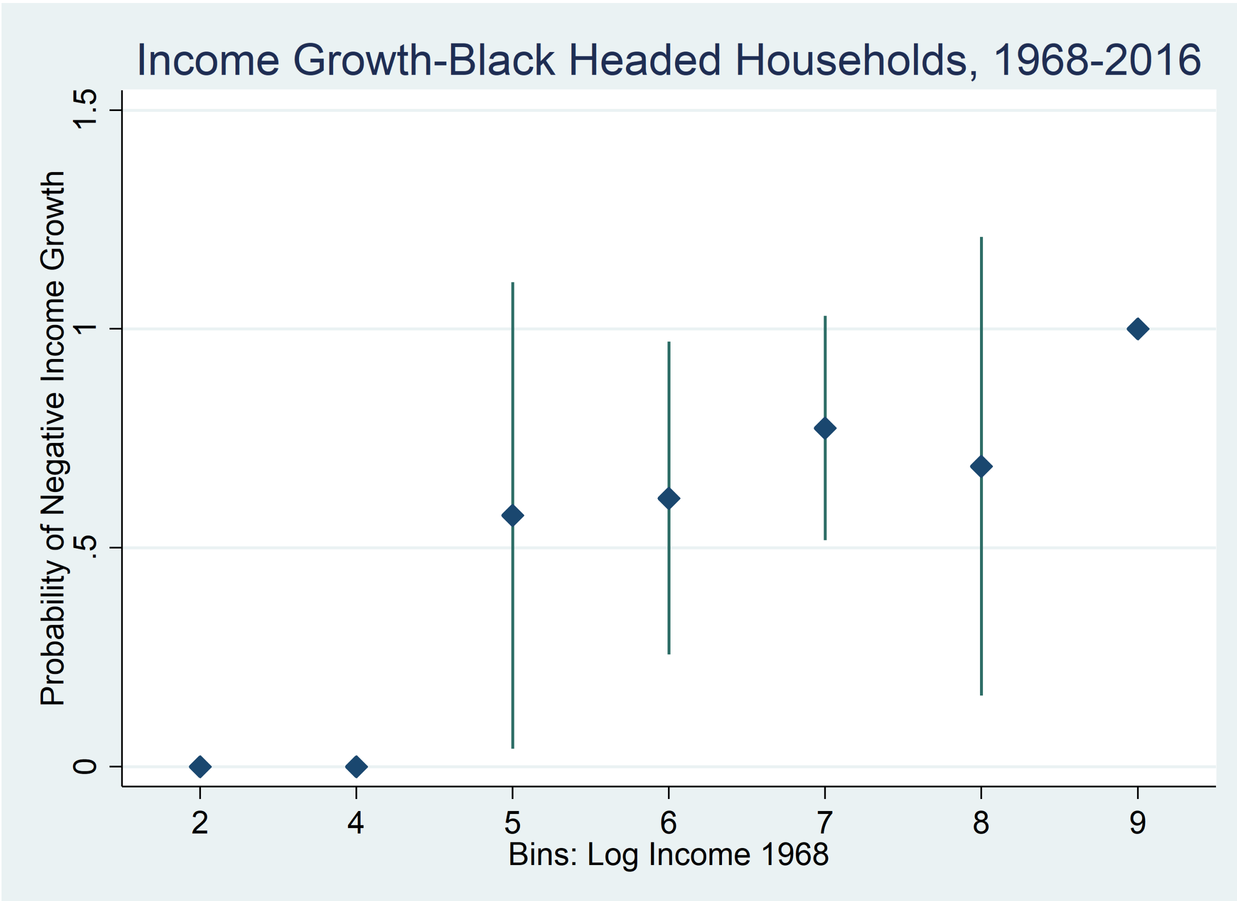
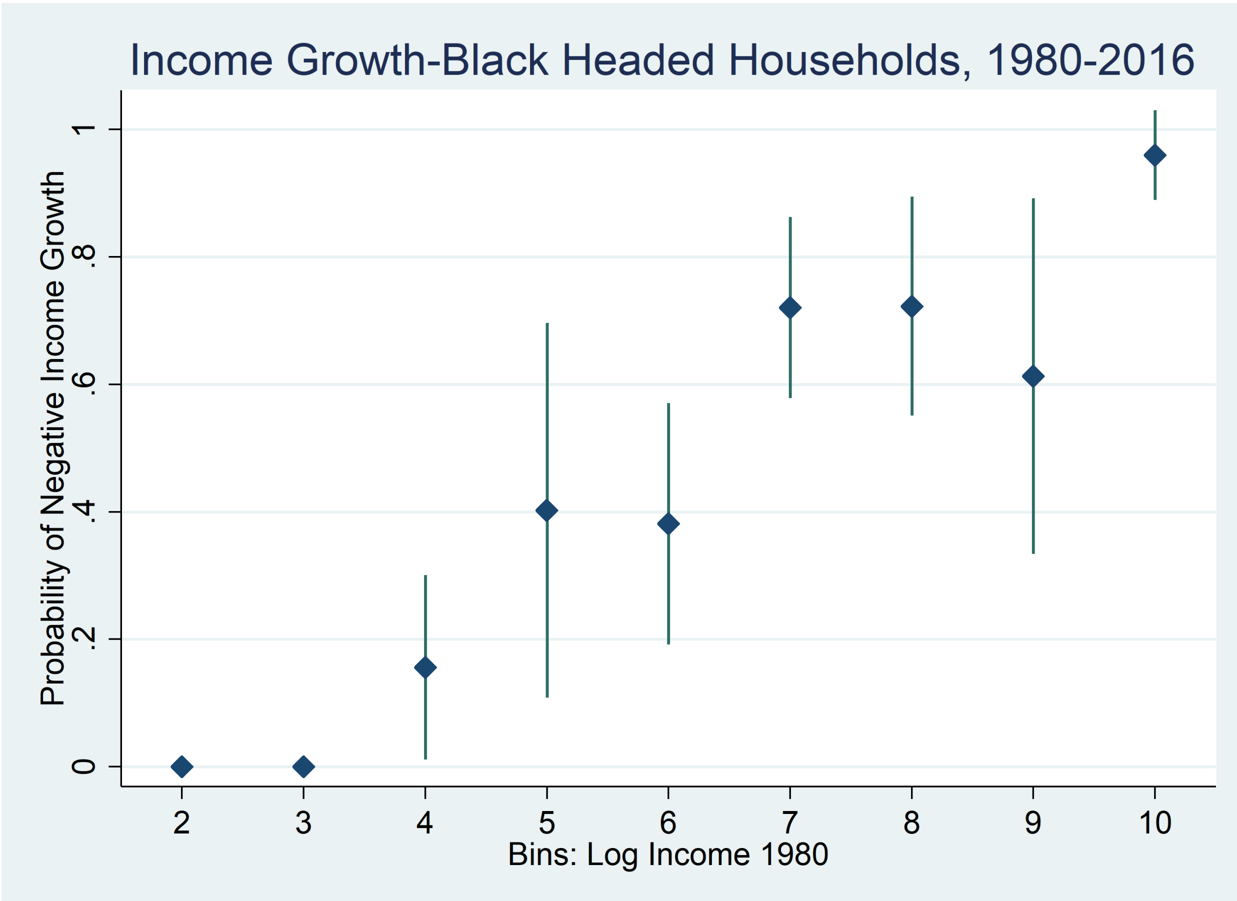


Figure 1.10: Coefficient plot for the sample of black headed households for waves 1969 to 2017.

Figure 1.11: Coefficient Plot for Black Headed Households, 1980-2016



While there are declines in the probability of negative income growth, Table 1.10 confirms the declines are not significant.

Figure 1.12: Coefficient Plot for Black Headed Households, 1996-2016

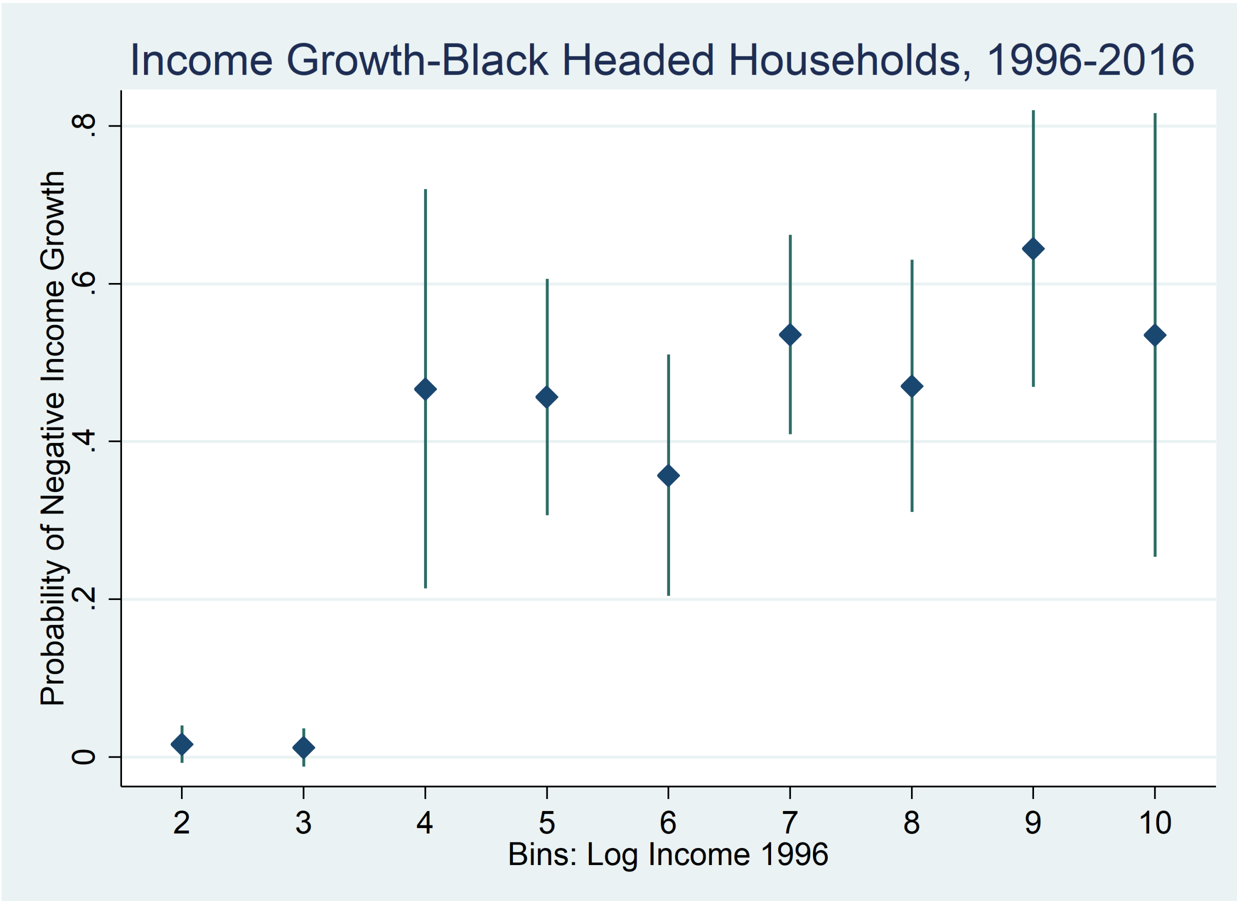


Figure 1.13: Coefficient Plot for Black Headed Households, 2000-2016

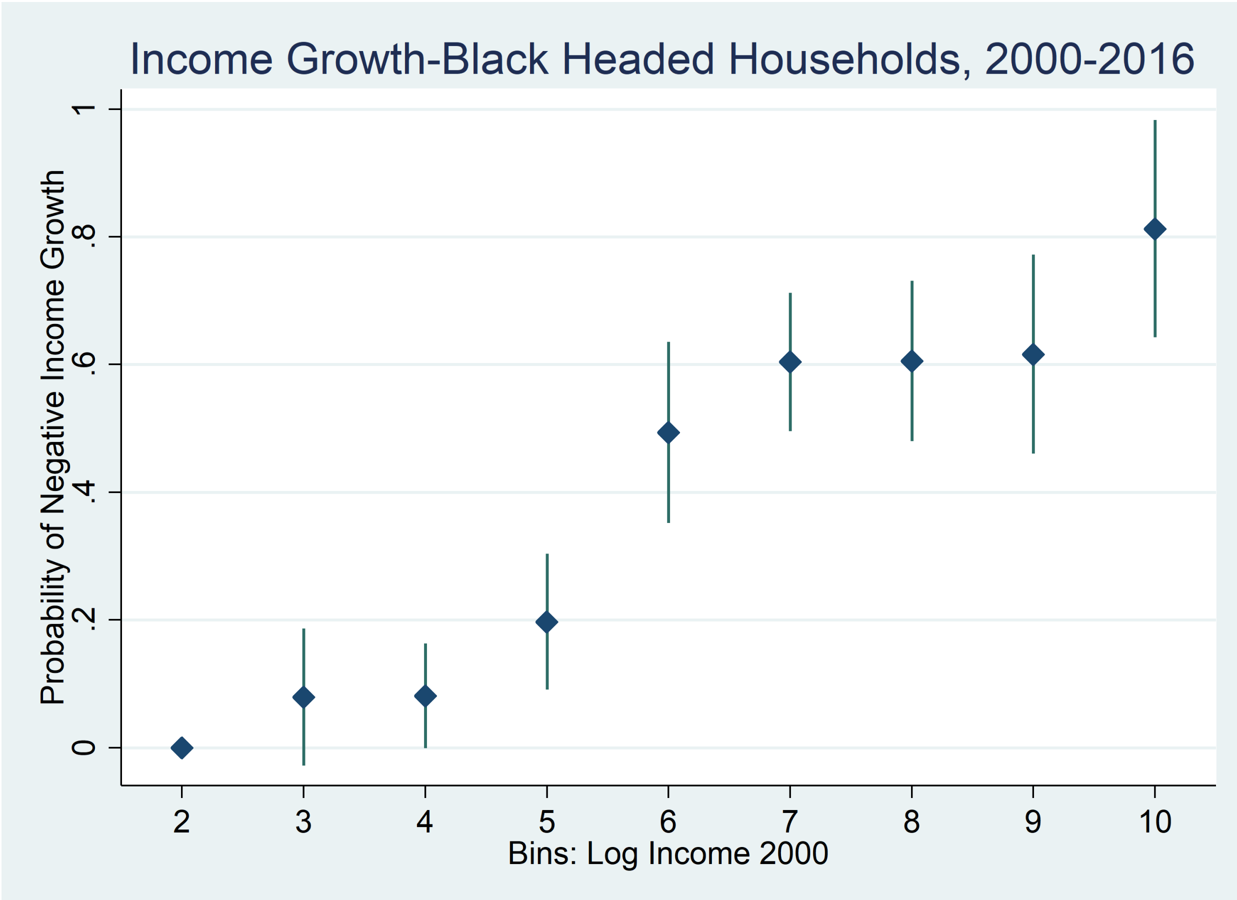
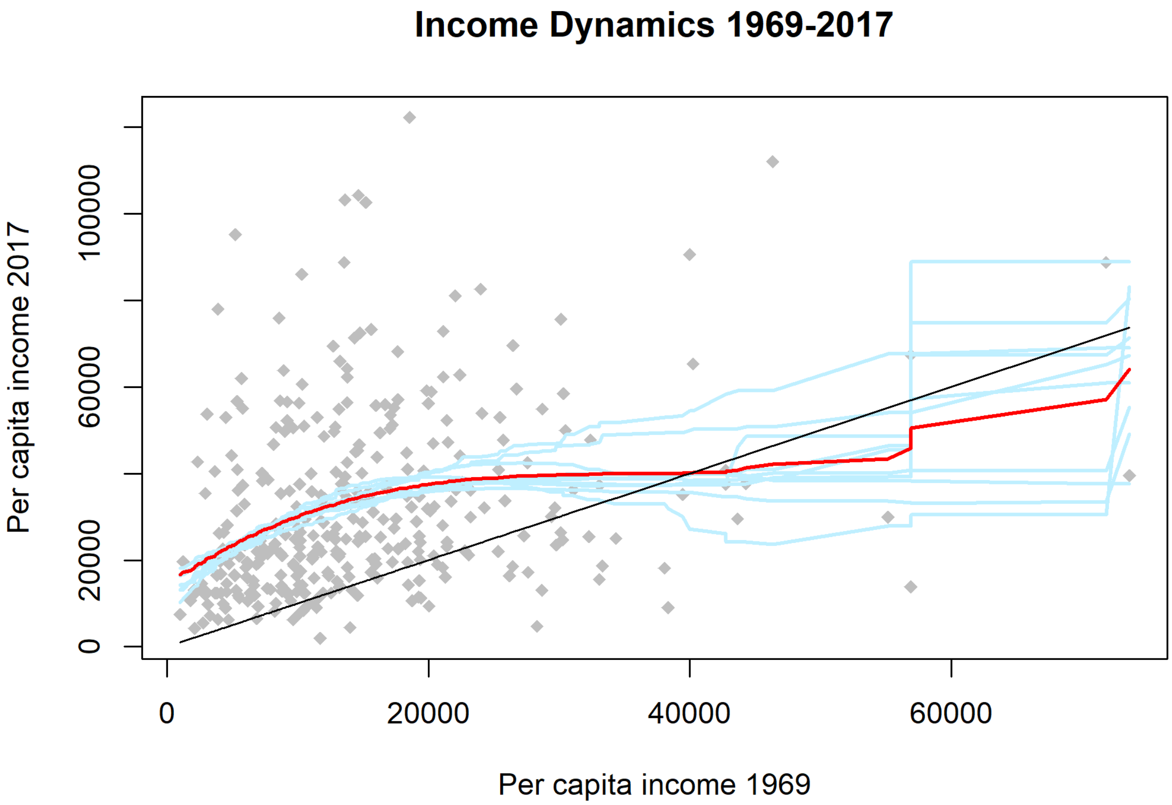
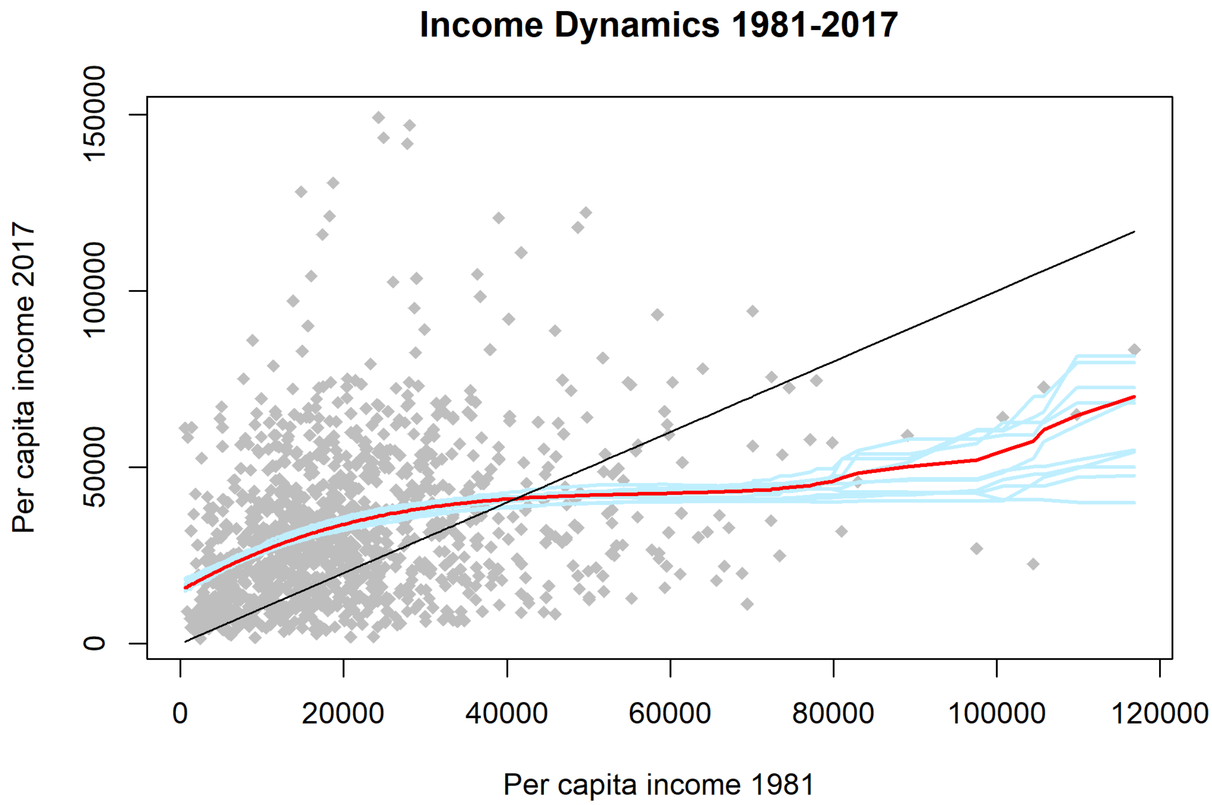


Figure 1.14: Kernel-Weighted Local Polynomial Regression with Bagging, 1969-2017



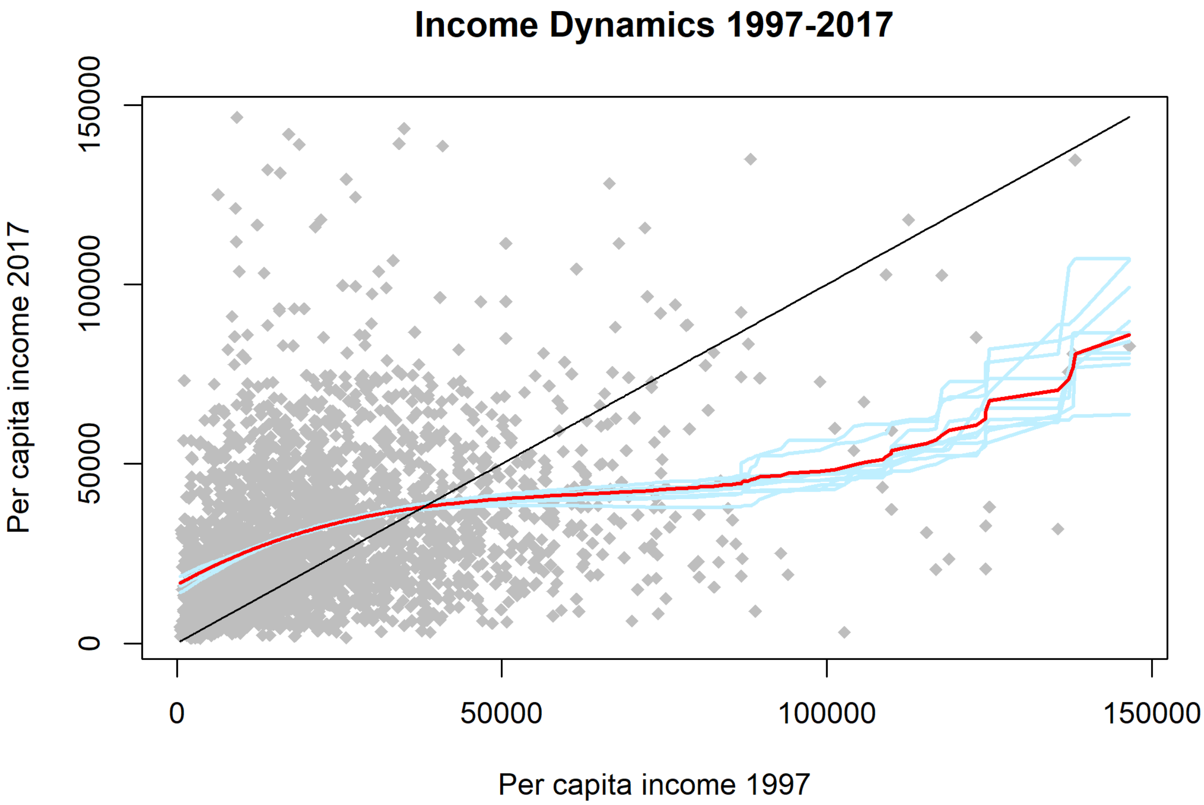
As we can see, many of the observations have dropped over the 48 year period. The blue lines in the plot represent 10 fitted values estimated from 10 random samples from the 1969-2017 observations. The red line is the average of the 1,000 fitted lines, each from a bootstrap sample. The results confirm no multiple equilibria poverty trap.

Figure 1.15: Kernel-Weighted Local Polynomial Regression with Bagging, 1981-2017



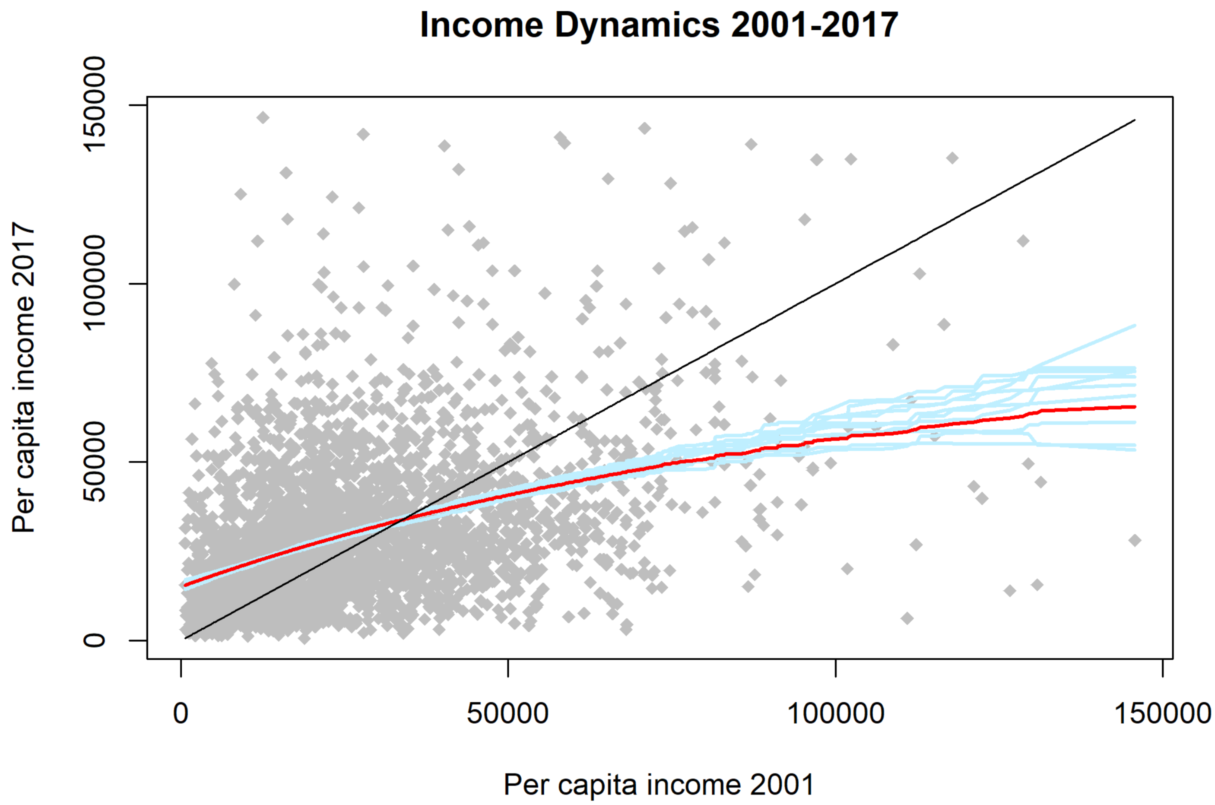
The results confirm no multiple equilibria poverty trap.

Figure 1.16: Kernel-Weighted Local Polynomial Regression with Bagging, 1997-2017



The results confirm no multiple equilibria poverty trap.

Figure 1.17: Kernel-Weighted Local Polynomial Regression with Bagging, 2001-2017



The results confirm no multiple equilibria poverty trap.

Figure 1.18: Kernel-Weighted Local Polynomial Plot with Bagging for Sample of Female Heads, 1981-2017

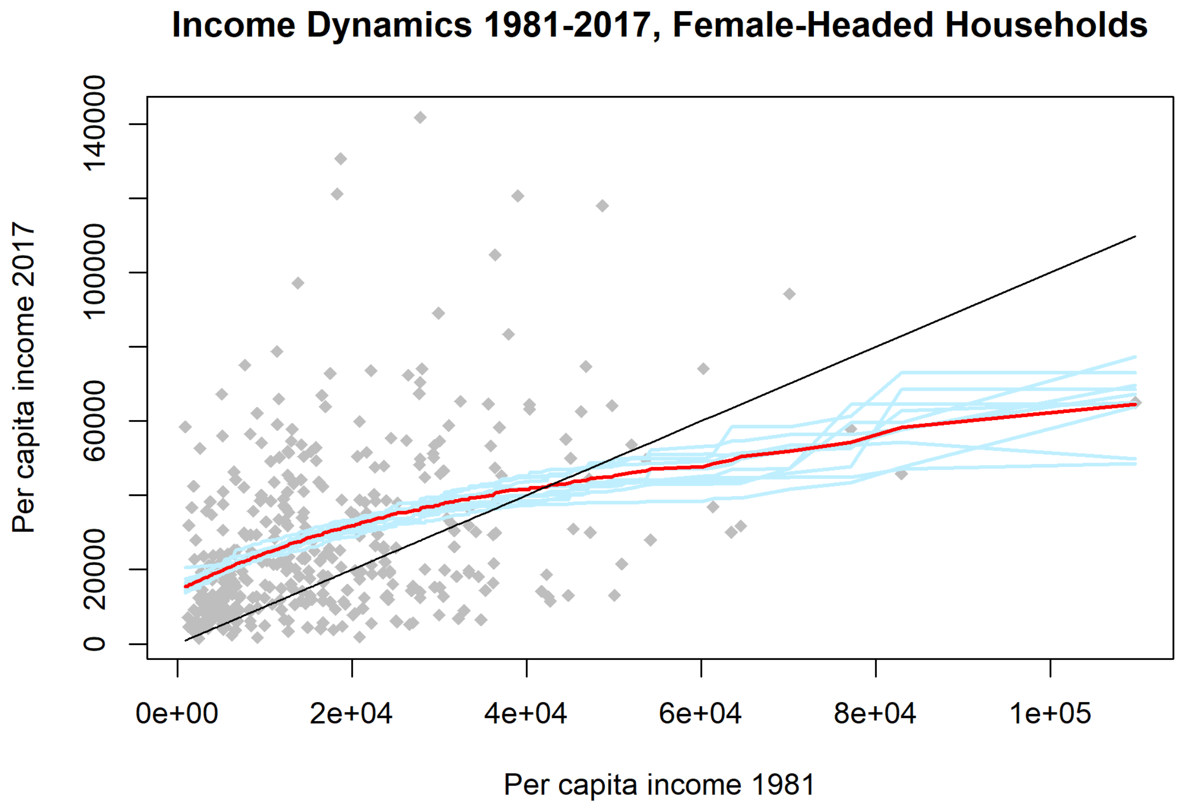


Figure 1.19: Kernel-Weighted Local Polynomial Plot with Bagging for Sample of Female Heads, 1997-2017

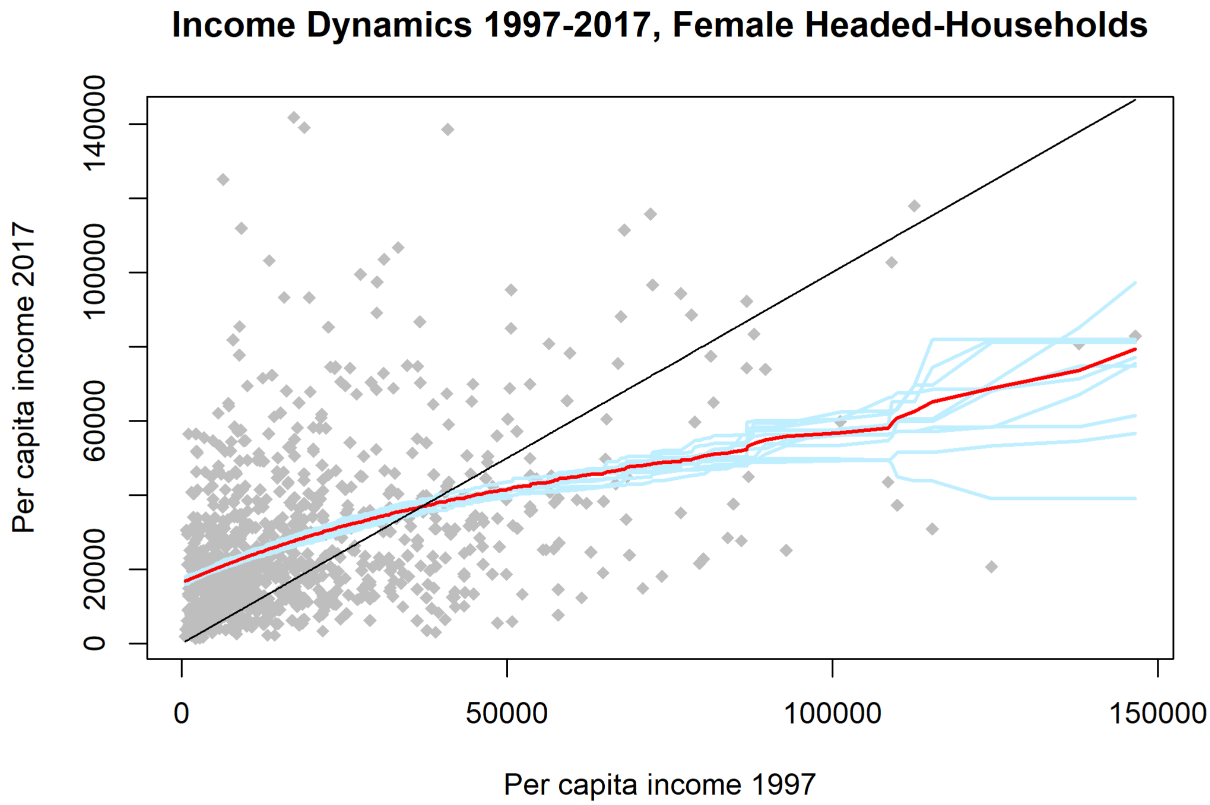


Figure 1.20: Kernel-Weighted Local Polynomial Plot with Bagging for Sample of Female Heads, 2001-2017

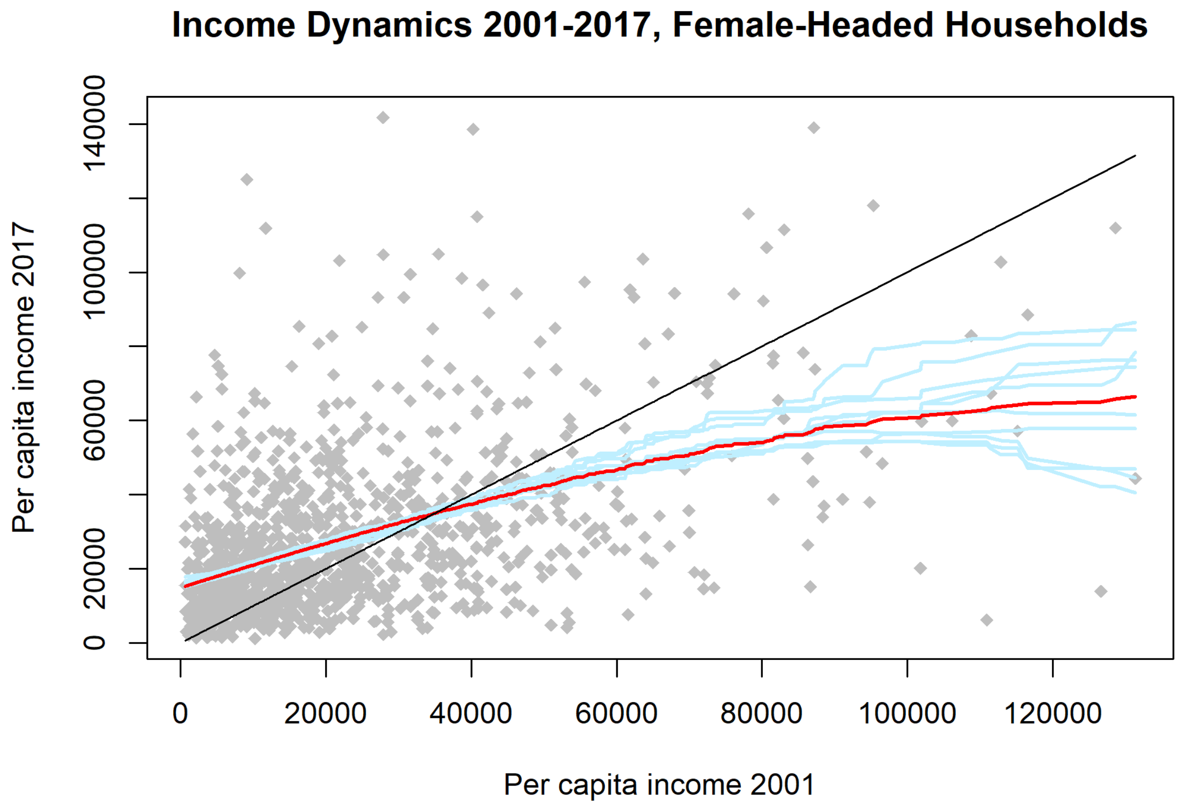


Figure 1.21: Kernel-Weighted Local Polynomial Plot with Bagging for Sample of Black Heads, 1969-2017

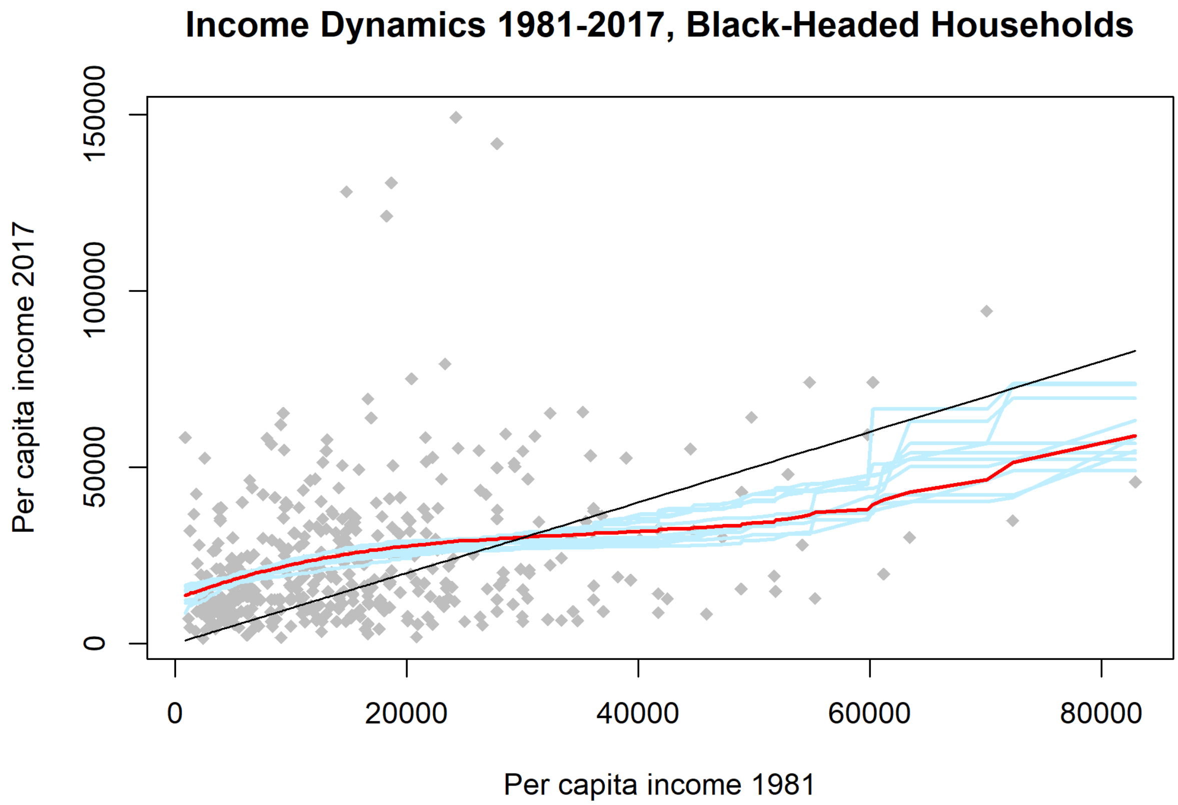


Figure 1.22: Kernel-Weighted Local Polynomial Plot with Bagging for Sample of Black Heads, 1997-2017

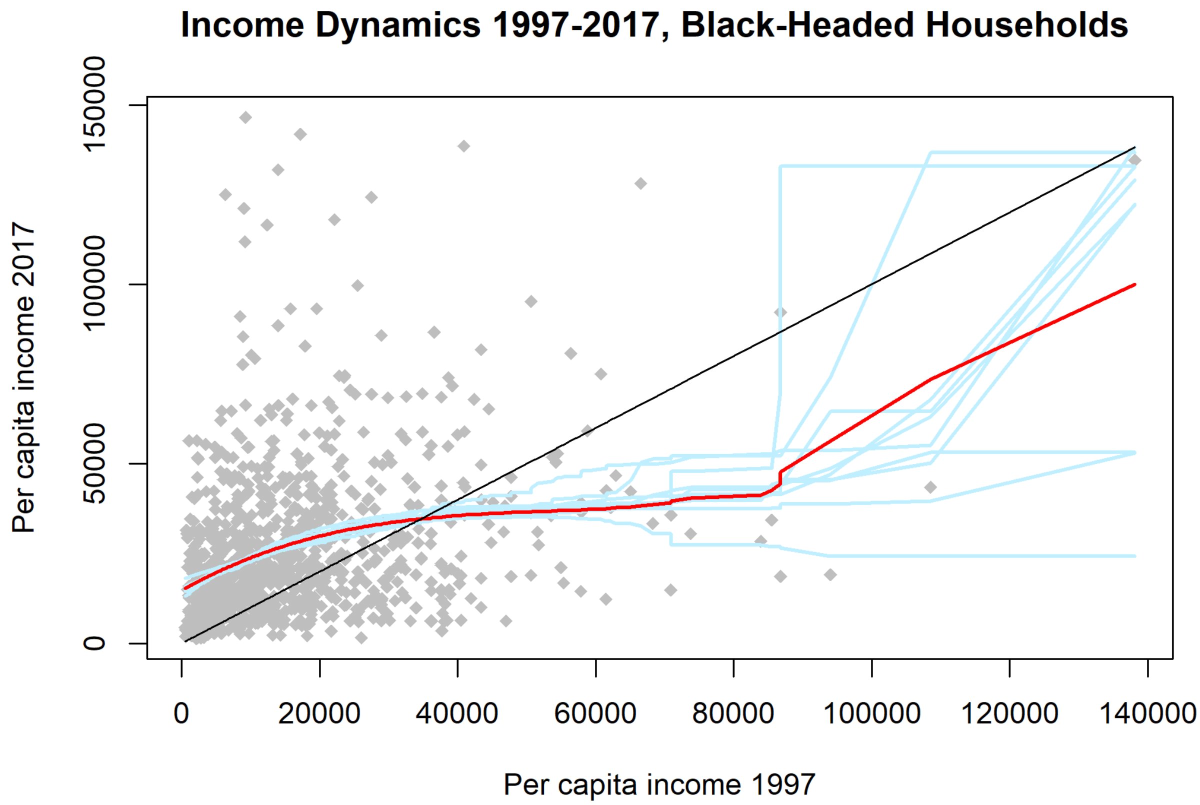


Figure 1.23: Kernel-Weighted Local Polynomial Plot with Bagging for Sample of Black Heads, 2001-2017

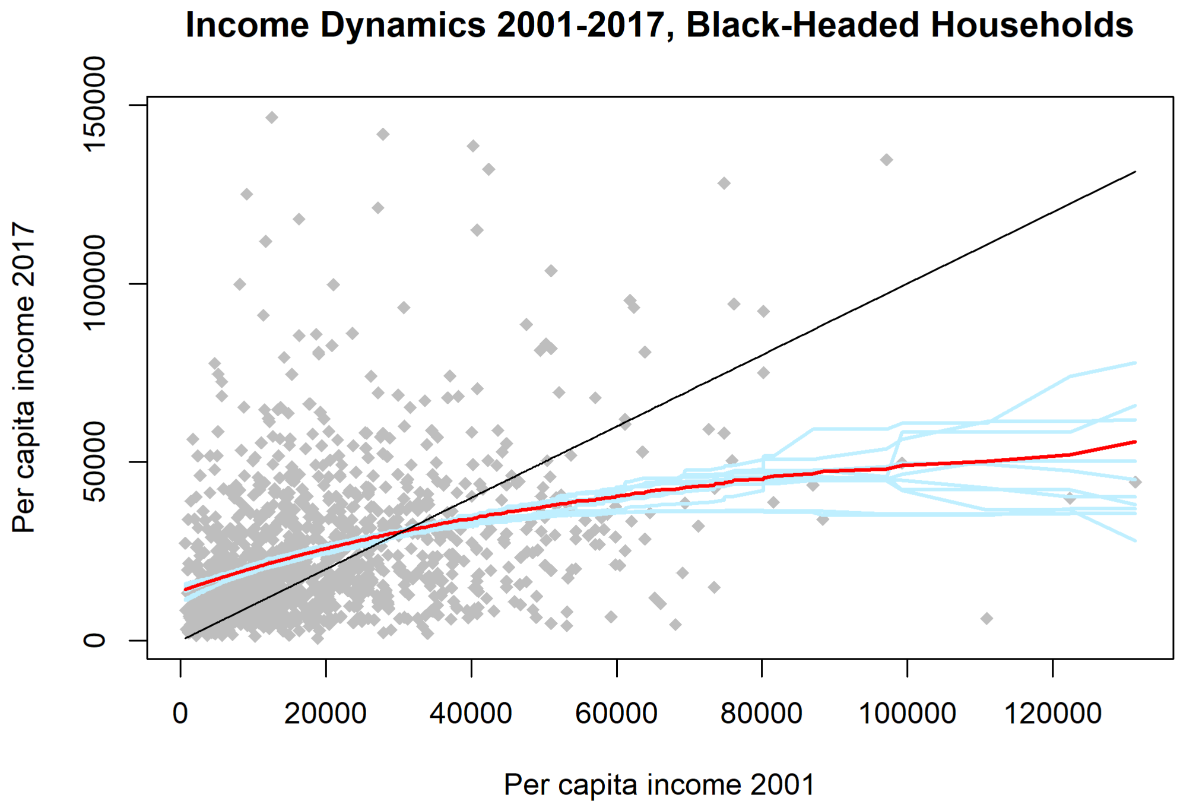


Figure 1.24: Plot of Fixed Effects Prediction

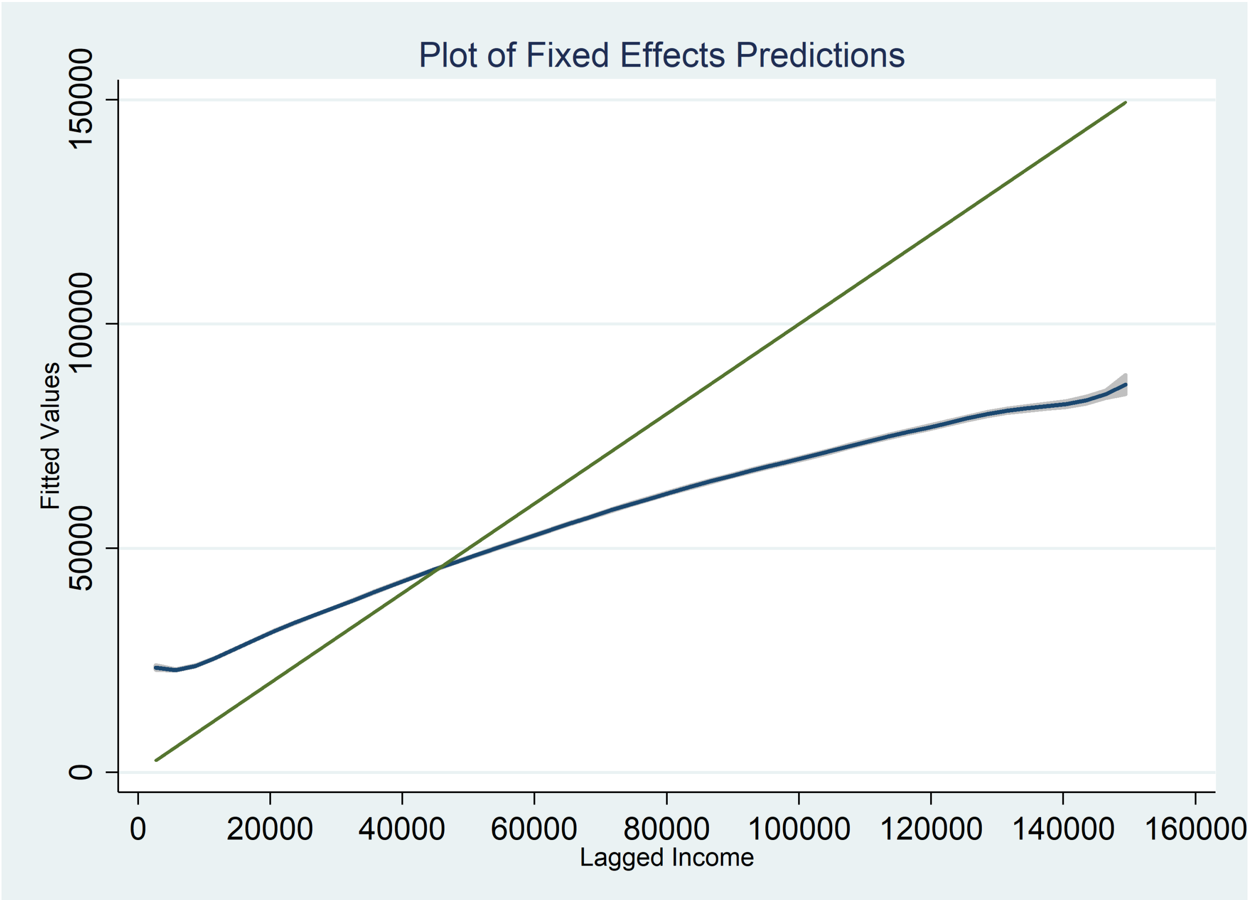
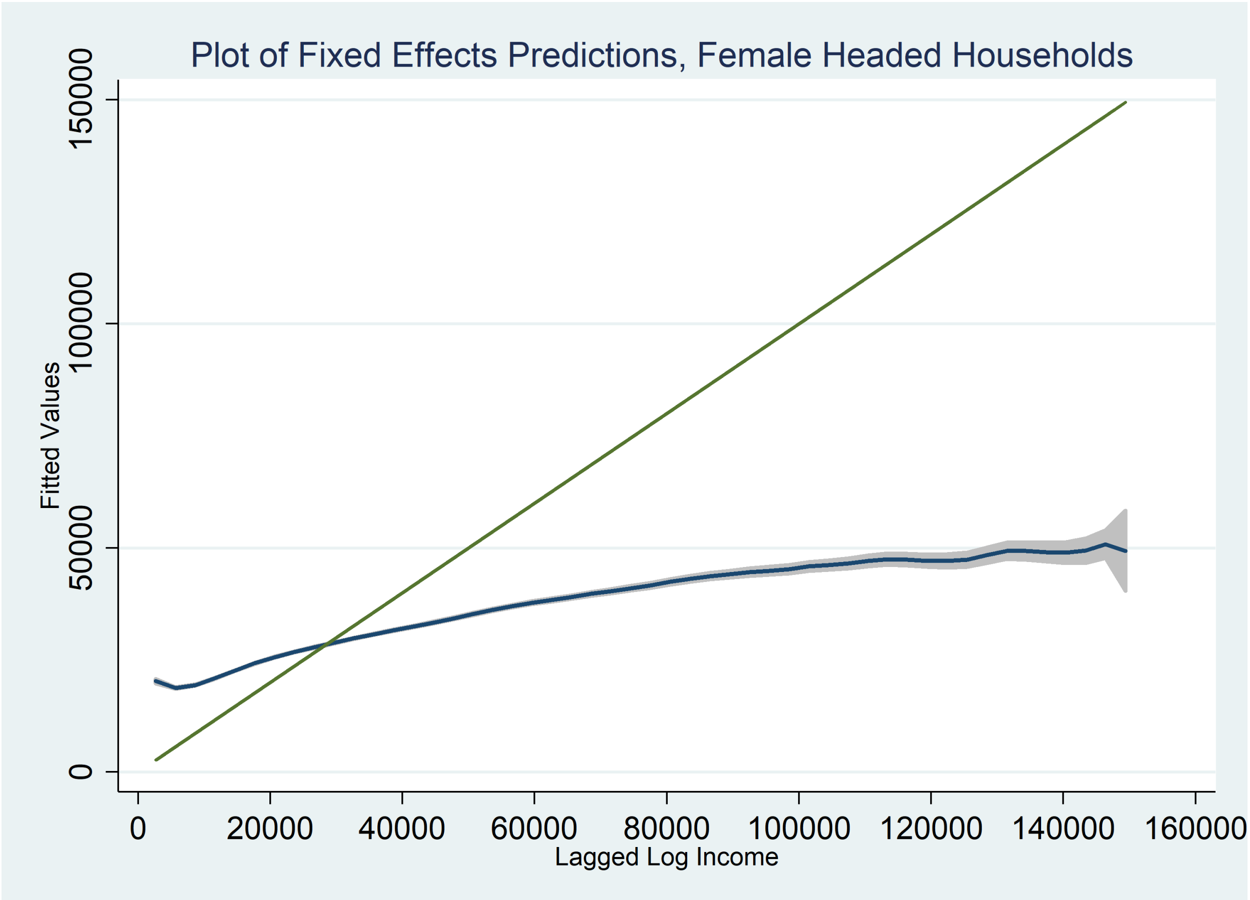


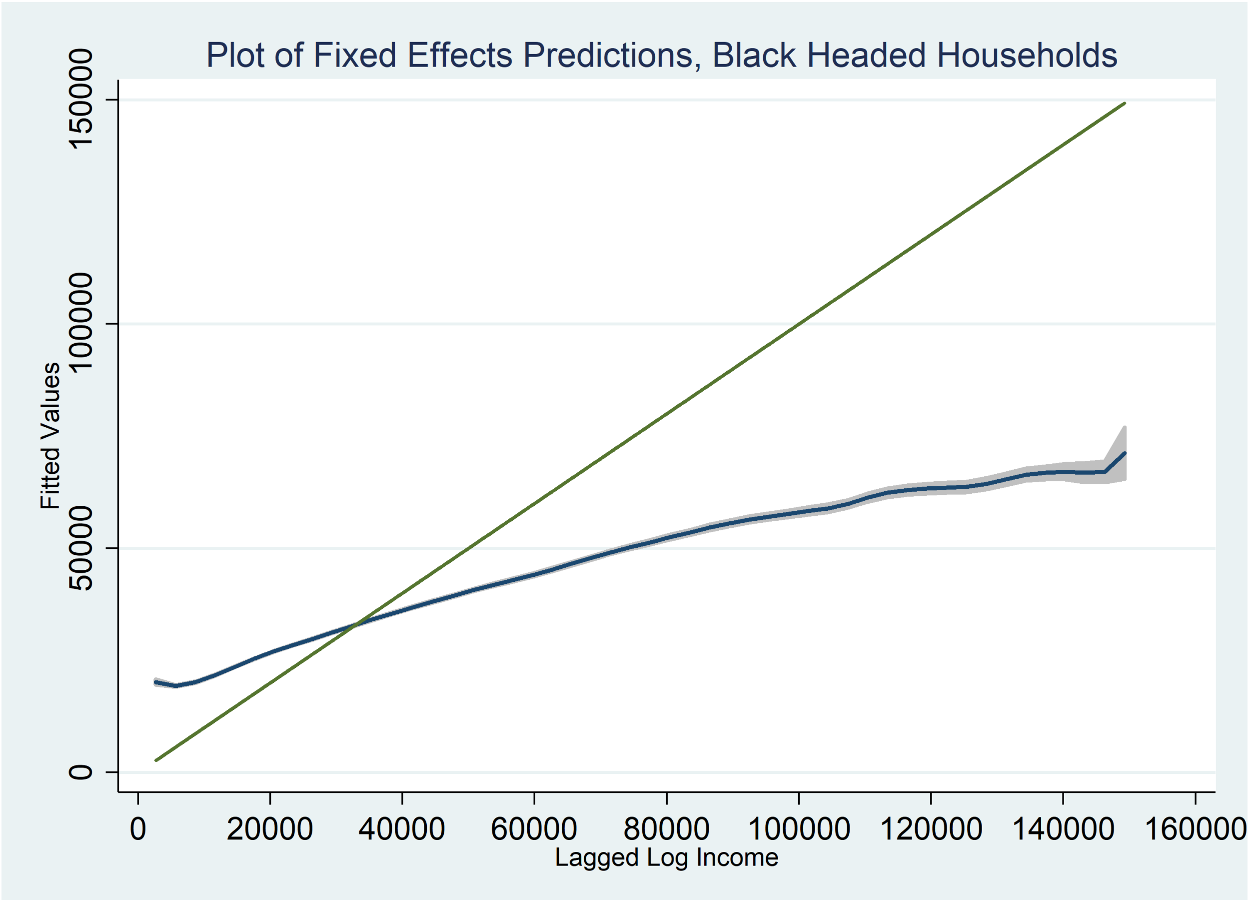
Figure 1.24: For the total sample, we fit a local polynomial regression with the fitted values from the fixed effects estimation in the y-axis and lagged income in the x-axis. The lack of an s-shape curve confirms that the significance of the income coefficients is not sufficient to guarantee a poverty trap.

Figure 1.25: Plot of Fixed Effects Prediction for Sample of Female Headed Households



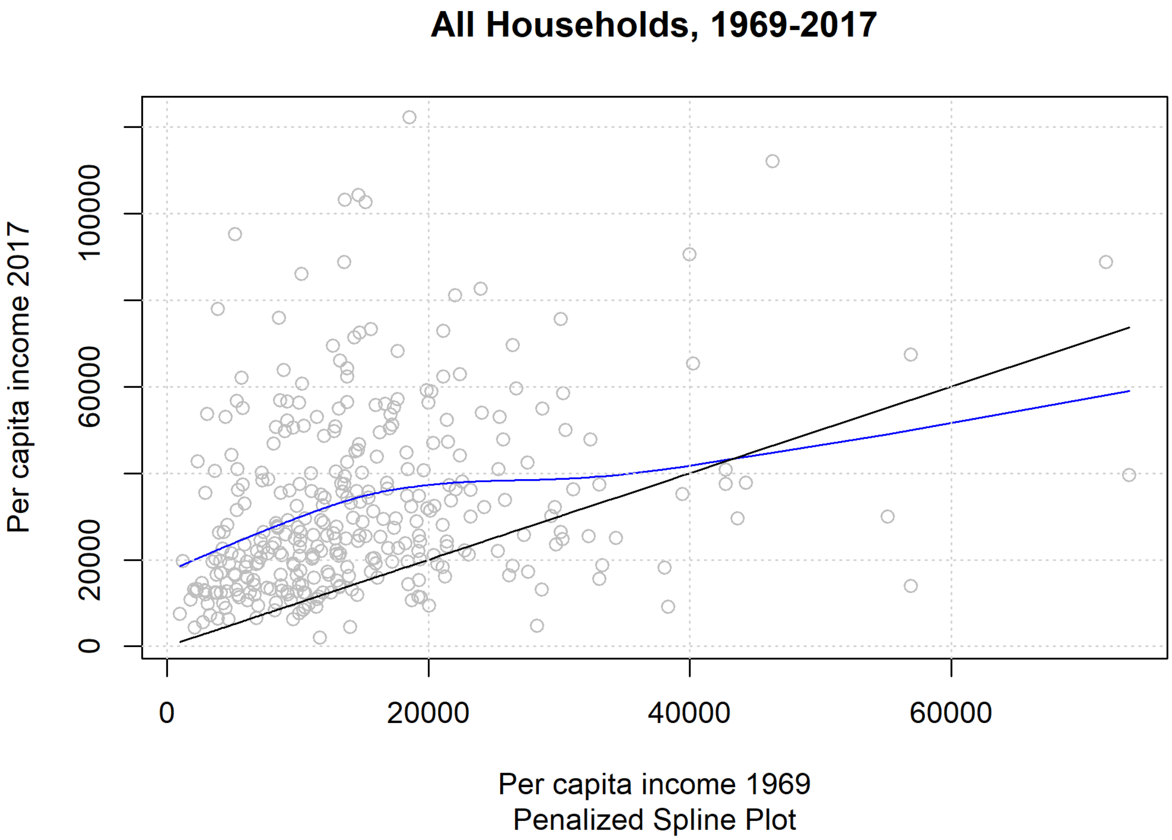
For the sample of female headed households, we fit a local polynomial regression with the fitted values from the fixed effects estimation in the y-axis and lagged income in the x-axis. The lack of an s-shape curve confirms that the significance of the income coefficients is not sufficient to guarantee a poverty trap.

Figure 1.26: Plot of Fixed Effects Prediction for Sample of Black Headed Households



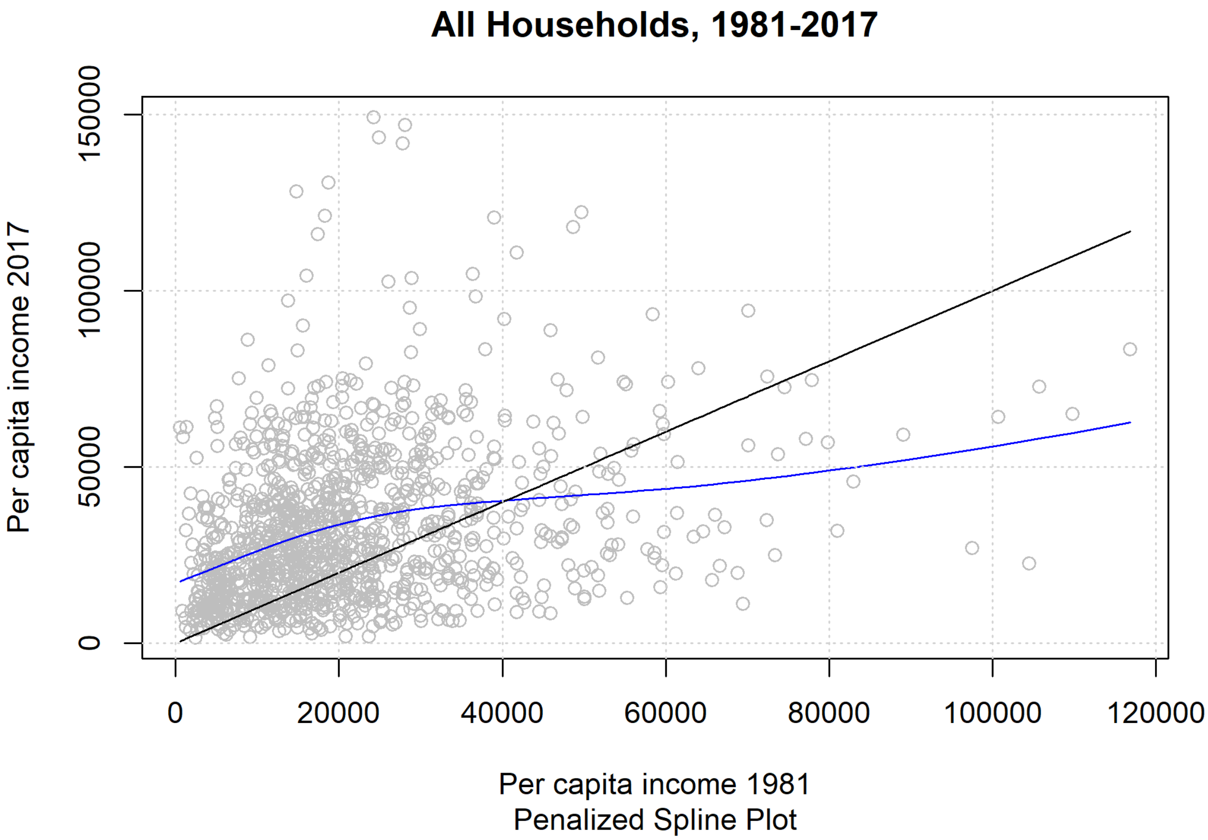
This fits a local polynomial regression with the fitted values from the fixed effects estimation in the y-axis and lagged income in the x-axis. The lack of an s-shape curve confirms that the significance of the income coefficients is not sufficient to guarantee a poverty trap.

Figure 1.27: Penalized Spline Smoothing Plot, Total Sample of Households 1969-2017



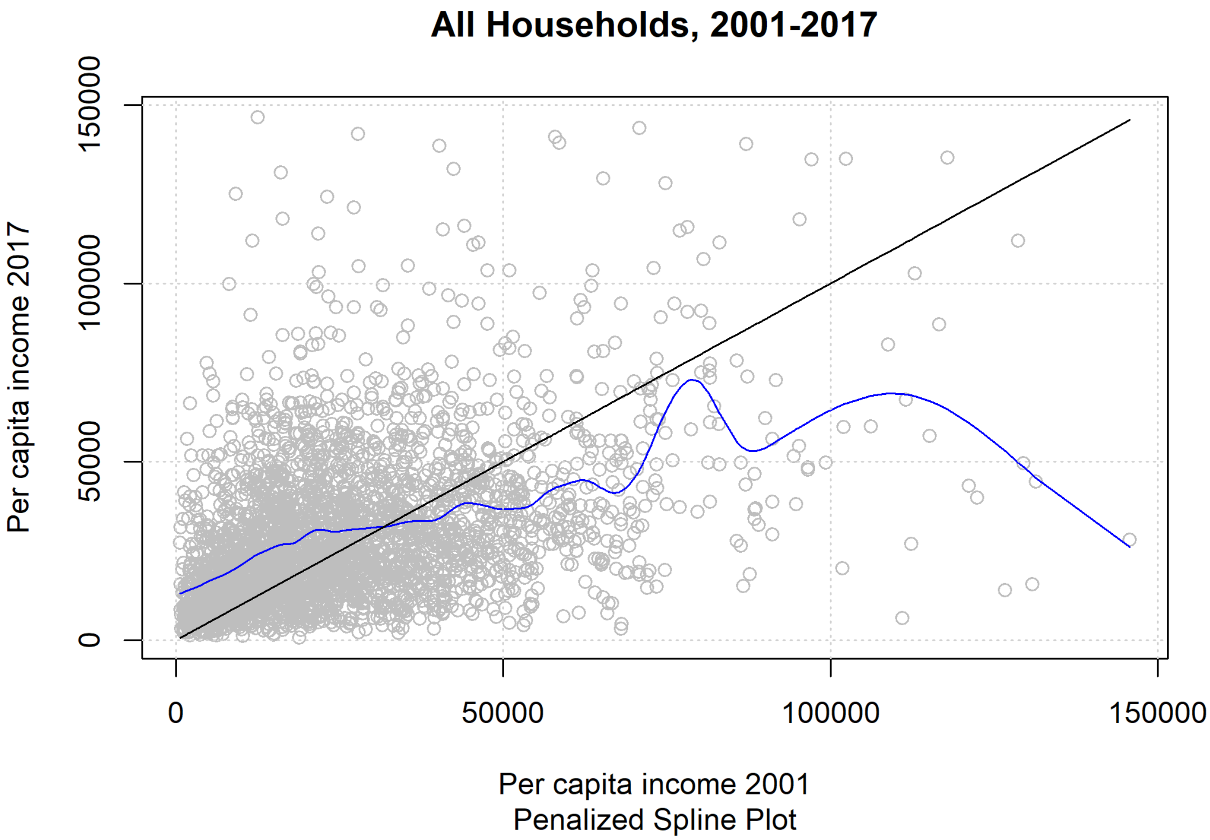
Using a penalized spline smoothing plot, we confirm there are no poverty traps in the U.S. from 1969-2017

Figure 1.28: Penalized Spline Smoothing Plot, Total Sample of Households 1981-2017



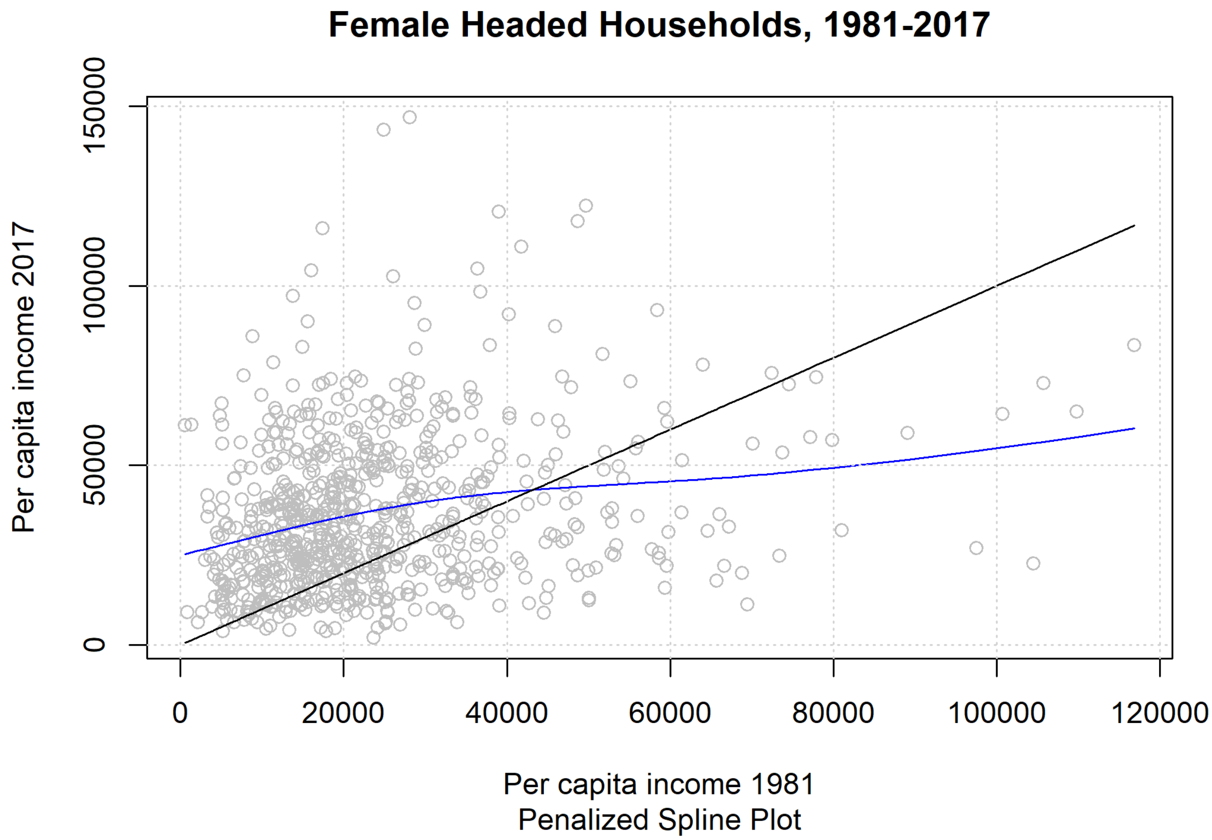
Using a penalized spline smoothing plot, we confirm there are no poverty traps in the U.S. from 1981-2017.

Figure 1.29: Penalized Spline Smoothing Plot, Total Sample of Households 2001-2017



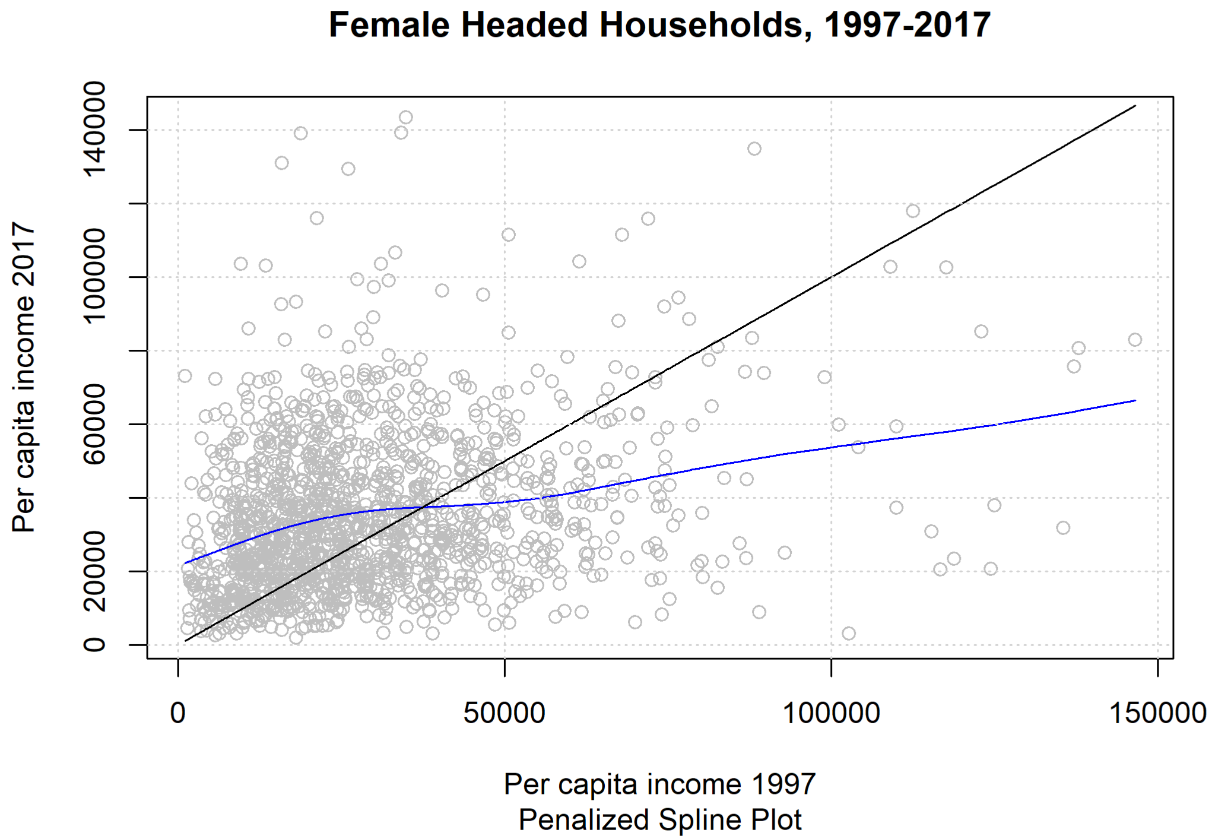
Using a penalized spline smoothing plot, we confirm there are no poverty traps in the U.S. from 2001-2017.

Figure 1.30: Penalized Spline Smoothing Plot, Sample of Female-Headed Households 1981-2017



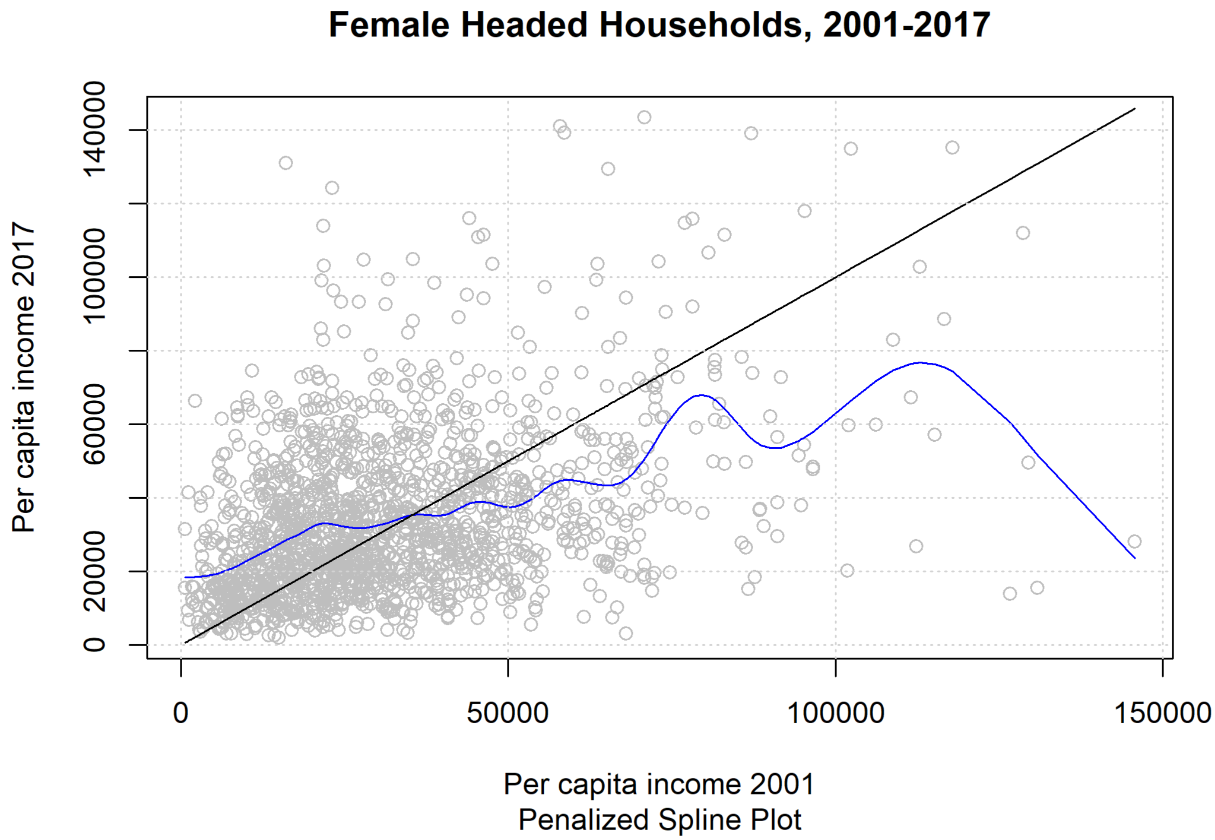
Penalized spline estimations in sample of female headed households confirm no poverty traps from 1981-2017. The single convergence point demonstrates the relationship between income and past income is does not have nonconvexities.

Figure 1.31: Penalized Spline Smoothing Plot, Sample of Female-Headed Households 1997-2017



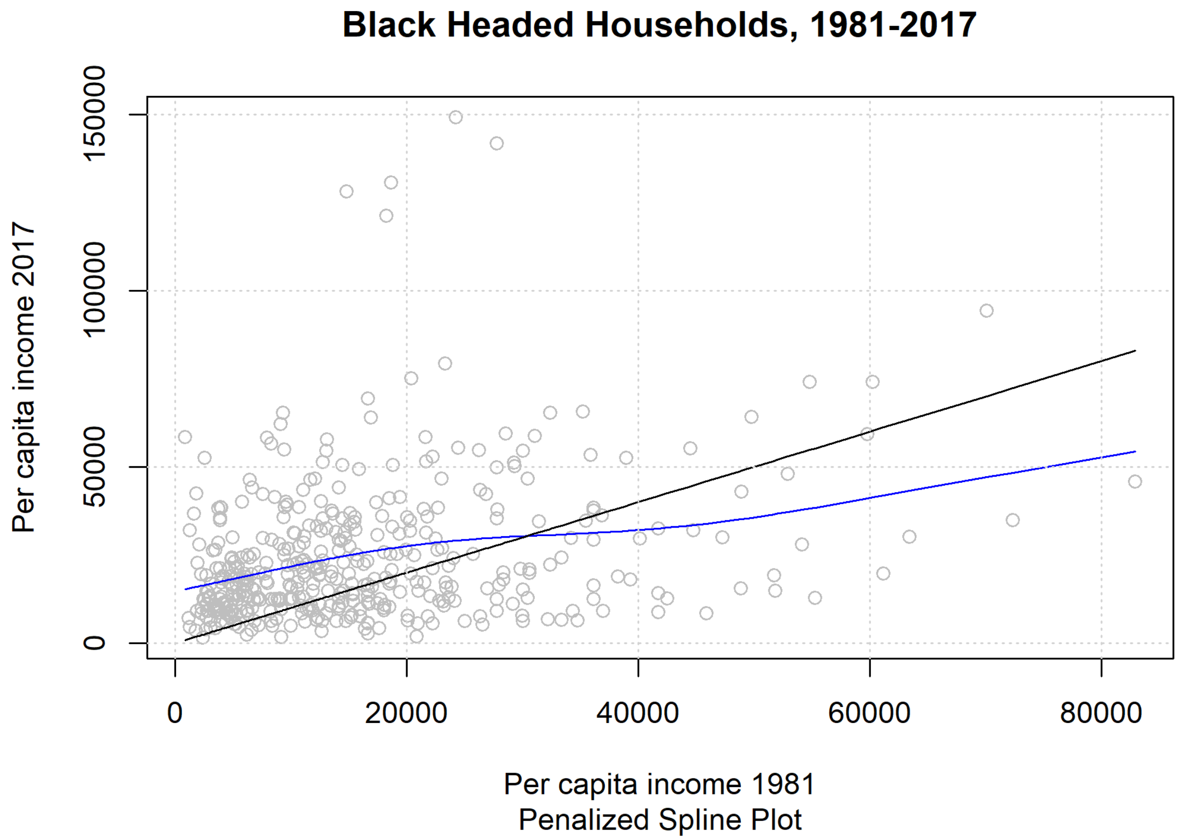
Penalized spline estimations in sample of female headed households confirm no poverty traps from 1997-2017. The single convergence point demonstrates the relationship between income and past income is does not have nonconvexities.

Figure 1.32: Penalized Spline Smoothing Plot, Sample of Female-Headed Households 2001-2017



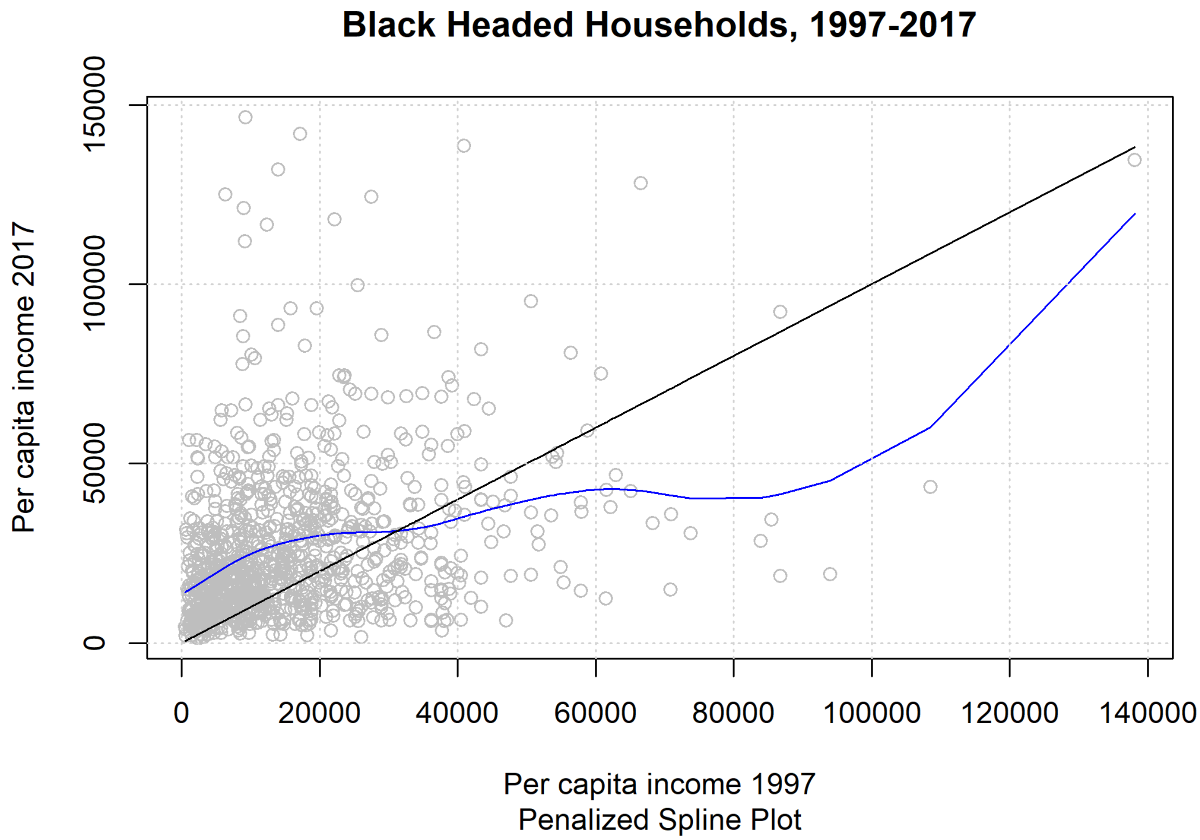
Penalized spline estimations in sample of female headed households confirm no poverty traps from 2001-2017. The single convergence point demonstrates the relationship between income and past income is does not have nonconvexities.

Figure 1.33: Penalized Spline Smoothing Plot, Sample of Black-Headed Households 1981-2017



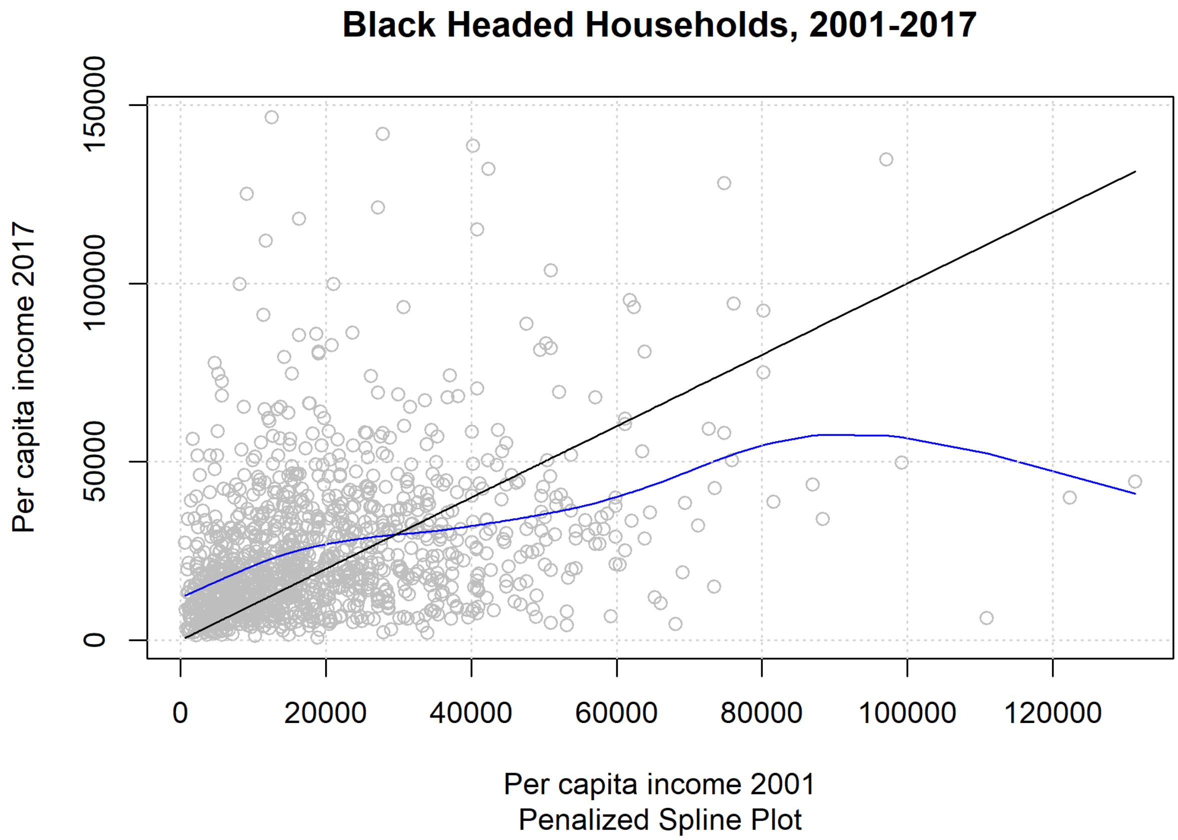
Penalized spline estimations in sample of black headed households confirm no poverty traps from 1981-2017.

Figure 1.34: Penalized Spline Smoothing Plot, Sample of Black-Headed Households 1997-2017



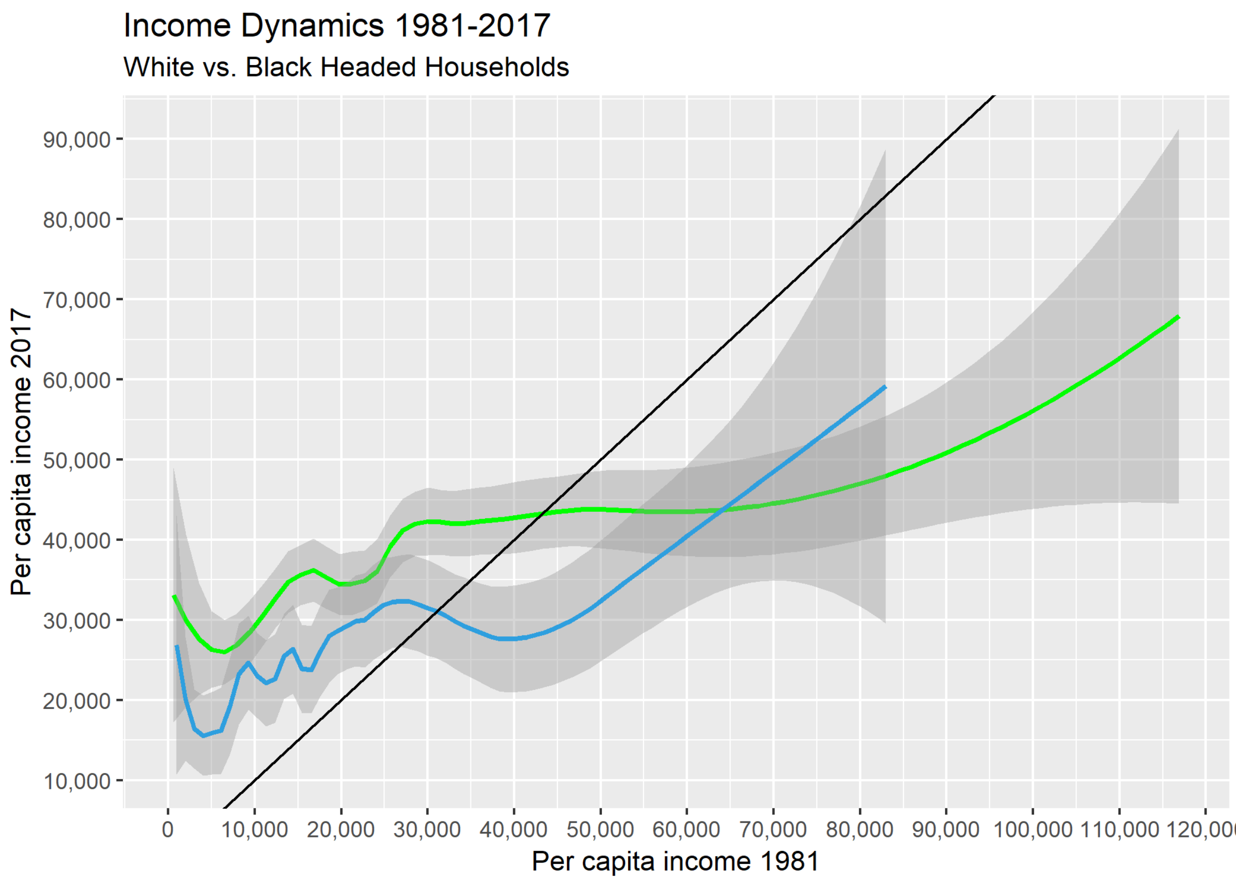
Penalized spline estimations in sample of black headed households confirm no poverty traps from 1997-2017.

Figure 1.35: Penalized Spline Smoothing Plot, Sample of Black-Headed Households 2001-2017



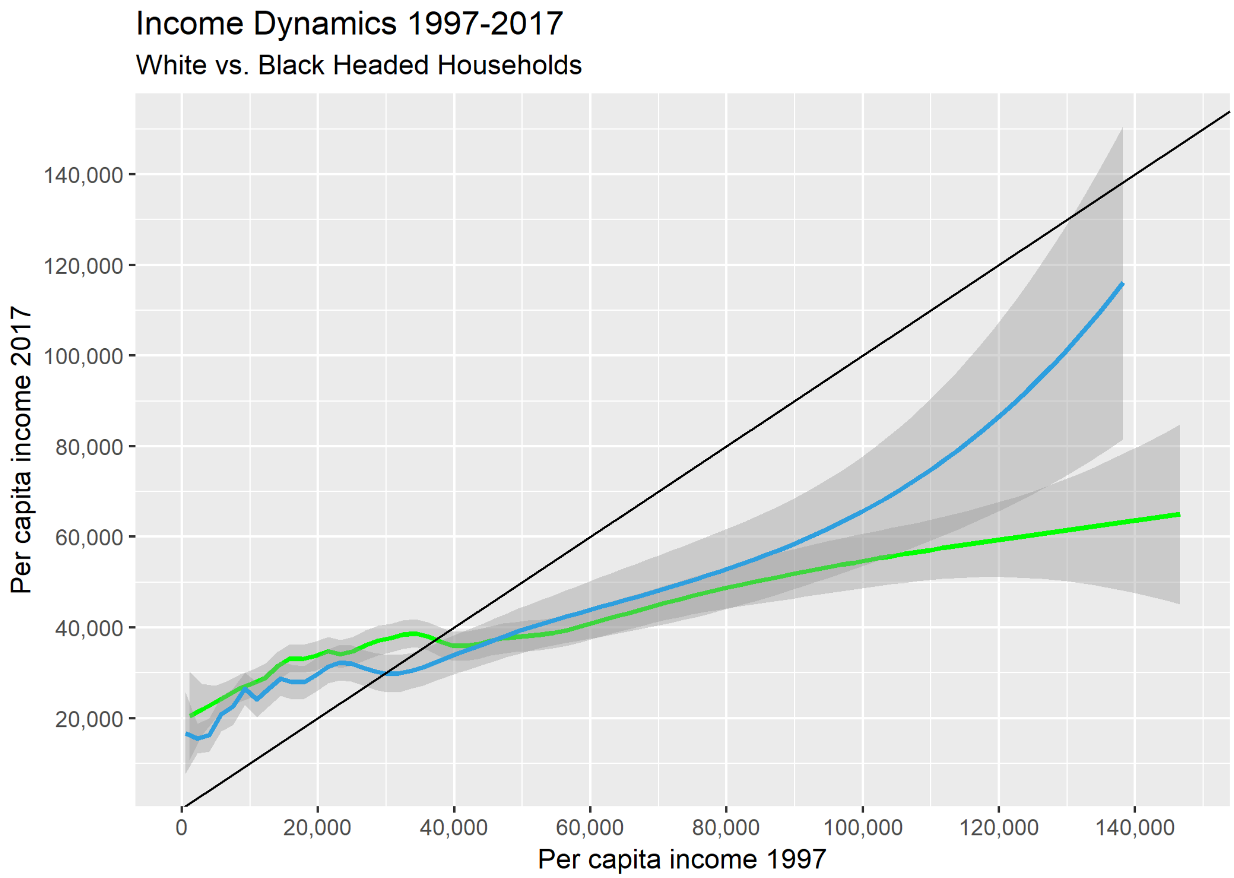
Penalized spline estimations in sample of black headed households confirm no poverty traps from 2001-2017.

Figure 1.36: LOESS Smoothing Plot by Race, 1981-2017



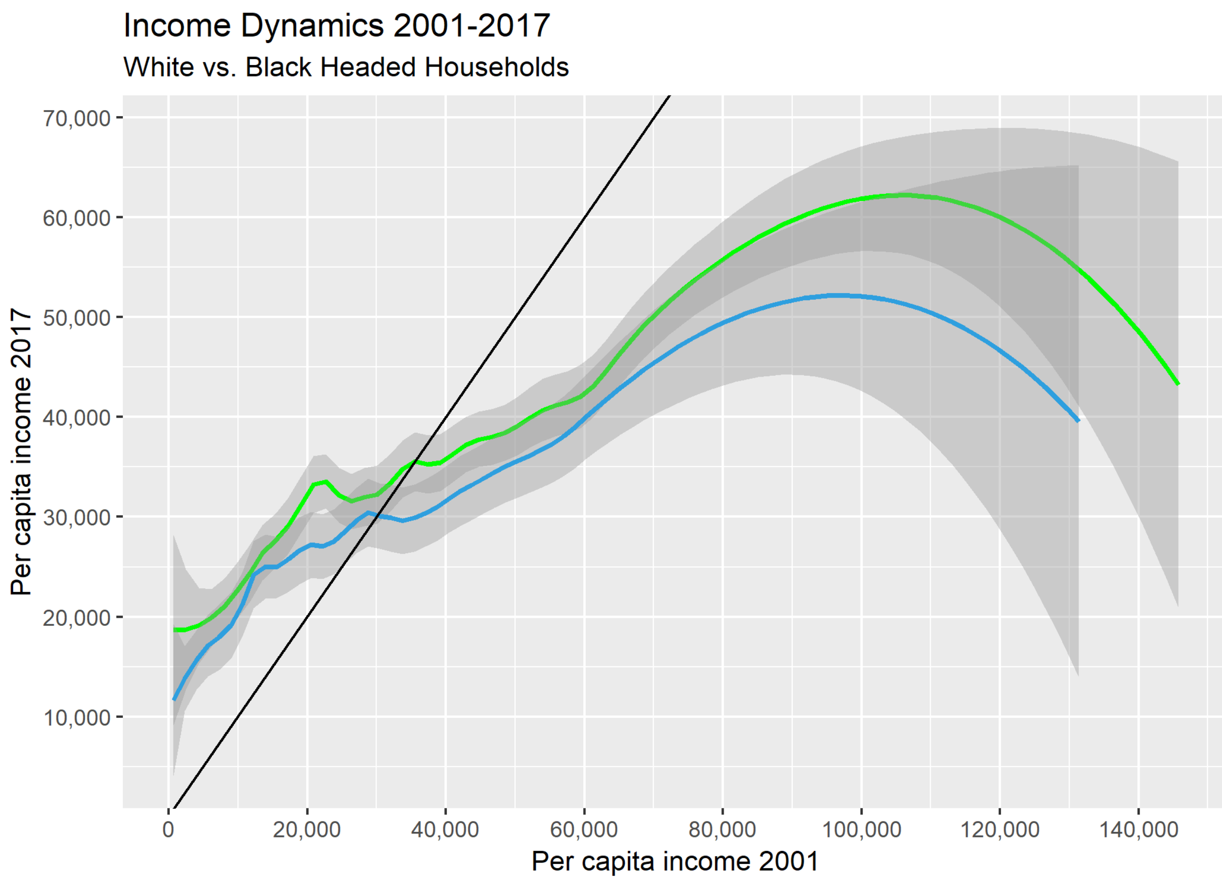
The green line represents the LOESS fitted line with 95% confidence intervals for households with a white head in 1981 and the blue line is for the sample of black headed households.

Figure 1.37: LOESS Smoothing Plot by Race, 1997-2017



The green line represents the LOESS fitted line with 95% confidence intervals for households with a white head in 1997 and the blue line is for the sample of black headed households. The gap between convergence points diminishes compared to the 1997-2017 period.

Figure 1.38: LOESS Smoothing Plot by Race, 2001-2017



The green line represents the LOESS fitted line with 95% confidence intervals for households with a white head in 2001 and the blue line is for the sample of black headed households.

APPENDIX 1C: Monte Carlo Simulation Results

To determine which estimator would perform better, we designed a simulation that replicates the most essential characteristics of the data generating process. We developed a panel data set in which observations can enter the panel at different times, much like the PSID. For each Monte Carlo simulation, age (a_{it}) and the initial income of each unit (y_{i1}) were drawn from a truncated normal distribution, parametrized with the mean, standard deviation, and upper and lower bounds from the PSID data set. The following income observations were simulated from past lagged values, education (e_{it}), and autocorrelated error terms:

$$y_{i,t>1} = \beta_0 + \beta_1 y_{t-1} + \beta_2 \left(y_{t-1}\right)^2 + \beta_3 \left(y_{t-1}\right)^3 + \ \beta_4 a_{it} + \beta_5 e_{it} + \epsilon_{it} \tag{1.11}$$

We randomly drew from a uniform distribution to generate education level and use transition probabilities from the PSID to allow for increases in education level. In addition, we developed a base attrition rate for each observation that increases with higher age (> 80), both low and high income (< 9, > 11) and low education level (less than a high school degree).

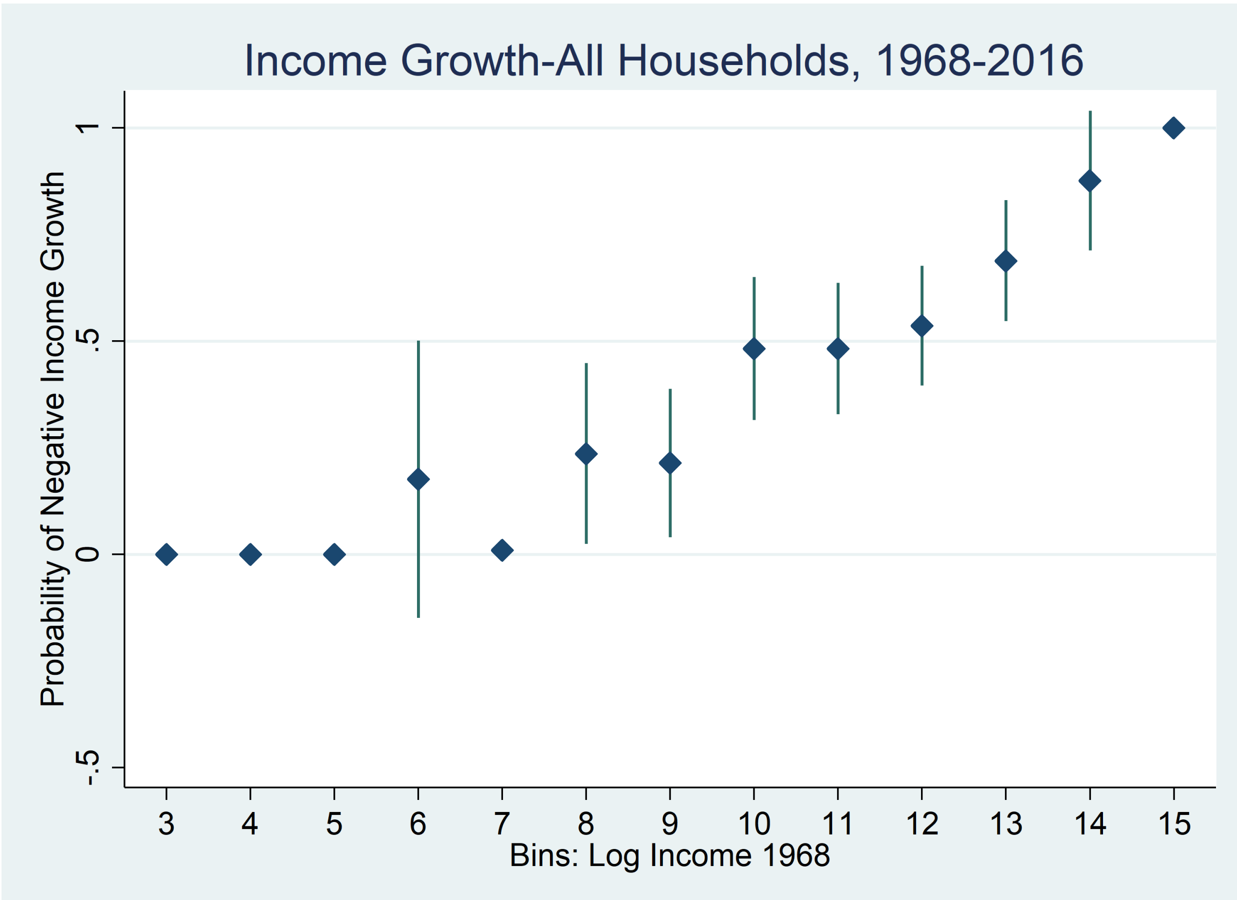
The results from 1,000 Monte Carlo show the fixed effects estimator and the Arellano and Bond estimator (two-step GMM with lag limits as instruments 1-3) produced coefficients closest to the true values. The estimates of all models are far from the true values due to undealt attrition in the simulated panel.

Table 1.16: Results from Monte Carlo Simulations

	β_1	β_2	β_3	se(β_1)	se(β_2)	se(β_2)
True values	0.014	0.02	-0.001			
OLS	3.426	-0.321	0.0112	1.276	0.12	0.00372
FE	-0.755	0.129	-0.00578	1.084	0.102	0.00317
AB (Lags 1-3, one-step GMM)	-0.937	0.146	-0.00636	1.086	0.102	0.00318
AB (Lags 1-3, two-step GMM)	-0.89	0.142	-0.00625	1.258	0.118	0.00369
AB (Lags 2-3, one-step GMM)	-5.08	0.544	-0.0187	1.82	0.178	0.00586
AB (Lags 2-3, two-step GMM)	-5.169	0.553	-0.019	2.026	0.198	0.00652
AB (Lags 1-4, one-step GMM)	-0.933	0.146	-0.00635	1.086	0.102	0.00318
AB (Lags 1-4, two-step GMM)	-0.896	0.143	-0.00626	1.255	0.118	0.00368
AB (Lags 2-4, one-step GMM)	-5.059	0.542	-0.0186	1.815	0.178	0.00584
AB (Lags 2-4, two-step GMM)	-5.136	0.55	-0.0189	2.022	0.198	0.0065

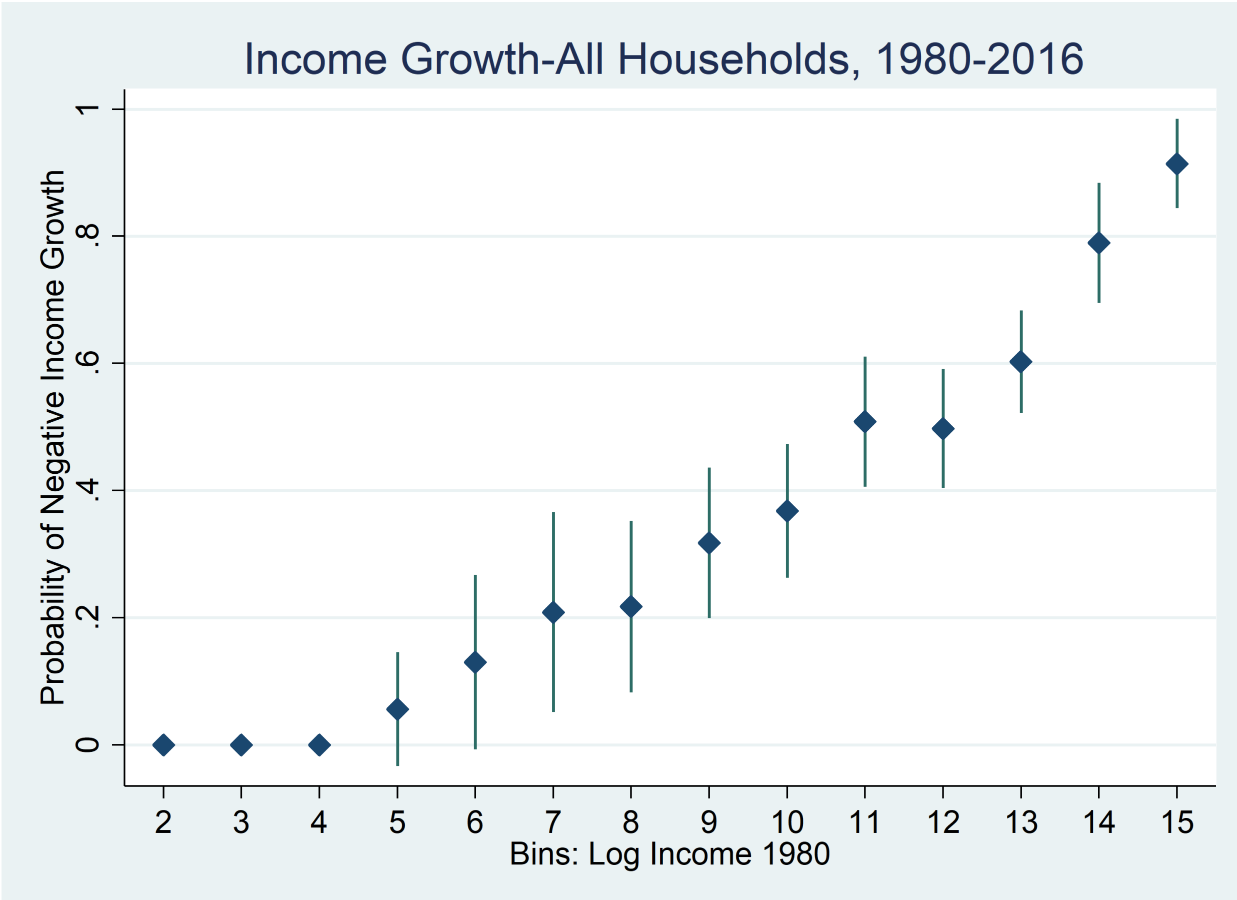
APPENDIX 1D: Additional Coefficient Plots from the Arunachalam and Shenoy Test

Figure 1.39: Coefficient Plot, 15 Bins 1968-2016



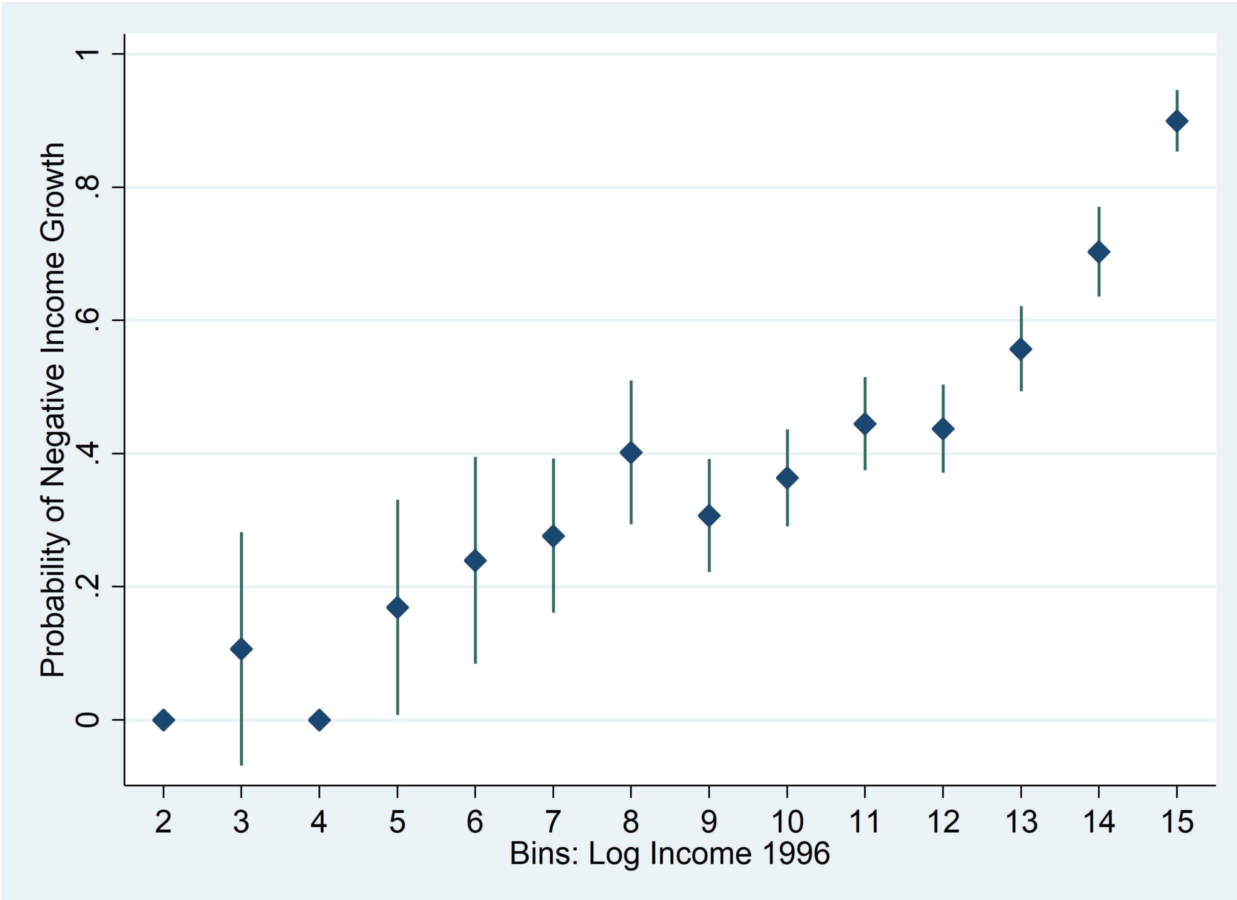
Graphical display of the coefficients from the bin regression for the Arunachalam and Shenoy test. The probability of negative income growth is always increasing in income.

Figure 1.40: Coefficient Plot, 15 Bins 1968-2016



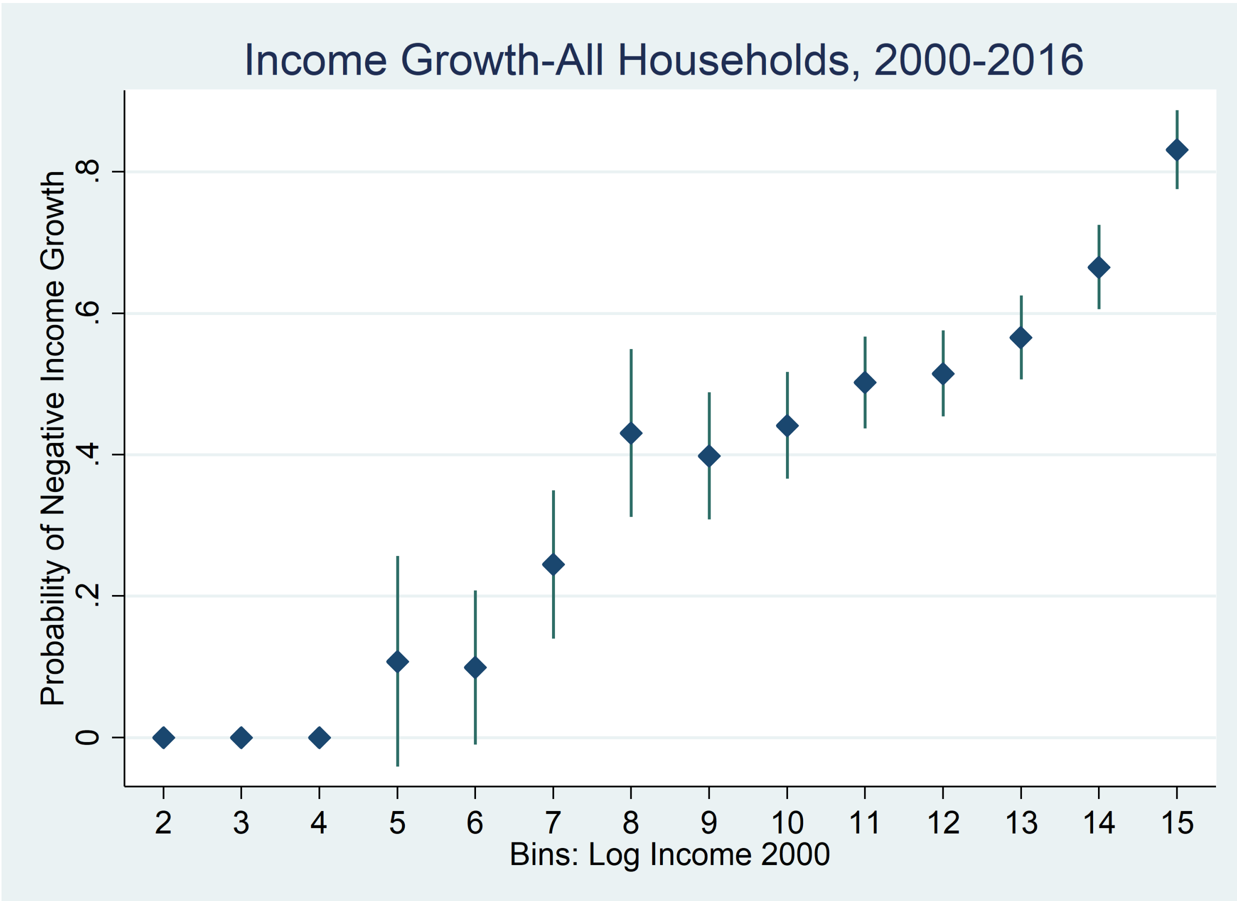
Graphical display of the coefficients from the bin regression (1981-2017 waves) for the Arunachalam and Shenoy test. The probability of negative income growth is always increasing in income.

Figure 1.41: Coefficient Plot, 15 Bins 1996-2016



Graphical display of the coefficients from the bin regression for the Arunachalam and Shenoy test. The probability of negative income growth is always increasing in income.

Figure 1.42: Coefficient Plot, 15 Bins 2000-2016



Graphical display of the coefficients from the bin regression for the Arunachalam and Shenoy test. The probability of negative income growth is always increasing in income.

APPENDIX 1E: Locally Weighted Polynomial Regression

Figure 1.43: LOESS Smoothing Plot, 1969-2017

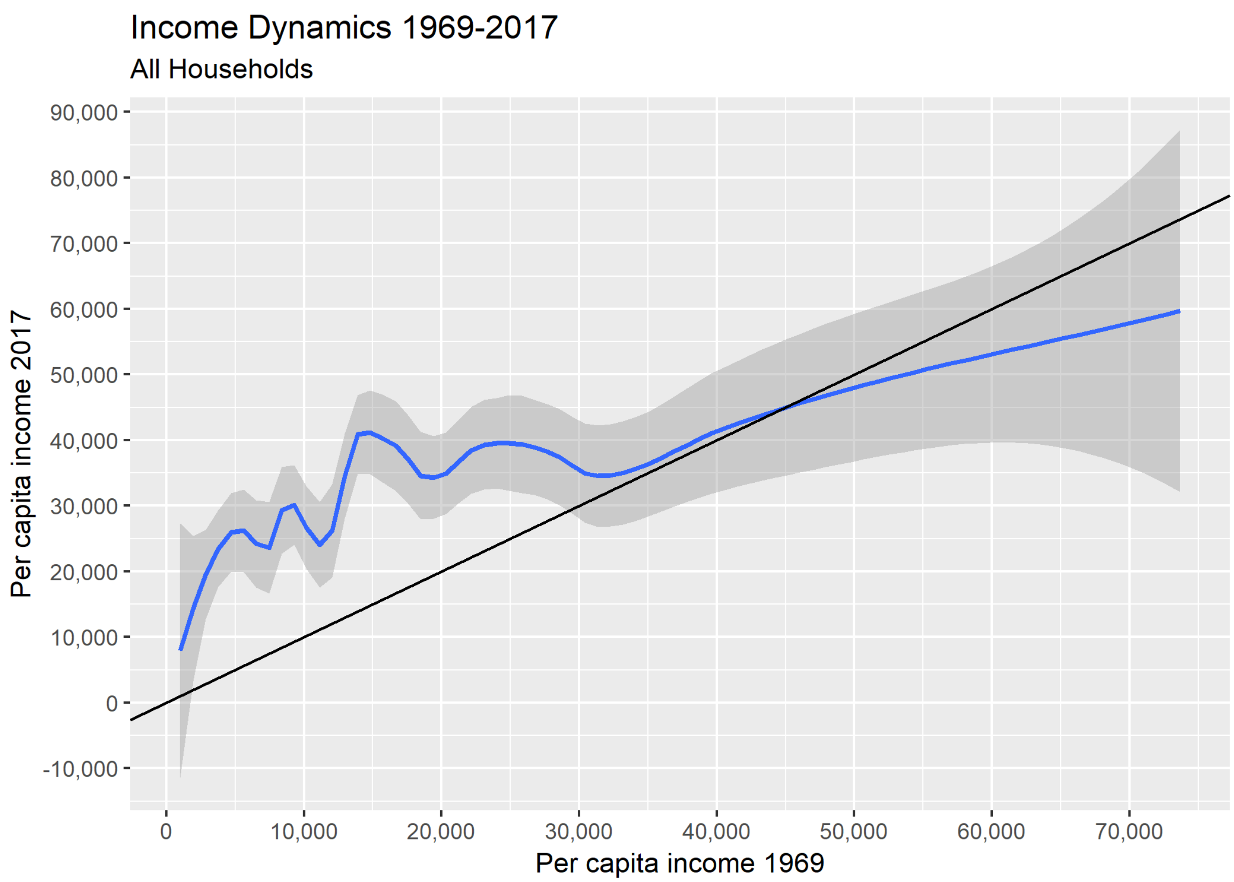
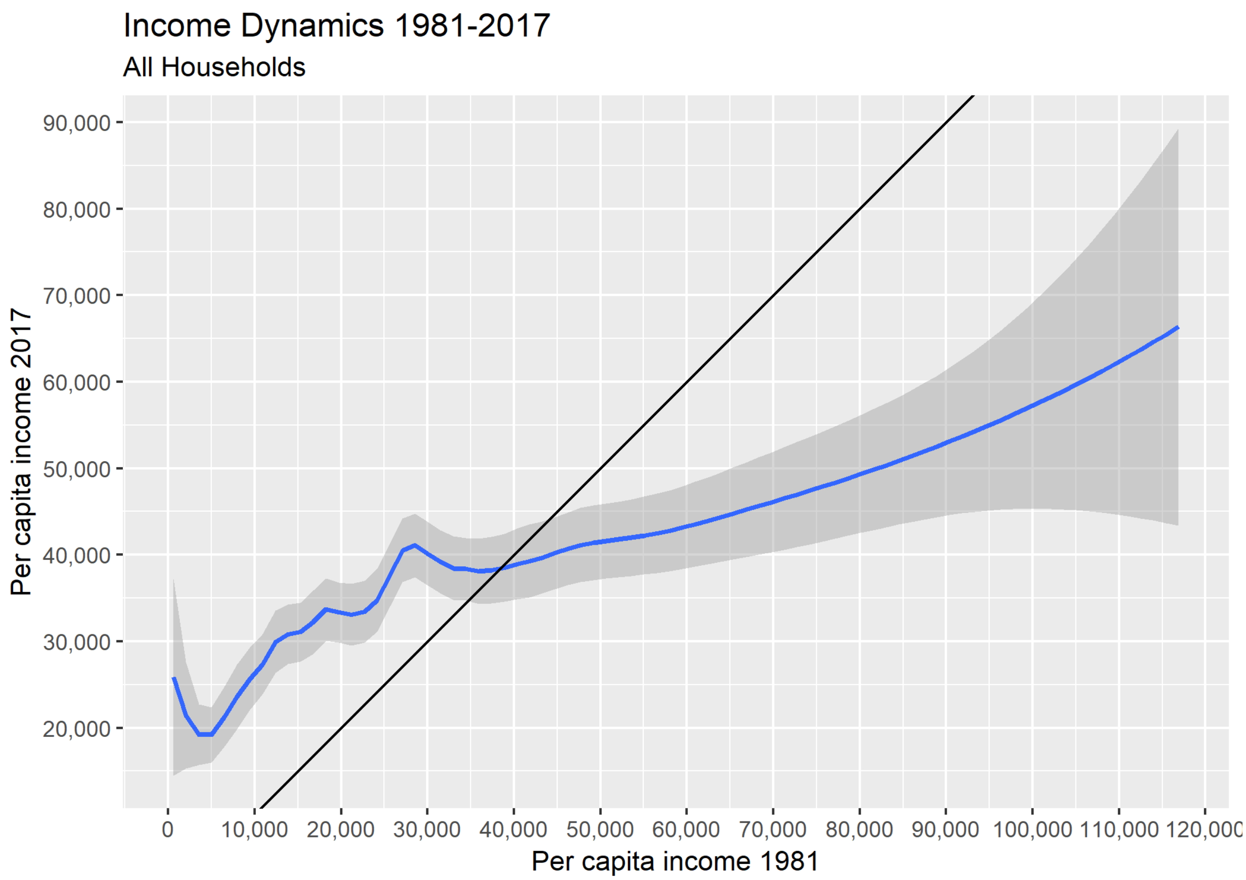


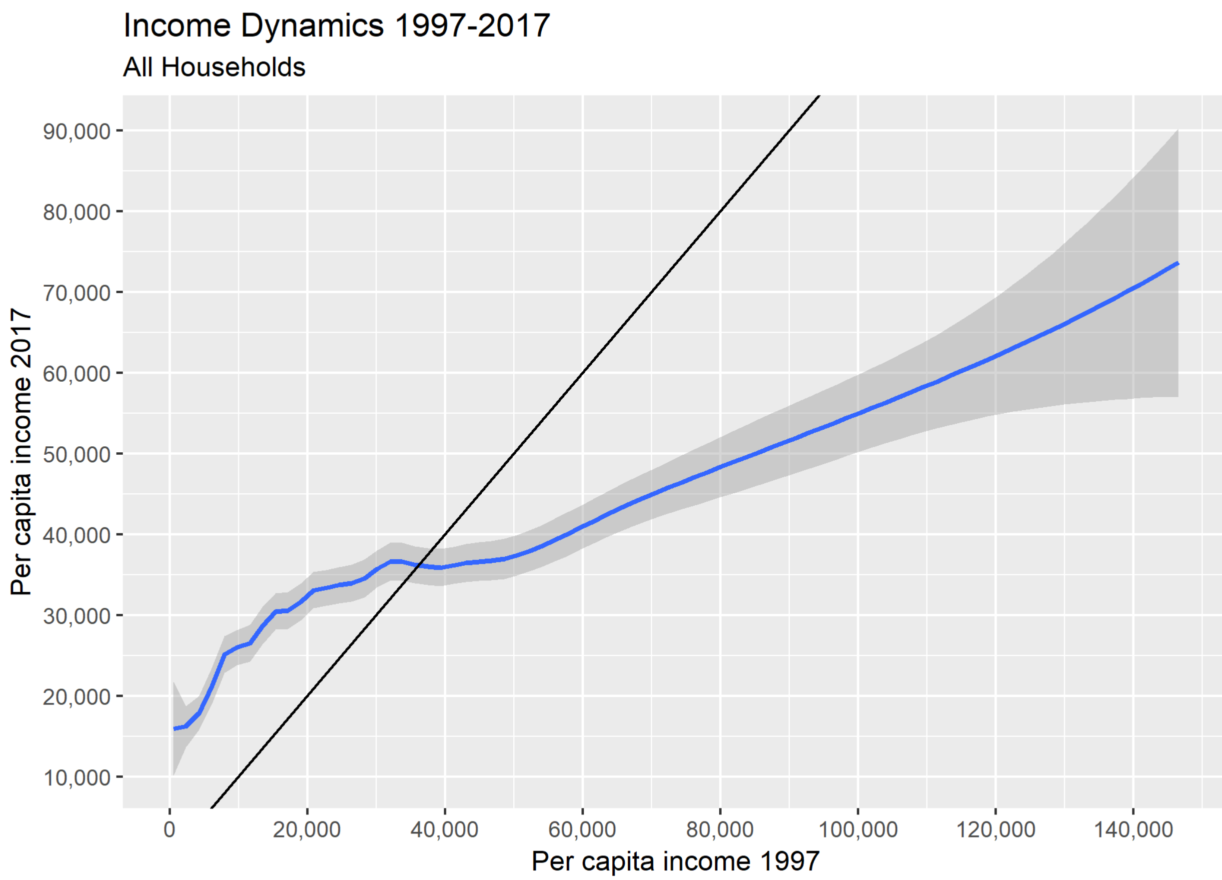
Figure 1.43: LOESS smoothing plot with 95% confidence intervals.

Figure 1.44: LOESS Smoothing Plot, 1981-2017



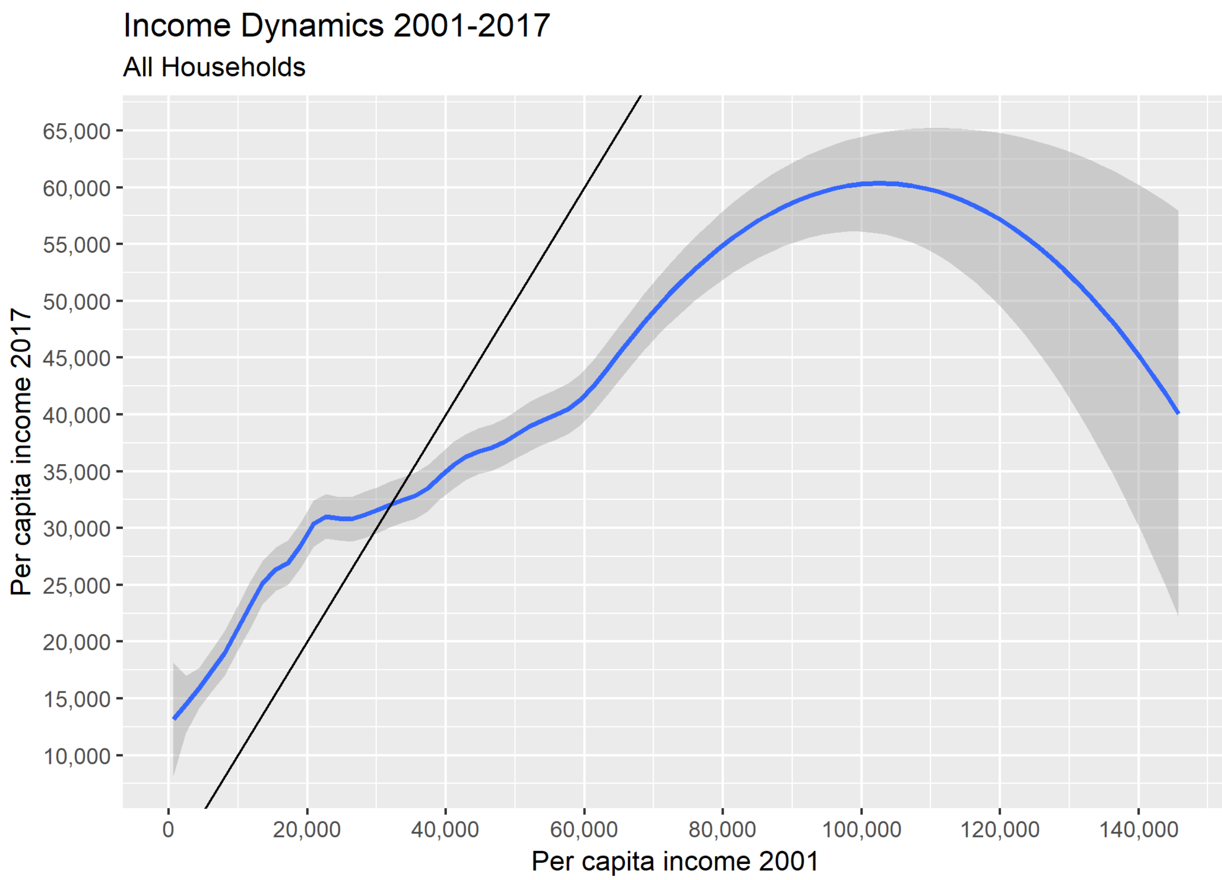
LOESS smoothing plot with 95% confidence intervals.

Figure 1.45: LOESS Smoothing Plot, 1997-2017



LOESS smoothing plot with 95% 95% confidence intervals.

Figure 1.46: LOESS Smoothing Plot, 2001-2017



LOESS smoothing plot with 95% confidence intervals.

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CHAPTER 2

THE EFFECTS OF FEED COSTS AND INCREASED ENERGY NEEDS ON BROILER FARM PRODUCTIVITY: A DYNAMIC PROGRAMMING APPROACH

2.1 Introduction

With rising incomes and urbanization, food systems in Sub-Saharan Africa (SSA) have transformed rapidly over the last two decades. One key characteristic of this transformation is the diversification of diets from largely starchy staples to increased consumption of animal proteins (Tschirley et al., 2015). Nigeria has followed comparable trends to the rest of Sub-Saharan Africa, with positive and large income elasticities of demand for beef, fish, and chicken (Desiere et al., 2018; Aborisade and Carpio, 2017).

While livestock operations generally keep trending towards larger and more efficient production systems, no other meat production in Africa has skyrocketed at a faster rate than poultry. For example, poultry production in Nigeria has expanded by 25% over the last two decades (Figure 2.1) and the industry is considered one of the most commercialized sub-sectors of agriculture.[1] The growth in poultry farms also stems from innate characteristics of the subsector: perceived high returns to investment, a short production cycle for broilers, and low investments needed to start a small poultry farm (Heise, Crisan, and Theuvsen, 2015) and the ban on imported chicken products, intended to promote domestic production.

As poultry farmers attempt to expand their capacity, there is a rising demand for factors of production at stable prices, such as water and electricity. However, there is a lack of rigorous economic analysis on how negative price shocks to essential production inputs and changing energy needs impact farmer profitability, optimal decisions, and the structure of the industry in developing countries. In this paper, we focus on feed costs, the largest production expense in a poultry operation, and energy costs, increasing with the use of electricity intensive

[1] (Liverpool-Tasie et al., 2017) estimate that from 1980-2012, egg and chicken output grew by 300% and 220%, respectively.

technologies employed to manage environmental changes.

Being a key ingredient for feed, increases in maize prices pose a severe threat to poultry farmers' profitability. For example, maize prices increased from ₦132 per kg in 2015 to ₦271 in early 2016 (FewsNet, 2019).[2] Then, prices declined to ₦122 per kg during the summer months of 2016, only to increase to ₦198 in 2017. These price spikes are typically the result of supply shortages caused by weather conditions and a reduction in imports due to the strengthening of the dollar against the Nigerian Naira (Ojosipe 2016).

As broiler operations expand, the energy needs of the farm and the share of the budget allocated to energy expenses typically rise. For poultry enterprises in developed countries, energy is one of the main operational expenses. For example, in the U.S., energy costs amount to 1.1-1.2 cents per pound of meat produced (the largest operational expense), with 54% of that calculation attributed to fuel costs for heating and 34% to electricity expenses (MacDonald, 2014)[3] In Nigeria, larger broiler farmers are starting to rely on energy intensive technologies to avoid heat stress losses and maintain optimal broiler temperatures.

This study explores the effect of current and expected input costs on the profitability of poultry farms. Specifically, we examine the role feed expenses, increasing energy needs, and farm size play in determining optimal decisions and firm survival. We employ a discrete state and control space, discrete time dynamic programming model to analyze optimal decisions of poultry farms. We compute farmers' intertemporal value functions and optimal strategy choices using models parameterized using two datasets collected from southwest Nigeria, the region of the country that has experienced the most rapid growth in medium and large-scale poultry farms over the last decade (Liverpool-Tasie et al., 2017).[4] We also explore the

[2] The current exchange rate is 1 USD = 350 Nigerian Naira (₦). The exchange rate at the beginning of the data collection process was 1 USD=305₦ (Central Bank of Nigeria). Thus ₦271 is approximate $0.75 given the current exchange rate.

[3] Similarly, studies about Brazilian poultry farms find electricity is the largest cost (Turco, Ferreira, and Furlan, 2002; Mendes et al., 2014) and suggest a 1% increase in electricity costs reduces profit by 0.46%, a larger and more significant effect than that of labor costs.

[4] In this study, medium and large-scale farms refer to poultry farms with 100-1000 birds and more than 1,000 birds, respectively. While we recognize that this might be very different from integrated poultry farms in the United States, it is specific to the reality of the emerging poultry industry in Nigeria.

potential heterogeneity of farm size and its influence on optimal choice, instead of assuming a single representative farm as is common in the existing literature. Instead, we model optimal decisions for medium and large sized farms separately. By disaggregating the data by farm size, we show the source of any existing economies of scale and expand on possible policy implications for each type of farm.

We construct hypothetical feed price regimes to capture the effect of an upward shift in feed prices on farmer decisions. This analysis is relevant to the Nigerian context given that maize prices have recently been on an upward trajectory which is likely to continue. We hypothesize that farm size, (average flock size) is an important determinant of whether a farm can withstand a permanent feed price increase. This relates to the idea that there might be a minimum threshold investment necessary to maintain a profitable poultry enterprise because of economies of scale.

Finally, we explore the effect of an increase an electricity consumption on optimal decisions of medium and large-scale farms. Approximately 12% of our sample of Nigerian farmers have adopted new electricity intensive methods and technologies to deal with rising temperatures and heat stress. Some examples include the use of cooling fans and sprinklers to regulate bird temperature. Modifying our model in this way, we can consider scenarios that are both consistent with the realities in Nigeria and also likely to occur in the future due to climate change.

Our results suggest that an increase in feed prices not only reduces the value of poultry farms, but triggers exit decisions among medium scale farms. Conversely, larger farms are better positioned to withstand these price increases; the shock reduces the value of large farms, but they can maintain positive profitability and remain in the industry. Similarly, we find that higher energy requirements drives medium scale farms out of business in certain price states while large farms can profitably incorporate these higher energy costs. Our findings suggest that large poultry farms are better equipped to both handle key input price shocks and make the necessary investments to manage a successful poultry operation.

This study makes three main contributions to the literature. This is the first study to consider the dynamic, decision-making process of poultry farmers in Sub-Saharan Africa and the potential triggers of farm exit decisions. Past literature on livestock systems in Nigeria and Africa have only modeled profit flows of farmers from a static perspective (Oyakhilomen, Daniel, and Zibah, 2015; Ohajianya, 2013; J. O., 2012).

Second, this is the first study in Africa (the authors are aware of) to incorporate multiple sources of energy costs into the analysis and consider the effect of changing energy needs. Based on the data we have collected in Oyo State, farmers receive between 40 and 63 hours of electricity per week and if their operations require more electricity, they must use a petrol or diesel-powered generator to make up the difference. Thus, only accounting for the cost of electricity underestimates the true cost of energy, since alternative sources of energy are needed to offset the limits on the hours of electricity received from the grid. As farms in the developing world are transitioning from isolated, backyard farms to organized, medium and large-scale farms, reevaluation and research on the roles of various inputs across the value chain becomes essential.

Lastly, this paper contributes to the literature by reducing aggregation bias and modeling optimal policy rules for medium and large-scale producers separately. Considering the importance of farm size heterogeneity in determining the success of a firm, this extension necessary to accurately model how an industry performs (Buckwell and Hazell, 1972; Spreen and Takayama, 1980; Chen and Onal, 2012).

The paper begins with a discussion of the feed and energy context in which Nigerian poultry farms operate, followed by the theoretical framework, a discussion of the data, and the parametrization of the model. Then, we describe the results, potential extensions of the model, and conclude with a discussion of the implications of this work.

2.2 Feed and Energy Costs in Nigeria

2.2.1 Maize as Primary Input for Feed

Currently, maize-based feed remains the largest expense item for Nigerian poultry farmers (Adebayo, Oseghale, and Adewumi, 2015). While other feedstuffs, such as cassava root, are used in addition to (or as a partial substitute for) maize, maize remains the primary component. High-quality feed is necessary for a successful fattening process and alternative feeds that use less maize can result in decreased feed intake, slower weight gain, and a higher feed conversion ratio (Uchegbu et al., 2011). However, maize production and prices are subject to market and weather fluctuations which can adversely affect poultry farmers' profitability and ability to stay in business.[5] In August 2016, the price of maize in Nigeria increased by 70% from ₦100 per kg in June to ₦170 (FewsNet, 2019). Large shocks in the price of maize affect the cost of feed, since maize accounts for between 50-70% of the cost (Olugbemi, Mutayoba, and Lekule, 2010).[6] In addition to feed, maize is also a staple food in Nigeria and livestock producers compete with an increasing demand for this commodity for food.

2.2.2 The Energy Sector in Nigeria

Although Nigeria has a plethora of energy resources (Akinbami, 2001), the power sector performs poorly and at a deficit. There is unstable energy supply, blackouts, and a weak transmission network that is privately managed but government owned. Some of the reasons the energy sector performs poorly include the declining maintenance budgets and lack of investments in capacity expansion (Oyedepo, 2012; Aliyu, Ramli, and Saleh, 2013).

The Nigerian National Electric Power Authority (NEPA) has experienced significant deregulation and restructuring over the last twenty years. As part of earlier restructuring

[5] Using data collected on Nigerian maize farmers in 2017, 19% of maize farmers indicated that they had experienced a significant increase in the price of fertilizer and 41% of respondents indicated the hike in price had a "great negative effect" on their business in 2016. About 12% of farmers coped with this price shock by reducing their farm size or exiting maize farming and 23% sold maize from the stored stock.

[6] In our data set, the average price of branded feed is ₦140 per kg.

plans, NEPA evolved into the Power Holding Company of Nigeria (PHCN) in 2005. The PHCN was later privatized but the problems of the sector remain today with 60% of the population lacking access to electricity (Osunmuyiwa and Kalfagianni, 2017). Consequently, the effects of a poorly managed power sector constrain the growth of firms in other sectors. A 2009 study revealed 97% of all firms in Nigeria experienced 196 hours of outages and relied on their own generators to overcome low electricity supply (USAID 2014). With climate change and expected global temperatures rising, the electricity needs of livestock farms will increase. Hypothesizing over the effect of these potential changes on cost of production should be anticipated by researchers and policymakers alike.

2.3 Model

Suppose a poultry farm purchases day old chicks[7] $q^B = \left\{q^M, q^L\right\}$ at price p^D per chick, where q^M and q^L correspond to the stock size of a medium and large-scale farm, respectively. In this model, a B superscript indicates that a variable varies between medium and large farms.[8] Each week t, the farmer decides whether to feed the broilers, sell the complete stock and restart the fattening process, or sell the stock and by assumption, exit the industry permanently. Because of limited capacity, we assume that if the farmer wants to restart the growing process, he must sell his current batch of broilers.[9] In addition, we assume both medium and large-scale farms have invested in assets such as cages, chicken houses, and a generator, based on the summary statistics detailed in Table 2.2.

[7]The quantity purchased of day-old chicks is the same as total stock sold when the bird reaches maturity. This assumption is supported by the fact farms do not report significant losses. On average, medium and large-scale farms report on average 5 and 33 broilers die before sale, respectively.

[8]While the analysis focuses on medium and large scale farms in the study context, we also analyze small, household farms for completeness. These results can be found in Appendix 2E.

[9]This is consistent with anecdotal evidence from the field which indicates most poultry farms tend to sell their birds in batches.

Let s_t be the farmer's choice set:

$$s_t = \begin{cases} 0, & \text{Feed with no replacement} \\ 1, & \text{Sell with replacement (restart the growing process)} \\ 2, & \text{Sell without replacement (exit the sector)} \end{cases}$$

The farmer will stop the process at a time that maximizes the discounted expected sum of farm profits. The reward function, conditional on s_t, is:

$$\pi_t = \begin{cases} \text{-c}(\text{p}_t^f, q_t^f, a_t)q^B - e(z_t, h_t^B, q^B) - l^B(p^w, q^B) & \text{if } s_t = 0 \quad (2.1) \\ (\text{r}(\text{w}_t, p_t^B) - p^D - c(p_t^f, q_t^f, a_t))q^B - e(z_t, h_t^B, q^B) - l^B(p^w, q^B) & \text{if } s_t = 1 \quad (2.2) \\ \text{r}(\text{w}_t, p_t^B)q^B & \text{if } s_t = 2 \quad (2.3) \end{cases}$$

$$c(p_t^f, q_t^f, a_t) = q_t^f p_t^f \quad (2.4)$$

$$q_t^f = (\beta_1 a_t + \beta_2 a_t^2 + \beta_3 a_t^3) \quad (2.5)$$

Equation (2.1) represents the profit function (π_t) conditional on continuing the feeding process ($s_t = 0$), equation (2.2) is the profit if the farmer chooses to restart the growing process ($s_t = 1$), and (2.3) when the farmer decides to sell and exit the sector, ($s_t = 2$). Under $s_t = 0$ and $s_t = 1$, the farm incurs the cost of feeding (2.4), a function increasing in the price of feed vector (p_t^f), quantity of feed bought (q_t^f), and the age of the batch (a_t). We allow for the feed price and their conditional transition probabilities[10] to vary by farm size to account for the possibility that size might influence the likelihood of experiencing different feed prices. Equation (2.5) is the feed quantity cubic function changing in the age of the batch (a_t). We assume the farmer always provides the optimal amount of feed. While this is a simplification, it allows us to focus on the replacement and exit decisions which are the main focus here. A potential extension and future area of research from this work is to study the effect of feed price increases on optimal feed quantity decisions. The farmer also incurs energy expenses $e_t^B(z_t, h_t^B, q^B)$ and labor costs $l^B(p^w, q^B)$ under $s_t = 0$

[10] In this article, a transition probability refers to the likelihood of facing a price in $t + 1$ conditional on the realizing certain price in time t.

and $s_t = 1$. We define a vector of energy prices (z_t) such that $z_t = \{\alpha_t, \gamma_t, \delta_t\}$, where α_t corresponds to the price of electricity from the grid, γ_t is the price of fuel, and δ_t is the price of diesel. Each energy price is multiplied by the corresponding element in the vector of energy quantities (h_t^B). The variation in total energy expenses between medium and large-scale farms comes from the quantity of energy used: $e_t^B = h_t^M z_t, h_t^L z_t$ and is a function of the stock size. The labor function depends on the quantity of broilers and the fixed wage rate (p^w). We expect energy expenses and the labor function to be the source of economies of scale driving different optimal decisions between medium and large-scale farms:

$$\frac{\partial \overline{l(p_t^w, q^B)}}{\partial q^B} \text{ and } \frac{\partial \overline{e(z_t, h_t^B, q^B)}}{\partial q^B} < 0$$

Finally, we assume the farmer incurs fixed vaccination and medical costs (m^B) every period. Based on the prophylactic measures Nigerian farmers employ, having weekly medical expenses is a reasonable assumption.

Equation (2.22) corresponds to the reward function when the farmer chooses to restart the growing process $(s_t = 1)$. Under this option, the farmer receives a return $r(w_t, p_t^B)$ that is a function of the broiler price (p_t^b) and the weight of the bird (w_t). Weight each period evolves following a Richards growth function:[11]

$$w_t = \frac{A}{\left(1 - \delta e^{-\lambda a_t}\right)^{\frac{1}{m}}} \tag{2.6}$$

Lastly, equation (2.3) represents the exit option of the firm $(s_t = 2)$. Here the farmer receives a return only for the sale of the stock of broilers $r(w_t, p_t^B)$. We assume the farmer is not able to sell his farm assets and machinery. This is a conservative assumption as it makes the exit decision less appealing and a last resort to farmers.

[11] See appendix for complete description. A = the asymptotic weight as age approaches infinity, k = the instantaneous relative growth rate (or maturing rate), B= constant, m = Richard's function shape parameter.

The farmer's objective function Π_t is:

$$\max_{s_t} \Pi_t = \sum_{t=1}^{\infty} \beta^{t-1} E\Big\{\{\pi_t|(s_t = 0)\}\mathbb{1}_{s_t=0} + \{\pi_t|(s_t = 1)\}\mathbb{1}_{s_t=1} + \{\pi_t|(s_t = 2)\}\mathbb{1}_{s_t=2}\Big\}$$

$$\text{s.t.} \quad a_{t+1} = p(a_t, s_t) \tag{2.7}$$

$$Pr(p_{t+1}^{fB} = i|p_t^{fB} = j) = p_{ij}^{fB} \tag{2.8}$$

$$Pr(p_{t+1}^{b} = m|p_t^{b} = n) = p_{mn}^{b} \tag{2.9}$$

$$\{p_t^b = 0\}\mathbb{1}_{a_t<5} \tag{2.10}$$

where β is the discount factor, (2.7) is a state transition equation for age, equations (2.8) and (2.9) represent the conditional feed and broiler price transition probabilities, (2.10) is a market constraint for sale of birds less than 5 weeks, as previously discussed.
Equation (2.7) depends on the decision of the farmer:

$$a_{t+1} = p(a_t, s_t) = \begin{cases} \mathrm{a}_t + 1, & s_t = 0 \\ 1, & s_t = 1 \\ 0, & s_t = 2 \end{cases}$$

We derive the Markov transition probabilities from the one-year panel data set by assuming a Markov transition process. For states $i = 1, 2, ...K$ and $j = 1, 2, ...K$, the feed transition probabilities vary by farm size and follow (8) to make up the $K \times K$ matrix[12] P^f:

$$P^{fB} = \begin{pmatrix} p_{1,1}^f & p_{1,2}^f & \cdots & p_{1,j}^f & \cdots & p_{1,K}^f \\ p_{2,1}^f & p_{2,2}^f & \cdots & p_{2,j}^f & \cdots & p_{2,K}^f \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ p_{i,1}^f & p_{i,2}^f & \cdots & p_{i,j}^f & \cdots & p_{i,K}^f \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ p_{K,1}^f & p_{K,2}^f & \cdots & p_{K,j}^f & \cdots & p_{K,K}^f \end{pmatrix}$$

[12]The size of this matrix varies between medium and large scale firms, but it is always a square matrix.

Similarly, the broiler price transition matrix P^b is composed of the one-step state transition probabilities also computed using the one-year panel data set. For $m = 1, 2, ...L$ and $n = 1, 2, ...L$ (m and n indexing broiler price states), the $L \times L$ matrix P^b:

$$P^b = \begin{pmatrix} p^b_{1,1} & p^b_{1,2} & \cdots & p^b_{1,n} & \cdots & p^b_{1,L} \\ p^b_{2,1} & p^b_{2,2} & \cdots & p^b_{2,n} & \cdots & p^b_{2,L} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ p^b_{m,1} & p^b_{m,2} & \cdots & p^b_{m,n} & \cdots & p^b_{m,L} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ p^b_{L,1} & p^b_{L,2} & \cdots & p^b_{L,n} & \cdots & p^b_{L,L} \end{pmatrix}$$

To create a joint conditional probability matrix for feed and broiler prices, we use the Kronecker product operator to create the $LM \times LM$ full transition probability matrix:

$$P^b \otimes P^f = \begin{pmatrix} p^b_{1,1}P^f & \cdots & p^b_{1,L}P^f \\ \vdots & \ddots & \vdots \\ p^b_{m,1}P^f & \cdots & p^b_{m,L}P^f \\ \vdots & \ddots & \vdots \\ p^b_{L,1}P^f & \cdots & p^b_{L,L}P^f \end{pmatrix}$$

We begin with a zero-value function and iterate to convergence on Bellman's equation:

$$\upsilon(k_t) = \max_{s_t} \left\{ \{\pi_t|(s_t = 0)\}\mathbb{1}_{s_t=0} + \{\pi_t|(s_t = 1)\}\mathbb{1}_{s_t=1} + \{\pi_t|(s_t = 2)\}\mathbb{1}_{s_t=2} + \beta E_t[\upsilon(k_{t+1})] \right\}$$

where $k_t = [w_t, a_t, p^b_t, p^f_t]$ is a vector of state variables. We solve this infinite horizon problem recursively in MATLAB using the dynamic programming algorithm developed by Miranda and Fackler (2002). We apply the Newton Method to solve the optimization problem.

2.4 Data

This paper uses two primary data sources from Ibadan, Oyo State, Nigeria. The first is a 2017 cross-sectional dataset including questions on farmers' input purchasing decisions, chicken farm activities, input and output prices, sale locations, maize procurement and feed production, labor use, energy consumption, and shocks and coping strategies.

The survey respondents include 365 farms that either produce only broilers or both broilers and layers from the 11 main poultry-producing Local Government Areas (LGAs)[13] in Greater Ibadan. This paper only uses the information from broiler farms with a stock size greater than 100 broilers. We assume that households with fewer than 100 broilers are not part of the commercial industry, but instead hold birds for consumption and informal sale to neighbors and family members. A household model might be better suited to analyze the decisions of these small, household-farms.

Partitioning the data by flock size in 2016, there are 70 small farms with a stock size of less than 100 birds, 118 medium-sized farms with 100-1,000 broilers, and 177 large farms with a stock size of more than 1,000 birds.[14] Medium and large-scale farms vary in terms of production practices and assets. A higher percentage of large-scale farms keep records and own freezers, trucks, bore holes, and generators (Table 2.2).

The second data set covers input purchases and prices as well as chicken prices and sales of 100 poultry farmers in Ibadan (Table 2.1). The data was collected weekly for one year between June 18th, 2017 and June 19th, 2018. This panel data set is randomly selected sample from the total list of non-household farms in the study area.

[13]Local Government Areas (LGAs) are the third tier of government in Nigeria, equivalent to a US county.

[14]This farm size classification is specific to Nigeria and we recognize that in other economies, the farms we consider to be large here might still be considered small or medium. The decision rule as to farm size is based on the terciles of the data and the natural breaks in the classification. For example, the minimum broiler batch size for medium-scale farms, based on the terciles, is 100 birds.

2.5 Parameterization of the Model

The base values of the parameters in the sell-feed model are summarized in Table 2.4. Each period represents a week and the maximum life of the chicken is set at 10 weeks.[15] We assume the weekly discount factor is between 0.98-0.995. The Central Bank of Nigeria (CBN) reports the interest rate is between 17.53% and 31.40% as of February 2018; if the maximum interest rate were imposed, that would still yield a weekly discount factor of 0.993. However, to allow for the possibility of informal credit at a higher interest rate than the one reported by CBN, we expand the range to include slightly smaller discount factors.

To have a rich state space but limit the curse of the dimensionality, we specify 14 different feed prices for medium farms and 12 for large scale farms in ₦ per kg:[16]

$$p_t^{fM} = [112, 120, 125, 130, 138, 140, 144, 150, 156, 160, 164, 168, 176, 180] \tag{2.11}$$

$$p_t^{fL} = [110, 120, 125, 128, 130, 136, 140, 144, 150, 160, 170, 200] \tag{2.12}$$

Both vectors include the lowest, the median, and the highest feed prices from the one-year panel data set. The feed transition probabilities demonstrate high state persistence with a high probability of realizing the same broiler price in period $t+1$ as in period t. Specifically, for all feed prices (for both medium and large-scale farms), the probability of realizing the same price in $t+1$ as in period t is greater than 0.8. However, comparing overlapping prices,[17] medium sized farms have higher persistence among lower feed price states than large-scale farms. For example, if the feed price in period t is $p_t^{fM} = 140$₦, then $Pr(p_{t+1}^{fM} = 140 | p_t^{fM} = 140) = 0.97$, but for large farms this probability equals 0.5. The full list of feed price conditional probabilities are listed in Appendix 2C.

Since there is less variation across the observed broiler prices and we want to keep the

[15] Most of the farmers in our sample slaughter the bird when it reaches 5-8 weeks, so we determine the terminal period T to equal 10 weeks.

[16] The current exchange rate is 1 USD = 350 Nigerian Naira (₦). The exchange rate at the beginning of the data collection process was 1 USD=305₦ (Central Bank of Nigeria).

[17] Overlapping in this context refers to prices that are reported by both medium and large scale farms.

state space manageable, we specify 7 broiler prices (₦ per kg) from our data set:

$$p_t^b = [900, 1000, 1150, 1200, 1250, 1350, 1500] \tag{2.13}$$

These probabilities also display high persistence and tend towards higher broiler prices. For example, if $p_t^b = 900$₦, then $Pr(p_{t+1}^b = 900|p_t^{fM} = 900) = 0.83$ and $Pr(p_{t+1}^b = 900|p_t^{fM} = 1500) = 0.17$. Under this broiler price state, the farm can only realize a price of ₦900 or the highest price of ₦1,500. The likelihood of remaining in a certain price state or switching to a much higher output price will affect the farm optimal decisions. For example, we might not see exit decisions among the highest feed price-lowest broiler price state ($p_t^{fM} = 180$, $p_t^b = 900$) due to high future expected broiler prices and/or lower expected future feed prices.

We use a fixed price of day-old chicks equal to ₦200, the median price reported in the cross-section data set, and a combined cost of medication and veterinary services from the cross-sectional values. The parameters we use for hours of electricity and liters of fuel and diesel are mean values from our weekly, year-long panel data set. We maintain fixed energy prices to reduce the dimensionality of the optimization problem. For the labor parameters, we utilize the average of workers hired per week and the average wage from the cross-sectional data set.

2.6 Results

A dynamic optimization model is applied to capture how constraints, costs, and prices affect farmers' decisions for a representative medium and large farm.[18] This disaggregation by farm size addresses one of the limitations of traditional dynamic models and allows us to explore how current conditions and potential negative price shocks induce different behaviors for farms of different sizes.

[18] The results of optimal decisions for small farms are located in Appendix B. They confirm the inadequacy of this model to elicit realistic optimal decision for household, non-commercial operations.

2.6.1 Medium vs. Large-Scale Farms

One key finding stands out when optimal behavior by firm size is considered. In the absence of negative feed price shocks, exit decisions are optimal for medium-scale farm under price states: $p_t^f = 164$, and $p_t^b = 1,000$ or $1,150$ (Table 2.5). Conversely, the optimal decision for large-scale farms is always to sell and restock (Table 2.6). This indicates that the average, medium-sized poultry farm in Nigeria is not profitable under certain input-output price combinations but large farms are. These findings are driven by economies of scale from labor and energy expenses, the inherent low profit margins of the sector, and the differences in transition probabilities faced by medium and large farms.

There are potential strategies firms could be adopting in lieu of an exit decision and we discuss the feasibility of those decisions in the extensions section of the paper. Interestingly, when $p_t^b = 900$, both medium and large firms have a delayed optimal sale and restock decisions among the lower tail of feed price vector space. This suggests farms strategically delay sales and opt to have a longer fattening period when the expected input and output prices are low.

2.6.2 Hypothetical Feed Price Regimes

We model the effect of feed price increase through new price regimes, where the current feed price vector in the state space shifts upward by 20% and 50% with the same transition probabilities as the baseline model. For medium-scale farms, the price vectors are:

$$p_{20\%}^{fM} = [134, 144, 150, 156, 166, 168, 173, 180, 187, 192, 197, 202, 211, 216] \tag{2.14}$$

$$p_{50\%}^{fM} = [168, 180, 188, 195, 207, 210, 216, 225, 234, 240, 246, 252, 264, 270] \tag{2.15}$$

A 20% hike in feed price for the representative medium-sized farm results in a decision to sell and exit the industry in states with high feed-low/med broiler prices. For example, if broiler price is ₦1000 per kg, it is optimal to sell and exit for all feed prices above 187₦ per kg[19] (Table 2.7). If broiler price increases to ₦1,250 per kg, it is optimal to exit if feed prices exceed ₦197 per kg. On the other hand, when broiler prices increase to ₦1,350 and ₦1,500, it is optimal sell and restock when the batch is five weeks old for all feed prices.

If prices were to increase by 50%, exit decisions are optimal for medium farms even at the highest broiler prices. For example if the broiler price reached ₦1,500 per kg, it is optimal to exit if feed prices reach ₦246 (Table 2.8).

Similarly for large-scale operations, the price vectors are (2.16) and (2.17) below:

$$p^{fL}_{20\%} = [132, 144, 150, 154, 156, 163, 168, 173, 180, 192, 204, 240] \tag{2.16}$$

$$p^{fL}_{50\%} = [165, 180, 188, 192, 195, 204, 210, 216, 225, 240, 255, 300] \tag{2.17}$$

For large scale farms, a 20% increase in feed prices has a small effect, resulting in exit decisions only at the highest feed price state of ₦240. For all other prices, it is optimal for the farm to sell and restock (Table 2.9).

With a 50% feed price increase and when broiler price is ₦900, large farms sell the batch sooner than in the prior scenarios. For example, at the lowest feed price state, sale and replacement is optimal when $a_t = 6$ (Table 2.10) while with a 20% shock, if feed price is the lowest (₦132), it is optimal decision to sell and restock when the batch age equals 8 weeks (Table 2.9). Exit decisions occur at every broiler price, but only when the feed price is the highest ($p^f_t = 300$). Otherwise, it is always optimal to sell and restock.

The results from hypothetical changes in the feed price regime demonstrate that medium-scale farms are more susceptible to feed price shocks than large farms. These differences are attributed to economies of scale.[20] Lastly, we attribute the optimality of some decisions to high persistence in both feed and broiler price states. This confirms the importance of

[19] There are some optimal exit decisions for lower feed prices if the batch is kept past 6 weeks.

[20] Differences stemming from farm size are also confirmed with the results of small scale farms in Appendix 2E. For this type of farm, exit decisions are much more common in all cases (baseline, 20% and 50% shock) and result in exit decisions in every price state with a 50% shock.

modeling the effects of dynamic price trends and transitions on farm behavior and profitability, as opposed to using a static budget analysis.

2.6.3 Hypothetical Changes in Energy Needs

One advantage of dynamic programming models is the ease with which hypothetical scenarios can be evaluated and optimal decisions can be computed. This flexibility is particularly advantageous when studying the growing importance of an input to a farm or industry. Here we are interested in modeling the effect of increased consumption of energy on optimal firm decisions. The expected rise in energy consumption is consistent with expansion as well as the adoption of electricity-intensive technologies used to mitigate the effect of rising temperatures. Cooling fans, sprinklers, and water pumps are becoming increasingly important tools utilized to counteract heat stress in developing countries. We find that 12% of our cross-sectional sample of poultry farms in Oyo State report using these technologies. These farms are also more likely to have higher energy consumption compared to the average farm (Table 2.11). This is consistent with the expectation that in the next 10 years, Nigeria's economic sector will transition towards more mechanized operations (S. N. Asoegwu and A. O. Asoegwu, 2007) that will require more energy. In addition, we would expect that consumption of diesel and fuel might increase if electricity from the grid is absent or insufficient, as occurs in Nigeria. If these adapting technologies are necessary to operate a successful farm, the lack of electricity from the grid could be augmented by using a diesel or fuel powered generator.

We consider the case of an increase in the weekly fuel consumption of medium and large poultry farms based on the difference in consumption between all farms and those using climate adapting technologies in our survey data. We found that medium (large) farms using climate adaptation technologies used 127% (180%) more fuel and 99% (212%) more electricity than the average farm of that size. For medium farms, a 127% increase in fuel consumption and 99% increase in electricity consumption result in some exit decisions when broiler prices equal ₦1,000, 1150, and 1,250 per kg and feed price is ₦164 (Table 2.12). For large-scale farms, there are no changes to the baseline results (Table 2.6) given a 180% increase in fuel consumption and a 212% increase in electricity use. The results for medium-scale farms suggest that while some exit decisions are optimal, restock decisions predominate. Both medium and large farms are positioned to evolve into electricity-intensive operations, barring any negative feed and energy price shocks to which medium scale farms are highly susceptible.

2.7 Discussion/Extensions

In this section we discuss the robustness of our analysis to relaxing certain assumptions, particularly the assumption that there are no alternative options/coping strategies that might allow firms to stay in the industry instead of exiting.

Credit: The use of credit to purchase inputs is a potential alternative to exiting the sector when a feed price shock occurs. Using credit, farms could purchase the inputs necessary to grow their broilers to a sellable weight, sell the chicken, and repay the loan. This is not likely in the Nigerian context. Only about 5% of farmers in our sample of over 1,000 farms report using credit to buy feed and/or medicines. The reason for the limited credit use is an issue that merits further discussion in future research.

Reducing other production costs: If a farmer is facing high feed prices and/or low broiler prices, a potential coping strategy would be to reduce the quantity of inputs used such as feed, antibiotics and medicines. However, reducing these production inputs can negatively affect the growth and survival rate of the broilers, resulting in reduced profits. One input cost that might be amenable to reduction is labor. A medium-scale farm could substitute hired labor with family labor at a wage rate equal to zero to reduce the total labor bill. However, the opportunity cost for family labor is not zero, given the off-farm employment options of the individual. Farms with over 100 broilers need at least two employees: one laborer to handle broiler operations and a security person, with the latter being hired, non-family labor. We account for the possibility that farms will operate with one worker instead of two, but even in this scenario we find exit decisions at low broiler/high feed price states for medium farms. In the case of farms with more than 1,000 birds, it is highly unlikely cutting labor would be an efficient strategy unless the entire farm were downsizing. Then the farm would be smaller and more vulnerable to shocks as our analysis suggests.

Self-compounded feed vs. branded feed: Since feed is the largest cost of a broiler farm, accounting for 48% of total costs of production (Adetola and Simeon, 2013), a logical solution would be to switch from buying branded feed to self-made feed. On average, self-made feed is 10% cheaper than branded feed (Table 2.3), but its primary component is still maize. Feed price would still be subjected to negative shocks and fluctuations in connection with maize prices. A farmer could change feed composition, but as discussed in the parametrization section, this is currently an unlikely situation due to the negative effect this has on the fattening process and poultry health.

Contracts: Another potential coping strategy that could influence optimal decisions but is not accounted for in our model is the use of contracts. This form of arrangement (formal or informal) between a potential buyer and a farm reduces production risk of farmers, search and transaction costs, and can potentially increase the bargaining power. For example, a farmer can use production contracts to secure a broiler price or transfer a large portion of the risk to a vertically integrated firm and manage only the broiler growth, as happens in the broiler industry in the United States. However, the majority of Nigerian poultry farms do not secure neither input nor production contracts. We find that only about 5% of farmers use contracts to secure a market for their stock. It is expected that institutional change including contract farming could become a structure under which livestock production can flourish and systems can integrate.

2.8 Conclusion

This article employed a discrete state and control space, discrete time dynamic programming model to analyze the effect of high feed costs and changes in energy needs on the optimal decisions of poultry farms in Nigeria by scale of operation. We find that medium poultry farms in Nigeria are not resilient to input price shocks. However, large poultry farms are equipped to handle both key input price shocks and make the necessary investments to manage a successful poultry operation. The findings of this paper have three key implications. First, as food systems transform in Africa and the number of commercialized farms expands, proper accounting of input and output prices as well as their fluctuations will be crucial to ascertain firm profitability and continued growth within the sector. Consequently, the development of accounting and financial training programs is essential for farmers to properly assess farm performance.

Second, the results highlight the importance of stabilizing maize prices. The sensitivity of the sector to increases in feed prices is a major threat to the growth farms have enjoyed thus far. We confirm that large increases in the price of feed switch the optimal decision from sale and restock to sale and exit, especially among medium scale farmers. This reveals a need for risk management mechanisms, such as input contracts, to regulate maize prices.

Third, our results emphasize the effects of increases in energy consumption on cost of production. We argue that the energy needs of farms will change to adjust to volatile and hotter temperatures, without necessarily increasing stock size. We find that to make investments to become an energy-intensive operation and remain profitable, farms must realize some economies of scale.

Though the analysis detailed in this work focuses on the poultry sector in Nigeria, it is applicable to livestock industries in other countries, particularly other developing countries where these livestock farms are rapidly expanding. The findings are relevant to the broader debate on food systems transformation in developing countries. As the domestic supply in these countries responds to rapid growth in animal protein consumption, the insights from this study can be applied in the development of appropriate programs and strategies to promote job creation, business development, and economic growth.

APPENDICES

APPENDIX 2A: Tables

Table 2.1: Summary Statistics (One-year data set)

	Oyo State	
VARIABLES	Mean	Std. Dev.
Price per broiler (₦/bird)	2342.91	759.47
Price of branded feed (₦/kg)	140.3	13.03
Price of self-made feed (₦/kg)	126.94	21.21
Price of diesel (₦/liter)	181.87	24.85
Price of fuel (₦/liter)	154.26	18.57
Price of electricity from the grid (₦/kwh)	23.5	0.24
Number of liters needed to power the generator for an hour	1.47	0.5
Number of hours of electricity received per week	51.54	13.44

Note: 1 USD = 360 Nigerian Naira (₦)

Table 2.2: Summary Statistics of Broiler Farmers by Farm Size in 2016

	Medium-Sized Farms (101-1000 birds)		Large Farms (1000 birds)	
VARIABLES	Mean	Std. Dev.	Mean	Std. Dev.
Management Characteristics				
Sex (Male=1, Female=0)	0.49	0.5	0.56	0.5
Age	50.05	13.55	47.94	11.06
Year business started	2011	0.41	2010	0.45
Keep records of expenditures (0/1)	0.2	0.4	0.56	0.5
Training in chicken production (0/1)	0.2	0.4	0.38	0.49
Production Practices				
Buy inputs, assemble own feed (0/1)	0.26	0.44	0.26	0.44
Buy chicken feed (0/1)	0.76	0.43	0.87	0.33
Freeze and store chicken meat (0/1)	0.01	0.1	0.04	0.2
Contract with poultry processor (0/1)	0.04	0.19	0.17	0.38
Deliver chicks to market or buyer (0/1)	0.51	0.5	0.38	0.49
Package chicken meat to retail (0/1)	0	0	0.05	0.23
Use vitamins (0/1)	0.47	0.5	0.71	0.46
Use medicines (0/1)	0.47	0.5	0.74	0.44
Chicken Characteristics				
Flock size in 2016	330.14	240.68	3,325.00	2,288.87
Average weight of broiler sold (kg)	2.47	1.32	2.87	1.13
Minimum weight of broiler sold (kg)	1.88	0.71	2.33	0.74
Maximum weight of broiler sold (kg)	2.32	0.9	3	0.7
Selling Channels				
Sold to neighbors (%)	35.91	41.05	14.9	23.96
Sold to rural retailers (%)	23.43	35.4	23.82	30.95
Sold to town retailers (%)	35.61	40.98	39.96	39.63
Sold to processors (%)	2.78	15.07	10.12	26
Sold to supermarkets (%)	1.01	10.05	0.66	2.9
Sold to northern wholesalers (%)	0	0	0.54	5.19
Sold to southern wholesalers (%)	1.26	9.02	10	26.37
Private Assets				
Own cages (0/1)	0.22	0.42	0.5	0.5
Number of trucks owned	0.03	0.17	0.4	0.83
Number of freezers owned	0.02	0.14	0.13	0.39
Number of freezers rented	0	0	0.02	0.13
Own well (0/1)	0.89	0.31	0.69	0.47
Own bore hole (0/1)	0.06	0.24	0.35	0.48
Own a bird slaughtering facility (0/1)	0.01	0.1	0.04	0.19
Own a generator (0/1)	0.15	0.36	0.6	0.49
Own a solar panel (0/1)	0	0	0.01	0.08
N	118		177	

Table 2.3: Summary Statistics of Energy Use by Farm Size in 2016

	Medium Farms (101-1000 birds)		Large Farms (>1000 birds)	
VARIABLES	Mean	Std. Dev.	Mean	Std. Dev.
Total spent on electricity from the grid (₦)	1,279.5	1,470.4	2,462.3	3,021.3
Quantity of electricity used (kWh/month)	69.5	100.1	81.0	122.9
Price of on-grid electricity (₦/kWh)	23.3	3.2	23.4	3.5
Keep track of generator expenses (0/1)	0.1	0.3	0.4	0.5
Monthly diesel expenses for generator (%)	3.5	14.0	10.6	18.2
Monthly fuel expenses for generator (₦)	2,736.1	3,356.0	8,926.5	9,655.4
Price of fuel (₦/Liter)	144.1	15.5	143.4	12.4
Monthly transportation expenses (₦)	1,333.3	2,737.9	6,554.6	6,574.3
Price of diesel (₦/Liter)	172.5	17.7	170.9	35.5
Average monthly solar energy expenses	0.0	0.0	0.0	0.0
Price of solar energy supply (₦/kWh)			25.0	.
Farms that use electricity (%)	0.5	0.5	0.3	0.5
Electricity needs that come from the grid (%)	67.2	33.4	41.4	28.7
Electricity needs that come from generator (%)	28.6	31.3	49.1	31.0
On-grid electricity used to power freezers (%)	4.2	11.5	9.5	19.1
Hours a day generator runs*	4.1	4.1	5.4	3.6
Capacity of generator (KVA)	9.5	8.3	9.5	6.9
Have petrol costs (0/1)	0.2	0.4	0.4	0.5
Diesel costs from maize dryer (%)	0.0	0.0	0.0	0.0
Diesel costs from pumping water (%)	16.0	35.8	18.8	23.9
Diesel costs from lighting (%)	74.0	37.2	62.5	25.0
Diesel costs from freezers (%)	0.0	0.0	6.3	12.5
N	118		177	

Table 2.4: Parametrization of Sell-Feed Model

Description	Value
Weekly discount rate	0.993
Maximum age of the bird (weeks)	10
Price of the day-old chick (₦)	200
Average total medical cost for medium farms (₦/week)	892
Average total medical cost for large farms (₦/week)	1,820
Labor wage rate (₦/week)	3000
Average number of employees hired by medium farms	2
Average number of employees hired by large farms	6
Asymptotic weight of the bird (kg)	5.97
Average stock size for medium farms in 2016 (# of broilers)	430
Average stock size for large farms in 2016	3,898
Price of diesel (₦/liter)	186.37
Price of fuel (₦/liter)	142.17
Price of electricity from the grid (₦/kWh)	30.5
Electricity from the grid used by medium farms (kWh/week)	32
Electricity from the grid used by large farms (kWh/week)	16.51
Diesel used by medium farms (liters/week)	16.26
Diesel used in large farms (liters/week)	32.91
Fuel used per week in medium farms (liters/week)	6.8
Fuel used per week in large farms (liters/week)	17

Note: 1 USD = 360 Nigerian Naira (₦)

Table 2.5: Results for Medium-Scale Farms (Baseline)

Broiler Price p_t^b (₦/kg)	Optimal Decisions
900	If p_t^f =112, 120 or 125, then feed for $a_t \leq 8$ and sell for $a_t > 8$ If p_t^f =130 or 138, then feed for $a_t \leq 7$ and sell for $a_t > 7$ If Ŕ140 $\leq p_t^f \leq$ Ŕ156, then feed for $a_t \leq 6$ and sell for $a_t > 6$ If $p_t^f \geq$ Ŕ160, then feed for $a_t \leq 5$ and sell for $a_t > 5$
1,000	If p_t^f =164, then feed for $a_t \leq 4$, sell for $a_t = 5$, and exit for $a_t > 5$ Otherwise, $\forall\ p_t^f$, sell for $a_t \geq 5$
1,150	If p_t^f =164, then feed for $a_t \leq 4$, sell for $a_t = 5$, and exit for $a_t > 5$ Otherwise, $\forall\ p_t^f$, sell for $a_t \geq 5$
1,200	$\forall\ p_t^f$, feed for $a_t < 5$ and sell for $a_t \geq 5$
1,250	$\forall\ p_t^f$, feed for $a_t < 5$ and sell for $a_t \geq 5$
1,350	$\forall\ p_t^f$, feed for $a_t < 5$ and sell for $a_t \geq 5$
1,500	$\forall\ p_t^f$, feed for $a_t < 5$ and sell for $a_t \geq 5$

Note: 1 USD = 360 Nigerian Naira (₦), p_t^b is broiler price, a_t is the age of the broiler batch, and p_t^f is feed price. For example, we can interpret the table as: if broiler price equals ₦1,000 and feed price equals ₦164, then it is optimal to feed the batch until it is at most 4 weeks old, sell the batch when it is 5 weeks old, and if the batch is kept longer than 5 weeks, it is optimal to exit the sector.

Table 2.6: Results for Large-Scale Farms (Baseline)

Broiler Price p_t^b (₦/kg)	Optimal Decisions
900	If p_t^f =110 then feed for $a_t \leq 7$ and sell for $a_t > 7$ If $120 \leq p_t^f \leq 130$, then feed for $a_t \leq 6$ and sell for $a_t > 6$ If $136 \leq p_t^f \leq 150$, then feed for $a_t \leq 5$ and sell for $a_t > 5$ If $p_t^f \geq$ Ŕ160, then feed for $a_t \leq 5$ and sell for $a_t > 5$
1,000	$\forall\ p_t^f$, feed for $a_t < 5$ and sell for $a_t \geq 5$
1,150	$\forall\ p_t^f$, feed for $a_t < 5$ and sell for $a_t \geq 5$
1,200	$\forall\ p_t^f$, feed for $a_t < 5$ and sell for $a_t \geq 5$
1,250	$\forall\ p_t^f$, feed for $a_t < 5$ and sell for $a_t \geq 5$
1,350	$\forall\ p_t^f$, feed for $a_t < 5$ and sell for $a_t \geq 5$
1,500	$\forall\ p_t^f$, feed for $a_t < 5$ and sell for $a_t \geq 5$

Note: 1 USD = 360 Nigerian Naira (₦), p_t^b is broiler price, a_t is the age of the broiler batch, and p_t^f is feed price.

Table 2.7: Results for Medium-Scale Farms (20% Feed Price Shock)

Broiler Price p_t^b (₦/kg)	Optimal Decisions
900	If $p_t^f = 134$, then feed for $a_t < 8$ and sell for $a_t \geq 8$ If $144 \leq p_t^f \leq$ Ŕ156, then feed for $a_t \leq 6$ and sell for $a_t > 6$ If $p_t^f = 160, 168$, then feed, for $a_t < 6$ and sell for $a_t \geq 6$ If $p_t^f = 197$, then feed, for $a_t < 7$ and exit for $a_t \geq 7$ If Ŕ187 $\leq p_t^f \leq$ Ŕ216, then feed for $a_t \leq 4$ and sell for $a_t > 4$
1,000	If $134 \leq p_t^f \leq 156$, then feed for $a_t \leq 4$ and sell for $a_t > 4$ If $p_t^f =$ Ŕ160, 168, then feed for $a_t < 5$, sell for $5 \leq a_t \leq 7$, and exit for $8 \leq a_t \leq 10$ If $p_t^f =$ Ŕ173, 180, then feed for $a_t \leq 4$, sell for $a_t = 5, 6$, and exit for $a_t > 6$ If $p_t^f \geq$ Ŕ187, then feed, for $a_t \leq 4$ and exit for $a_t \geq 5$
1,150	If $p_t^f =$ Ŕ134, then feed, for $a_t < 5$ and sell for $a_t \geq 5$ $\forall\ p_t^f$, feed for $a_t < 5$ and exit for $a_t \geq 5$
1,200	If $134 \leq p_t^f \leq 192$, feed for $a_t < 5$ and sell for $a_t \geq 5$ If $p_t^f \geq$ Ŕ197, then feed for $a_t \leq 4$ and exit for $a_t \geq 5$
1,250	If $134 \leq p_t^f \leq 192$, then feed for $a_t \leq 4$ and sell for $a_t \geq 5$ If $p_t^f \geq$ Ŕ197, then feed for $a_t \leq 4$ and exit for $a_t \geq 5$
1,350	$\forall\ p_t^f$, feed for $a_t < 5$ and sell for $a_t \geq 5$
1,500	$\forall\ p_t^f$, feed for $a_t < 5$ and sell for $a_t \geq 5$

Note: 1 USD = 360 Nigerian Naira (₦), p_t^b is broiler price, a_t is the age of the broiler batch, and p_t^f is feed price.

Table 2.8: Results for Medium-Scale Farms (50% Feed Price Shock)

Broiler Price p_t^b (₦/kg)	Optimal Decisions
900	If $p_t^f = 168$, then feed for $a_t < 6$ and sell for $a_t \geq 6$ If $p_t^f = 180$, then feed for $a_t < 6$, sell for $a_t = 6$, and exit for $a_t \geq 7$ If $p_t^f = 188, 195$, then feed for $a_t \leq 4$, sell for $a_t = 5, 6$, and exit for $a_t \geq 7$ If $p_t^f \geq 207$, then feed, for $a_t < 5$ and exit for $a_t \geq 5$
1,000	$\forall\ p_t^f$, feed for $a_t < 5$ and exit for $a_t \geq 5$
1,150	$\forall\ p_t^f$, feed for $a_t < 5$ and exit for $a_t \geq 5$
1,200	If $p_t^f = 168$, feed for $a_t < 5$ and sell for $a_t \geq 5$ If $p_t^f = 180$, feed for $a_t < 5$ and exit for $a_t \geq 5$ If $p_t^f = 188$, feed for $a_t < 5$, sell for $a_t = 5$, and exit for $a_t \geq 6$ If $p_t^f \geq 198$, feed for $a_t < 5$ and exit for $a_t \geq 5$
1,250	If $p_t^f = 168$, then feed for $a_t \leq 4$, sell for $a_t = 5, 6, 7$, and sell for $a_t > 7$ If $p_t^f \geq 180$, then feed for $a_t \leq 4$ and exit for $a_t \geq 5$
1,350	If $168 \leq p_t^f \leq 195$, feed for $a_t < 5$ and sell for $a_t \geq 5$ If $p_t^f = 207, 210$, feed for $a_t < 5$, sell for $a_t = 5, 6$, and exit for $a_t \geq 7$ If $p_t^f \geq 216$, feed for $a_t < 5$ and exit for $a_t \geq 5$
1,500	If $168 \leq p_t^f \leq 210$, feed for $a_t < 5$ and sell for $a_t \geq 5$ If $p_t^f = 216, 225$, feed for $a_t < 5$, sell for $5 \leq a_t \leq 8$, and exit for $a_t = 9, 10$ If $p_t^f = 234$, feed for $a_t < 5$ and exit for $a_t \geq 5$ If $p_t^f = 240$, feed for $a_t < 5$, sell for $5 \leq a_t \leq 7$ and exit for $a_t \geq 8$ If $p_t^f \geq 246$, feed for $a_t < 5$ and exit for $a_t \geq 5$

Note: 1 USD = 360 Nigerian Naira (₦), p_t^b is broiler price, a_t is the age of the broiler batch, and p_t^f is feed price.

Table 2.9: Results for Large-Scale Farms (20% Feed Price Shock)

Broiler Price p_t^b (₦/kg)	Optimal Decisions
900	If p_t^f =132 then feed for $a_t \leq 7$ and sell for $a_t > 7$ If $144 \leq p_t^f \leq 156$, then feed for $a_t \leq 6$ and sell for $a_t > 6$ If $163 \leq p_t^f \leq 180$, then feed for $a_t \leq 5$ and sell for $a_t > 5$ If $p_t^f \geq 192$, then feed for $a_t \leq 5$ and sell for $a_t > 5$
1,000	If $p_t^f \neq 240$, then feed for $a_t < 5$ and sell for $a_t \geq 5$ If $p_t^f = 240$, then feed for $a_t < 5$ and exit for $a_t \geq 5$
1,150	If $p_t^f \neq 240$, then feed for $a_t < 5$ and sell for $a_t \geq 5$ If $p_t^f = 240$, then feed for $a_t < 5$ and exit for $a_t \geq 5$
1,200	$\forall\ p_t^f$, feed for $a_t < 5$ and sell for $a_t \geq 5$
1,250	$\forall\ p_t^f$, feed for $a_t < 5$ and sell for $a_t \geq 5$
1,350	$\forall\ p_t^f$, feed for $a_t < 5$ and sell for $a_t \geq 5$
1,500	$\forall\ p_t^f$, feed for $a_t < 5$ and sell for $a_t \geq 5$

Note: 1 USD = 360 Nigerian Naira (₦), p_t^b is broiler price, a_t is the age of the broiler batch, and p_t^f is feed price.

Table 2.10: Results for Large-Scale Farms (50% Feed Price Shock)

Broiler Price p_t^b (₦/kg)	Optimal Decisions
900	If p_t^f =165, 180 then feed for $a_t \leq 5$ and sell for $a_t > 5$ If $188 \leq p_t^f \leq 255$, then feed for $a_t \leq 4$ and sell for $a_t > 4$ If $p_t^f = 300$, then feed for $a_t < 5$ and sell for $a_t \geq 5$
1,000	If $p_t^f \neq 300$, then feed for $a_t < 5$ and sell for $a_t \geq 5$ If $p_t^f = 300$, then feed for $a_t < 5$ and exit for $a_t \geq 5$
1,150	If $p_t^f \neq 300$, then feed for $a_t < 5$ and sell for $a_t \geq 5$ If $p_t^f = 300$, then feed for $a_t < 5$ and exit for $a_t \geq 5$
1,200	If $p_t^f \neq 300$, then feed for $a_t < 5$ and sell for $a_t \geq 5$ If $p_t^f = 300$, then feed for $a_t < 5$ and exit for $a_t \geq 5$
1,250	If $p_t^f \neq 300$, then feed for $a_t < 5$ and sell for $a_t \geq 5$ If $p_t^f = 300$, then feed for $a_t < 5$ and exit for $a_t \geq 5$
1,350	If $p_t^f \neq 300$, then feed for $a_t < 5$ and sell for $a_t \geq 5$ If $p_t^f = 300$, then feed for $a_t < 5$ and exit for $a_t \geq 5$
1,500	If $p_t^f \neq 300$, then feed for $a_t < 5$ and sell for $a_t \geq 5$ If $p_t^f = 300$, then feed for $a_t < 5$, sell for $a_t = 5$, and exit for $a_t > 5$

Note: 1 USD = 360 Nigerian Naira (₦), p_t^b is broiler price, a_t is the age of the broiler batch, and p_t^f is feed price.

Table 2.11: Average Energy Use of Broiler Farms

	Medium Farms	Medium Farms*	%Δ	Large Farms	Large Farms*	%Δ
Electricity used (kWh/week)	31.43	62.62	**99%**	16.51	51.5	**212%**
Fuel used (Liters/week)	6.8	15.42	127%	16.99	47.65	180%
Diesel used (Liters/week)	16.26	15.97	-2%	32.91	70.38	114%

*These farms use energy intensive technologies to deal with temperature changes, such as automated sprinklers, fans, and cooling systems.

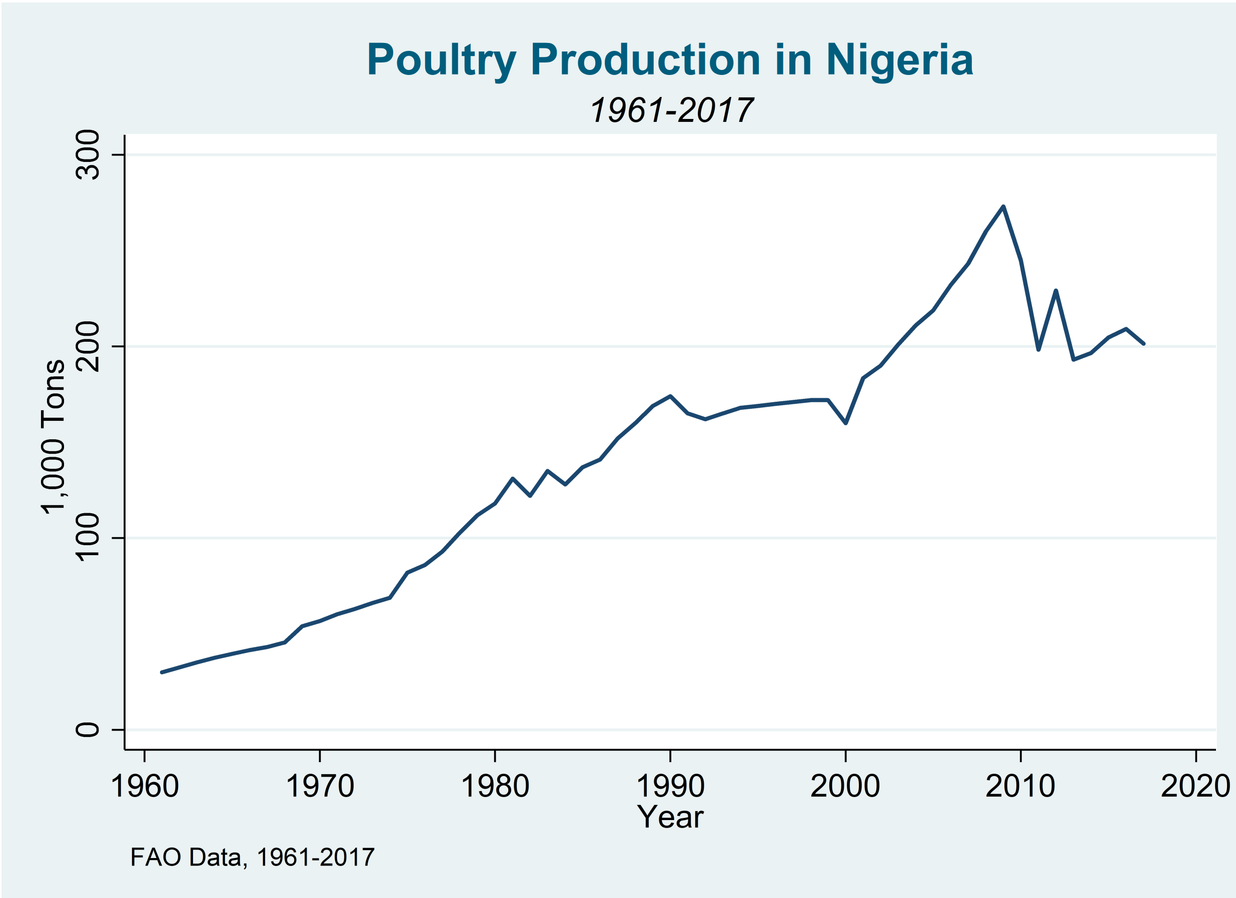
Table 2.12: Results for Medium-Scale Farms (Increased Energy Consumption Scenario)

Broiler Price p_t^b (₦/kg)	Optimal Decisions
900	If p_t^f =112, 120 or 125, then feed for $a_t \leq 8$ and sell for $a_t > 8$ If p_t^f =130 or 138, then feed for $a_t \leq 7$ and sell for $a_t > 7$ If Ŕ140 $\leq p_t^f \leq$ Ŕ156, then feed for $a_t \leq 6$ and sell for $a_t > 6$ If $p_t^f \geq$ Ŕ160, then feed for $a_t \leq 5$ and sell for $a_t > 5$
1,000	If p_t^f =164, then feed for $a_t \leq 4$, sell for $a_t = 5$, and exit for $a_t > 5$ Otherwise, $\forall\ p_t^f$, sell for $a_t \geq 5$
1,150	If p_t^f =164, then feed, for $a_t \leq 4$, sell for $a_t = 5$, and exit for $a_t > 5$ Otherwise, $\forall\ p_t^f$, sell for $a_t \geq 5$
1,200	$\forall\ p_t^f$, feed for $a_t < 5$ and sell for $a_t \geq 5$
1,250	If p_t^f =164, then feed, for $a_t \leq 4$, sell for $a_t = 5$, and exit for $a_t > 5$ Otherwise, $\forall\ p_t^f$, sell for $a_t \geq 5$
1,350	$\forall\ p_t^f$, feed for $a_t < 5$ and sell for $a_t \geq 5$
1,500	$\forall\ p_t^f$, feed for $a_t < 5$ and sell for $a_t \geq 5$

Note: 1 USD = 360 Nigerian Naira (₦), p_t^b is broiler price, a_t is the age of the broiler batch, and p_t^f is feed price.

APPENDIX 2B: Figures

Figure 2.1: Poultry Production in Nigeria



Over the past 50 years, there has been a steady increase in chicken production with a decline in 2009 due to an avian flu outbreak. The importance of poultry continues to rise, in a similar matter than it has all over the world.

APPENDIX 2C: Feed and Broiler Transition Probabilities

Table 2.13: Feed Price Transition Probability Matrix for Large-Sized Farms

	110	120	125	128	130	136	140	144	150	160	170	200
110	0.833	0.167	0	0	0	0	0	0	0	0	0	0
120	0	0.875	0.063	0	0	0	0.063	0	0	0	0	0
125	0	0	0.929	0	0.071	0	0	0	0	0	0	0
128	0	0	0.059	0.882	0.059	0	0	0	0	0	0	0
130	0	0.009	0.009	0.009	0.938	0.018	0.018	0	0	0	0	0
136	0	0	0	0	0.024	0.951	0	0	0	0.024	0	0
140	0	0	0	0	0.375	0.125	0.5	0	0	0	0	0
144	0	0	0	0	0	0	0	1	0	0	0	0
150	0	0	0	0	0.091	0	0	0	0.909	0	0	0
160	0	0	0	0	0.02	0.02	0	0	0	0.959	0	0
170	0	0	0	0	0	0.033	0	0	0	0	0.967	0
200	0	0	0	0	0	0	0	0	0	0	0	1

Table 2.14: Feed Price Transition Probability Matrix for Medium-Sized Farms

	112	120	125	130	138	140	144	150	156	160	164	168	176	180
112	1	0	0	0	0	0	0	0	0	0	0	0	0	0
120	0	0.86	0.04	0.07	0	0	0	0	0	0	0	0	0	0.04
125	0	0.02	0.95	0.02	0	0	0	0	0	0	0	0	0	0
130	0	0.00	0.01	0.98	0	0.00	0	0.01	0	0	0	0	0	0
138	0	0	0	0	0.93	0.07	0	0	0	0	0	0	0	0
140	0	0.002	0	0.01	0.01	0.97	0.01	0.01	0	0	0	0	0	0
144	0	0	0.01	0	0	0.05	0.92	0.01	0	0.01	0.01	0	0	0
150	0	0	0	0	0	0.14	0.04	0.82	0	0	0	0	0	0
156	0	0	0	0	0	0.03	0	0	0.97	0	0	0	0	0
160	0	0.05	0	0	0	0.05	0	0.05	0.05	0.80	0	0	0	0
164	0	0	0	0	0	0	0	0	0	0.05	0.95	0	0	0
168	0	0	0	0.06	0	0	0.04	0	0	0	0	0.87	0.04	0
176	0	0	0	0	0	0	0	0	0	0	0	0.22	0.78	0
180	0	0	0	0	0	0.09	0	0.09	0	0	0	0	0	0.82

Table 2.15: Broiler Price Transition Probability Matrix

	900	1000	1150	1200	1250	1350	1500
900	0.833	0	0	0	0	0	0.167
1000	0	0.92	0	0	0.04	0	0.04
1150	0	0	0.962	0	0.038	0	0
1200	0	0	0	0.909	0.027	0	0.064
1250	0	0	0.005	0	0.976	0.002	0.017
1350	0	0	0	0	0.021	0.915	0.064
1500	0	0	0.004	0.006	0.029	0.006	0.955

APPENDIX 2D: Growth Function Estimations

Non-linear models are used to describe weight as a function of age for different breeds of chicken. The growth pattern tends to have a sigmoid shape and as such, many different functional forms can capture this relationship. There are two main types of growth functions: those with a fixed point of inflection[21] and those with a variable point of inflection (Yang et al., 2006; Kaplan and Gurcan, 2018). To parametrize the weight gain function in the simulation, we empirically estimate the logistic, Gompertz, Bertalanffy, and Richards functions (Table 2.16). These are the four most commonly used functions in the poultry literature, with Bertalanffy and Richards having a flexible point of inflection.

Previous literature determines the goodness of fit of growth models using the coefficient of determination R^2, the adjusted R^2, the root mean square error (RMSE), and the graphical depiction of each of the curves (Selvaggi et al., 2015; Darmani Kuhi, Porter, et al., 2010). Based on these criteria, the Richards function seems to be the best fit for our data, followed by the Bertalanffy growth curve (Table 2.17). The fitted lines for each of the functions (Graphs 2.2-2.5) also suggest the Richards curve is a better fit than the other growth curves.

Table 2.16: Growth Curves

Logistic	$W_T = \frac{A}{1+Be^{-kt}}$
Gompertz	$W_T = Ae^{-Be^{-kt}}$
Bertalanffy	$W_T = A(1+Be^{-kt})^3$
Richards	$W_T = \frac{A}{(1-Be^{-kt})^{\frac{1}{m}}}$

A is the asymptotic weight as age approaches infinity, k is the instantaneous relative growth rate (or maturing rate), B is a constant, m is the Richard's function shape parameter determining the inflection point when the acceleration growth phase moves to the retardation phase (Tompic et al., 2011; Goliomytis, Panopoulou, and Rogdakis, 2003; Darmani Kuhi, Kebreab, et al., 2003)

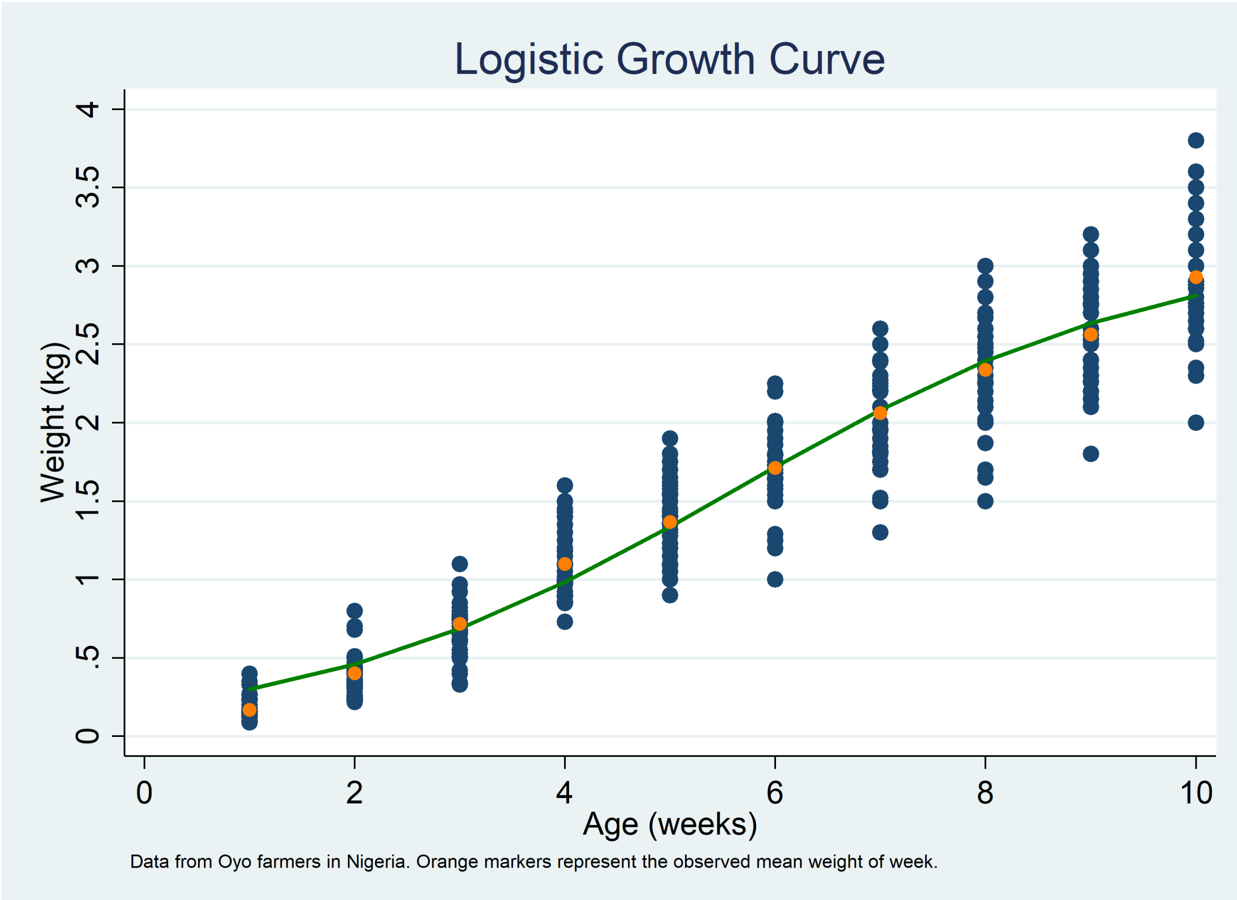
[21] Point at which the growth rate is the highest (Segura-Correa, Santos-Ricalde, and Palma-Avila, 2017)

Table 2.17: Estimated Parameters for Nonlinear Growth Curves

	(1) Logistic	(2) Gompertz	(3) Bertalanffy	(4) Richards
A	3.14***	3.78***	4.39***	5.97**
	-0.11	-0.18	-0.28	-1.877
k	0.49***	0.26***	0.18***	0.09*
	-0.01	-0.01	-0.01	-0.047
B	15.41***	3.64***	0.77***	1.00***
	-0.8	-0.07	-0.01	-0.0392
m				-0.65***
				-0.159
Observations	646	646	646	646
R-squared	0.9805	0.9818	0.982	0.9822
Adjusted R-Squared	0.9781	0.9795	0.9798	0.9799
Root MSE	0.2438	0.236	0.2342	0.2337

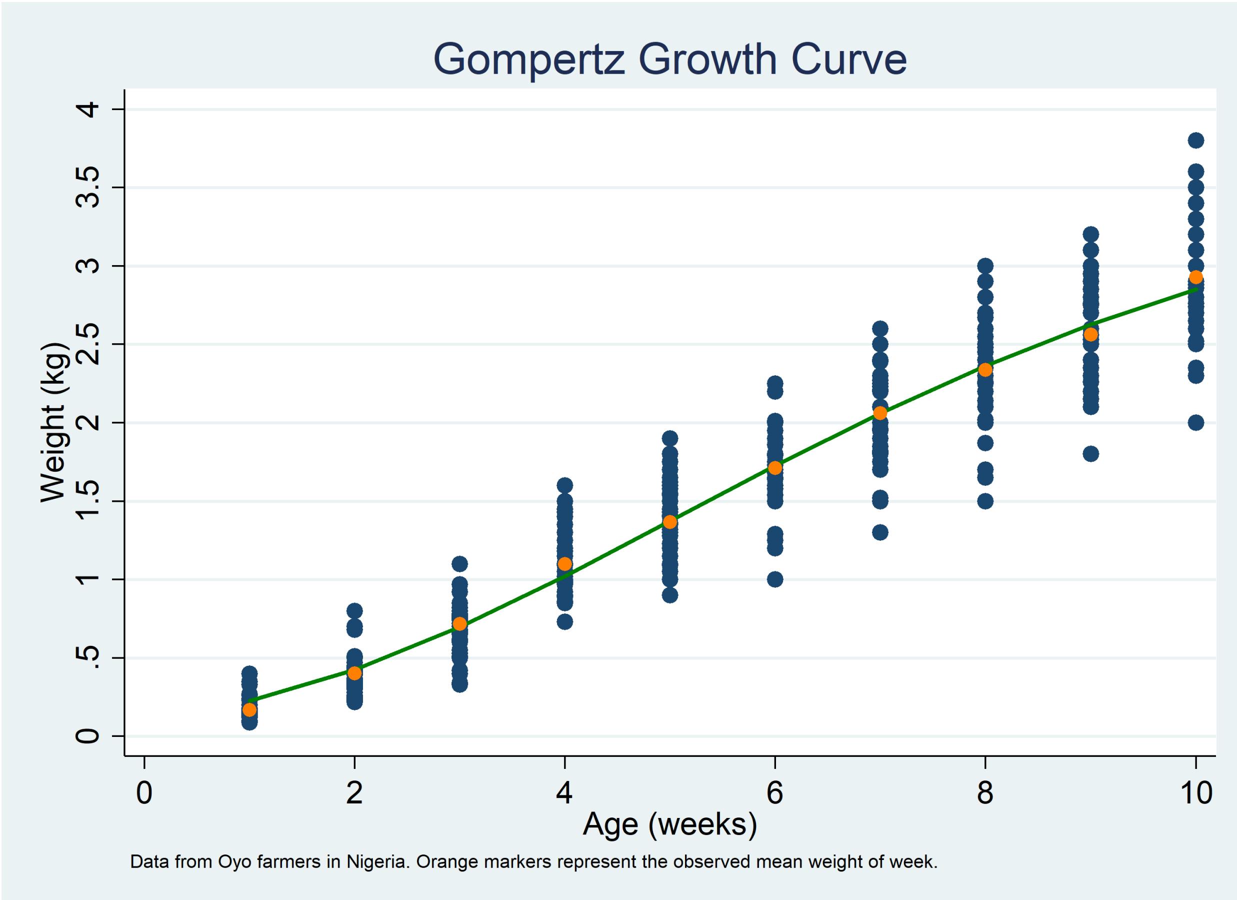
Robust standard errors: $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$

Figure 2.2: Logistic Growth Curve



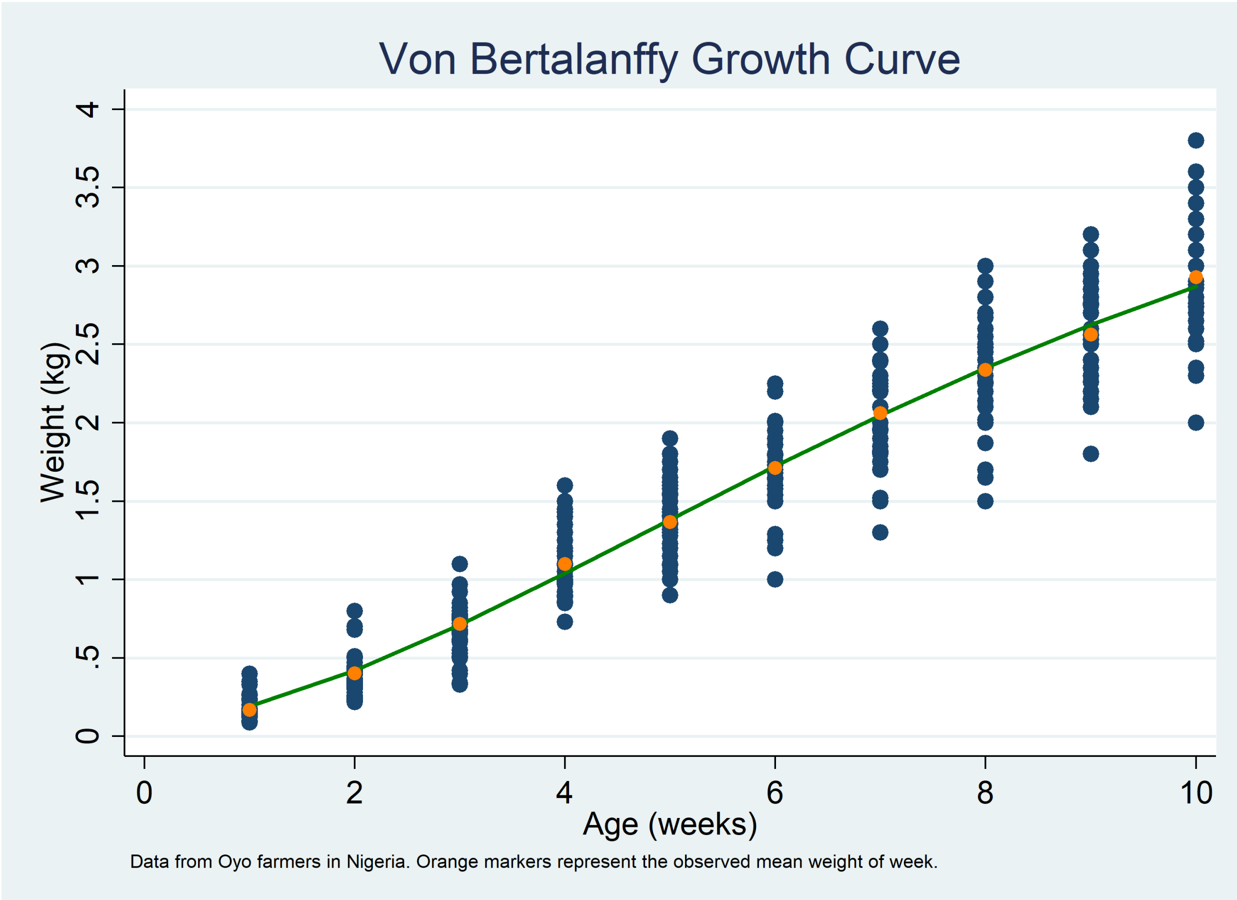
Visual display of the logistic growth curve for farmers in Oyo State. Orange markers represent median prices.

Figure 2.3: Gompertz Growth Curve



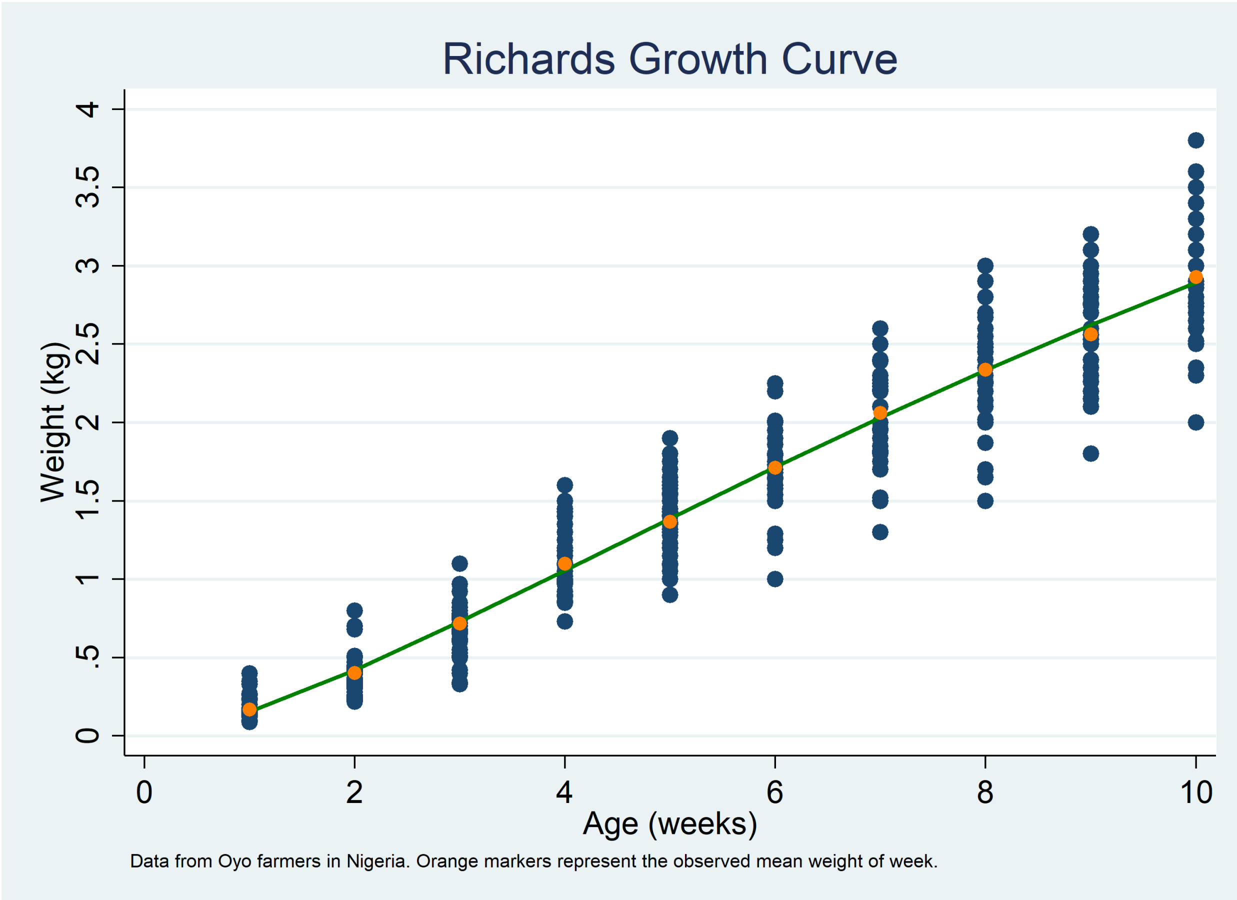
Visual display of the Gompertz growth curve for farmers in Oyo State. Orange markers represent median prices.

Figure 2.4: Von Bertalanffy Growth Curve



Visual display of the Von Bertalanffy growth curve for farmers in Oyo State. Orange markers represent median prices.

Figure 2.5: Richards Growth Curve



visual display of the Richards growth curve for farmers in Oyo State. Orange markers represent median prices.

APPENDIX 2E: Results for Small Household Farms

Table 2.18: Parametrization of Sell-Feed Model for Small Households

Description	Value
Weekly discount rate	0.993
Maximum age of the bird (weeks)	10
Average total medical cost for small farms (₦/week)	0
Labor wage rate (₦/week)	2500
Average number of employees hired by small farms	0
Asymptotic weight of the bird (kg)	5.97
Average stock size for small farms in 2016 (# of broilers)	57
Price of diesel (₦/liter)	186.37
Price of fuel (₦/liter)	142.17
Price of electricity from the grid (₦/kWh)	30.5
Electricity from the grid used by small farms (kWh/week)	13
Diesel used by small farms (liters/week)	8
Fuel used per week in small farms (liters/week)	0

Note: 1 USD = 360 Nigerian Naira (₦)

Table 2.19: Results for Small-Scale Farms

Broiler Price p_t^b (₦/kg)	Optimal Decisions
900	If $p_t^f \leq 116$, then feed for $a_t < 10$ and sell for $a_t = 10$ If $p_t^f = 120, 130$, then feed for $a_t < 9$ and sell for $a_t \geq 9$ If $p_t^f = 135, 136$, then feed for $a_t < 8$ and sell for $a_t \geq 8$ If $140 \leq p_t^f \leq 154$, then feed for $a_t < 7$ and sell for $a_t \geq 7$
1,000	If $p_t^f \leq 120$, then feed for $a_t < 5$ and sell for $a_t \geq 5$ If $p_t^f > 120$, then feed for $a_t < 5$ and exit for $a_t \geq 5$
1,150	If $p_t^f \leq 120$, then feed for $a_t < 5$ and sell for $a_t \geq 5$ If $p_t^f > 120$, then feed for $a_t < 5$ and exit for $a_t \geq 5$
1,200	If $p_t^f < 160$, then feed for $a_t < 5$ and sell for $a_t \geq 5$ If $p_t^f = 160$, then feed for $a_t < 5$, sell for $5 \leq a_t \leq 9$, and exit if $a_t = 10$ If $p_t^f = 164, 168$, then feed for $a_t < 5$, sell for $5 \leq a_t \leq 7$ and exit if $a_t > 7$
1,250	If $p_t^f < 160$, then feed for $a_t < 5$ and sell for $a_t \geq 5$ If $p_t^f \geq 160$, then feed for $a_t < 5$ and exit for $a_t \geq 5$
1,350	$\forall\, p_t^f$, feed for $a_t < 5$ and sell for $a_t \geq 5$
1,500	$\forall\, p_t^f$, feed for $a_t < 5$ and sell for $a_t \geq 5$

Note: 1 USD = 360 Nigerian Naira (₦), p_t^b is broiler price, and p_t^f is feed price.

Table 2.20: Results for Small-Scale Farms (20% Feed Price Shock)

Broiler Price p_t^b (₦/kg)	Optimal Decisions
900	If $p_t^f \leq 116$, then feed for $a_t < 5$ and sell for $a_t \geq 5$
	If $p_t^f > 116$, then feed for $a_t < 5$ and exit for $a_t \geq 5$
1,000	$\forall\ p_t^f$, feed for $a_t < 5$ and exit for $a_t \geq 5$
1,150	$\forall\ p_t^f$, feed for $a_t < 5$ and exit for $a_t \geq 5$
1,200	If $p_t^f \leq 116$, then feed for $a_t < 5$ and sell for $a_t \geq 5$
	If $p_t^f > 116$, then feed for $a_t < 5$ and exit for $a_t \geq 5$
1,250	$\forall\ p_t^f$, feed for $a_t < 5$ and exit for $a_t \geq 5$
1,350	If $p_t^f \leq 148$, then feed for $a_t < 5$ and sell for$a_t \geq 5$
	If $p_t^f = 150, 154$, then feed for $a_t < 5$ and sell for $a_t \geq 5$
	If $p_t^f > 154$, then feed for $a_t < 5$ and exit for $a_t \geq 5$
1,500	If $p_t^f \leq 154$, then feed for $a_t < 5$ and sell for $a_t \geq 5$
	If $p_t^f > 154$, then feed for $a_t < 5$, sell for $5 \leq a_t \leq 6$ and, exit for $a_t > 6$

Note: 1 USD = 360 Nigerian Naira (₦), p_t^b is broiler price, and p_t^f is feed price.

Table 2.21: Results for Small-Scale Farms (50% Feed Price Shock)

Broiler Price p_t^b (₦/kg)	Optimal Decisions
900	If $p_t^f \neq 1$, then feed for $a_t < 5$ and sell for $a_t \geq 5$ If $p_t^f >$, then feed for $a_t < 5$ and exit for $a_t \geq 5$ If $p_t^f = 135, 136$, then feed for $a_t < 8$ and sell for $a_t \geq 8$ If $140 \leq p_t^f \leq 154$, then feed for $a_t < 7$ and sell for $a_t \geq 7$
1,000	$\forall\ p_t^f$, feed for $a_t < 5$ and exit for $a_t \geq 5$
1,150	$\forall\ p_t^f$, feed for $a_t < 5$ and exit for $a_t \geq 5$
1,200	$\forall\ p_t^f$, feed for $a_t < 5$ and exit for $a_t \geq 5$
1,250	$\forall\ p_t^f$, feed for $a_t < 5$ and exit for $a_t \geq 5$
1,350	$\forall\ p_t^f$, feed for $a_t < 5$ and exit for $a_t \geq 5$
1,500	$\forall\ p_t^f$, feed for $a_t < 5$ and exit for $a_t \geq 5$

Note: 1 USD = 360 Nigerian Naira (₦), p_t^b is broiler price, and p_t^f is feed price.

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CHAPTER 3

COLD STORAGE INVESTMENT DECISIONS UNDER ELECTRICITY UNCERTAINTY: CASE OF COMMERCIAL POULTRY FARMING IN NIGERIA

3.1 Introduction

Changing consumer preferences continue to motivate production improvements and value addition in the agri-food sector across Africa. Livestock production systems are generally improving efficiency, building linkages with other supply chain actors, and in some cases, vertically integrating (Liverpool-Tasie et al., 2017). Evidence from data on the Nigerian poultry sector suggest that only 17% of poultry farms and 55% retailers apply value added strategies.[1] Investing in a cold storage unit and storing meat would allow livestock farmers to engage in strategic delay of sales, capture premiums from value-added products, diversify their product portfolios,[2] and relax the constraint on the shelf life of meat.

The literature on commodity storage dynamics, (Deaton and Laroque, 1996; M. J. Miranda, 1999) why farmers store grain, (Saha and Stroud, 1994; Chavas, Despins, and Fortenbery, 2000) and the effects of on-farm storage on farm profitability (Lai, Myers, and Hanson, 2003) is rich and well developed. However, few studies have documented the use of cold storage in developing countries (Reardon et al., 2016; Jaffee and Masakure, 2005) with none found on the African continent. Furthermore, no rigorous studies exist on the use of cold storage to enhance profitability by facilitating on-farm storage of livestock products. One possible reason for this research gap could be the low adoption rates of these technologies. However, as farms continue to grow investments in freezers could facilitate delay of sales until the output price increases,[3] price premiums, and reduce production risk through diversified product

[1] These strategies include processing, packaging, branding, labeling, and freezing and storing chicken.

[2] By having a cold storage unit, farmers can hold at least two different products: live birds and slaughtered frozen chicken.

[3] This is particularly important in countries where poultry demand increases significantly around religious holidays.

holdings.

To fully exploit the benefits from the adoption of cold storage technologies, farmers need sufficient and stable access to electricity. However, stable electricity remains a challenge across Sub-Saharan Africa (Alby, Dethier, and Straub, 2013; Cole et al., 2018). This paper studies the effect of energy supply fluctuations on storage and investment decisions within the context of commercial poultry production in Nigeria, Africa's most populous country and largest economy. Although Nigeria is rich in natural resources, inadequate government policies, weak transmission networks, and poor infrastructure maintenance limit the efficient distribution of electricity and alternative energy sources. These institutional challenges can affect investments in electricity-intensive technologies in many growing industries and economic sectors. For the livestock sector, particularly poultry, electricity supply disruptions can have important effects on investment in cold storage as well as the pattern of on-farm frozen meat storage.

Using cross-sectional data and a one-year weekly panel data set of farm input and output prices from Oyo State, Nigeria, we employ a discrete time and space dynamic programming (DP) replacement model with storage to derive optimal decision rules. The replacement portion of the model focuses on finding optimal decision rules regarding the options to feed or sell and restock broiler chickens. The storage model expands the original choice set to include the option to store and maintain stocks of both frozen and live birds. We then use the derived net payoffs from storage to characterize the freezer investment decision in a real options framework.[4] This framework is ideal to describe the dynamics of poultry farmers in a context of uncertain electricity because it can incorporate both uncertainty in prices and electricity supply that affect future returns, the irreversibility[5] of investment, and the ability to wait to invest.

This study makes three main contributions. The analytical model used is the first

[4]Real option theory views investments as "options in that, at any point in time, a firm may choose to either invest immediately or delay and observe the evolution of the investment's payoff" (Kellogg, 2014).

[5]Irreversability refers to the idea that investment costs cannot be recovered due to low resale value or absence of a market.

to incorporate energy related costs of operating a farm when energy supply is uncertain and variable. As businesses grow from a subsistence-orientation to a more commercialized enterprise, their need for reliable inputs such as water and electricity intensifies. If electricity supply fluctuates or the farmer does not get enough hours of power each day, the value of owning a freezer is less since its role for storage is compromised every time the power goes off. Without a limited number of hours of electricity, farmers are more likely to invest in freezer capacity that prolongs the shelf life of their broiler stock because they would be able to take full advantage of the benefit of the investment. In the absence of reliable electricity to power the storage unit, a farmer would be less likely to consider the unit a sound investment. This model can be applied to other livestock systems, industries, and firms that face variable input supply.

Second, this is the first study to merge a replacement and a storage model for livestock. By allowing for on-farm frozen storage, we can enrich the decision environment to be closer to the actual situation faced by the economic agent.

The third contribution this paper makes is to the storage literature. This is the first paper to document in detail the optimal cold storage decisions of poultry farmers, applying modified versions of models originally designed for grain storage. In addition, this article sheds light on the market conditions that are necessary to expand the widespread adoption of improved technologies that can increase profitability of business enterprises. Though applied in Nigeria, the importance of this work transcends the specific context as many developing countries in Africa and Latin American face scarce and variable input supply (e.g. electricity and water) and must develop business enterprises in the presence of such resource constraints.

3.2 The Energy Sector of Nigeria

Nigeria has a plethora of energy resources (Akinbami, 2001); for example, crude oil and natural gas reserves are estimated at 37,500 million barrels and 5,600 billion cu. m., respectively (Annual Statistical Bulletin, 2019). Compared to other OPEC members, Nigeria has the 6th and 3rd largest reserves of crude oil and natural gas, respectively.

Despite these abundant resources, the power sector and transmission networks perform poorly and operate at a deficit, with the current access rate at 45% in rural areas and 55% in urban areas (USAID, 2018a). In 2018, Nigeria had the most significant power deficit in the West Africa region (-3,407 MW) and the deficit is expected to grow by 2025 (USAID, 2018b). Some of the reasons the energy sector performs poorly today include declining maintenance budgets and lack of investments in capacity expansion (Oyedepo, 2012; Aliyu, Ramli, and Saleh, 2013).

In addition to insufficient electricity supply, Nigeria also experiences constant power outages. Based on the 2014 World Bank Enterprise Survey (WBES) from Nigeria, 78% of firms experience electrical outages and on average, there are 33 outages in a typical month that have an average duration of 11 hours. Both the number of outages and the average duration supersede the average figures for Sub-Saharan Africa (Table 3.1) and result in 15% loss in production output.

The effects of poor infrastructure and inadequate power supply have important implications for firm behavior and the development of business sectors. Ebohon (1996) demonstrates the positive and significant relationship between energy supply and economic growth in Nigeria and Tanzania, while Moyo (2012) shows the negative effect of power outages, and subsequent output loss on manufacturing productivity. Cole et al. (2018) find evidence of a negative relationship between unreliable energy supply and firm sales in their study of 12 African countries. These negative effects are stronger among firms that do not have a generator.

3.3 Theoretical Framework

The dynamic programming approach of this paper stems from real options theory. The real options literature was first developed by Marschak (1949) and Arrow (1968), followed by McDonald and Siegel (1986) and Dixit and Pindyck (1994). This theory challenges the neoclassical framework in which the net present value (NPV) rule determines whether an actor makes an investment decision. The NPV rule fails to consider the potential gains from waiting to invest when uncertainty over the returns is high.

To model the decision to invest in a cold storage unit (freezer) in a real options framework, we must first characterize the value of the investment if implemented. To do so, we model the replacement decision with storage, assuming adequate freezer space is available (Model 1). Then, we estimate the storage profits and input these into the Model 2 to derive optimal rules for the cold storage technology under uncertainty about future returns, irreversibility, and the ability to wait to invest.

3.3.1 Model 1: Determining the Cash Flows from Cold Storage

Suppose a price-taking, poultry farmer purchases q^B day-old chicks (one batch) at price p^D per chick.[6] Every week t, the farmer can feed, sell live, or store in a freezer of capacity $F = q^B$. The farmer receives p_t^B per live broiler sold. We consider three cases for the price of frozen chicken; first, a price equal to a fixed broiler price plus a premium ($p^F = p^B + \alpha$); second, no price premium but with stochastic broiler prices ($p_t^F = p_t^B$) and lastly, stochastic broiler prices plus a price premium ($p_t^F = p_t^B + \alpha$). Our objective is to determine the nature of storage; whether it is used to sell a premium product (case 1), to strategically delay sales (case 2) or a combination of both (case 3).[7] Therefore, the decision to use the freezer will depend on storage costs driven by the stochastic supply of electricity from the grid and the increased reliance on generators for off-grid electricity. Formally, every week t, let s_{it} be the

[6] The quantity purchased of day-old chicks is the same as total stock sold when the bird reaches maturity. This assumption is supported by the fact farms do not report significant losses. On average, large-scale farms in our study area report a loss of 5 broilers (about 5% for the smallest medium farmer) per batch prior to sale.

[7] Based on data from poultry retailers in Oyo State, Nigeria, the average price of frozen chicken is approximately between ₦100-₦200 higher than that of a live broiler. The source of this premium can be attributed to additional processing of frozen chickens (cleaning, plucking of feathers, packaging). Since we lack historical data on frozen chicken prices, we consider two potential functions for frozen chicken.

proportion of the batch the farmer stores and/or sells, of the total q^B live broilers:[8]

$$s_{it} = \begin{cases} \mathrm{s}_{0t} \in [0,1], & \text{Store } s_{0t} \text{ of the batch, with replacement} \\ \mathrm{s}_{1t} \in [0,1], & \text{Sell } s_{1t} \text{ of the batch, with replacement} \end{cases}$$

After the broilers reach maturity, the farmer can either sell and/or store the batch or can indirectly choose to feed an additional period, by neither selling nor storing ($s_{0t} = 0$ and $s_{1t} = 0$). The farmer replaces the batch with new day old chicks when the batch is sold and/or stored. Conditional on having a stock of frozen chicken ($q_t^F > 0$), the farmer has the option to sell u_t shares of the frozen product from storage:

$$u_{1t} = \begin{cases} \mathrm{u}_{1t} = 0, & \text{Keep the stock frozen an additional period} \\ \mathrm{u}_{1t} \in (0,1], & \text{Sell } u_{1t} \leq q_t^F \end{cases}$$

We assume the farmer has limited growing and storage capacity. If the farmer wants to purchase more day old chicks, he must sell and/or freeze the complete batch of live birds, in the form of a binding constraint:[9,10]

$$s_{1t} + s_{0t} = 1 \tag{3.1}$$

If the farmer has a frozen stock, he must sell all of the frozen chicken in order to store more. In contrast to the live-batch case, farmers can sell partial amounts of their frozen stock if there is no storage in the current period ($u_{1t} < q_t^F$ if $s_{0t} = 0$).[11] Lastly, we assume farms

[8] Replacement refers to selling or storing the batch and buying a new batch of day-old chicks.

[9] However, when the farmer feeds the chicken, the constraint is not binding.

[10] This is consistent with anecdotal evidence from the field which indicates most poultry farms tend to sell their birds in batches.

[11] This is an important and necessary assumption. If the farmer is allowed to store more while having a frozen stock, the storage unit can potentially contain stocks of broilers slaughtered and stored at different ages. Since the return from sales of frozen chicken depends on the terminal age/weight of the bird, the model would have to track the final ages of the all stored batches, which is computationally intensive and can result in a intractable model.

have already invested in assets such as cages, chicken houses, and a generator, based on the summary statistics in Table 3.2.

The conditional reward function π_t depends on share of live broilers sold and/or stored and sales from cold storage:

$$\pi_t = r(w_t, p_t^B)s_{1t} + y(w_T, p_t^F)u_{1t} - (c(p^f, q_t^f) + p^D)q^B - e(z_t, h_t) - fc \tag{3.2}$$

$$c(p^f, q_t^f) = p^f q_t^f \tag{3.3}$$

$$q_t^f = (\beta_1 a_t^B + \beta_2 a_t^2 + \beta_3 a_t^3) \tag{3.4}$$

$$e(z_t, h_t) = (p^x x_t + (x^* - x_t)p^g) + p^d d + p^g g \tag{3.5}$$

$$fc = l(p_w, x_t, s_{it}) + m \tag{3.6}$$

Under π_t, the farmer receives a return $r(w_t, p_t^B)$ from selling live broilers, $y(w_T, p_t^F)$ from frozen sales, incurs feeding costs (equation 3.3), energy expenses (equation 3.5), and fixed costs (equation 3.6) that include labor $l(p^w, x_t, s_{it})$, and medical costs m.[12,13]

The return for live broiler sales is a function of the sale price (p_t^B) and the weight of the bird, $w(a_t^B)$. Weight each period evolves following a Richards growth function:[14]

$$w(a_t^B) = \frac{A}{\left(1 - e^{-\lambda a_t^b}\right)^{\frac{1}{m}}} \tag{3.7}$$

The return $y(w_T, p_t^F)$ per frozen chicken sold is a function of the terminal weight of the broiler (w_T) and the price of frozen chicken.

The feed cost function (equation 3.3) is increasing in quantity of feed bought q_t^f and the

[12] The labor function depends indirectly on the quantity of broilers (q^B) and the fixed wage rate (p^w).

[13] We assume the farmer incurs fixed vaccination and medical costs (m^B) every period. Based on the prophylactic measures Nigerian farmers employ, having weekly medical expenses is a reasonable assumption.

[14] See Appendix 2D for complete description. A = the asymptotic weight as age approaches infinity, k = the instantaneous relative growth rate (or maturing rate), b= constant, m = Richards function shape parameter.

feed price p^f, that is a cubic function of the age of the live broiler (a_t^B), as shown in equation 3.4. The price of feed in this paper is fixed. This is a necessary limitation, in order to add flexibility from energy variables and maintain a sensible state space.[15]

For the energy cost function (equation 3.5), we define a vector of energy prices $z_t = \{p^x, p^d, p^g\}$ and quantities $h_t = \{x_t, d_t, g_t\}$ where p^x corresponds to the price of electricity from the grid, p^d is the price of diesel, and p^g is the price of petrol/fuel. For the elements in the vector of energy quantities, x_t is the number of hours of on-grid electricity, d_t is the liters of diesel used, and g_t is the liters of diesel used to power the generator.

We assume the optimal amount of electricity needed to power the cold storage unit is $x^* = 168$; the farmer will need to power the freezer all week conditional on storage being positive (regardless of the quantity stored). All the electricity received from the grid is used and the remaining hours needed ($x^* - x_t$) are supplied by a diesel-powered generator. In addition to the costs of powering the freezer, if the number of hours of electricity from the grid falls below the average (40.8 per week), we assume the farmer will need to hire an additional employee to power the freezer during non-standard business hours.[16] By having an additional hired worker, the farmer can mitigate risk and reduce the uncertainty regarding when electricity was received (an unobserved source of uncertainty in the dataset). Lastly, we assume the hours of electricity from the grid received follow a binomial Markov process and either increase or decrease every week t by the same proportion, a common way of modeling stochastic processes.

[15] Earlier preliminary results showed the optimal decision did not vary much across the different 8 feed price states.

[16] Interactions with poultry farmers and retailers in Nigeria revealed that hiring an additional worker or extend work shifts are approaches currently used to manage powering the generator when electricity is down.

The farmer's objective function Π_t is:

$$\max_{s_{0t}, s_{1t}, u_{1t}} \Pi_t = \sum_{t=1}^{\infty} \beta^{t-1} E[r(w_t, p_t^B) s_{1t} + y(w_T, p_t^F) u_{1t} - (c(p_t^f, q_t^f) + p^D) q^B - e(z_t, h_t) - fc]$$

$$\text{s.t.} \quad a_{t+1}^B = p(a_t^B, s_t) \tag{3.8}$$

$$a_{t+1}^F = p(a_T^B, s_{0t}, u_{1t}) \tag{3.9}$$

$$w_{t+1}^B = n(w(a_t^B), s_t) \tag{3.10}$$

$$w_{t+1}^F = n(w(a_T^B), s_t, u_t) \tag{3.11}$$

$$Pr(p_{t+1}^f | p_t^f) \tag{3.12}$$

$$Pr(x_{t+1} | x_t) \tag{3.13}$$

$$q_{t+1}^F = q_t^F - u_{1t} \tag{3.14}$$

$$r(w_t, p_t^B) = 0 \text{ for } a_t^B < 5 \tag{3.15}$$

where β is the discount factor and equations (3.8)-(3.11) are the deterministic age and weight transition equations for live and frozen broilers, respectively. Equations (3.12) and (3.13) represent the conditional feed price and hours of electricity transition probabilities. Equation (3.14) is the frozen stock deterministic transition equation. Lastly, equation (3.15) is a market constraints for sale of birds less than 5 weeks.[17]

The age transition equation (3.8) for the live birds depends on s_t:

$$a_{t+1}^B = p(a_t^B, s_t) = \begin{cases} \mathrm{a}_t^B + 1, & \text{if } s_{0t} = 0 \text{ and } s_{1t} = 0 \\ 1, & \text{if } s_{0t} > 0 \text{ and/or } s_{1t} > 0 \end{cases}$$

For the frozen batch, the age transition equation (3.9) depends on the age of the batch when stored (the terminal period T) and whether the the batch remains in storage or is sold frozen:

[17] Anecdotal evidence from the field suggests there is no market for birds that have not reached a certain age/weight. In the context of Nigeria, the age of sale or storage should be at least 5 weeks, when the bird weights more than 1 kg.

$$a_{t+1}^F = p(a_t^B, s_{0t}, u_{1t}) = \begin{cases} \mathrm{a}_T^B = a_t^F, & \text{if } s_{0t} > 0 \text{ and } u_{1t} = q_t^F \\ \mathrm{a}_t^F, & \text{if } s_{0t} = 0 \text{ and } u_{1t} < q_t^F \\ 0, & \text{if } s_{0t} = 0 \text{ and } u_{1t} = q_t^F \end{cases}$$

The weight transition equation for live birds (equation 3.10) depends on the Richard's growth function (equation 3.7) and the choice sets s_t and u_t:

$$w_{t+1}^B = n(w(a_t^B), s_t) = \begin{cases} \mathrm{w}(\mathrm{a}_{t+1}^B), & \text{if } s_{0t} = 0 \text{ and } s_{1t} = 0 \\ \mathrm{w}(\mathrm{a}_t^B = 1), & \text{if } s_{0t} > 0 \text{ and/or } s_{1t} > 0 \end{cases}$$

The weight transition equation for the frozen stock (equation 3.11) depends on the terminal weight of the live batch (the weight when stored):

$$w_{t+1}^F = w(a_t^F)$$

The replacement storage model can be solved using discrete time, stochastic dynamic programming (M. Miranda and Fackler, 2002). We begin with a zero-value function and iterate to convergence on Bellman's equation:

$$\upsilon(k_t) = \max_{s_t, u_t} \left\{ \{\pi_t | (s_{0t}, s_{1t}, u_{1t})\} + \beta E_t[\upsilon(k_{t+1})] \right\} \tag{3.16}$$

where $k_t = [w_t^B, w_t^F, a_t^F, a_t^B, p_t^B, x_t]$ is a vector of state variables. We solve this infinite horizon problem recursively subject to the transition equations (3.8)-(3.15) and the constraints q_t^B. We apply the Newton Method to solve the optimization problem.

We hypothesize storage will be optimal if there is price premium α high enough to cover electricity expenses or if under a no premium condition, variation in weekly broiler prices can result in potential delay gains. In the latter, positive storage occurs if the gains from withholding sales through freezing outweigh feeding the batch an additional period.

3.3.2 Model 2: The Investment Decision

A representative poultry farmer is presented with the option to invest in an on-farm, cold storage unit (freezer) which will need to be powered by his generator when there is no electricity from the grid. Following the real options framework, we assume the value of the freezer is uncertain and investment decision is irreversible.

Even though a freezer is not an industry-specific asset, the irreversibility assumption holds because the resale value of the freezer depends on the uncertain supply of electricity from the grid and cost of alternative power sources. If electricity supply decreases or fluctuates more, prospective buyers could believe the investment will increase operating costs above the returns from using the freezer, therefore negatively affecting the resale value of the freezer.[18] In addition, we argue for the irreversibility of a freezer investment following Dixit and Pindyck's (1994) argument of the "lemons" problem in used machine markets (Akerlof, 1970). Potential buyers have imperfect information over the quality of used machines and sellers, who know the true value, are hesitant to sell an "above-average" items. This lowers market quality and sale price for the asset.

Without a freezer, the farmer sells the batch when they reach maturity in period t at price p_t^B per kg. Then, the discounted sum of returns from live broiler sales under no investment is N_t:

$$N_t = \sum_{t=1}^{\infty} \beta^{t-1} p_t^B q_t^B \tag{3.17}$$

If the farmer invests in a freezer, he can sell the batch the following period at a price $p_t^F = p_t^B + \alpha$. We write the net discounted sum of future returns from the freezer investment as the revenue from frozen chicken sales and the energy costs from operating the freezer, R_t:

$$R_t = \sum_{t=1}^{\infty} \beta^t p_t^F u_{t+1} - \beta^{t-1} E[e(z_t, h_t)] \tag{3.18}$$

This model formulates the objective function without the implicit feed-only choice. This simplification is inconsequential in this context because the farmer must incur growing costs

[18] There is an active second hand market for freezers in Nigeria, but it is expected irreversibility holds because of low resale values.

regardless of whether the investment is made. The uncertainty of the freezer investment comes from the stochastic number of hours of electricity received from the grid x_t. The farmer will insure against the risk of a power outage by hiring an additional employee when electricity supply is low.

An important assumption is that farmers have already invested in a generator and we focus only on the freezer investment cost. In the Nigerian context, the generator is essential to the adoption and use of a freezer, but its operating costs are also uncertain because of stochastic diesel prices p_t^d. We continue to assume hours of electricity continue to follow a binomial process while diesel price evolves by an AR(1) model. The transition probabilities are discussed in the parametrization section.

The investment decision then depends on the discounted premium (the difference between live and frozen product), the uncertainty from the freezer operating costs and the investment cost I. The Bellman equation can be expressed as the payoff in current period t plus the continuation value:

$$v(R_t, N_t) = \max\left\{ c_t(R_t - I) + (1 - c_t)N_t,\ \beta E_t[v(R_{t+1}, N_{t+1})] \right\} \tag{3.19}$$

where c_t is a binary control equal to 1 if the farmer invests in the freezer at time t. By iterating on the Bellman equation we will find the solution has the following form:

$$c_t = \begin{cases} 0 & \text{if } R_t - N_t - I \leq e^*(z_t, h_t) \quad (3.20) \\ 1 & \text{if } R_t - N_t - I > e^*(z_t, h_t) \quad (3.21) \end{cases}$$

The optimal policy is to invest when the value of the freezer (in terms of the return from frozen chicken sales) net the live broiler returns and the investment cost is greater than $e^*(z_t, h_t)$, the value of the energy cost function. We solve this infinite horizon problem recursively in MATLAB using the dynamic programming algorithm developed by M. Miranda and Fackler (2002). We apply the Newton Method to solve the optimization problem.

3.4 Data Sources

This paper uses three data sources from Ibadan, Oyo State, Nigeria. The first is a 2017 cross-sectional dataset on poultry farm operations and the second is a one-year, weekly panel data set of poultry farmers' input and output prices. The third dataset is a time-series on diesel prices from the National Bureau of Statistics (NBS) in Nigeria.

3.4.1 Data on Poultry Farmers

The cross-sectional dataset on poultry farmers includes questions on input purchasing decisions, chicken farm activities, input and output prices, sale locations, maize procurement and feed production, labor use, energy consumption, and shocks and coping strategies.

There are 365 farms that either produce only broilers or both broilers and layers from the 11 main poultry-producing Local Government Areas (LGAs) in Greater Ibadan. This paper only uses the information from broiler farms with a stock size greater than 100 broilers. We assume that households with at least 100 broilers are definitely part of the commercial industry and not engaged in bird production for consumption and informal sale to neighbors and family members.

Partitioning the data by flock size in 2016, there are 118 medium-sized farms with 100-1,000 broilers and 177 large farms with a stock size of more than 1,000 birds.[19] Medium and large-scale farms vary in terms of production practices and assets. A higher percentage of large-scale farms keep records and own trucks, bore holes, and generators. The marketing channels used to sell chicken also varies by farm size, with the majority of large farms selling to rural and town retailers and medium farms selling to neighbors and town retailers (Table 3.2). Only a small percentage of medium and large scale poultry farms store chicken in freezers.

[19]This relative characterization is maintained from Chapter 2 and is derived from the terciles of the data.

3.4.2 One Year, Weekly Panel Dataset on Input and Output Prices

The second data set contains weekly input and output prices, as well as sales of 100 poultry farmers in Ibadan, Oyo State. This panel data set is from a randomly selected sample from the total list of non-household farms in the study area. The data was collected weekly for one year between June 18th, 2017 and June 19th, 2018. The summary statistics demonstrate the average number of hours of electricity received from the grid is fairly low, at approximately 40 kwH per week[20] (Table 3.4) and fluctuating over time (Figure 3.1). Broiler prices do not appear to have a visible trend, but tend to be higher during the holiday season (Figure 3.2). We use the weekly data on hours of electricity and feed and broiler prices to calculate the transition probabilities for Model 1 and 2.

3.4.3 Monthly Diesel Prices (2016-2019)

We use data from the National Bureau of Statistics in Nigeria on monthly diesel prices from January 2016 to April 2019. The dataset is maintained for several regions in Nigeria, but we focus on monthly prices in Oyo State. Figure 3.3 displays the trend in prices over the three year period.

3.5 Parametrization of the Models

The base values of the parameters in Model 1 and 2 are summarized in Table 3.5. Each period represents a week and the maximum life of the chicken is set at 7 weeks.[21] We assume the weekly discount factor is between 0.98-0.995. The Central Bank of Nigeria (CBN) reports the interest rate is between 17.53% and 31.40% as of February 2018; if the maximum interest rate were imposed, that would still yield a weekly discount factor of 0.993. However, to allow for the possibility of informal credit at a higher interest rate than the one reported by CBN, we expand the range to include slightly smaller discount factors.

To reduce the dimensionality of the state and action space we discretize the proportion of

[20] Median number of hours is 46kwH.

[21] Most of the farmers in our sample slaughter the bird when it is between 5 and 8 weeks.

the batch the farmer can sell and store, hours of electricity and the broiler and diesel price vectors. The action space is then:

$$s_{0t}, s_{1t}, u_{1t} = [0, 0.5, 1],$$

and broiler price (Naira per kg) vector has 6 different prices:footnote₦360=$1

$$p_t^B = [900, 950, 1000, 1050, 1100, 1150]$$

Broiler prices are ₦50 increments from the lowest price reported; we discretize the price space to limit the curse of dimensionality. In the replacement with storage model, we maintain fixed energy prices (Table 3.5), but then relax this assumption for diesel prices in the real options model. We use 9 different values from ₦120 - ₦170 and increasing by ₦10:

$$p_t^d = [160, 170, 180, 190, 200, 210, 220, 230, 240]$$

We use a fixed price for day-old chicks equal to ₦200, the median price reported in the cross-section data set. We combine cost of medication and veterinary services into a single, fixed value and for the labor parameters, we utilize the average number of workers hired per week and the average wage from the cross-sectional data set.

3.5.1 Hours of Electricity from the Grid

We assume the hours of electricity from the grid evolve following a binomial Markov process, first formalized by Cox, Ross, and Rubinstein (1979):

$$x_{t+1} = \begin{cases} \theta x_t \\ \theta^{-1} x_t \end{cases}$$

for $\theta > 1$. The possible states for some initial number of hours of electricity x_0 is determined by the number of time periods T:

$$x = \{x_0 \theta^i | i = -T, -T+1, ..., -1, 0, 1, ...T-1, T\}$$

Then, we write the one-step transition probabilities as:

$$Prob(x_{t+1}|x_t) = \begin{cases} q, & \text{if } \mathrm{x}_{t+1} = \theta x_t \\ 1-q, & \text{if } \mathrm{x}_{t+1} = \theta^{-1} x_t \end{cases}$$

where $q \in [0,1]$ is the probability of an upward jump in the number of hours of electricity from the grid. Both θ and q can be computed using estimates of the drift and volatility parameters, μ and σ^2 and the time duration of a step τ:

$$\theta = e^{\sigma\sqrt{\tau}} \text{ and } q = 0.5 + \frac{\mu\sqrt{\tau}}{2\sigma} \tag{3.22}$$

To find μ and σ^2, we estimate the model:

$$x_t - x_{t-1} = \mu + \epsilon_t \tag{3.23}$$

We assume ϵ_t follows a normal distribution with mean zero and standard deviation σ_t. Using OLS, we use the constant as an estimate of μ and predict the residuals to get $\hat{\sigma_t}$. We find $\theta = 1.04$ and $q = 0.51$ following (3.22). Then we set $x_0 = 40.8$ (average hours of electricity per week), and to limit the state space, $T = 7$. The vector x_t possible hours of electricity from the grid is:

$$x_t = [27.1, 28.7, 30.4, 32.2, 34.1, 36.2, 38.4, 40.9, 43.5, 46.3, 49.4, 52.7, 56.4, 60.3]$$

3.5.2 Estimation of the Diesel and Live Broiler Price Transition Probabilities

Diesel and Broiler prices are assumed to follow a first-order autoregressive, stochastic price process:

$$p^i_{t+1} = \mu + \alpha_1 p^i_t + \epsilon_{t+1} \quad \text{for } i = d, B \tag{3.24}$$

where $\epsilon_{t+1} \sim N(0, \sigma^2_t)$. To derive the transition probabilities, we follow Lai, Myers, and Hanson (2003) and use Monte Carlo simulations. We start with the first price in the price state (₦160) and use it as the first value, p^d_t. Then we use the estimated model (24) to make random draws on ϵ_{t+1}. The simulated price gives the first realization of feed price in the next period. We repeat this process 10,000 times and keep count of the simulated prices. The transition probabilities are the relative frequency with which the simulated outcome falls in the price bin, conditional on an initial price level. We repeat the same steps for broiler prices. Tables 3.6 and 3.7 display the estimated probabilities.

3.6 Results for Replacement/Storage Model

For the replacement/storage model, we consider three possible cases for the price of live and frozen broilers. In the first case, we hold broiler price fixed and allow for a positive frozen chicken price premium. In the second and third case, we allow for stochastic broiler prices and consider optimal decisions under a premium and no premium condition, respectively. By deriving optimal decisions for each of the cases, we can determine the value of storage: either to sell a premium product at a later date or to delay sales when broiler prices are low. By considering different scenarios and exploring the effect of alternative price specifications on optimal decisions, we mitigate the limitation of not having historical data on frozen chicken prices.

3.6.1 Case 1: Fixed Broiler Price and Positive Frozen Chicken Premium

The results show that in the absence of variation in broiler prices, storage is not an optimal choice with low electricity supply from the grid. However, with a sufficiently high premium,[22] the effect of number of hours of on-grid electricity on optimal decisions diminishes. For example, under the lowest price premium (10% above median broiler price[23]), storage is never optimal for medium-sized farms (< 1,000 broilers). Farms will sell the complete batch of live broilers when the broilers are aged 5 weeks or older (Table 3.8). Storage is not an optimal choice because a 10% price increase per frozen chicken sold does not cover the freezer's electricity expenses. When the highest number of hours of electricity from grid is

[22] We consider four possible values for the frozen chicken price premium: ₦100, ₦125, ₦150, ₦200. These numbers were selected based on reported frozen chicken prices from the poultry retailer data set, collected at the same time as the poultry farmer cross-sectional dataset in Nigeria.

[23] The median broiler price is ₦1,000.

received (60 hours), the cost of running the freezer one week is ₦44,884 ($124), while the total revenue from the premium is equivalent to ₦43,000 ($118) given the average size of a medium-scale farm (stock of 430 broilers).

When the premium is 12.5% above the median live broiler price (₦125 per bird), storage is optimal when the farm receives more than 52 hours of electricity a week (30% more than the average hours typically received in Nigeria) and the batch is 5 weeks or older (Table 3.8). The increase in the premium makes storage more valuable when the cost from generator use are minimized. For every additional hour of on-grid electricity received, the farm saves 370 ($1) from not running the generator. Once the frozen chicken price is 15% above the median live broiler price, storage becomes optimal, even when on-grid hours of electricity is low. As the premium continues to increase, storage becomes a more viable option.

The results from case 1 confirm that when broiler prices are fixed, storage will be used as a way to capture a price premium by medium-scale farms. The cost of storage relative to live broiler sales is particularly important in this case, as we observe the optimal choice varying depending on the number of on-grid electricity hours.

For large farms, storage is always optimal at all price premiums considered (Table 3.9). The stock size of large farms makes the gains from storage much larger, since the premium is per chicken sold. These results are consistent even with a 50% increase to the cost of powering the freezer with a generator (assuming a larger generator is needed to power a cold room large enough to hold the complete stock). However, the assumption of fixed broiler prices is not a realistic assumption, given the seasonality of prices[24] (Figure 3.2).

[24] Seasonality is primarily due to higher prices during the holiday season in Nigeria.

3.6.2 Case 2: Stochastic Broiler Prices and No Frozen Chicken Premium

When we relax the fixed broiler price assumption and allow for stochastic prices, results suggests that in the absence of a price premium, storage decisions are equivalent to a strategy in which sale decisions are delayed based on realizing a low broiler price. In this case, the number of hours of electricity received from the grid appear to be largely irrelevant to sale and storage decisions. Contrary to case 1, for most of the broiler prices considered,[25] there is no variation in optimal decisions across the number of hours of electricity received. These results are consistent between medium and large-scale farms, with the only difference between both types of farms being the timing of sale and storage decisions.

Specifically, we find medium-sized farms will feed the broilers until the batch is 6 weeks old and store in week 7 (Table 3.10), if broiler prices are low ($\leq$ ₦1,000) and there is no frozen chicken price premium. The delay in storage until the terminal age of the broiler allows for a longer fattening process to compensate for the low broiler price. Under the same broiler price states, if the cold storage unit has a positive stock, the farmer will not sell the stock while growing the live batch; frozen chicken sales will only happen in week 7 when the live batch is ready to be sold.

When broiler prices increase (₦1,100, ₦1,150), it is optimal to sell the boilers live, beginning in week 6 and 5, respectively (Table 3.10). The farmer will also sell his frozen stock (if available) while growing the batch, to take advantage of the high broiler price state. This confirms the strategy of delaying sales through storage, until a high broiler price is realized.

For large-scale farms, the optimal decisions remain the same, but the timing of sale and storage are different those for medium-scale farms. The variation in the timing of sale is driven by the differences in stock size; if large-scale farms withhold sales, the gains from a longer fattening period might not compensate the additional, higher feeding costs (Table 3.11).

[25]With the exception of ₦900 for large-scale farms.

3.6.3 Case 3: Stochastic Broiler Prices and Positive Frozen Chicken Premium

When broiler prices are stochastic and there is a premium on frozen chicken prices, we find that both electricity supply and broiler prices matter. Overall, these results demonstrate that electricity supply and broiler prices have an effect on sale and storage decisions. If the premium and broiler prices are low, storage is used as an delay strategy (as in case 2) but with electricity supply affecting the timing of storage decisions. Similar to case 1, with a high enough premium storage is always optimal even if there is low electricity supply.

For example, when the premium equals ₦100 (10% above the median live broiler price), we find that the average medium-size farm facing the lowest broiler price (₦900), will delay storage and frozen chicken sale decisions depending on the amount of frozen stock. When the frozen stock is zero, it is optimal to store beginning in week 6 if the farm receives less than 40 hours of electricity per week and week 5 otherwise. If the farm has half a batch stored, it is optimal to sell the frozen stock and restock the freezer beginning when the live broiler batch is 6-weeks old, irrespective of the electricity supply. When a complete batch is in storage, the farmer will sell from storage and restock in week 7 (Table 3.12). A potential reason driving different optimal decisions by frozen stock size could be that in a low broiler price state, the loss in expected revenue (net of additional feed costs) is larger when the freezer is full, thus resulting in frozen sale delays.

As broiler prices increase, the optimal decision is to start the storage process sooner (with 40 hours of electricity determining if storage starts at week 5 or 6) and whether to sell the available frozen stock while growing the batch or delay until the terminal week (Table 3.12). If broiler prices increase enough, the delay in cold storage sales we observed when broiler price equaled ₦900 does not happen. At higher prices, medium-scale farmers do not engage in longer fattening periods and store based on whether they must hire an additional laborer to mitigate low electricity.

Lastly, when broiler price is the beyond 15% the median live broiler price, it is optimal to sell the complete batch live starting in week 5 (Table 3.12). Given the high broiler price realized, there is no delay of live broiler sales through storage or longer fattening periods. If the farmer has a positive frozen stock, the optimal decision is to sell while growing the live batch, confirming the farmer will take advantage of the high broiler price. As the price premium increases, the optimality of live sales decreases and the influence of the number of hours of electricity on the optimal decision disappears.

We observe a similar trend for large scale farms that face a 10% price premium beyond the median live broiler price. As broiler prices increase, the optimal of storage time shifts from week 7 to week 5. However, for large firms, it is never optimal to sell the broilers live due to the larger gains from storage, given stock size differences. The farm will always chose to store, independent of broiler prices and the number of hours of electricity (Table 3.13).

The results from the three cases evaluated demonstrate that storage can result in positive gains to farmers in the form of a premium or delayed sales when faced with low broiler prices. We use case 3 in the investment model since it most accurately depicts the reality of broiler farmers in Nigeria.

3.7 Investment Model Results

The results from the investment model reveal that given the current price of freezers, it is not optimal for poultry farms to make large freezer investments. Even though there are positive gains from cold storage, such as a price premiums and potentially higher future broiler prices, these are not sufficient for medium or large scale farms to optimally make a freezer investment.

In this model, we use stochastic prices and a frozen chicken price premium (case 3), since it is consistent with the reality of poultry farmers in Nigeria, given seasonality in broiler prices and cross-sectional data on frozen chicken prices. We also relax the assumption of a fixed diesel price, and consider optimal investment decisions under more complex but realistic operating costs.

3.7.1 Medium-Sized Farms

With up to a 20% premium above the median live broiler price, we find it is never optimal to invest in a freezer, given current operating and investment costs. A medium-sized farm with a stock size of 430 broilers would need a 700L deep chest freezer with an estimated cost of ₦230,000 ($634), but can only afford to invest up to ₦40,000 ($110), conditional on receiving a high number of hours of electricity from the grid (Table 3.14).

3.7.2 Large-Scale Farms

While large-scale farms are in a better position to make larger investments, the results from the model reveal investing in a cold room would not be optimal. A farm with approximately 4,000 birds needs a cold room to fit the complete batch or 9 deep chest 700L freezers. A cold room of the necessary capacity (8x8x8 ft/5 tons of product) is priced between ₦2.6 - ₦3 million ($7,192-$8,298). The maximum the farm can invest is ₦690,000 ($1,903), conditional on receiving a 20% frozen chicken price premium above the median live broiler price, realizing a low diesel price, and high number of hours of electricity (Table 3.15). If the freezer costs ₦650,000 ($1,792), the investment is optimal under all broiler prices and electricity states.

As expected, hours of electricity, diesel prices, and the investment cost had an effect on whether the farm should purchase a freezer. This is consistent with the current behavior of Nigerian farmers; on average, only 1% (4%) of medium (large)-scale farmers freeze and store chicken (Table 3.2).

3.8 Conclusion

As food systems across Africa transform and farms become more commercialized, their energy needs expand. Poor and unstable electricity supply increases the operational costs of firms due to the increased reliance on generator power and high diesel prices. This article employs a discrete state and control space, discrete time dynamic programming model to analyze the effect of low and variable electricity supply on optimal storage and investment decisions of poultry farms in Nigeria.

Our results demonstrate the importance of electricity supply for storage decisions. We find evidence in favor of cold storage, particularly when broiler prices are low. When broiler prices are fixed, the size of the frozen chicken price premium and the average number of hours of electricity received were important determinant of storage decisions. With no premium and variable broiler prices, storage was found to be used to delay sales and take advantage of higher expected prices in the future. In this case, both medium and large scale farms stored in low broiler price states and sold the batch live otherwise. Combining stochastic broiler prices with a positive frozen chicken premium, we find that storage is optimal under higher price premium regardless of the current broiler price. Finally, the investment model results reveal that although storage is a positive venture for farmers to increase revenue and capture price premiums, both medium and large farms in Nigeria are not in a position to invest in brand-new cold storage technologies, given current freezer prices and operation costs. Our findings are consistent with the cross-sectional data-set that shows very few farms (both medium and large) own and operate freezers.

Given the positive gains from storage in terms of increased sale flexibility and higher output prices (through investments in value added products), efforts to make old storage affordable for poultry farmers could significantly improve the profitability of the poultry sub-sector. If farmers could purchase the cold storage technology at a reduced price (through a government subsidy or by access to cheaper, domestically produced freezers) the decision to invest would be feasible and could trigger an expansion of the poultry value chain. Selling a cold/frozen product, farmers can expand sales into distant markets and reach segments of consumers interested in processed poultry products. Another policy implication is the need for improved infrastructure for electricity generation and supply. Reliable access to electricity would help mitigate high operating costs, resulting in even larger gains from storage and increased investment.

The findings of this research (and its implications) are applicable across developing countries in Africa and Latin America that face scarce electricity supply and are in the process of expanding commercialized agricultural value chains as a way to increase farm incomes and stimulate economic growth.

APPENDICES

APPENDIX 3A: Tables

Table 3.1: Evidence from 2014 World Bank Enterprise Survey (WBES) in Nigeria

	All Countries	SSA	Nigeria
Firms experiencing electrical outages (%)	57.4	77.5	77.6
Number of electrical outages in a typical month	7	8.9	32.8
Average duration of a electrical outage (hours)	4.8	5.7	11.6
Average losses due to electrical outages (% of sales)	5.1	8.3	15.6
Percent of firms owning or sharing a generator	34.5	52.6	70.7
Proportion of electricity from a generator (%)	20.2	29.1	58.8
Days to obtain an electrical connection	37.9	38.1	9.4
Firms identifying electricity as major constraint (%)	30.5	40.5	48.4
Firms experiencing water insufficiencies (%)	14.8	22.7	16.4
Number of water insufficiencies in a typical month	1.2	1.9	2.5
N			2676

Table 3.2: Summary Statistics of Broiler Farmers by Farm Size in 2016

	Medium-Sized Farms (101-1000 birds)		Large Farms (1000 birds)	
VARIABLES	Mean	Std. Dev.	Mean	Std. Dev.
Management Characteristics				
Sex (Male=1, Female=0)	0.49	0.5	0.56	0.5
Age	50.05	13.55	47.94	11.06
Year business started	2011	0.41	2010	0.45
Keep records of expenditures (0/1)	0.2	0.4	0.56	0.5
Training in chicken production (0/1)	0.2	0.4	0.38	0.49
Production Practices				
Buy inputs, assemble own feed (0/1)	0.26	0.44	0.26	0.44
Buy chicken feed (0/1)	0.76	0.43	0.87	0.33
Freeze and store chicken meat (0/1)	0.01	0.1	0.04	0.2
Contract with poultry processor (0/1)	0.04	0.19	0.17	0.38
Deliver chicks to market or buyer (0/1)	0.51	0.5	0.38	0.49
Package chicken meat to retail (0/1)	0	0	0.05	0.23
Use vitamins (0/1)	0.47	0.5	0.71	0.46
Use medicines (0/1)	0.47	0.5	0.74	0.44
Chicken Characteristics				
Flock size in 2016	330.14	240.68	3,325.00	2,288.87
Average weight of broiler sold (kg)	2.47	1.32	2.87	1.13
Minimum weight of broiler sold (kg)	1.88	0.71	2.33	0.74
Maximum weight of broiler sold (kg)	2.32	0.9	3	0.7
Selling Channels				
Sold to neighbors (%)	35.91	41.05	14.9	23.96
Sold to rural retailers (%)	23.43	35.4	23.82	30.95
Sold to town retailers (%)	35.61	40.98	39.96	39.63
Sold to processors (%)	2.78	15.07	10.12	26
Sold to supermarkets (%)	1.01	10.05	0.66	2.9
Sold to northern wholesalers (%)	0	0	0.54	5.19
Sold to southern wholesalers (%)	1.26	9.02	10	26.37
Private Assets				
Own cages (0/1)	0.22	0.42	0.5	0.5
Number of trucks owned	0.03	0.17	0.4	0.83
Number of freezers owned	0.02	0.14	0.13	0.39
Number of freezers rented	0	0	0.02	0.13
Own well (0/1)	0.89	0.31	0.69	0.47
Own bore hole (0/1)	0.06	0.24	0.35	0.48
Own a bird slaughtering facility (0/1)	0.01	0.1	0.04	0.19
Own a generator (0/1)	0.15	0.36	0.6	0.49
Own a solar panel (0/1)	0	0	0.01	0.08
N	118		177	

Table 3.3: Summary Statistics of Energy Use by Farm Size in 2016

	Medium Farms (101-1000 birds)		Large Farms (>1000 birds)	
VARIABLES	Mean	Std. Dev.	Mean	Std. Dev.
Total spent on electricity from the grid (₦)	1,279.5	1,470.4	2,462.3	3,021.3
Quantity of electricity used (kWh/month)	69.5	100.1	81.0	122.9
Price of on-grid electricity (₦/kWh)	23.3	3.2	23.4	3.5
Keep track of generator expenses (0/1)	0.1	0.3	0.4	0.5
Monthly diesel expenses for generator (%)	3.5	14.0	10.6	18.2
Monthly fuel expenses for generator (₦)	2,736.1	3,356.0	8,926.5	9,655.4
Price of fuel (₦/Liter)	144.1	15.5	143.4	12.4
Monthly transportation expenses (₦)	1,333.3	2,737.9	6,554.6	6,574.3
Price of diesel (₦/Liter)	172.5	17.7	170.9	35.5
Average monthly solar energy expenses	0.0	0.0	0.0	0.0
Price of solar energy supply (₦/kWh)			25.0	.
Farms that use electricity (%)	0.5	0.5	0.3	0.5
Electricity needs that come from the grid (%)	67.2	33.4	41.4	28.7
Electricity needs that come from generator (%)	28.6	31.3	49.1	31.0
On-grid electricity used to power freezers (%)	4.2	11.5	9.5	19.1
Hours a day generator runs*	4.1	4.1	5.4	3.6
Capacity of generator (KVA)	9.5	8.3	9.5	6.9
Have petrol costs (0/1)	0.2	0.4	0.4	0.5
Diesel costs from maize dryer (%)	0.0	0.0	0.0	0.0
Diesel costs from pumping water (%)	16.0	35.8	18.8	23.9
Diesel costs from lighting (%)	74.0	37.2	62.5	25.0
Diesel costs from freezers (%)	0.0	0.0	6.3	12.5
N	118		177	

Table 3.4: Summary Statistics for Farms in Ibadan, Oyo State (One-year data set)

	Oyo State	
VARIABLES	Mean	Std. Dev.
Price of live broiler (₦/kg)	985.8	297.2
Price of branded feed (₦/kg)	140.3	13.0
Price of self-made feed (₦/kg)	126.9	21.2
Price of diesel (₦/liter)	171.6	14.9
Price of fuel (₦/liter)	151.3	15.7
Price of electricity from the grid (₦/kwh)	23.5	0.2
Number of liters needed to power the generator for an hour	1.5	0.5
Number of hours of electricity received per week	40.5	11.3

Note: 1 USD = 360 Nigerian Naira (₦)

Table 3.5: Baseline Values for the Model

Description	Value
Weekly discount rate	0.993
Maximum age of the bird (weeks)	7
Price of the day-old chick (₦)	200
Broiler price (₦/kg)	1,000
Frozen chicken price premium (₦/broiler)	[0,100,125]
Average total medical cost for medium farms (₦/week)	892
Average total medical cost for large farms (₦/week)	1,820
Labor wage rate (₦/week)	3000
Average number of employees hired by medium farms	2
Average number of employees hired by large farms	6
Asymptotic weight of the bird (kg)	5.97
Median stock size for medium farms in 2016 (# of broilers)	430
Median stock size for large farms in 2016	3,898
Price of diesel (₦/liter)	186.37
Price of fuel (₦/liter)	142.17
Price of electricity from the grid (₦/kWh)	24
Diesel used by medium farms (liters/week)	16.26
Diesel used in large farms (liters/week)	32.91
Fuel used per week in medium farms (liters/week)	6.80
Fuel used per week in large farms (liters/week)	17
Number of liters necessary to power generator for an hour	2
Value for $\hat{\mu}$ and $\hat{\sigma}$ for log hours of electricity	0.017, 0.11

Note: 1 USD = 360 Nigerian Naira (₦)

Table 3.6: Diesel Price Transition Probabilities

	160	170	180	190	200	210	220	230	240
160	.3918	.3587	.1891	.0522	.0079	.0003	0	0	0
170	.1335	.3039	.3312	.1751	.0487	.0071	.0005	0	0
180	.03	.1508	.3099	.3022	.156	.0432	.007	.0009	0
190	.0064	.0446	.1809	.3152	.2719	.1353	.0384	.0067	.0006
200	.0001	.009	.0702	.2067	.3139	.2478	.1158	.0303	.0062
210	0	.0018	.0187	.092	.237	.2937	.2224	.101	.0334
220	0	.0002	.0038	.0297	.1226	.2534	.2768	.1956	.1179
230	0	0	.0004	.0077	.0449	.1483	.2577	.2731	.2679
240	0	0	0	.0008	.0135	.0683	.1766	.269	.4718

Table 3.7: Broiler Price Transition Probabilities

	p900	p950	p1000	p1050	p1100	p1150
p900	0.6587	0.3086	0.0319	0.0008	0	0
p950	0.174	0.5166	0.2781	0.0305	0.0008	0
p1000	0.0116	0.216	0.496	0.2469	0.0281	0.0014
p1050	0.0005	0.0225	0.2429	0.478	0.2282	0.0279
p1100	0	0.0008	0.0364	0.2734	0.4632	0.2262
p1150	0	0	0.0013	0.052	0.3035	0.6432

Table 3.8: Case 1 Results for Medium-Scale Farms

Hours of Electricity (e_t)	Optimal Decisions Storage=0	 Storage=0.5	 Storage=1
₦100 Price Premium			
$\forall\, e_t$	$s_{1t} = 1$ for $a_t^B \geq 5$	$s_{1t} = 1$ for $a_t^B \geq 5$ $u_{1t} = 0.5$ for $a_t^B \geq 1$	$s_{1t} = 1$ for $a_t^B \geq 5$ $u_{1t} = 1$ for $a_t^B \geq 1$
₦125 Price Premium			
$e_t < 52$	$s_{1t} = 1$ for $a_t^B \geq 5$	$s_{1t} = 1$ for $a_t^B \geq 5$ $u_{1t} = 0.5$ for $a_t^B \geq 1$	$s_{1t} = 1$ for $a_t^B \geq 5$ $u_{1t} = 1$ for $a_t^B \geq 1$
$e_t > 52$	$s_{0t} = 1$ for $a_t^B \geq 5$	$s_{0t} = 1$ for $a_t^B \geq 5$ $u_{1t} = 0.5$ for $a_t^B \geq 1$	$s_{0t} = 1$ for $a_t^B \geq 5$ $u_{1t} = 1$ for $a_t^B \geq 1$
₦150 Price Premium			
$e_t \leq 36$	$s_{1t} = 1$ for $a_t^B \geq 5$	$s_{1t} = 1$ for $a_t^B \geq 5$ $u_{1t} = 0.5$ for $a_t^B \geq 1$	$s_{1t} = 1$ for $a_t^B \geq 5$ $u_{1t} = 1$ for $a_t^B \geq 1$
$e_t > 36$	$s_{0t} = 1$ for $a_t^B \geq 5$	$s_{0t} = 1$ for $a_t^B \geq 5$ $u_{1t} = 0.5$ for $a_t^B \geq 1$	$s_{0t} = 1$ for $a_t^B \geq 5$ $u_{1t} = 1$ for $a_t^B \geq 1$
₦200 Price Premium			
$\forall\, e_t$	$s_{0t} = 1$ for $a_t^B \geq 5$	$s_{0t} = 1$ for $a_t^B \geq 5$ $u_{1t} = 0.5$ for $a_t^B \geq 1$	$s_{0t} = 1$ for $a_t^B \geq 5$ $u_{1t} = 1$ for $a_t^B \geq 1$

Note: 1 USD = 360 Nigerian Naira (₦), p_t^b is broiler price, s_{1t} refers the proportion of the batch sold, s_{0t} is the share of the batch stored, u_{1t} is the share of the batch sold frozen, and a_t^B is the age of the live batch. For example, under a ₦100 frozen chicken price premium and for all number of hours of electricity evaluated, if there is no frozen stock (storage=0), the farmer will sell the complete batch ($s_{1t} = 1$) when the batch is at least five weeks old ($a_t^B \geq 5$).

Table 3.9: Case 1 Results for Large-Scale Farms

Hours of Electricity (e_t)	Optimal Decisions Storage=0	Storage=0.5	Storage=1
₦100, ₦125, ₦150, ₦200 Price Premium			
$\forall\, e_t$	$s_{0t} = 1$ for $a_t^B \geq 5$	$s_{0t} = 1$ for $a_t^B \geq 5$ $u_{1t} = 0.5$ for $a_t^B \geq 1$	$s_{0t} = 1$ for $a_t^B \geq 5$ $u_{1t} = 1$ for $a_t^B \geq 1$

Note: 1 USD = 360 Nigerian Naira (₦), p_t^b is broiler price, s_{1t} refers the proportion of the batch sold, s_{0t} is the share of the batch stored, u_{1t} is the share of the batch sold frozen, and a_t^B is the age of the live batch.

Table 3.10: Case 2 Results for Medium-Scale Farms

Hours of Electricity (e_t)	Optimal Decisions Storage=0	 Storage=0.5	 Storage=1
If broiler price (p_t^b) equals ₦900, 950, 1,000:			
27.2	$s_{0t} = 1$ for $a_t^B = 7$	$s_{0t} = 1$ for $a_t^B = 7$ $u_{1t} = 0.5$ for $a_t^B \geq 6$	$s_{0t} = 1$ for $a_t^B = 7$ $u_{1t} = 1$ for $a_t^B = 7$
$e_t \geq 28.7$	$s_{0t} = 1$ for $a_t^B = 7$	$s_{0t} = 1$ for $a_t^B = 7$ $u_{1t} = 0.5$ for $a_t^B = 7$	$s_{0t} = 1$ for $a_t^B = 7$ $u_{1t} = 1$ for $a_t^B = 7$
If broiler price (p_t^b) equals ₦1,100:			
$\forall\, e_t$	$s_{1t} = 1$ for $a_t^B \geq 6$	$s_{1t} = 1$ for $a_t^B \geq 6$ $u_{1t} = 0.5$ for $a_t^B \geq 1$	$s_{1t} = 1$ for $a_t^B \geq 6$ $u_{1t} = 1$ for $a_t^B \geq 1$
If broiler price (p_t^b) equals ₦1,150:			
$\forall\, e_t$	$s_{1t} = 1$ for $a_t^B \geq 5$	$s_{1t} = 1$ for $a_t^B \geq 5$ $u_{1t} = 0.5$ for $a_t^B \geq 1$	$s_{1t} = 1$ for $a_t^B \geq 5$ $u_{1t} = 1$ for $a_t^B \geq 1$

Note: 1 USD = 360 Nigerian Naira (₦), p_t^b is broiler price, s_{1t} refers the proportion of the batch sold, s_{0t} is the share of the batch stored, u_{1t} is the share of the batch sold frozen, and a_t^B is the age of the live batch.

Table 3.11: Case 2 Results for Large-Scale Farms

Hours of Electricity (e_t)	Optimal Decisions Storage=0	Storage=0.5	Storage=1
If broiler price equals ₦900, 950, 1,000:			
$e_t \leq 40.9$	$s_{0t} = 1$ for $a_t^B \geq 6$	$s_{0t} = 1$ for $a_t^B = 7$ $u_{1t} = 0.5$ for $a_t^B = 7$	$s_{1t} = 1$ for $a_t^B = 7$ $u_{1t} = 1$ for $a_t^B = 7$
$e_t > 40.9$	$s_{0t} = 1$ for $a_t^B \geq 5$	$s_{0t} = 1$ for $a_t^B = 7$ $u_{1t} = 0.5$ for $a_t^B = 7$	$s_{1t} = 1$ for $a_t^B \geq 5$ $u_{1t} = 1$ for $a_t^B = 7$
If broiler price equals ₦1,050:			
$e_t < 43.5$	$s_{0t} = 1$ for $a_t^B \geq 6$	$s_{0t} = 1$ for $a_t^B \geq 6$ $u_{1t} = 0.5$ for $a_t^B \geq 6$	$s_{1t} = 1$ for $a_t^B = 7$ $u_{1t} = 1$ for $a_t^B = 7$
$e_t = 43.5$	$s_{0t} = 1$ for $a_t^B \geq 5$	$s_{0t} = 1$ for $a_t^B \geq 6$ $u_{1t} = 0.5$ for $a_t^B \geq 6$	$s_{1t} = 1$ for $a_t^B \geq 5$ $u_{1t} = 1$ for $a_t^B = 7$
$e_t \geq 46.3$	$s_{0t} = 1$ for $a_t^B \geq 5$	$s_{0t} = 1$ for $a_t^B \geq 6$ $u_{1t} = 0.5$ for $a_t^B \geq 6$	$s_{1t} = 1$ for $a_t^B = 7$ $u_{1t} = 1$ for $a_t^B = 7$
If broiler price equals ₦1,100:			
$e_t \leq 41$	$s_{0t} = 1$ for $a_t^B \geq 6$	$s_{0t} = 1$ for $a_t^B \geq 6$ $u_{1t} = 0.5$ for $a_t^B \geq 1$	$s_{0t} = 1$ for $a_t^B \geq 6$ $u_{1t} = 1$ for $a_t^B \geq 6$
$e_t \geq 43.5$	$s_{0t} = 1$ for $a_t^B \geq 5$	$s_{0t} = 1$ for $a_t^B \geq 5$ $u_{1t} = 0.5$ for $a_t^B \geq 1$	$s_{0t} = 1$ for $a_t^B \geq 6$ $u_{1t} = 1$ for $a_t^B \geq 6$
If broiler price equals ₦1,150:			
$\forall\, e_t$	$s_{1t} = 1$ for $a_t^B \geq 5$	$s_{1t} = 1$ for $a_t^B \geq 5$ $u_{1t} = 0.5$ for $a_t^B \geq 1$	$s_{1t} = 1$ for $a_t^B \geq 5$ $u_{1t} = 1$ for $a_t^B \geq 1$

Note: 1 USD = 360 Nigerian Naira (₦), p_t^b is broiler price, s_{1t} refers the proportion of the batch sold, s_{0t} is the share of the batch stored, u_{1t} is the share of the batch sold frozen, and a_t^B is the age of the live batch.

Table 3.12: Case 3 Results for Medium-Scale Farms (Price premium is ₦100)

Hours of Electricity (e_t)	Optimal Decisions Storage=0	 Storage=0.5	 Storage=1
If broiler price equals ₦900, 950			
$e_t \leq 41$	$s_{0t} = 1$ for $a_t^B \geq 6$	$s_{0t} = 1$ for $a_t^B \geq 5$ $u_{1t} = 0.5$ for $a_t^B \geq 6$	$s_{0t} = 1$ for $a_t^B = 7$ $u_{1t} = 1$ for $a_t^B = 7$
$e_t \geq 43.5$	$s_{0t} = 1$ for $a_t^B \geq 5$	$s_{0t} = 1$ for $a_t^B \geq 5$ $u_{1t} = 0.5$ for $a_t^B \geq 6$	$s_{0t} = 1$ for $a_t^B = 7$ $u_{1t} = 1$ for $a_t^B = 7$
If broiler price equals ₦1,000			
$e_t \leq 41$	$s_{0t} = 1$ for $a_t^B \geq 6$	$s_{0t} = 1$ for $a_t^B \geq 6$ $u_{1t} = 0.5$ for $a_t^B \geq 1$	$s_{0t} = 1$ for $a_t^B = 7$ $u_{1t} = 1$ for $a_t^B = 7$
$e_t \geq 43.5$	$s_{0t} = 1$ for $a_t^B \geq 5$	$s_{0t} = 1$ for $a_t^B \geq 5$ $u_{1t} = 0.5$ for $a_t^B \geq 1$	$s_{0t} = 1$ for $a_t^B \geq 6$ $u_{1t} = 1$ for $a_t^B \geq 6$
If broiler price equals ₦1,050, 1,100			
$e_t \leq 41$	$s_{0t} = 1$ for $a_t^B \geq 6$	$s_{0t} = 1$ for $a_t^B \geq 6$ $u_{1t} = 0.5$ for $a_t^B \geq 1$	$s_{0t} = 1$ for $a_t^B = 7$ $u_{1t} = 1$ for $a_t^B = 7$
$e_t \geq 43.5$	$s_{0t} = 1$ for $a_t^B \geq 5$	$s_{0t} = 1$ for $a_t^B \geq 5$ $u_{1t} = 0.5$ for $a_t^B \geq 1$	$s_{0t} = 1$ for $a_t^B \geq 6$ $u_{1t} = 1$ for $a_t^B \geq 6$
If broiler price equals ₦1,050, 1,100			
$\forall e_t$	$s_{1t} = 1$ for $a_t^B \geq 5$	$s_{1t} = 1$ for $a_t^B \geq 5$ $u_{1t} = 0.5$ for $a_t^B \geq 1$	$s_{1t} = 1$ for $a_t^B \geq 5$ $u_{1t} = 1$ for $a_t^B \geq 1$

Note: 1 USD = 360 Nigerian Naira (₦), p_t^b is broiler price, s_{1t} refers the proportion of the batch sold, s_{0t} is the share of the batch stored, u_{1t} is the share of the batch sold frozen, and a_t^B is the age of the live batch.

Table 3.13: Case 3 Results for Large-Scale Farms (₦100 Price premium)

Hours of Electricity (e_t)	Optimal Decisions Storage=0	Storage=0.5	Storage=1
If broiler price (p_t^b) equals ₦900:			
$e_t \leq 34.1$	$s_{0t} = 1$ for $a_t^B \geq 5$	$s_{0t} = 1$ for $a_t^B = 7$ $u_{1t} = 0.5$ for $a_t^B = 7$	$s_{0t} = 1$ for $a_t^B = 7$ $u_{1t} = 1$ for $a_t^B = 7$
If broiler price (p_t^b) equals ₦950, 1000:			
$e_t \leq 32.2$	$s_{0t} = 1$ for $a_t^B \geq 5$	$s_{0t} = 1$ for $a_t^B \geq 6$ $u_{1t} = 0.5$ for $a_t^B \geq 6$	$s_{0t} = 1$ for $a_t^B = 7$ $u_{1t} = 1$ for $a_t^B = 7$
If broiler price (p_t^b) equals ₦1050:			
$\forall\, e_t$	$s_{0t} = 1$ for $a_t^B \geq 5$	$s_{0t} = 1$ for $a_t^B \geq 5$ $u_{1t} = 0.5$ for $a_t^B \geq 5$	$s_{0t} = 1$ for $a_t^B \geq 6$ $u_{1t} = 1$ for $a_t^B \geq 6$
If broiler price (p_t^b) equals ₦1100:			
$\forall\, e_t$	$s_{0t} = 1$ for $a_t^B \geq 5$	$s_{1t} = 1$ for $a_t^B \geq 5$ $u_{1t} = 0.5$ for $a_t^B \geq 1$	$s_{0t} = 1$ for $a_t^B \geq 5$ $u_{1t} = 1$ for $a_t^B \geq 5$
If broiler price (p_t^b) equals ₦1150:			
$\forall\, e_t$	$s_{0t} = 1$ for $a_t^B \geq 5$	$s_{0t} = 1$ for $a_t^B \geq 5$ $u_{1t} = 0.5$ for $a_t^B \geq 1$	$s_{0t} = 1$ for $a_t^B \geq 5$ $u_{1t} = 1$ for $a_t^B \geq 1$

Note: 1 USD = 360 Nigerian Naira (₦), p_t^b is broiler price, s_{1t} refers the proportion of the batch sold, s_{0t} is the share of the batch stored, u_{1t} is the share of the batch sold frozen, and a_t^B is the age of the live batch.

Table 3.14: Optimal Investment Decisions of Medium-Scale Farm when I = ₦40,000

	Broiler Prices (₦/kg)			
	900	950	1,000-1,050	≥1,100
e_t				
≤ 41	0	0	0	0
43.5	1 if $d_t = 160$	0	0	0
46.3	1 if $d_t = 160$	1 if $d_t = 160$	1 if $d_t = 160$	0
49.3	1 if $d_t = 160$	1 if $d_t = 160$	1 if $d_t = 160$	1 if $d_t = 160$
52.6	1 if $d_t = 160, 170$	1 if $d_t = 160, 170$	1 if $d_t = 160$	1 if $d_t = 160$
56.2	1 if $d_t = 160, 170$	1 if $d_t = 160, 170$	1 if $d_t = 160, 170$	1 if $d_t = 160, 170$
60.8	1 if $d_t = 160, 170, 180$	1 if $d_t = 160, 170, 180$	1 if $d_t = 160, 170$	1 if $d_t = 160, 170$

Note: 1 USD = 360 Nigerian Naira (₦) and d_t is diesel price.

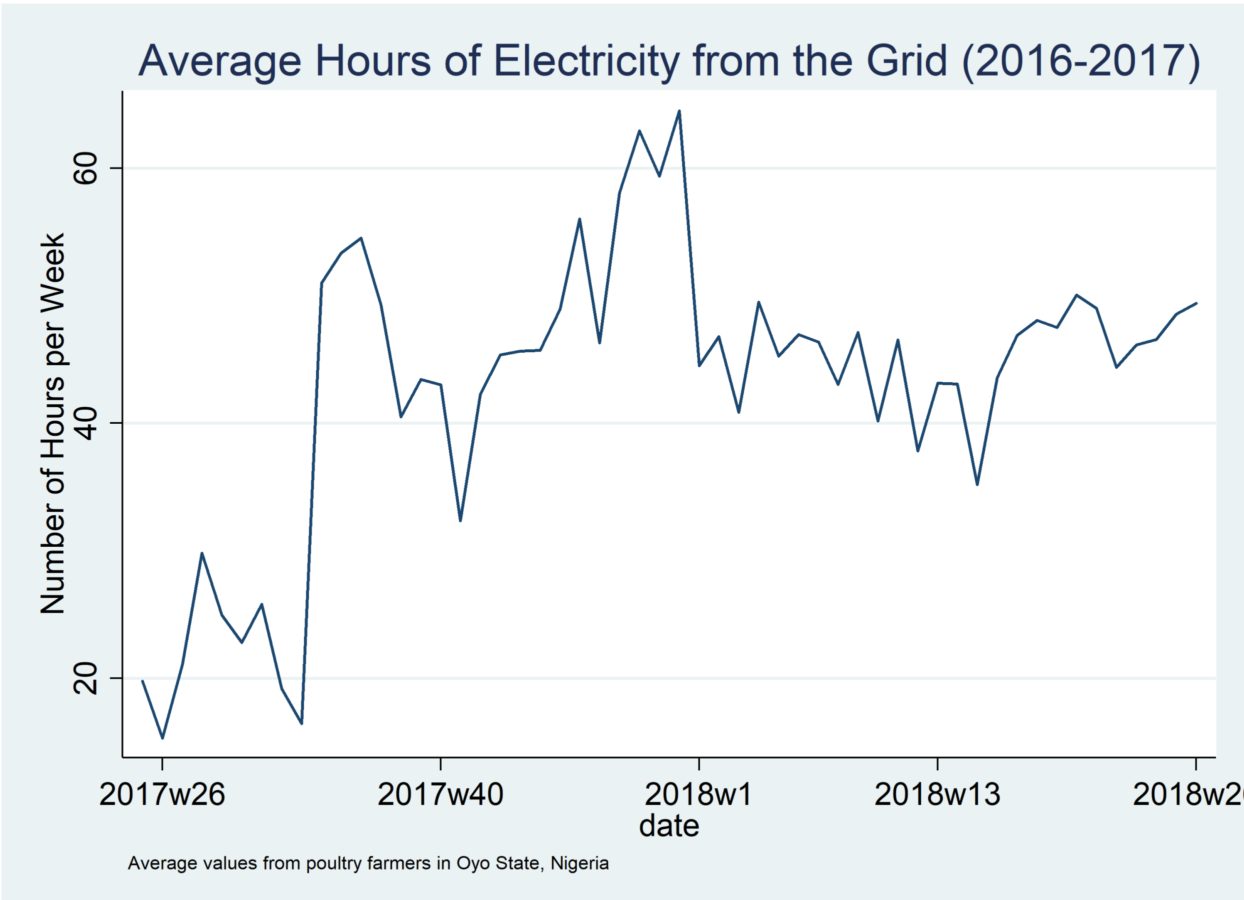
Table 3.15: Optimal Investment Decisions of Large-Scale Farm when I = ₦690,000

	Broiler Prices (₦/kg)				
	900	950	1,000	1,050	≥1,100
e_t					
≤ 36.2	0	0	0	0	0
38.4	1 if $d_t = 160$	0	0	0	0
40.9	1 if $d_t = 160$	0	0	0	0
43.5	1 if $d_t = 160$	0	0	0	0
46.3	1 if $d_t = 160, 170$	1 if $d_t = 160$	0	0	0
49.3	1 if $d_t = 160, 170$	1 if $d_t = 160$	0	0	0
52.6	1 if $d_t = 160, 170$	1 if $d_t = 160$	1 if $d_t = 160$	0	0
56.2	1 if $d_t = [160, 180]$	1 if $d_t = 160, 170$	1 if $d_t = 160$	0	0
60.8	1 if $d_t = [160, 190]$	1 if $d_t = [160, 180]$	1 if $d_t = 160, 170$	1 if $d_t = 160$	0

Note: 1 USD = 360 Nigerian Naira (₦) and d_t is diesel price.

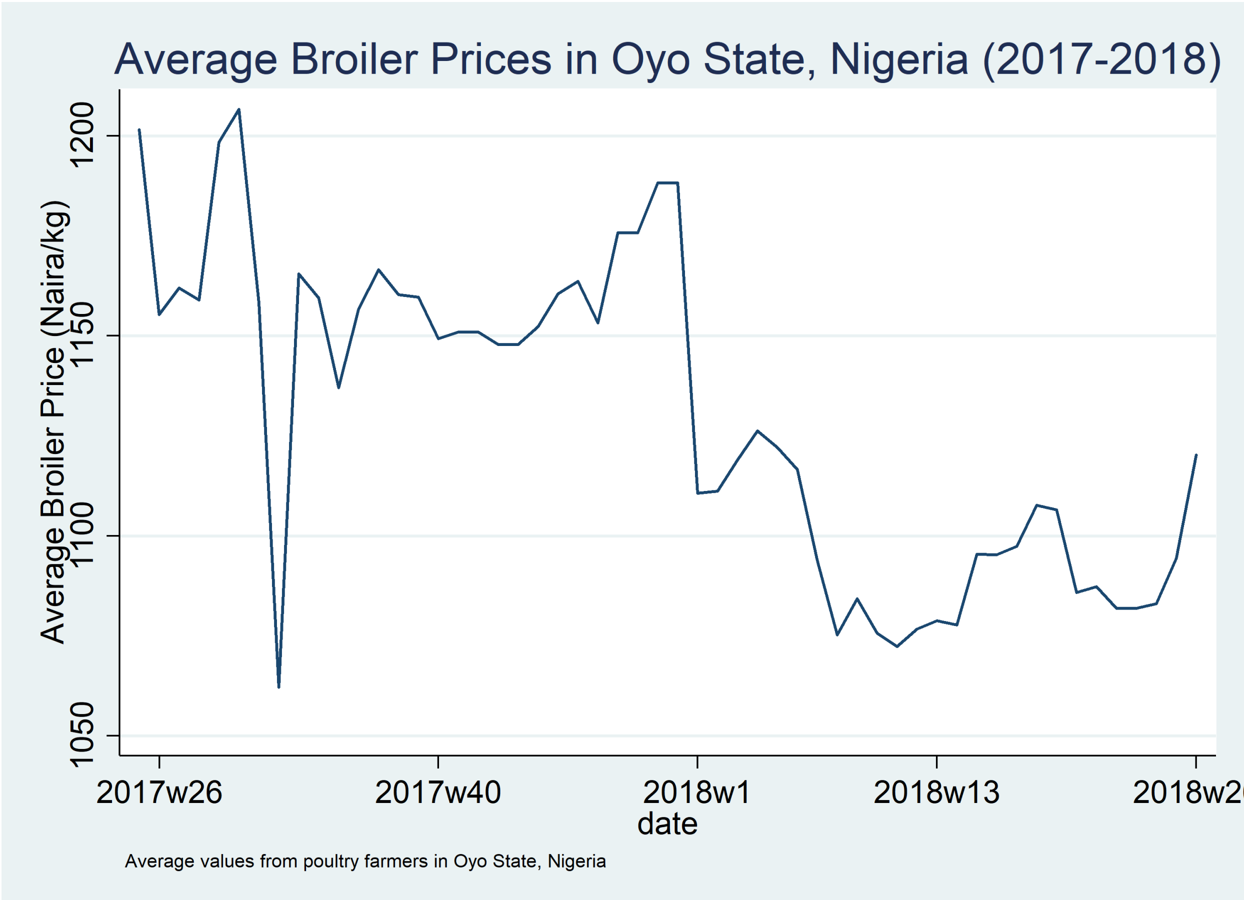
APPENDIX 3B: Figures

Figure 3.1: Average Hours of Electricity from the Grid (2016-2017)



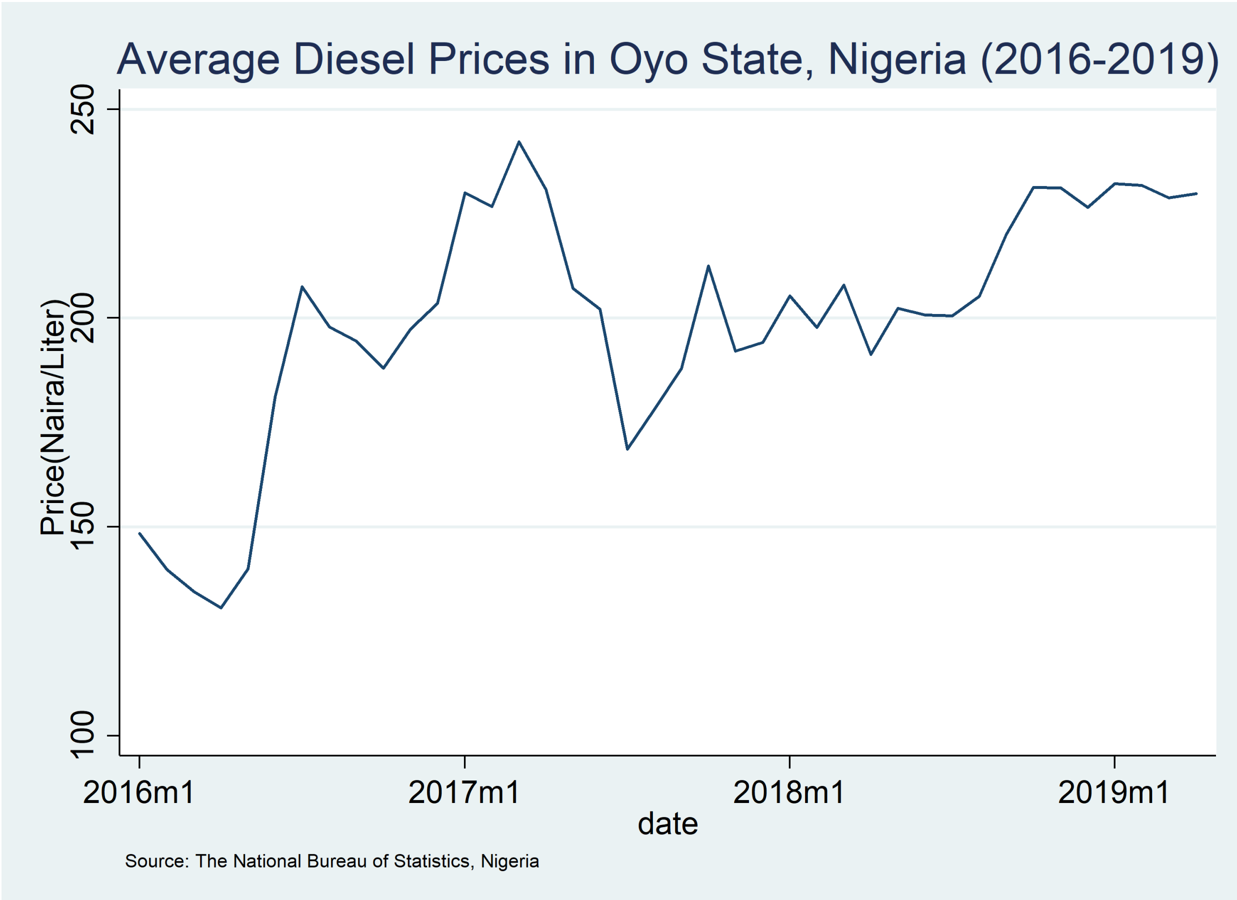
From the primary collected weekly panel data set, we see large variation in the number of hours of electricity received. The lowest amount was approximately 19 hours, and the highest at approximately 65, during the holiday season in December.

Figure 3.2: Average Broiler Prices in Oyo State, Nigeria (2017-2018)



Broiler Prices in Naira/kg in 2017-2018. There appears to be a spike in prices around the holiday season (week 45-week 1, 2018).

Figure 3.3: Average Diesel Prices in Oyo State, Nigeria (2016-2019)



Using data from the National Bureau of Statistics, we graph diesel prices over time in Oyo State, Nigeria. In 2016, diesel prices were at its lowest (less than ₦150) and since then have been mostly increasing.

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