Three Essays in Development Economics

by

Godwin Kwesi Nutsugah

(Under the Direction of Ellen McCullough)

Abstract

This dissertation examines how behavioral biases, producer–consumer linkages, and household constraints shape agricultural and labor decisions in sub-Saharan Africa. Chapter 1 tests whether weather-induced recency bias lowers fertilizer use among Nigerian maize farmers. Using nationally representative panel data merged with historical rainfall, I show that—conditional on past profit (proxied by livestock accumulation and the prior season's maize price)—recent rainfall shocks significantly influence current fertilizer use even though shocks are serially uncorrelated and transitory; the effect is also negatively asymmetric, with prior negative shocks reducing fertilizer use more than prior positive shocks increase it. Chapter 2 quantifies bias in consumer demand estimation when the farm profit effect—the additional income producers receive when staple prices rise—is ignored. Using consumption data from Malawi, I compare elasticities and simulated outcomes from the standard Exact Affine Stone Index (EASI) and fully interacted EASI models to a preferred agricultural household EASI model that incorporates the profit effect by endogenizing real total expenditure. Chapter 3 studies how child health (stunting) affects mothers' labor supply in Malawi. Instrumenting stunting with in-utero exposure to extreme heat, I find that poor child health reduces maternal farm-wage participation—especially for sons—while other labor margins show no effect and maternal education remains a strong predictor of work.

Index words: Development Economics, Recency Bias, Fertilizer Adoption, Rainfall Shocks, Nigeria, Malawi, Profit Effect, EASI Model, Food Demand, Maize Farming, Child Health, Maternal Labor, Agricultural Households, Instrumental Variables

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Dedication

I dedicate this dissertation to the three most important women in my life: my mother, Afia Akyaa; my first fruit, Britney Akyaa Nutsugah; and to you, who I promised you this Ph.D., among other things, on January 18, 2018, a promise I did not keep. Please find it in your heart to forgive me.

As always: **8.... 3......1**.

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I will never forget the early support of my beloved sisters, Evelyn Sarkodie and Philomena Sarkodie, who stood by my education from kindergarten through the University level. One day, I hope to repay your love and kindness. May every day be a blessing to you and your children. And to all my brothers and sisters, God bless you.

My deepest gratitude goes to my host parents in Fredericksburg, VA, Lionel and Gertrude Nortey. You have been there whenever I needed you. As I type this under your roof, may God bless you with a long life, good health, and prosperity in all you do and in the lives of your children. To Gilda, Jayden, and Zion Nortey: because of how well your parents treated me, I owe you a lifetime.

Finally, borrowing from my supervisor's dissertation acknowledgments: I have been fortunate to study at some of the world's leading institutions. I am profoundly grateful for the opportunities this education has given me, and I pledge, on my honor, to use them in service of those who have not been as fortunate.

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Chapter 1

Recency Effect of Weather Shocks on Fertilizer Adoption: Evidence from Nigeria

1.1 Introduction

A fundamental question in development economics is whether smallholder farms in low-income countries are managed optimally or whether behavioral factors systematically limit agricultural productivity. An extensive literature has documented that behavioral constraints such as intra-household bargaining failures (C. Doss, 2013; Duflo & Udry, 2004; Udry, 1996a), hyperbolic discounting and time-inconsistent preferences (Duflo et al., 2011), and cognitive burdens associated with poverty (Mani et al., 2013) cause smallholders to deviate from standard profit-maximizing behaviors. These behavioral constraints are particularly critical in rainfed agricultural systems, where optimal management depends on expectations about weather and where productivity is highly sensitive to shocks (M. R. Rosenzweig & Udry, 2020).

Beyond these known constraints, recent evidence in psychology and economics shows that people often display recency bias, giving too much weight to recent events when forming expectations even when those events have little predictive value (Hogarth & Einhorn, 1992; Kahneman, 2011; Kahneman & Tversky, 1979; Tversky & Kahneman, 1973). Although widely observed in the insurance literature, the role of recency bias in farm management in developing countries has received little attention. This paper studies the role of weather-induced recency bias—the tendency to overweigh recent weather when forming expectations about the upcoming season—in the context of the adoption of agricultural technologies in developing countries.

I study this new behavioral channel that has not yet been used to explain technology adoption low- and middle-income countries. Specifically, I examine the effect of weather-induced recency bias on households' decision to use fertilizer, a powerful input for raising agricultural productivity (Evenson & Gollin, 2003; Pingali, 2012). I focus on Nigeria, where agriculture depends on rainfall and productivity is sensitive to weather variability (Ajetomobi et al., 2015). Thus, I ask, can recent rainfall shocks explain low fertilizer adoption through behavioral channels (the recency effect)? Maize farming provides an ideal case study in Nigeria because it is one of the three most important cereal crops, along with sorghum and millet, providing employment and improving food security across households(Liverpool-Tasie et al., 2017; USAID, 2010). Consequently, reduced fertilizer adoption driven by weather uncertainty could pose a major threat.

This research question is important for the following reasons. First, fertilizer use rate in Nigeria by larger extend sub-Saharan Africa is low, lagging behind the rest of the world. The average fertilizer application rate in SSA is only 14 kg/ha, considerably below the application rates in South Asia (141 kg/ha), the European Union (154 kg/ha), South America (175 kg/ha) and East Asia (302 kg/ha) (see Figure 1.1) (FAO, 2021). Although existing explanations for this phenomenom highlight both economic and agronomic factors, such as credit, institutions, climatic and soil conditions[1], behavioral explanations—how farmers' perceptions, biases, and expectations shape their decisions—remain underexplored. Second, fertilizer use decisions must be made before or early in the growing season, at a time when actual weather conditions are still uncertain. Without timely and reliable forecasts, farmers may form expectations about

[1] See Suri et al., 2024 for a comprehensive review.

upcoming weather based primarily on recent experiences. Third, while weather shocks, both current and past, are known to depress agricultural productivity in SSA (Jones & Thornton, 2003; Ortiz-Bobea et al., 2021), little is known about how the expectations formed after such shocks reduce fertilizer adoption.

Using nationally representative household panel data merged with geo-referenced historical rainfall data, I first test the presence of recency bias by checking whether recent rainfall shocks (lags of 1 to 5 years) have a larger influence on current fertilizer use outcomes than distant shocks (defined block averages for the past 6-10, 11-15, 16-20, and 21-25 years). For each household location, I define rainfall shocks as standardized deviations (z-scores) from the long-term mean. To rule out liquidity constraints as a confounding channel, I control for the previous season's maize price and livestock accumulation (in Tropical Livestock Units) between the beginning of the calendar year and the end of the growing season. I also include a rich set of household-, plot-, and community-level covariates to absorb unobserved factors that might correlate with both lagged rainfall shocks and fertilizer use. Conditional on these controls, I treat rainfall shocks as plausibly exogenous, following common practice in the literature. Finally, I define a recency effect as present if at least one coefficient on recent shocks is significant, while the corresponding coefficients on distant shocks are not.

I find that recent rainfall shocks, not distant shocks, drive fertilizer decisions even after I control for past profits. In my preferred specification, a one standard deviation (SD) increase in last season's rainfall shock (t-1) raises the likelihood of adopting fertilizer in the current season by 7.5 percentage points (pp), while shocks from t-2 to t-5 and more distant periods have no detectable effects. Similar results hold in my least preferred specification. A 1 SD increase in last season's rainfall shock also raises fertilizer application by 16.55 kg/acre (about 19% of the sample mean), with negligible effects from intermediate or distant shocks. These results are consistent with my conceptual framework, in which behavioral farmers overweight recent weather when forming expectations about the coming season, even though rainfall shocks are exogenous and transitory. For them, past rainfall affects current input use through two channels: a liquidity channel (lower yields and income last season) and a behavioral channel (recency bias). In contrast, a rational farmer who does not anchor his beliefs on recent weather would adjust inputs only through the liquidity channel.

After establishing that recency bias is present, I then turn to the central question of this study which is weather weather-induced recency can help explain the low level of fertilizer use. To answer this, I show that the impact of recency bias on fertilizer use is asymmetric, that is, households cut fertilizer use more after bad weather than they increase it after good weather, hence on average leads to overall reduction in fertilizer use. Empirically, I follow similar methods in Kaur, 2019. For each location, I construct three rainfall shock dummies for last season: a negative shock dummy (below the 25th percentile), a positive shock dummy (above the 75th percentile), and a no-shock dummy (between the 25th and 75th percentiles) based on the historical distribution. Using the "no shock" last season as my omitted category, I estimate the same fertilizer use model described above but with positive and negative rainfall shock dummies as my main variable of interest. The coefficients on these dummies are therefore interpreted relative to a no-shock prior season.

I find that, conditional on past profit, a negative rainfall shock last season reduces the probability of fertilizer use this season by 9.3 percentage points relative to a no-shock last season. A positive shock last season is associated with a 4.3 percentage point decrease, but this estimate is imprecise. Unconditional application rates show a similar pattern: a negative shock last season lowers use by about 28 kg/acre, while the increase after a positive shock (about 19.87 kg/ha) is not statistically significant. These results are robust to alternative definitions of rainfall shocks. Heterogeneity analysis shows that the asymmetry is strongest among low-income households; in a setting like Nigeria, where weather volatility is common and is projected to worsen (Ajetomobi et al., 2015; Amanchukwu et al., 2015), these households are especially vulnerable to recency bias. Together, negative rainfall shocks reduce fertilizer use more than positive shocks increase it, demonstrating how recency bias may contribute to persistently low fertilizer use.

I probe the main behavioral mechanism and rule out alternatives. The results suggest that maize households act as if rainfall shocks are serially correlated and use last season to form expectations for the next, likely because rainfall strongly affects contemporaneous yields. In my setting, however, rainfall shocks are serially uncorrelated and transitory, so last season does not predict next season's yield. I then test whether reduced fertilizer use after a negative shock reflects broad discouragement from farming; the evidence points the other way. Recency effects are associated with a net increase in the likelihood of planting maize next season, in total farm size, and in the share of land allocated to maize, with positive shocks raising these outcomes more than negative shocks reduce them. This pattern is consistent with belief formation that wrongly assumes serially correlated rainfall rather than exit from farming. A low-cost information program that tells farmers that last season's rainfall does not predict next season, paired with timely seasonal forecasts delivered by SMS or through extension programs, can help them rely less on recent experience and keep fertilizer use steady even after bad weather.

This paper relates to the literature on behavioral constraints to adoption of agricultural technology in developing countries. Recent studies show that present bias (Duflo et al., 2011), misperceptions about input quality (Michelson et al., 2021), beliefs about soil quality (Harou & Tamim, 2024) and the environment (Zappala, 2024), and inflated expectations about new technologies (Miehe et al., 2025) can limit input use and slow productivity growth. In the case of fertilizer, (Michelson et al., 2021) finds that in Tanzania marketed fertilizer generally meets nutrient standards, yet farmers believe that the quality is poor. These pessimistic beliefs lower farmers' willingness to pay; when the fertilizer is lab-verified, willingness to pay increases. On average, farmers offer about 48% less for untested urea than for tested urea. Building on these studies, I add a new unexplored behavioral explanation for low fertilizer adoption in a developing country setting by showing that farmers overweight very recent rainfall when deciding whether and how much fertilizer to apply, even though these shocks are transitory and not predictive of the next season. This study is closely related to Zappala, 2024, who examine how drought beliefs and their accuracy affect irrigation in Bangladesh by eliciting beliefs with a binary question asking farmers whether drought has increased. Although the study links low irrigation adoption to inaccurate beliefs, it does not examine how those beliefs are formed or through which mechanisms they arise, a limitation the authors note. I focus on one plausible mechanism, weather-induced recency, and present evidence consistent with farmers forming expectations from recent weather realizations.[2] These findings suggest that simple information policies that explain last season's rainfall is a poor signal for the next season, combined with timely seasonal forecasts, can help farmers form accurate expectations and keep fertilizer use at efficient levels.

This paper also speaks to the broad literature on the effect of farmers' behavioral responses induced by climate-related shocks on agricultural productivity (Gallagher, 2014; Huang et al., 2024; Jagnani et al., 2021; Karlan et al., 2014; Sesmero et al., 2018; Zappalà, 2023). In Ghana, Karlan et al., 2014 shows that providing insurance against rainfall shocks increased risky, but higher-return, agricultural investments such as fertilizer purchases. Demand for such insurance spiked following recent poor rainfall in the community, suggesting farmer decisions are influenced by recent weather experiences, potentially overweighting these events in their risk calculations. In a comparable setting, Huang et al., 2024 find that positive rainfall shock last season leads low-productivity farmers in China to considerably reduce the area of land rented out, increase the time allocated to farm work, and decrease the time allocated to off-farm work, implicitly suggesting recency bias. Although Huang et al., 2024 did not explicitly account for the associated effect of farmers' liquidity on factor allocation, they argue that this effect is fully explained by farmers' irrational response to exogenous rainfall shocks. Using information on household livestock accumulation and the previous season's maize price, I control for liquidity constraints as a channel through which weather shocks could affect fertilizer use. I then compare recent and distant shocks within the same framework, conditioning on past profit. Specifically, I estimate the effects of shocks from the last one to five years alongside block averages from six to twenty-five years prior and find that only the prior season's shocks affect fertilizer use. This design strengthens the interpretation of recency bias, since much of the literature infers recency from recent events alone without testing against distant shocks.

Lastly, this paper highlights a broader set of channels through which weather shocks negatively affect smallholder farmers by highlighting their role in limiting the adoption of productivity-enhancing technologies. Existing studies in this area have largely attributed the effects of lagged weather shocks on current input use to income or liquidity channels (Alem et al., 2010; Bora, 2022; Dercon & Chris-

[2] Other cognitive processes, such as availability bias (Gallagher, 2014) and motivated reasoning or confirmation bias (Zappalà, 2023), may also shape decisions, but the available data do not allow me to test these mechanisms in this setting.

tiaensen, 2011; Heisse & Morimoto, 2024). Alem et al., 2010 finds that favorable rainfall in Ethiopia increases fertilizer adoption by improving yields and, in turn, farmers' ability to purchase inputs. Similarly, Heisse and Morimoto, 2024 associate extreme temperature events with reduced fertilizer use in subsequent seasons, potentially due to income effects, while acknowledging the need for deeper research into the behavioral factors influencing smallholder decisions. In contrast, I provide evidence that households' fertilizer choices respond to recent weather even after I explicitly control for past profits, which challenges the view that liquidity alone explains the response. The results imply that negative rainfall shocks reduce fertilizer use through both liquidity and belief formation, and that studies focusing only on liquidity may misattribute part of the behavioral effect to liquidity. Hence policy tools aimed at reducing the adverse effects of weather shocks through liquidity enhancing measures, such as credit access, may be ineffective unless combined with interventions addressing the effect of recency, such as providing timely and accurate weather forecasts.

The remainder of the paper is organized as follows. Section 1.2 lays out the conceptual framework. Section 1.3 describes the data and methods. Section 1.4 presents the empirical framework and identification strategy. Section 3.4 reports the results. Section 1.6 discusses how recency bias could explain low fertilizer use, and Section 1.7 explores the behavioral mechanisms behind the results. Section 1.8 briefly discusses the economic implications of recency, and Section 3.7 concludes with policy recommendations.

1.2 Conceptual Framework

This section develops a simple conceptual framework for how past rainfall shocks can shape current fertilizer decisions. I contrast two ways farmers can form expectations about this season's weather: a rational benchmark that uses the full history without overweighting recent draws, and a behavioral rule that places extra weight on recent shocks (recency). I also allow for liquidity constraints, which are common when rural credit markets are imperfect.

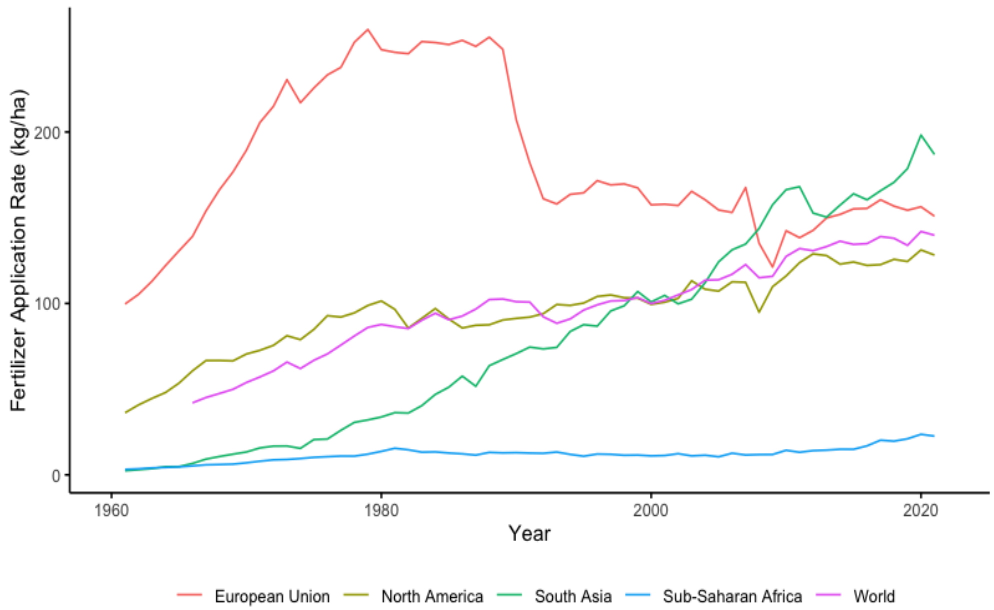


Figure 1.1: Fertilizer application rate (kg/ha of arable land) by region.

Source: World Development Indicators (2023)

Setup. To conceptualize the role of the recency effect in households' fertilizer use, I consider a simple farm model with financial market failures so that households face a liquidity constraint. I start with a risk–neutral, price–taking maize farmer who chooses fertilizer at the start of season t to maximize expected current profit. Let π_t denote profit, q_t output, X_t an $M \times 1$ input vector, w_t' the corresponding $1 \times M$ price vector, P_t^M the maize price, and z_t the (anticipated) rainfall outcome relevant for production. The farmer faces a standard borrowing limit tied to last season's realized profit. Formally:

$$\begin{aligned} &\max_{X_t} \; E_t(\pi_t) = \max_{X_t} \; E_t\big(P_t^M \, q_t - w_t' X_t\big) \quad \text{s.t.} \\ &q_t = F(X_t; z_t), \\ &w_t' X_t \leq \pi_{t-1}^*(w_{t-1}, P_{t-1}^M; z_{t-1}), \\ &X_{i,t} \geq 0, \end{aligned} \tag{1.1}$$

where $F(\cdot)$ is twice continuously differentiable and concave in inputs and rainfall. The third equation sets a borrowing constraint on the acquisition of inputs in the current season. That is, the farmer's expenditure on inputs should not exceed last season's profit π^*_{t-1}. This borrowing constraint reflects the financial market failures prevalent in developing countries, where imperfect rural credit markets that force farmers to finance inputs from past profits (Conning & Udry, 2007; Croppenstedt et al., 2003). For tractability, I take fertilizer to be the only variable input (so X_t can be read as fertilizer) with price w_t.

Given an interior solution, the first–order condition with respect to fertilizer is:

$$E_t\left[P_t^M \frac{\partial F(\cdot)}{\partial x_t} - w_t\right] \; - \; \lambda w_t \; = \; 0, \tag{1.2}$$

where λ is the multiplier on the borrowing constraint. This delivers the reduced-form fertilizer demand at the start of season t:

$$X_t^* \; = \; f\big(E_t(P_t^M),\; E_t(w_t),\; \pi^*_{t-1}(w_{t-1}, P^M_{t-1}; z_{t-1});\; E_t(z_t)\big). \tag{1.3}$$

Equation (1.3) highlights two pathways through which rainfall can matter: via expected rainfall $E_t[z_t]$ (beliefs) and via last season's profit π^*_{t-1} (liquidity). Since the farmer is a price taker ($E_t(P_t^M) \; = \; P_t^M$ and $E_t(w_t) = w_t$), the only uncertainty steering optimal fertilizer choice is expected rainfall $E_t[z_t]$.

Expectations: rational vs. behavioral. There is empirical support for the idea that behavioral farmers form beliefs about weather based on adaptive expectations. Previous research indicates that behavioral farmers react to biophysical events and patterns, such as local climate and weather, over both short and long terms, which in turn influences production decisions (Morton et al., 2017; Nerlove, 1958). Although in a different context, Wilke and Morton, 2017 show that farmers in the Mid-western US base their future climate and weather expectations on references to past historical events and cycles. In contrast, a rational benchmark would base expectations on the full historical distribution at the location, without placing excess weight on the most recent realization. When rainfall shocks are serially uncorrelated, last season's shock carries no special predictive power under the rational rule[3].

Therefore, following Ramsey et al., 2021, I consider a process whereby behavioral farmers form beliefs about current season's weather based on past seasons as follows:

$$E_t[z_t] = S(p_l; z_{t-1}, z_{t-2}, \ldots, z_{t-L}); l = 1, 2, \ldots, L \tag{1.4}$$

where p_l is the weight that behavioral farmers assigns to previous weather observations and $S(*)$ is a weighting function.

In forming perceptions about current weather, behavioral farmers are likely to generalize distant past observations, a simplification strategy rooted in cognitive ease (Kahneman, 2011). This approach would be consistent with the psychological principle of recency effect, wherein recent memories are more vivid while earlier ones tend to decay over time (Ebbinghaus, 2013; Murdock Jr, 1962). Consequently, I assume that the weight assigned to past weather observation stabilizes after period $t - b$, such that from $t - (b + 1)$ onward, the household assign equal weights on weather observations (i.e., $p_{b+1} = p_{b+2} = \cdots = p_L = p^a$). As an example, Figure 1.2 shows how a typical behavioral farmer assigns weight to past rainfall observations can stabilize from starting period $t - (b + 1)$.

Thus I can simplify equation (2.4) as:

$$E_t[z_t] = p_l S(z_{t-1}, z_{t-2}, \ldots, z_{t-b}) + p^a S(z_{t-(b+1)}, \ldots, z_{t-L}); l = 1, \ldots, b \tag{1.5}$$

where p_l is weight assigned to the recent past time periods $t-1$ to $t-b$ and p^a is the equal weight assigned to the more distant past up to time horizon L. Thus, I expect the weight a behavioral farmer places on past weather observation to be monotonically increasing in time t.

The weight placed on past events will depend on factors such as cognitive processes, level of ambiguity, and other considerations (Hogarth & Einhorn, 1990). For instance, a behavioral farmer might respond

[3] This is consistent with the objective processing of information in a Bayesian setting, where individual prior beliefs do not affect the interpretation of information

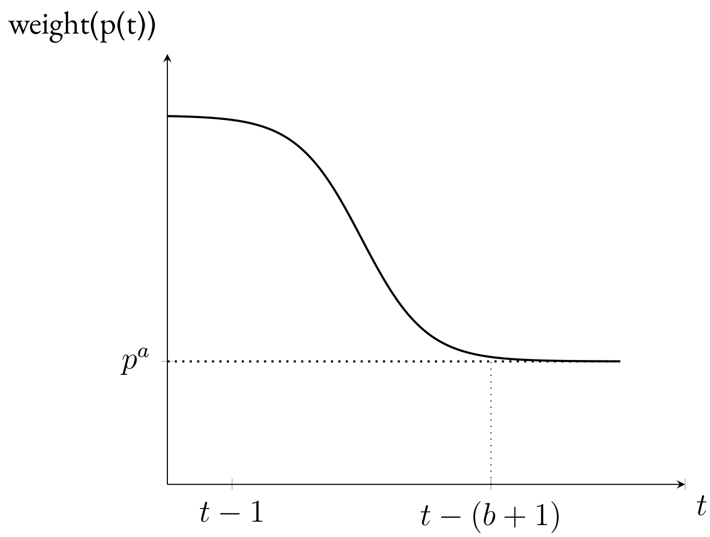


Figure 1.2: Illustration of How Households May Assign Weights to Past Weather Observations
Note: The figure depicts how behavioral farmers may assign weights to past weather observations when forming expectations about current weather conditions. The horizontal axis indicates time periods relative to the current period t, while the vertical axis shows the weight $p(t)$ assigned to each past period's weather outcome. The curve demonstrates that households place larger weights on recent weather observations ($t-1$ to $t-b$) and that the weights decrease and stabilize at a constant value p^a for more distant past periods ($t-(b+1)$ to $t-L$).

sensitively to a higher-than-normal rainfall intensity last season, if the farmer considers it as a signal of larger rainfall occurring this season or consider it as a signal of lower-than-normal rainfall occurring. The behavioral farmer's current weather expectation would be fully informed by the previous season's weather if it places larger weight on previous weather events.

Recency effect. Substituting the behavioral belief rule into fertilizer demand gives

$$X_t^* = f\left(P_t^M,\ w_t,\ \pi_{t-1}^*(w_{t-1}, P_{t-1}^M, z_{t-1}),\ E_t[z_t] = S(p_\ell; z_{t-1}, \dots, z_{t-L})\right), \quad \ell = 1, \dots, L. \tag{6}$$

Here, the model in equation (6) is to be viewed as illustrative rather than assertive. Last season's weather can shift current input choices through two paths. Differentiating with respect to z_{t-1} yields

$$\begin{aligned}\frac{\partial X_t^*}{\partial z_{t-1}} &= \underbrace{\frac{\partial f}{\partial E_t[z_t]} \cdot \frac{\partial E_t[z_t]}{\partial z_{t-1}}}_{\text{belief (recency) channel}} + \underbrace{\frac{\partial f}{\partial \pi_{t-1}^*} \cdot \frac{\partial \pi_{t-1}^*}{\partial z_{t-1}}}_{\text{liquidity channel}} \\ &= \underbrace{p_1\, S'(\cdot)}_{\text{Recency Effect}} + \underbrace{\frac{\partial f}{\partial \pi_{t-1}^*} \cdot \frac{\partial \pi_{t-1}^*}{\partial z_{t-1}}}_{\text{Liquidity Effect}}.\end{aligned} \tag{7}$$

Under rational expectations, $\partial E_t[z_t]/\partial z_{t-1} = 0$, the recency term vanishes, and last season's weather affects fertilizer only via liquidity carried into this season. With behavioral updating, $p_1 > 0$ and $\partial E_t[z_t]/\partial z_{t-1} \neq 0$; both channels operate. Figure 1.3 provides a graphical representation of the channels through which past rainfall shock affect fertilizer use under both scenarios.

Recency could amplify the effect of liquidity constraints stemming from the previous season's weather; that is, negative weather shocks in the prior season could signal the likelihood of similar adverse conditions in the current season, leading farmers to reduce fertilizer application even further beyond what liquidity constraints alone would suggest. Second, recency could partially or fully offset the liquidity effect if farmers interpret recent negative shocks as temporary and anticipate a subsequent return to normal conditions, thus choosing to maintain or even increase fertilizer use despite immediate liquidity constraints. The direction and magnitude of the recency effect (p_1) depend on whether farmers perceive recent weather outcomes as predictive of future conditions, either positively or negatively.

Economic theory suggests that fertilizer, being a normal good, should exhibit increased (decreased) demand following good (bad) weather in the previous season due to the corresponding liquidity changes. Although there is empirical support for this (e.g. Alem et al., 2010), evidence from some studies also suggests that this may not always be the case. In particular, M. Rosenzweig and Udry, 2013 finds evidence from India showing that while rainfall positively impacts crop profits, these higher profits do not significantly affect input decisions in the following season. These findings highlight that the relationship between weather shocks, recency, and liquidity effects on fertilizer use is nuanced,context-specific and fundamentally an empirical question.

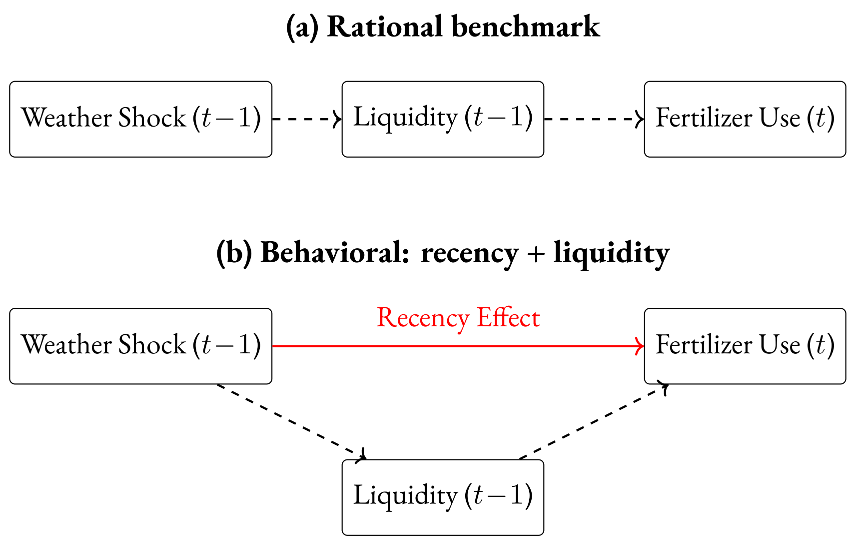


Figure 1.3: Mechanisms linking past weather to current fertilizer use

Panel (a) shows the rational benchmark (liquidity channel only). Panel (b) adds a belief-based recency channel under behavioral updating.

Asymmetric recency. Recency can lower fertilizer use through asymmetric belief updating. If behavioral farmers put extra weight on recent weather when forming expectations, then negative rainfall shock in the previous year could depress fertilizer use by more than what a positive shock of the same size increases it. Holding liquidity fixed so only beliefs move, the recency channel implies $[\left|\frac{\partial X_t^*}{\partial z_{t-1}^-}\right|; \geq; \frac{\partial X_t^*}{\partial z_{t-1}^+},]$ where (z_{t-1}^-) and $z_{t-1}^+)$ are equally sized negative and positive rainfall shocks. In the notation of equation (7), this is a larger belief term $(p_1 S'(\cdot))$ after bad news than after good news. Loss aversion makes recent losses more salient than gains (Kahneman & Tversky, 1979), so a poor season triggers a stronger downward revision in $(E_t[z_t])$. Present bias and timing frictions between harvest and planting further mute scale-up after good shocks, even when cash is available (Duflo et al., 2011). After a positive rainfall shock, farmers often expect conditions to revert toward normal and increase fertilizer only slightly. After a negative shock, they are more likely to expect continued shortfall and cut fertilizer sharply. Conditional on past profit—or after ruling out the liquidity channel—this asymmetry puts more weight on negative shock than on positive shock. Thus, over time, asymmetric effect from recency would reduce overall fertilizer use on average.

Implications for empirical analysis. The framework motivates a simple test: compare the influence of recent versus distant rainfall shocks on fertilizer use after conditioning on past profit. If beliefs overweight the immediate past, recent shocks should show clear effects while older shocks should fade out. This pattern provides evidence of a belief-driven recency margin rather than a general response to the entire weather history. The framework also predicts that adverse recent shocks cut fertilizer use more than favorable shocks of the same size raise it, holding liquidity fixed. Empirically, this shows up as larger effects for negative shocks than for positive shocks when both are measured on the same scale. Such an asymmetry points to belief updating that is more sensitive to bad news, which lowers average fertilizer use even when shocks average to zero.

1.3 Data and Variable Definitions

1.3.1 Household-level Data

This study uses household-level data from the Nigerian General Household Survey-Panel (GHS). The GHS is a nationally representative survey of approximately 5,000 households, which are also representative of the six geopolitical zones. It is implemented in collaboration with the World Bank Living Standards Measurement Study (LSMS) team as part of the Integrated Surveys on Agriculture (ISA) program. The survey reports detailed farm information at the plot and household levels, including geo-referenced plot locations, input use, cultivation practices, and output. Data collection occurs in two household visits per survey cycle: a post-planting visit between August and October, and a post-harvest visit between February and April. My analysis focuses on data collected during the main planting season.

The final sample includes only household–wave observations from waves 1 and 2[4] that meet two conditions. First, the household reports a nonzero maize harvest during the main growing season. Second, the maize plot area is nonzero. I therefore drop all household–wave observations with zero maize harvest or zero plot area. Plot areas are GPS-measured to reduce measurement error; when GPS is unavailable, I use the farmer's self-reported area. The resulting dataset is an unbalanced panel with 1,647 household–wave observations from [N] unique households. This subset accounts for about 35% of all farm household–wave observations and more than 60% of plots in the study sample. While not nationally representative, it is representative of the main maize production system in Nigeria.

I examine two fertilizer outcomes for maize-growing households. The first is the unconditional fertilizer use rate (intensive margin). For each plot, I calculate the application rate as total fertilizer use (specifically NPK and Urea) divided by the plot's GPS-measured area (kg/acre). I then sum these plot-level rates by household during the main growing season (including zero values). To limit the influence of outliers, I winsorize the fertilizer use rate at the 99th percentile. The second outcome is fertilizer adoption (extensive margin), defined as a binary equal to 1 if the household's total fertilizer use is greater than zero and 0 otherwise. Table 1.1 shows that 52% of the households use fertilizer on their maize farm during the main growing season. However, the mean unconditional fertilizer application rate in the households surveyed is 87.95 kg/acre, with a standard deviation of 115.38 kg/acre, indicating significant variability in the intensity of fertilizer use in my sample.

Next, I compute fertilizer unit values from farmer-reported purchase quantities and expenditures for each household and season. To reduce unit value bias, I use the median fertilizer price among households in the same enumeration area and season. This assumes households in the same local market face similar prices at a given time. When there are fewer than three observations in an enumeration area, I impute the price using the median from a larger area in steps: first the local government area, then the state, and finally the zone.

[4] I justify this choice in Section 1.3.3

To derive the market price of maize for each household at the enumeration area level, I use the community questionnaire. It reports unit maize prices for each enumeration area during the survey period. When multiple prices are reported for the same enumeration area, I take their mean to obtain a single representative price for that area.

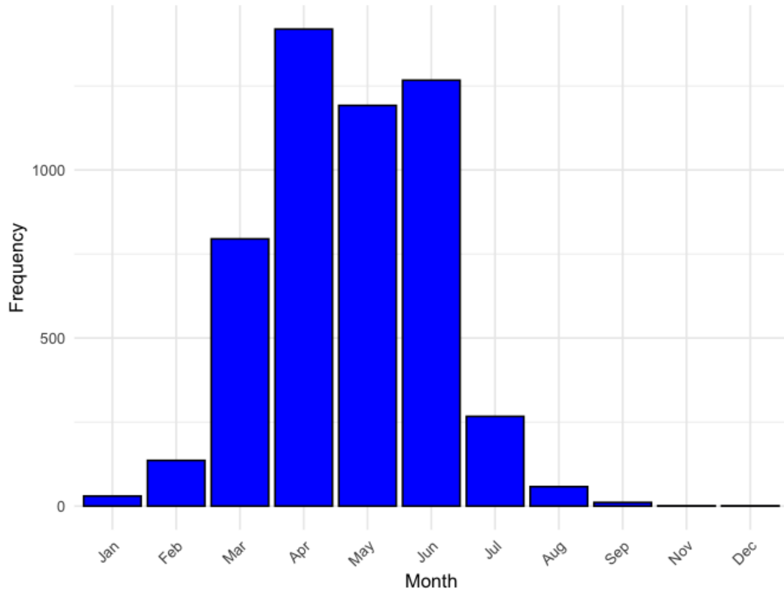
Table 1.1: Summary Statistics of Key Variables

Dependent variables	Mean	St. Dev	Min	Max
Fertilizer adoption (1/0)	0.52	0.49	0.00	1.00
Unconditional fertilizer use rate (kg/acre)	87.95	115.38	0.00	398.06
Independent variables				
Growing season rainfall shock (z-score)	0.42	0.79	-2.03	3.03
Household size (adult equivalence unit)	4.30	2.11	1.00	25.90
Education of households head (in years)	4.63	5.00	0.00	18.00
Distance to nearest market (km)	27.59	72.21	1.50	214.36
Value of household assets owned (000' Naira)	38.38	33.64	0.005	180.25
Livestock accumulation (TLU)	0.332	0.964	-1.37	7.50
Fertilizer price (Naira/kg)	81.675	17.22	23.33	150.00
Maize price (Naira/kg)	85.97	36.390	10.00	250.00
Previous season maize price (Naira/kg)	48.900	8.407	35.352	70.031
Size of maize farm (acres)	1.068	0.926	0.01	4.29
Maize yield (kg/acre)	739.763	694.52	3.401	4062.003
Plot slope (%)	3.513	2.614	0.610	30.59
Plot elevation (mm)	393.34	271.38	11.00	1427.00
Soil potential wetness index	13.818	2.240	11.00	36.00
Soil nutrient availability	1.694	0.77	1.00	3.00
Soil nutrient retention capacity	1.47	0.55	1.00	3.00
N	1647			

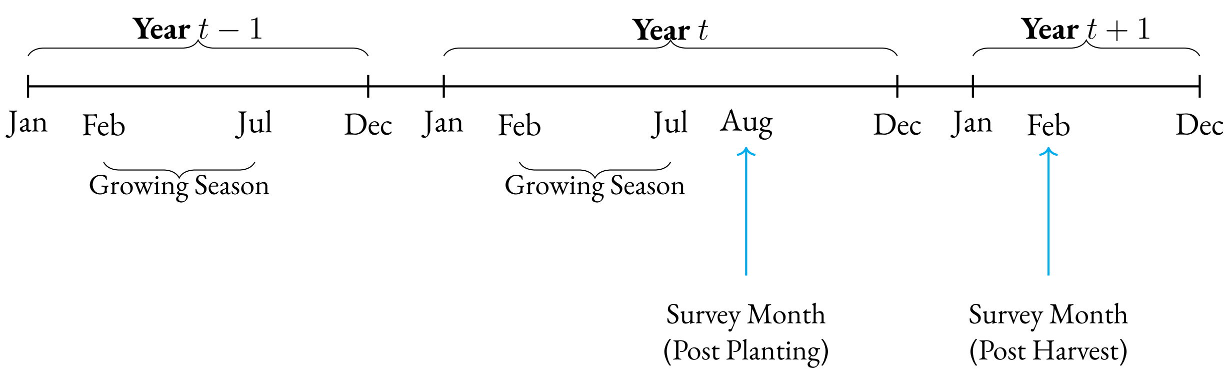
Source:**Notes:** Author's calculations from Nigeria GHS 2010 and 2012. All prices and monetary values are deflated to 2010 constant terms using the World Bank CPI. Soil potential wetness index, nutrient availability, and nutrient retention are coded as counts: 1 = no/slight constraint, 2 = moderate constraint, 3 = severe constraint.

1.3.2 Rainfall Data

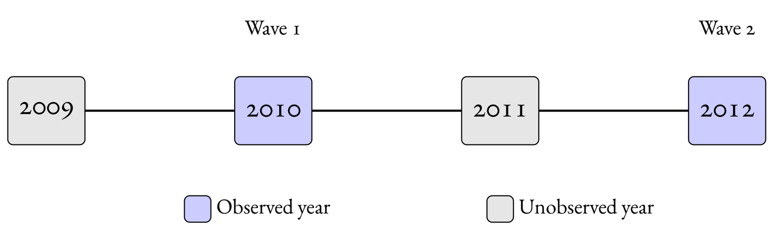
I merge household data with historical rainfall data at the local government area (LGA) level. The rainfall series comes from CHIRPS for 1981–2016 (Funk et al., 2015). CHIRPS blends satellite images with



(a) Maize planting months



(b) Growing season and survey timing



(c) Panel coverage by year

Figure 1.4: Graphical representation of the timing and coverage of the study.

Notes: The bar plot in panel (a) illustrates the frequency of maize planting activities across different months in Nigeria in my sample. Panel (b) aligns growing seasons with the survey months used for measurement. Panel (c) shows which years are observed in the data and which are not.

station readings to create a gridded dataset. It provides $0.05^\circ \times 0.05^\circ$ resolution and supports trend analysis and drought monitoring.

I measure rainfall shocks as standardized deviations (z-scores) from the long-term mean. For each survey year $y \in \{2010, 2012\}$, I compute the average daily rainfall during the growing season and subtract the historical mean for the same LGA and season over $[1983, y-1]$. I then divide by the historical standard deviation. I define the growing season as the six months when most maize planting occurs. Figure 1.4 shows that planting is possible year-round but is concentrated from February to July. I use this window as the growing season[5]. Figure 1.5 maps growing-season rainfall shocks across maize-growing LGAs in the sample.

A central identification assumption is that rainfall shocks are serially uncorrelated. Profit-maximizing households therefore should not use last season's rainfall to predict this season's rainfall. The literature often treats year-to-year rainfall variation as exogenous (Kaur, 2019; Kazianga & Udry, 2006; Miguel et al., 2004; Paxson, 1992). I verify this in my data by regressing the current season's rainfall shock on the previous season's shock, with location and year fixed effects. As shown in Table 1.2 (columns 1–2), the lagged shock has a coefficient near zero and is not statistically significant, supporting the assumption of no serial correlation.

Next, I test whether rainfall shocks are transitory. If shocks persist through soil moisture, last year's shock could directly affect this year's yield and may justify using lagged shocks in input decisions. I regress current maize yield on the previous season's rainfall shock and its square, alongside controls. As shown in Table 1.2 (columns 3–4), the lagged terms are small and not statistically significant, while the current-season shock is strongly related to yield at harvest. This pattern supports the view that shocks are transitory and contemporaneous, consistent with why farmers may adjust input use upward after positive shocks and downward after negative shocks.

[5]Although climatological studies place Nigeria's maize season roughly from March or May to September or October, depending on the agro-ecological zone (Odekunle, 2004), I follow Aragón et al., 2021 and Mayorga et al., 2025 in defining the growing season as the six months with the highest planting intensity.

Table 1.2: Serial Correlation in Rainfall and Effect of Lagged Rainfall Shocks on Maize Yield

	Rainfall Shock		Log Maize Yield	
	(1)	(2)	(3)	(4)
Rainfall Shock (t)			-0.532***	-0.536***
			(0.172)	(0.220)
Squared Rainfall Shock (t)			0.272**	0.272**
			(0.129)	(0.132)
Rainfall Shock (t-1)	0.013	0.007		-0.067
	(0.011)	(0.011)		(0.246)
Squared Rainfall Shock (t-1)				-0.159
				(0.161)
LGA FE	Yes	Yes	Yes	Yes
Year FE		Yes		Yes
N	7502	7502	399	399

Note: The unit of observation is a LGA–year. Rainfall shock is defined as the standardized deviations (z-scores) from the long-term mean. Standard errors, clustered at the LGA level, are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

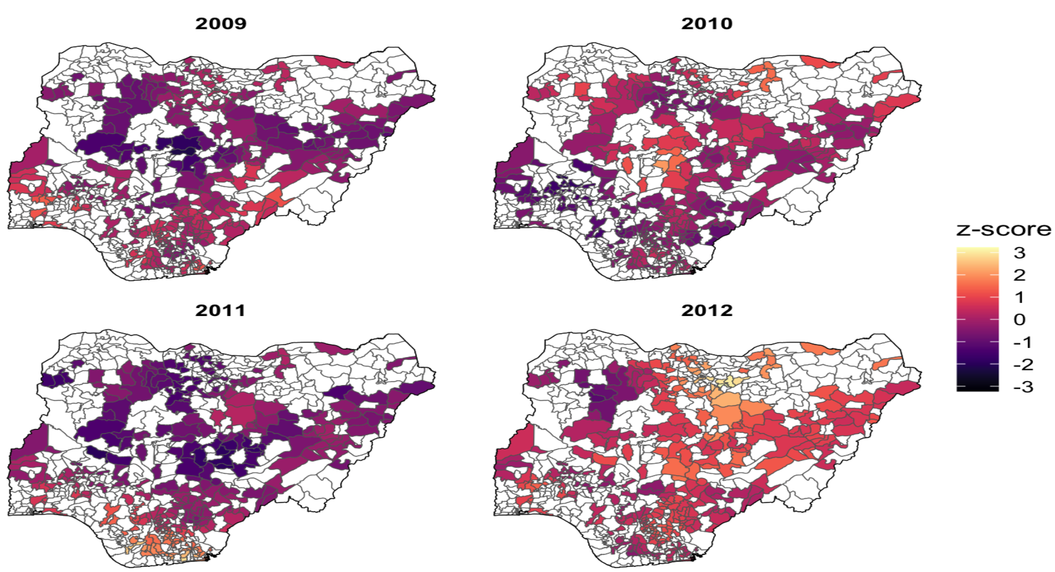


Figure 1.5: Spatial Distribution of Rainfall Shock

Note: Map shows the spatial distribution of growing-season rainfall shocks across maize-growing LGAs in Nigeria, for both the current and the prior seasons.

1.3.3 Controlling for Previous Season's Profit

To isolate the recency effect of weather shocks on fertilizer demand, it is important to control for previous season's income. However, the GHS dataset does not provide household income data for the most recent growing season (e.g., 2009 for the 2010 survey). To address this limitation, I use household livestock accumulation as a proxy for the previous season's profit. Evidence from low-income settings shows that households sell livestock to finance inputs when cash is limited (Alem et al., 2010; Dercon & Christiaensen, 2011). Thus, lower profit in the prior season tends to reduce herds, while higher profit supports accumulation. Livestock holdings, therefore, serve as a reliable proxy for lagged profit when direct income data are unavailable.

The GHS (waves 1 and 2) records livestock ownership at two points that bracket input decisions. First, households report stocks at the start of the calendar year, before planting begins (see Figure 1.4b). Second, they report current stocks during the post-planting visit in August, after inputs such as fertilizer have been purchased and used. I convert both stocks to Tropical Livestock Units (TLU), a standardized measure of livestock assets, and define livestock accumulation as the post-planting TLU minus the start-of-year TLU. Positive values indicate net accumulation; negative values indicate drawdown. In later waves (3–5), livestock questions were asked in the post-harvest season around February, which does not align with input timing. I therefore use only waves 1 and 2 to measure accumulation over the relevant window in this study. Summary statistics in Table 1.1 show that, on average, households accumulated livestock between the start of the year and post-planting, though some experienced net reductions.

I also control for past profit using the state-level maize price for the most recent season. For maize producers, a higher output price raises revenue and cash on hand, which can relax financing constraints for input purchases in the next season. Using the World Bank market dataset (Andrée, 2021), I compute state–level maize price by averaging the monthly maize price for all markets within a state during the growing season (Figure A.1). For states where they are no market locations for which estimates of maize price are available, I use a database of maize prices across markets in Nigeria compiled by Cedrez et al., 2020 and followed their methodology to predict maize price during the growing season as a function of location (longitude and latitude), month in which the price data was recorded, access to market, price type (retail or wholesale), annual precipitation, population density and cropland (Table A.1). The most important variables are population density, precipitation, and the month in which the price is reported.

1.4 Empirical Strategy

Building on the conceptual framework, I empirically examine how recent rainfall shock influences households' current fertilizer use decisions, beyond the effects of liquidity constraints. To do so, I estimate a reduced-form fertilizer demand model (equation (6)), derived from a Cobb-Douglas production function, following the empirical approaches of Aragón et al., 2021 and Dillon and Barrett, 2017.

Since households' beliefs about current season rainfall conditions are unobserved, I approximate their expectation formation using a flexible linear weighting approach of past rainfall realizations (Nerlove, 1958). Specifically, households are assumed to formulate expectations as:

$$E_t[z_t] = p_1 z_{t-1} + p_2 z_{t-2} + \cdots + p_L z_{t-L} \tag{1.6}$$

where each p_l denotes the (unobserved) weight assigned to previous weather outcomes from l seasons ago. Given data constraints, I operationalize this approach by including separate lagged rainfall shocks, capturing both recent (1–5 years) and distant (block moving averages of 6–10, 11–15, 16–20, and 21–25 years) rainfall shocks. Thus, I specify my empirical model as:

$$\begin{aligned} X^*_{idst} &= \sum_{k=1}^{5} \beta_k \, Z_{dst-k} + \beta_m \, \overline{Z}_{dst_{6:10}} + \beta_n \, \overline{Z}_{dst_{11:15}} + \beta_s \, \overline{Z}_{dst_{16:20}} + \beta_v \, \overline{Z}_{dst_{21:25}} \\ &+ \delta_1 \, LS_{idt-1} + \delta_2 \, P^m_{st-1} + \mathbf{D}'_{idst} \, \Gamma + \tau_i + \gamma_t + \varepsilon_{idst}. \end{aligned} \tag{1.7}$$

where i indexes households; d local government areas (LGAs); s states; and t growing seasons. The outcomes X^*_{idst} are a binary indicator of fertilizer adoption (extensive margin) and the unconditional fertilizer use rate in season t. The main variable of interest is the rainfall shock Z, defined as the standardized deviation from the long-term mean for the same season and location. To capture effects from both recent and distant shocks, I split exposure into two components. Recent exposure comprises the five most recent seasonal shocks, $Z_{dst-1}, \ldots, Z_{dst-5}$. Distant exposure is summarized by block averages—the mean rainfall shock over seasons 6–10, 11–15, 16–20, and 21–25 prior to t—denoted $\overline{Z}_{dst,6:10}$, $\overline{Z}_{dst,11:15}$, $\overline{Z}_{dst,16:20}$, and $\overline{Z}_{dst,21:25}$.

I control for the liquidity channel using two proxies for past profit: livestock accumulation $LS_{i,d,t-1}$ and the recent season maize price $P^m_{s,t-1}$. I also include $\mathbf{D}_{idst}$, a vector of time varying household-, field-, and community-level covariates, described below, to address time varying factors that could jointly be correlated with household rainfall shocks and the decision to use fertilizer. All specifications include season fixed effects γ_t; ε_{idst} is the idiosyncratic error term. For the fertilizer adoption outcome, I estimate a model with household fixed effects τ_i –my preferred specification– to absorb time-invariant unobserved heterogeneity such as cultural or religious beliefs and norms. For the unconditional fertilizer use rate, which is censored at zero, I estimate a Tobit model with LGA fixed effects to account for censoring at zero. Standard errors are clustered at the enumeration area level to account for the potential correlation of errors within household clusters.

I add a rich set of covariates in my analysis to address a wide variety of potential omitted variables. My choice of observed covariates is based on the agricultural household model (that recognizes the dual role of agricultural households as both producers and consumers of numerous agricultural products (Sing et al., 1986). At the household level, controls are household size (adult-male equivalents), the head's age and education (years), value of household assets (log transformed), and distance to the nearest market (km). At the community level, I add current fertilizer and maize prices to capture contemporaneous budget constraints and incentives. At the field level, I include plot elevation, slope, potential wetness index, nutrient retention capacity, and nutrient availability to control for soil quality, along with the total maize area cultivated (log transformed). In addition, inclusion of household fixed effect in my preferred model is expected to control for additional soil characteristics that are time invariant such as soil color and texture that might be correlated with both rainfall shocks and the decision to use fertilizer.

The parameters $\beta_1, \ldots, \beta_5$ capture the effects of recent rainfall shocks, and $\beta_m, \beta_n, \beta_s, \beta_v$ capture the effects of more distant shocks. I test for recency by comparing the influence of recent shocks to that of distant shocks after accounting for past profit. Evidence consistent with recency arises if at least one recent-lag coefficient β_k is statistically different from zero, while coefficients on distant rainfall shocks $(\beta_m, \beta_n, \beta_s, \beta_v)$ are all statistically indistinguishable from zero. This pattern would indicate that households place greater weight on recent rainfall when making fertilizer decisions.

The key identifying assumption is that variation in past rainfall shocks is exogenous to time-varying unobserved household factors. I provide three stylized facts to support this claim. First, Table 1.2 shows that rainfall shocks are not serially correlated, so recent shocks do not predict future shocks. Second, shocks are transitory for yields: last season's shock (and its square) does not affect current maize yield, while current-season shocks do, which rules out carryover through soil moisture. Third, I rule out the liquidity channel by controlling for past profit. Thus, any remaining association between recent rainfall shocks and fertilizer use, conditional on observed covariates, is consistent with evidence of recency bias.

1.5 Results

In the section, I present suggestive evidence that fertilizer use among maize farmers in Nigeria feature weather-induced recency effect. That is conditional on past profit, recent rainfall shocks affects current fertilizer use, especially rainfall shock from the previous season than distant ones. I OLS results for the binary measure of fertilizer adoption–my preferred model– and Tobit estimates for fertilizer application rates based on equation (1.7).

1.5.1 Recency Effect and the Binary Measure of Fertilizer Adoption

Table 1.3 presents the OLS estimated effect of lagged rainfall shocks on fertilizer adoption (extensive margin). All estimations are based on equation equation (1.7), which controls which controls for household and year fixed effects and other control variables detailed in the previous section. The results suggest that within the lag structure, only the most recent shock (t−1) predicts adoption, while more distant shocks do not. In Column (1), a one–standard-deviation increase in last season's rainfall shock raises the probability of fertilizer use by 8.7 percentage points, significant at the 10% level. None of the other recent lags (t−2 through t−5) nor any of the four distant-shock averages are statistically different from zero. Column (2) adds last season's maize price as an additional proxy for liquidity, alongside livestock accumulation. The t−1 coefficient attenuates to 7.5 percentage points but remains significant at the 10% level, even after adding additional proxy for past profit. The coefficients on all distant shocks continue to be indistinguishable from zero, and the liquidity proxies themselves are imprecisely estimated: livestock accumulation is small and insignificant, and last season's maize price is positive but not statistically significant.

The findings are consistent with the behavioral farmer benchmark set out in the conceptual framework. Conditional on past profit, recent rainfall shocks—especially last season's shock—strongly predicts current fertilizer use. In a standard profit-maximizing model, the last seaon's rainfall shock, which is exogenous and transitory, should affect the likelihood of current fertilizer use only past profit. The fact that the (t-1) shock still predicts after ruling out the liquidity channel points to a behavior consistent with recency bias: households appear to place more weight on very recent weather when forming expectations about current-season conditions, and this expectation affects investment in risky inputs like fertilizer. The findings also align with studies showing that recent weather can shape agricultural investments (Huang et al., 2024; Karlan et al., 2014; Sesmero et al., 2018). For example, in Malawi, Sesmero et al., 2018 report that scarce and volatile rainfall in the previous season is associated with lower spending on fertilizer and improved seed, which they interpret as reflecting more pessimistic beliefs about returns; in rural China, Huang et al., 2024 find that favorable rainfall can be followed by overly optimistic input choices.

1.5.2 Recency Effect and Fertilizer Use Rate

Next, I present pooled Tobit estimates of equation (1.7) in Table 1.4, using unconditional fertilizer use (kg/acre) as the outcome to accommodate zeros. The model includes LGA fixed effects, year fixed effects,

Table 1.3: Impact of Lagged Rainfall Shocks on Fertilizer Adoption

		Fertilizer Adoption (1/0)			
		(1)	(2)	(3)	(4)
		Coeff.	St. error	Coeff.	St. error
Rainfall Shock (z-score)					
	t-1	0.087*	0.046	0.075*	0.0436
	t-2	-0.028	0.047	-0.024	0.0452
	t-3	0.025	0.059	0.043	0.0625
	t-4	-0.037	0.055	-0.007	0.0536
	t-5	-0.097	0.065	-0.079	0.059
	t:{6:10}	-0.330	0.203	-0.183	0.193
	t:{11:15}	-0.237	0.153	-0.163	0.154
	t:{16:20}	-0.345	0.260	-0.346	0.250
	t:{21:25}	-0.189	0.191	-0.202	0.189
Livestock Accumulation (t-1)		-0.023	0.023	-0.023	0.023
Log Maize Price (t-1)				0.576	0.419
Controls		Yes		Yes	
Household FE		Yes		Yes	
Year FE		Yes		Yes	
Within R squared		0.105		0.110	
N		1647		1647	

Note: This table presents the OLS estimation of equation (1.7). The dependent variable is binary measure of fertilizer adoption (extensive margin). The time lags are defined as follows: t-1, t-2, t-3, t-4, t-5 refers to the previous season, past two seasons, past three seasons, past four seasons and past five seasons respectively. t:{6:10}, t:{11:15}, t:{16:20} and t:{20:25} represents the averages for the past 6 to 10, 11 to 15, 16 to 20 and 21 to 25 seasons respectively. Controls include household head age and education, household size, average plot slope, plot elevation, soil nutrient retention and nutrient availability, potential wetness index, distance to the nearest market, log asset value, log maize plot area, and current maize and fertilizer prices. Standard errors are clustered at the enumeration area level. *, **, *** indicate the statistical significance at the 10%, 5%, and 1% level, respectively.

and the covariates described in the data section. LGA fixed effects absorb time-invariant LGA characteristics that might influence fertilizer intensity. The coefficient on the most recent rainfall shock (t−1) is positive and statistically significant in both specifications: in Column (1), a one–standard–deviation increase in last season's shock is associated with 19.42 kg/acre more fertilizer (10% level); in Column (2), after adding last season's maize price as a liquidity proxy, the effect is 16.55 kg/acre (10% level). Relative to the sample mean of 87.95 kg/acre, these estimates are sizable at roughly 22% and 19%. Other recent lags (t−2 to t−4) and the distant shocks are not statistically different from zero overall. Two coefficients are only weakly suggestive in Column (1): t−5 and the average over t:6−10 are negative and marginally significant; however, both lose significance and become imprecisely estimated once maize price is included in Column (2). Livestock accumulation is small and not significant, while higher last-season maize prices are associated with greater fertilizer intensity (5% level).

These results are consistent with the results from the binary fertilizer adoption model and with the behavioral benchmark in the conceptual framework. Conditional on past profit, the most recent rainfall shock continues to predict fertilizer use, which is consistent with recency bias. This suggests that households place extra weight on last season's weather when deciding not only whether to use fertilizer but also how much to apply.

1.6 Asymmetric Effects of Weather-Induced Recency

The baseline results provide evidence for the effect of recency in farmers' fertilizer use decisions induced by recent rainfall shocks. Specifically, I find that recent weather shocks have a greater influence on fertilizer use than distant shocks even after ruling out liquidity channel. Therefore, farmers may tend to increase fertilizer use after recent favorable weather and reduce it after unfavorable shocks, as they expect current weather conditions to mirror recent outcomes. However, one might argue that if the effect of recency reduces fertilizer use below optimal levels after unfavorable weather but increases it above optimal levels after favorable weather, then the net effect could still increase or leave overall fertilizer use unchanged. Therefore, in principle, recency bias might not have a negative net effect on fertilizer use decisions.

Table 1.4: Impact of Lagged Rainfall Shocks on Fertilizer Use Rate

		Fertilizer Use Rate (kg/acre)			
		(1)	(2)	(3)	(4)
		Coeff.	st. error	Coeff.	st. error
Rainfall Shock (z-score)					
	t-1	19.42*	9.24	16.55*	8.86
	t-2	-8.97	9.86	-11.04	9.54
	t-3	10.26	13.40	17.55	13.86
	t-4	-17.20	12.45	-5.00	13.39
	t-5	-25.68*	13.86	-15.86	13.00
	t:{6:10}	-92.10*	48.01	-40.36	49.73
	t:{11:15}	-21.33	30.11	-2.42	30.34
	t:{16:20}	-57.18	54.41	-67.12	53.18
	t:{21:25}	-28.18	41.54	-44.33	41.95
Livestock Accumulation (t-1)		0.70	2.89	0.62	2.95
Log Maize Price (t-1)				186.03**	94.13
Controls		Yes		Yes	
LGA FE		Yes		Yes	
Year FE		Yes		Yes	
Pseudo R squared		0.11		0.11	
N		1647		1647	

Note: This table shows the Tobit estimation of equation (1.7), with coefficients representing the average marginal effects calculated using the *margins* command in STATA. The dependent variable is unconditional fertilizer use rate (kg/acre) (intensive margin). The time lags are defined as follows: t-1, t-2, t-3, t-4, t-5 refers to the previous season, past two seasons, past three seasons, past four seasons and past five seasons respectively. t:{6:10}, t:{11:15}, t:{16:20} and t:{20:25} represents the averages for the past 6 to 10, 11 to 15, 16 to 20 and 21 to 25 seasons respectively. Controls include household head age and education, household size, average plot slope, plot elevation, soil nutrient retention and nutrient availability, potential wetness index, distance to the nearest market, log asset value, log maize plot area, and current maize and fertilizer prices. Standard errors are clustered at the enumeration area level. *, **, *** indicate the statistical significance at the 10%, 5%, and 1% level, respectively.

To address this concern, I demonstrate that the weather-induced recency effect could reduce overall fertilizer use through its asymmetric impact on households' fertilizer use decisions. Specifically, I show that unfavorable weather shocks in the previous season reduce current fertilizer use, while favorable shocks do not necessarily lead to an equivalent increase. Since the baseline results strongly indicate that last season rainfall shocks significantly influence both the intensive and extensive margins of fertilizer use, I construct positive, negative and no rainfall shock dummies from the previous season to accomplish this task. I then compare the effects of positive and negative rainfall shocks against the omitted category of no shock from previous season to assess the asymmetric influence of recency bias.

Following a similar methodology as Kaur, 2019, I define an LGA as subject to a discrete positive (negative) rainfall shock in a given season if the total rainfall is above the 75th percentile (below the 25th percentile) of the historical rainfall distribution for that LGA. Rainfall realizations that fall between these percentiles are classified as no shock.[6] I ran the following empirical model;

$$X_{idlt} = \alpha_0 + \beta_p Pos_{dt-1} + \beta_w Neg_{dt-1} + \theta_1\, LS_{idt-1} + \theta_2\, P^m_{st-1} + \mathbf{D'}_{idt}\mu + v_i + v_t + \varepsilon_{idt} \quad (1.8)$$

Let X_{idt} denote the outcome for household (i) in district (d) and season (t); in the main specifications it is a binary indicator for fertilizer use (1 = any use, 0 = otherwise). $Pos_{d,t-1}$ and $Neg_{d,t-1}$ are indicators for, respectively, a positive and a negative rainfall shock in the previous season. The omitted category is "no shock last season," so coefficients on $Pos_{d,t-1}$ and $Neg_{d,t-1}$ are interpreted relative to that baseline. Control variables are the same as in equation (1.7). All regressions include household fixed effects v_i, season fixed effects v_t, and an idiosyncratic error term ε_{idt}. In complementary results, I also estimate a Tobit model for unconditional fertilizer use rate, using LGA fixed effects in place of household fixed effects but otherwise the same specification.

Table 1.5 reports asymmetric responses to last season's rainfall shocks. Column 1 shows OLS estimates for the binary fertilizer adoption outcome with household fixed effects; Column 2 reports Tobit

[6]As robustness, Table A.2 includes columns for alternative percentile cutoffs for defining positive and negative rainfall shocks.

estimates for fertilizer use rate (kg/acre) with LGA fixed effects. In Column 1, conditional on past profit, a positive rainfall shock last season is associated with a 4.3 percentage point increase in the probability of using fertilizer relative to no shock, but this effect is not statistically significant. By contrast, a negative shock last season lowers the probability of fertilizer use by 9.3 percentage points, significant at the 5% level. The intensive margin results tell the same story. Relative to no shock, a positive shock is assciated with a 20.78 kg/acre decrease in fertilizer use that is not statistically different from zero, whereas a negative shock reduces fertilizer use by 28.09 kg/acre, significant at the 1% level.

Consistent with the conceptual framework, the results suggest that farmers cut fertilizer use sharply after negative rainfall shocks but do not raise it by a comparable amount after positive shocks. This asymmetric response means that, even if good and bad shocks balance over time, the average effect on fertilizer use is downward. In a setting like Nigeria, where weather volatility is common and expected to worsen (Ajetomobi et al., 2015; Amanchukwu et al., 2015), such recency bias can help explain persistently low input use: bad years pull usage down more than good years push it up.

1.6.1 Heterogeneity

Section 1.6 establishes that recency effect induced by weather shocks exhibits an asymmetric effect on fertilizer use: negative rainfall shocks significantly reduce fertilizer demand, while positive shocks do not proportionally increase it. However, the impact of recency bias is unlikely to be uniform across all households. Low income households, which typically face more severe liquidity constraints, may be particularly sensitive to recent negative rainfall shocks due to their limited capacity to absorb financial constraints after negative weather shocks (Alem et al., 2010; Amare et al., 2018; Dercon & Christiaensen, 2011). Indeed, existing studies (e.g., Huang et al., 2024; Sesmero et al., 2018) highlight that poorer or low-productivity households disproportionately drive observed behavioral responses to recent weather events. To this end, I examine heterogeneity in the previously reported results in Section 1.6 by estimating equation (1.8) separately across household income level (proxied by value of household asset).

Table 1.5: Asymmetric Impact of Prior Season's Rainfall Shock on Fertilizer Use

	Fertilizer Adoption (1/0)	Fert. Use Rate (kg/acre)
	OLS	Tobit
	(1)	(2)
Positive Shock (t-1)	-0.043	-20.780
	(0.088)	(18.815)
Negative Shock (t-1)	-0.093**	-28.094***
	(0.040)	(9.286)
Livestock Accumulation (t-1)	-0.019	1.288
	(0.023)	(3.098)
Log Maize Price (t-1)	0.569*	150.087**
	(0.336)	(68.063)
Controls	Yes	Yes
Household Fixed Effects	Yes	
District Fixed Effects		Yes
Year Fixed Effects	Yes	Yes
N	1647	1647

Note: Column (1) reports estimates from the OLS regression, while Column (2) presents results from the Tobit model with coefficients representing the average marginal effects calculated using the *margins* command in STATA. A positive (negative) shock is an indicator equals to 1 if total rainfall is above (below) 75th (25th) percentile of the historical distribution. Controls include household head age and education, household size, average plot slope, plot elevation, soil nutrient retention and nutrient availability, potential wetness index, distance to the nearest market, log asset value, log maize plot area, and current maize and fertilizer prices. Standard errors are clustered at the enumeration area level. *, **, *** indicate the statistical significance at the 10%, 5%, and 1% level, respectively.

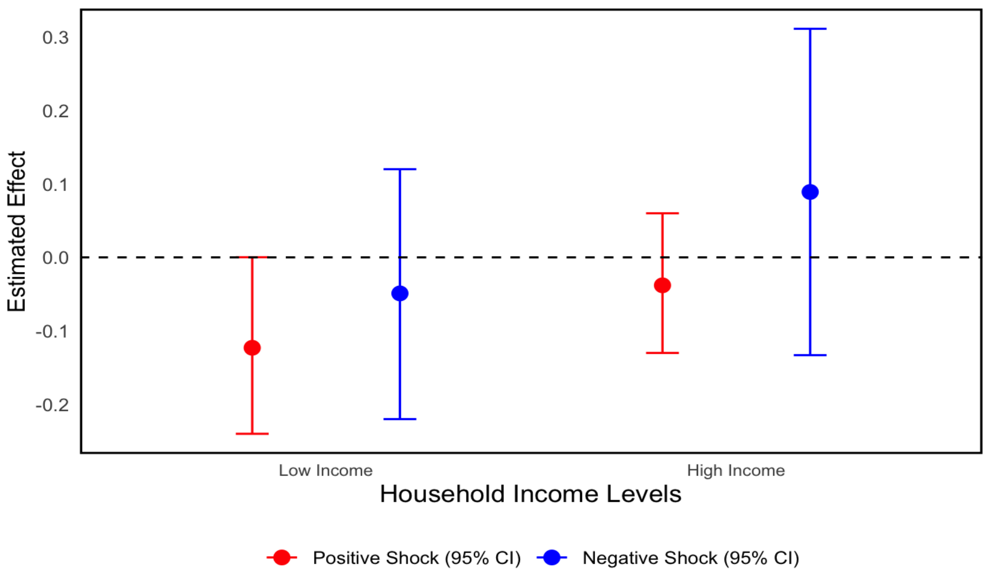
Figure 1.6a (Panel A) presents the estimated coefficients and the 95% confidence interval for the binary adoption outcome by household income. Conditional on past profit, low-income households reduce the likelihood of fertilizer use after a negative rainfall shock, while a positive shock has no detectable effect; for high-income households, neither positive nor negative shocks significantly affects adoption. Figure 1.6b (Panel B) shows that negative shocks also reduce quantities applied for high income group, whereas positive shocks are not statistically different from zero. Taken together, the main implication—based on Panel A as the preferred specification—is that high households are less prone to biases arising from past rainfall shocks than low income households. A possible explanation could be that higher income households may have better access to timely and accurate weather forecast than low income households.

1.7 Behavioral Mechanism

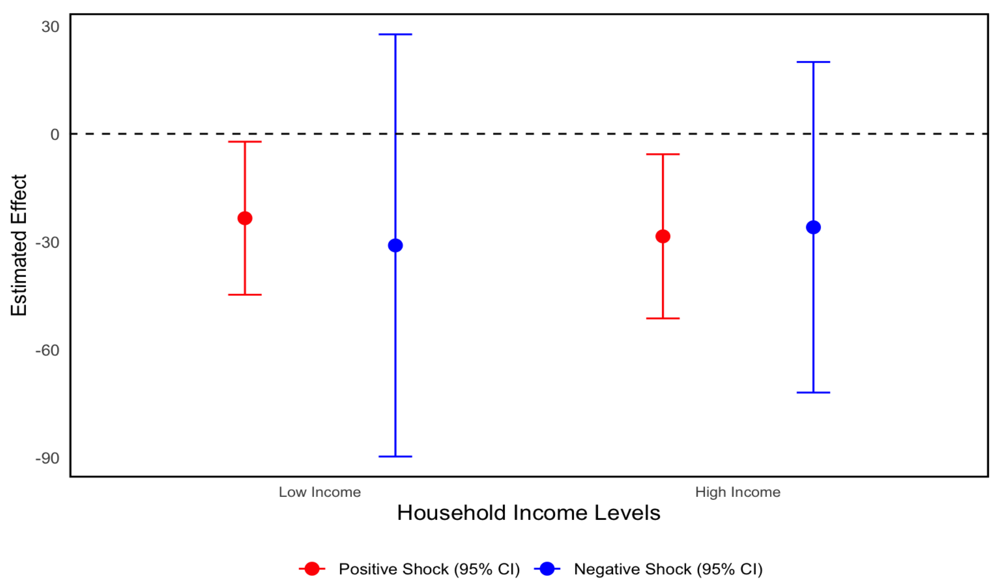
Given the evidence of recency bias and the resulting asymmetric responses that can depress average fertilizer use, this section examines the behavioral mechanisms that may explain why households place extra weight on last season's rainfall when deciding how much fertilizer to use in the next season.

A plausible explanation is that households may believe rainfall shocks carry over from one season to the next (i.e., rainfall shocks are serially correlated). In our data, current rainfall strongly affects current maize yields (Table 1.2), so last year's rainfall may appear to be a useful signal about this year's conditions. If farmers read a bad (good) shock as informative about what is coming, they may cut (or raise) planned fertilizer use, even though the shocks are not serially correlated and last season's shock is transitory (it does not affect current maize yields).

A second competing explanation is that the recency pattern reflects discouraged maize production rather than households believing that rainfall shocks are serially correlated. After a bad year, households may decide not to "throw good money away" and cut fertilizer simply because they plan to grow less (or no) maize. To assess this, I examine whether past rainfall shocks differentially reduce maize farming itself. I estimate equation (1.8) with three outcomes: (i) an indicator for growing maize this season, (ii)



(a) Asymmetric effect of recency bias on fertilizer adoption (1/0)



(b) Asymmetric effect of recency bias on fertilizer use rate (kg/ha)

Figure 1.6: Asymmetric Effect of Recency by Household Income Level

the share of cultivated land allocated to maize, and (iii) the log of total farm size. If discouragement drives the results, we should observe a negative asymmetry on these margins—that is, last season's negative shock should lower these outcomes more, in absolute value, than a positive shock of the same size raises them, relative to the no-shock category.

Table 1.6 reports asymmetric effects of last season's rainfall shocks on three outcomes. Column (1) uses the full sample of agricultural households–whether they grow maize or not–and regresses an indicator for growing maize (Maize Grower) this season on positive and negative rainfall shocks, conditioning on past profit. Column (2) uses the same full sample and replaces the outcome with the log of total farm size (Farm Size). Column (3) focuses on the allocation margin and regresses the share of cultivated land allocated to maize (Maize Share) on the same shock indicators, restricting the sample to households that grow maize (original sample for the study).

Table 1.6 does not support the "discouragement" explanation. In Column (1), conditional on past profit, a positive shock last season is associated with a large increase in the probability of growing maize (0.385, 1% level), while a negative shock lowers that probability by a much smaller amount (−0.084, 1% level). Column (2) shows a similar pattern for total farm size: positive shocks raise farm size (0.215, 10% level) and negative shocks are small and not statistically different from zero (−0.038). By contrast, Column (3) indicates that effects on the share of land allocated to maize are imprecisely estimated for both shock types. Taken together, the asymmetry on these farming margins is positive rather than negative: increases after good years are larger than cuts after bad years. This pattern is inconsistent with the view that households primarily respond to a bad year by exiting maize or contracting their operated area, and instead points toward the role of how last season's rainfall informs current-season input choices.

1.8 Economic Implications

In this section, I present a back-of-the-envelope calculation to estimate the economic implication of recency bias under a conservative warming scenario. Recent assessments project increases in consecutive dry days over West Africa during June–August under a 2°C world (Diedhiou et al., 2018; Klutse et al.,

Table 1.6: Asymmetric Impact of Prior Season's Rainfall Shock on Farming Outcomes

	Maize Grower (1/0)	Log Farm Size	Maize Share
	(1)	(2)	(3)
Positive Shock (t-1)	0.385***	0.215*	-10.596
	(0.080)	(0.125)	(8.060)
Negative Shock (t-1)	-0.084***	-0.038	-0.589
	(0.045)	(0.101)	(2.634)
Livestock Accumulation (t-1)	-0.021	0.008	1.374
	(0.015)	(0.032)	(1.873)
Log Maize Price (t-1)	-1.643***	-0.230	82.174
	(0.28)	(0.595)	(98.834)
Controls	Yes	Yes	Yes
Household FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
R squared (within)	0.198	0.029	0.009
N	3,105	3,105	1,647

Note: Each column estimates asymmetric effects of last season's rainfall shocks relative to the omitted category no shock. A positive (negative) shock is an indicator equals to 1 if total rainfall is above (below) 75th (25th) percentile of the historical distribution. Column (1) uses the full sample of agricultural households and the outcome Maize Grower, an indicator for planting maize this season. Column (2) uses the same full sample and replaces the outcome with the log of total farm size. Column (3) uses the original sample of maize-growing households and reports results using Maize Share, the percentage of total cultivated land allocated to maize, as the outcome variable. Controls include household head age and education, household size, average plot slope, plot elevation, soil nutrient retention and nutrient availability, potential wetness index, distance to the nearest market, log asset value, log maize plot area, and current maize and fertilizer prices. Standard errors are clustered at the enumeration area level. *, **, *** indicate the statistical significance at the 10%, 5%, and 1% level, respectively.

2018). If, conservatively, the probability of a negative rainfall shock (defined as seasonal rainfall below the 25th percentile) rises by 10 percentage points, applying the estimates in Table 1.5 implies average changes of about 0.9 pp (0.10×9.3) lower fertilizer adoption and 2.8 kg/acre (0.10×28.1) lower unconditional fertilizer application. The latter is roughly 5.0% ($2.8/56.2$) of the average unconditional use rate of 56.2 kg/acre in Nigeria (Sheahan et al., 2014).

To translate this input shortfall into output, I use an average marginal physical product (MPP) of nitrogen of 2.83 kg/acre of maize per kg/acre of fertilizer (nutrient-equivalent) (Liverpool-Tasie et al., 2017). Multiplying the projected reduction in application by this MPP gives a yield loss of 7.9 kg/acre (2.8×2.83). This back-of-the-envelope calculation indicates that, even with conservative climate assumptions, rainfall-induced recency can measurably reduce fertilizer use and, in turn, maize output.

1.9 Conclusion and Policy Recommendations

A large literature in development economics shows that behavioral constraints can prevent rural households from managing farms efficiently. These constraints matter especially in rainfed systems, where good decisions depend on weather expectations and productivity is highly sensitive to shocks. In this paper, I study weather-induced recency bias—the tendency to base expectations about the coming season on very recent weather—in the context of fertilizer adoption in Nigeria. Using maize farming as a case study, I ask whether recent rainfall shocks could explain the low fertilizer use through a behavioral channel (the recency effect) and what this means for agricultural production. By focusing on this underexplored mechanism in a low-income, rainfed setting, I provide new evidence on an additional factor that could, in part, explain the low use of fertilizers in SSA.

I first test whether households display recency bias by comparing the effects of recent versus distant rainfall shocks in a fertilizer-use regression. In terms of specifications, recent shocks, especially in the prior season, have a much stronger effect on current fertilizer use, even after I account for liquidity channels as a potential mechanism. This pattern is surprising because, in my setting, rainfall shocks are serially uncorrelated, so past rainfall does not predict future conditions. The results point to belief formation driven by recent experience rather than information on the full historical context.

The core of my analysis documents that prior season rainfall shocks affect fertilizer adoption asymmetrically, helping to explain the low fertilizer use. I show that, relative to a no-shock year, households reduce fertilizer use much more after a negative shock than they increase it after a positive shock. In Nigeria, where rainfall is predicted to be erratic, this net negative asymmetry of recency bias could depress fertilizer use on average and lower yields. The evidence points to inaccurate beliefs as the main mechanism rather than exit from farming. Households appear to treat last season's rainfall as informative about the next season even though in my setting, rainfall shocks are serially uncorrelated and transitory. Consistent with this interpretation, I do not find that bad shocks lead households to disengage from maize farming; instead, the results indicate that households adjust their fertilizer use because they wrongly believe last season's rainfall will continue into the next season.

One clear policy recommendation emerging from this study is to provide a timely and accurate weather forecast before planting. A practical approach is a low-cost program that explains, in simple terms, that last season's rainfall does not predict the next, coupled with seasonal climate forecasts shared through a digital extension platform using SMS-based chat (Lasdun et al., 2025). There is growing evidence that farmers value this information. Kamau et al., 2026 find a strong willingness to pay for localized SMS agro-weather advisories in Kenya. In India, Burlig et al., 2024 show that reliable monsoon-onset forecasts lead farmers to update beliefs and increase cultivation, input use, and profits while reducing off-farm work. Because low fertilizer use often reflects information and knowledge gaps (Burlig et al., 2024; Lasdun et al., 2025; M. Rosenzweig & Udry, 2013; M. R. Rosenzweig & Udry, 2019), combining simple education about what weather data can and cannot predict with targeted seasonal forecasts can help farmers form more accurate expectations, increase fertilizer adoption, and strengthen resilience in Nigeria and similar settings.

Despite the valuable insights from this study, some limitations must be acknowledged. First, due to data limitations, I do not directly observe how individual households weigh on past rainfall shocks.

Instead, I infer this from the direct effect of lagged weather shocks after ruling out the liquidity channel. Lastly, a limitation of my study is the assumption of risk neutrality in the profit maximization approach. Although this assumption is commonly made in the agricultural economics literature (e.g., in Suri, 2011), it may be contested, as farmers are generally found to be risk- and loss-averse in SSA (Alemayehu et al., 2019; Duflo et al., 2011; Shin et al., 2022).

The limitations of this study highlight the need for further research to use primary data to directly observe how households form weather expectations based on past weather events and to assess the rationality of their behavioral responses. In addition, comparative studies across different crops and regions are necessary to validate the generalizability of my findings and to better understand weather-induced behavioral factors affecting fertilizer use in SSA.

Chapter 2

Are Consumer Demand Models in Developing Countries Biased When they Ignore Farm Profit Effects? Evidence from Malawi

2.1 Introduction

Consumer demand models play a critical role in shaping and evaluating policy instruments in developing countries, particularly in the agricultural sector (Attanasio et al., 2013; Behrman & Wolfe, 1984; Pitt, 1983; Pitt & Rosenzweig, 1985; Sahn, 1988). Governments and development agencies in these regions use these models to anticipate the effects of price regulations, subsidies, and market interventions on what households buy and how they allocate scarce resources (Ecker & Qaim, 2011; E. McCullough et al., 2022; E. B. McCullough et al., 2024). By linking prices and incomes with consumption choices and welfare, demand systems inform decisions aimed at improving food security, stabilizing markets, and supporting sustainable production.

One main assumption of traditional consumer theory is that households do not produce what they consume (Sadoulet & de Janvry, 1995; Sing et al., 1986). Under this assumption, changes in commodity prices do not affect household income or total expenditure. Although this may be reasonable in many high-income settings, it is often not applicable in developing countries, where households produce and consume staple foods. In such contexts, a price increase can raise producer income through the farm profit effect, altering both budgets and food demand. Despite its relevance for demand estimation in developing countries (Sing et al., 1986), most empirical studies treat households as pure consumers and, therefore, overlook how price changes are transmitted through income or expenditure, risking distorted predictions and policy conclusions.

In this study, I examine how preferences change when profit effects are incorporated into agricultural household demand systems in Malawi, where about 80% of rural households produce maize (De Weerdt et al., 2024; Tchale, 2009). Using household food consumption data from the Malawi Integrated Panel Survey, I quantify the bias from omitting farm profit effects by estimating food demand elasticities for three major food groups—maize, pulses and nuts, and fruits and vegetables—under variants of the Exact Affine Stone Index (EASI) demand model. First, I estimate a standard EASI with an indicator for net maize seller status as a demand shifter, following common practice in the literature to proxy production status (Sahn, 1988). Second, I estimate a fully interacted EASI (FI-EASI) that, in addition to the net seller indicator as demand shifter, interacts with prices and real total expenditure so that preferences can differ by household type; this tests whether profit effects can be captured simply by allowing elasticities to vary with producer status. Third, I propose an agricultural household EASI (Ag–EASI) model that endogenizes real total expenditure in a two-stage least squares (2SLS) framework, instrumenting real expenditure with household asset value, indicators for net maize seller and maize grower, the maize price, and their interactions. The motivation here is to allow maize price changes to shift real expenditure indirectly (via producer income) in ways that depend on household type, while prices also enter the demand equation directly. Across all models, I also address bias arising from the endogenous determination of preferences, quality, and prices.

After estimating single-equation demand for each food group, I compare total expenditure and Marshallian elasticities across models and household types to see how conclusions change by specification. Across the board, consumption quantities respond strongly to total expenditure, and EASI and FI-EASI deliver very similar expenditure elasticities. By contrast, Ag-EASI sometimes reverses signs or shrinks magnitudes. For example, Ag-EASI classifies maize as inferior for non-maize growing net buyers (-0.72) and for net sellers (-0.26), but as a normal good for maize growing net buyers (0.19), whereas EASI and FI-EASI treat maize as normal for all groups (roughly between 0.45–0.62). For pulses and nuts, EASI/FI-EASI show broadly similar responsiveness across household types (about 0.79–0.89), but Ag-EASI implies much lower responsiveness for non-maize growing net buyers (0.16), "luxury-like" responsiveness for maize growing net buyers (1.04), and an intermediate response for net sellers (0.92). Own-price elasticities are negative and fairly similar across models, though Ag-EASI attenuates maize's own-price sensitivity for maize growing net buyers (−0.14 vs. −0.20 under EASI) and for net sellers (−0.11 vs. -0.18). Cross-price patterns are alike in EASI and FI-EASI, but Ag-EASI often amplifies or flips them. For maize, the elasticity with respect to cereals and grains shifts from −0.01 (EASI) to 0.31 (Ag-EASI), and with respect to roots and tubers from −0.05 (EASI) to 0.48 (Ag-EASI), indicating that close starches behave as substitutes for maize under Ag-EASI even though EASI suggests complementarity.

I examine policy implications of the demand models by simulating a 10% maize price increase and tracing its effects through the substitution and income channels in EASI and FI–EASI, and additional profit effect channel in Ag–EASI. The results suggest that the Ag-EASI attribute most of the total effect to the profit effect especially for net sellers. For example, with net sellers, EASI and FI–EASI show a fall in maize demand driven by a negative substitution effect and a larger negative income effect. Ag–EASI also shows a decline, but it is accompanied by a relatively smaller negative substitution effect that is reinforced by negative income and negative profit components. This pattern indicates that analyses based on EASI or FI–EASI may inadvertently attribute part of the profit effect to the income effect, which can misguide policy design. Even where the profit effect is negligible, as for non-maize growing net buyers, the decomposition differs: EASI and FI–EASI point to a reduction in maize consumption with roughly similar negative substitution and income effects, while Ag–EASI indicates that the reduction is driven mainly by a large negative substitution effect with a comparatively small negative income effect.

This study adds to the demand estimation literature in developing countries by explicitly allowing staple prices to feed into households' total expenditure. I do so by endogenizing real expenditure in a 2SLS framework, which lets maize prices shift income (and thus budget shares) for agricultural households. My results suggest that this mechanism cannot be captured simply by adding producer status as a demand shifter or by interacting producer status with prices to let elasticities vary by household type. To my knowledge, no prior developing country application has incorporated the additional income from staple price increases in this way. Most existing studies treat nominal (or real) expenditure as exogenous or proxy producer responses with a demand shifter whose coefficient is rarely discussed (e.g., Sahn, 1988). My approach is simple and tractable within a standard demand-system: prices can affect both budget shares and the income term itself. Consistent with earlier Malawian work (Ecker and Qaim, 2011; Maganga et al., 2014; E. B. McCullough et al., 2024), EASI and FI-EASI yield similar expenditure elasticities, but Ag-EASI often departs, sometimes delivering larger magnitudes, opposite signs, or smaller responses. Own- and cross-price elasticities also differ from these previous studies, with Ag-EASI producing higher or lower responses depending on household type. The study most related in methodology to ours is Zhen et al., 2016, who instrument total expenditure using cross-sectional data from Tanzania, but not to capture the profit effect. I build on their approach and instrument total expenditure specifically so that income gains from staple price increases are reflected inside the demand system.

2.2 Data and Variable Construction

This study uses household characteristics and food consumption data from three waves (2010, 2012, 2016) of the Malawian Integrated Household Survey (IHS) program, jointly managed by the World Bank and Malawi's National Statistical Office through the Integrated Surveys of the Living Standards Measurement Study (LSMS-ISA) project. The Third Integrated Household Survey (IHS3), conducted between March 2010 and March 2011, was based on the agricultural focus of IHS2. IHS3 covered 768 enumeration areas (EAs), with a subset of 204 EAs selected for panel tracking. Within these, 3,246 households were surveyed twice to improve the precision of agricultural data. In 2013, the Integrated Household Panel Survey (IHPS) resurveyed these households from April to October, with additional tracking in November and December. Subsequently, the Fourth Integrated Household Survey (IHS4) was conducted from April 2016 to April 2017, covering 780 EAs. My IHS estimation panel consists of 3,104 unique households with 7,702 household-wave observations.

Based on the agricultural module, a household is classified as a net maize seller if it sold any quantity of maize harvested in the wet or dry season. Households who reported no maize sales in both seasons are classified as net maize buyers.[1] Table 2.1 presents summary statistics of key variables and demand shifters by household maize market position (hereafter, household type). As expected, net sellers harvest significantly more maize on average than net buyers. They also possess slightly greater asset wealth, measured as the total monetary value of durable goods such as beds, refrigerators, televisions, and air conditioners.

Table 2.1: Summary Statistics of Key Variables

	Net Buyers		Net Sellers	
	Mean	Std. dev	Mean	Std. dev
Value of Asset ('000 MWK)	18.65	23.72	21.09	25.13
Annual maize harvest (kg)	249.67	301.73	456.79	348.29
Household size (Adjusted for adult equivalence)	3.16	1.39	3.12	1.27
Household dependency ratio	0.79	0.97	0.86	0.99
Gender of household head (1=Male, 0=Female)	0.76	0.42	0.80	0.39
Marital status of household head (1=Married, 0=Single)	0.79	0.41	0.83	0.37
Age of household head (years)	41.79	15.36	41.03	14.85
Observations	6,790		912	

Note: This table presents mean and standard deviation of demand shifters and key variables by household type (i.e., net buyers or sellers of maize).

[1] While some studies (e.g., Bellemare and Barrett, 2006; Burke et al., 2015; Melkani et al., 2024) define the market position by comparing the quantities or monetary values of maize sold versus purchased or consumed, my approach differs due to data limitations. The consumption module in my survey is based on a seven-day recall, while the agricultural module captures harvest and sales during both growing seasons. Estimating annual maize consumption from a one-week recall would require strong assumptions, including the conversion of processed maize (e.g., maize meal) into grain equivalents. To avoid this, I define market position solely based on maize sales in the wet and dry seasons.

2.2.1 Food Consumption and Price Data

The household food consumption module collects consumed quantities of 58 food items during the 7 days preceding the interview. Consumption of each food item is differentiated by source, whether purchased, self-provisioned (i.e., household productions) or received as a gift. The survey records the total expenditure for purchased items that were consumed. I aggregated the 58 food items into 7 food categories, grouping items with similar nutritional functions and characteristics. The seven food groups are maize; cereals and grains; pulses and nuts; meat, fish, and animal products; roots, tubers, and starches; fruits and vegetables and other foods (which include all other food items). I include a numéraire good representing non-food goods and services consumed by the household. This category covers weekly household expenditures on alcoholic beverages and tobacco, food away from home, education, health, clothing, transportation, celebrations, and other non-food items.

I calculate total household expenditures during the 7-day period preceding the household interview based on the food and non-food expenditures described above. Table 2.2 presents the average total budget share of households spent on each food group and on food in the aggregate, as well as on non-food expenditures, by type of household. On average, households that are net maize buyers allocate a slightly higher share of their total expenditures to food compared to net maize sellers.

Since market prices for food items consumed by households are not directly observed, I estimate market-level unit values using household-reported expenditures and quantities for purchased items[2]. These unit values represent the opportunity cost of consumption, regardless of whether the item was purchased in a market. I begin by standardizing units, converting consumption quantities to the unit most frequently reported for each food item. Next, I clean consumption outliers by trimming values at the 1st and 99th percentiles of item-level consumption per adult male equivalent. I then compute unit values by dividing total expenditure by the quantity purchased for each item and further clean the data by top- and bottom-coding unit values at the 1st and 99th percentiles.

[2]The procedures for cleaning and curating household consumption and price data borrow heavily from the publicly available replication codes (Mccullough et al., 2024) associated with E. B. McCullough et al., 2024 study.

For households that did not purchase an item during the recall period, I impute unit values using the median price at the most disaggregated geographic level with at least three observations. This process starts at the level of the enumeration area (EA) and progressively expands to the district, region (differentiating urban areas), and finally the national level. Following Perali and Chavas, 2000, this approach ensures robust price imputation while minimizing the influence of outliers. Table 2.2 displays the mean unit value for each group according to the type of household. On average, net maize buyers incur higher food costs than net sellers, potentially due to households' cost-minimizing behavior. To address this unit value bias, I apply an instrumental variable approach in Section 2.3.

Table 2.2: Budget share and unit value, by food group and household type

	Average Share in Total Exp.			Average Unit Value (MWK/kg)		
	Full Sample	Net Buyers	Net Sellers	Full Sample	Net Buyers	Net Sellers
Maize	0.18	0.18	0.18	121.46	121.62	120.28
Cereals, Grains and Cereal Products	0.06	0.06	0.04	530.93	531.39	527.54
Pulses and Nuts	0.05	0.05	0.06	461.57	464.17	442.22
Meat. Fish and Animal Products	0.11	0.11	0.13	1088.52	1093.10	1054.49
Roots, Tubers and Other Starches	0.04	0.04	0.04	89.27	89.29	89.04
Fruits and Vegetables	0.09	0.09	0.09	168.25	167.68	172.51
Other Foods	0.21	0.21	0.19	785.22	787.05	771.59
Food (total)	0.74	0.74	0.73			
Non-food	0.27	0.27	0.26			
N (total)	7702	6790	912			
N (rural)	5726	4882	844			
N (urban)	1976	1908	68			

Note: This table shows the mean value of each food group's share in total expenditures (and the non-food numéraire good's share) in columns 1-3 and each food group's mean unit value in columns 4-6. Both budget shares and unit values are summarized by type of households (i.e., net buyers or sellers of maize). The food items contained in each food group are listed in Table B.1.

2.3 The Demand Model

I estimate household demand for maize—the main staple crop—as well as pulses and nuts, and fruits and vegetables, using a two-way approximate linearized Exact Affine Stone Index (EASI) demand model (Lewbel & Pendakur, 2009). Although the EASI model is incomplete in the sense that it excludes leisure, it explicitly accounts for all non-food consumption via a single numéraire good. This specification circumvents the problematic assumption commonly used in demand analyses, wherein demands for individual food items are modeled conditional only on total food expenditures rather than total household expenditures, an approach known to bias welfare estimates even under separability conditions (Hanemann & Morey, 1992; LaFrance & Hanemann, 1989). Moreover, unlike the Almost Ideal Demand (AID) system and its variants, which restrict Engel curves to a quadratic form (Banks et al., 1997), the EASI framework allows for flexible, data-driven relationships between income and demand, making it particularly suitable for developing country contexts characterized by wide income variations and substantial heterogeneity in food expenditure elasticities (E. McCullough et al., 2022).

To assess bias from ignoring the profit effect—the extra income households may receive when staple prices rise—and to compare modeling strategies, I estimate three variants of the EASI demand model. (i) A standard EASI, adding a net-maize-seller dummy as a demand shifter to implicitly account for the profit effects (e.g., Sahn, 1988). (ii) A Fully Interacted EASI (FI-EASI), where in addition to including the net seller dummy as a demand shifter, I interact it with prices and real expenditure so that price and expenditure elasticities vary by household type; this captures preference heterogeneity but does not model the profit channel. (iii) The preferred agricultural household EASI (Ag-EASI) model, which explicitly endogenizes real expenditure through a two-stage instrumental variable (2SLS) approach, allowing maize prices to shift household income or total expenditure (and thus demand) differentially for net sellers or net buyers, thus accounting for the profit effect channel directly.

My standard two-way approximate linearized EASI demand system is specified as:

$$w_{hit} = \sum_{j=1}^{J}(\alpha_{ij}P_{hjt} + \alpha_{ijy}Y_{ht}P_{hjt}) + \sum_{r=1}^{L}\beta_{ir}Y_{ht}^{r} + \sum_{k=1}^{K}\gamma_{ik}Z_{hkt} + \mu_i + \mu_t + u_{hit}, \quad (h = 1, \dots, H; \quad i = 1, ..., J-5; \quad t = 1, 2, 3) \tag{2.1}$$

where w_{hit} is the budget share of household h allocated to food group i during survey wave t. The log price index faced by household h for food group j is denoted by P_{hjt}, with $J = 8$ (seven food groups plus a numéraire). Real household expenditure, Y_{ht}, is constructed following Lewbel and Pendakur, 2009 as $Y_{ht} = log x_{ht} - \sum_{j=1}^{J} w_{hjt}p_{hjt}$, where x_{ht} is nominal total household expenditure. The polynomial degree L of real expenditure is selected based on model selection criteria discussed in the results section. Demand shifters, Z_{hkt}, include demographic and socioeconomic characteristics: household head's age, gender, and marital status, household size adjusted for adult equivalence, dependency ratio, and an indicator for household type (1=net maize seller). Household fixed effects (μ_i) and survey-wave fixed effects (μ_t) control, respectively, for time-invariant unobserved heterogeneity and common time shocks. The term u_{hit} is the error component.

The fully interacted EASI (FI-EASI) model is specified as:

$$w_{hit} = \sum_{j=1}^{J}(a_{ij}P_{hjt} + a_{ijz}Z_{hK}P_{hjt} + a_{ijy}Y_{ht}P_{hjt}) + \sum_{r=1}^{L} b_{ir}Z_{hK}Y_{ht}^{r} + b_{iz}Y_{ht} + \sum_{k=1}^{K} g_{ik}Z_{hkt} + a_i + a_t + v_{hit},$$
$$(h = 1, \ldots, H; \quad i = 1, ..., J-5; \quad t = 1, 2, 3) \tag{2.2}$$

where Z_{hK} is a dummy indicating net maize sellers, allowing for interactions with prices and expenditures to explicitly account for differential effects by household type. a_i and a_t are household and survey-wave fixed effects respectively, and v_{hit} is the error term. I discuss my proposed Ag-EASI model in the next section.

2.4 Estimation Strategy

Studies estimating price and expenditure elasticities using micro-level data commonly encounter a significant number of zero consumption observations, typically due to reporting large number of goods over short recall periods. Such zero consumption values pose estimation challenges, leading many studies to employ censored regression approaches, such as Tobit models (e.g., E. McCullough et al., 2022; Zhen et al., 2014, 2024). However, in my context, because I estimate the demand for the three most consumed food groups—maize, pulses and nuts, and fruits and vegetables—I do not face substantial zero consumption problems.[3] Therefore, I exploit the panel structure of my data and employ a linear fixed effects two-stage least squares estimator (FE-2SLS) to estimate a single-equation demand system for

[3]Zero consumption observations are fewer than 1% for maize and fruits and vegetables, and fewer than 10% for pulses and nuts.

each food group. Using parameters obtained from these estimated demand models, I calculate predicted budget shares and compute household-level price and expenditure elasticities of demand for each food group. Each elasticity is a function of the household's observed prices, total expenditures, demographic demand shifters, and the estimated model parameters (see the Mathematical Appendix for food demand elasticity derivation). I present median elasticity estimates, given their robustness to outliers, and report bootstrapped standard errors.

2.4.1 Addressing Endogenous Regressors in EASI and FI-EASI Models

Following E. McCullough et al., 2022, I address two sources of endogeneity in the EASI and FI-EASI demand systems. The first arises from the construction of the real total expenditure variable, $y_{ht} = \log x_{ht} - \sum_{j=1}^{J} w_{hjt} P_{hjt}$, which uses the Stone price index. Since this index incorporates household budget shares w_{hjt}—the dependent variables in my demand equations—endogeneity is mechanically introduced. The conventional solution in the literature (e.g., E. McCullough et al., 2022; Zhen et al., 2014, 2024) is to replace the endogenous y_{ht} with an instrumented version, $\bar{y}_{ht} = \log x_{ht} - \sum_{j=1}^{J} \bar{w}_{jt} P_{hjt}$, where $\bar{w}_{jt}$ denotes the sample mean budget share for food group j in period t. Similarly, income polynomial terms y_{ht}^r are instrumented using $\bar{y}_{ht}^r$. Although this approach is widely adopted, it has important limitations in the context of agricultural households with endogenous income/expenditure, as I elaborate in my Ag-EASI model subsection.

The second source of endogeneity stems from using unit values—defined as the ratio of total expenditure on a food group to the quantity purchased—as proxies for prices. Because unit values combine market-price variation with a household's endogenous quality choice, they are not exogenous price measures. In response to higher market prices, consumers may substitute toward lower-quality goods, so the observed unit value reflects both the true price and the quality margin (Cox & Wohlgenant, 1986; Deaton, 1988). In fact, my descriptive evidence in my data shows that net maize buyers pay higher unit values than poorer households (Table 2.2), consistent with systematic quality differences. Endogeneity can also arise from price search behavior: households that actively search for lower prices may differ in unobserved preferences or search costs (Gauri et al., 2008). Consequently, unit values are jointly determined with demand, biasing conventional price elasticity estimates unless appropriately instrumented.

To mitigate unit–value bias arising from both unobserved quality heterogeneity and household price–search behavior, I adopt a two–pronged strategy. First, following E. McCullough et al., 2022 and Zhen et al., 2011, I construct household Fisher Ideal price indexes at the food group level using food item level unit values as elements. For household h and food group j $(j = 1, \ldots, J-1)$ in the survey wave t, the index is calculated as

$$p_{hjt} = \sqrt{\frac{\sum p_{kh}q_{k0} \sum p_{kh}q_{hk}}{\sum p_{k0}q_{k0} \sum p_{k0}q_{hk}}} \tag{2.3}$$

Here, p_{hkt} and q_{hk} denote, respectively, the unit value and quantity of item k in food group j for household h. p_{k0} and q_{k0} are respectively the average unit value and quantity over the 7-day recall across sample households. The base unit value p_{k0} and q_{k0} are calculated as the average unit value for item k across the full sample. The Fisher Ideal price index offers a second-order approximation to a linearly homogeneous expenditure function. It corrects for unit value bias arising from substitution across items within a food group, as each group contains multiple food items. However, it does not address bias from within-item quality variation or endogeneity due to price search behavior. For the numéraire good, I use Malawi's consumer price index (CPI), excluding food, alcoholic beverages, tobacco, and narcotics.

To address residual endogeneity stemming from price search and within-item quality substitution, I construct instrumental variables for each household-level price index. Specifically, I generate three instruments for each price: one based on donor households within the same enumeration area (EA) and survey wave, another from households within the same region and wave, and a third from households in the same zone and survey month-year. I then regress the observed price index p_{hjt} on these three instruments and use the fitted values as my final instrument. This strategy, initially developed by Hausman, 1996 and later applied in empirical demand settings by Nevo, 2001, relies on the assumption that household h's idiosyncratic demand shocks are uncorrelated with those of its donor households. Although this exclusion restriction cannot be verified directly, the use of household fixed effects in my two-stage least squares (FE-2SLS) estimation substantially mitigates the risk of bias from correlated unobservables. For the numéraire good, I instrument using the consumer price index (CPI) lagged by two months.

2.4.2 Estimating the Ag-EASI Model

The EASI and FI–EASI approaches recognize that constructing real expenditure by deflating log x_{ht} with the Stone price index places budget shares inside y_{ht}, which creates a mechanical correlation between real expenditure and the budget share errors. Although this form of endogeneity is corrected by using $\bar{w}_{jt}$ to instrument w_{jt}, this has been found to have little impact econometrically (Lewbel & Pendakur, 2009; Zhen et al., 2014). A second concern is that, as $logx_{ht}$ is a household decision variable, it is more likely to be endogenous with category demand, that is, household demand for specific foods (like maize) helps determine their total expenditure, just as their total expenditure limits those very food choices. This endogeneity can have an adverse effect on estimation if not addressed (LaFrance, 1991; Zhen et al., 2016).

To address both problems, following similar methods in Zhen et al., 2016, I treat real household expenditure as endogenous within the standard EASI specification in a two-stage least squares setup. I use household assets (AS), indicators for net maize seller (MS) and maize grower (MG), maize price (P_1), and their interactions (maize price by AS, maize price by MS, maize price by MG) as instruments. The assumption here is that I model endogeneity in real expenditure by allowing maize price to vary across households incomes/expenditure based on household type while also addressing the econometric implications of endogenous real expenditure. Thus, in addition to a decrease in real income from an increase in the maize price, there is also a profit effect arising from additional income, for example, gained from selling maize at that price. Because the standard EASI model treats staple price changes as having no impact on real expenditure except through reduction in purchasing power (the income effect), it misses an important channel which is likely to hold in a setting like rural Malawi where most households are producers and consumers of agricultural staples.

By also simultaneously addressing the endogeneity from the unit values, I run the following first stage regression for each endogenous variable in equation 2.1 as follows:

$$
\begin{aligned}
y^r_{ht} = \lambda_0 + \lambda_1 \mathrm{AS}_{ht} + \lambda_2 \mathrm{MS}_{ht} + \lambda_3 \mathrm{MS}_{ht} \times P^{IV}_{h1t} + \lambda_4 \mathrm{MG}_{ht} + \lambda_5 \mathrm{MG}_{ht} \times P^{IV}_{h1t} \\
+ \sum_{j=1}^{J} \theta_j \mathrm{AS}_{ht} \times P^{IV}_{hjt} + \sum_{j=1}^{J} \tau_j P^{IV}_{hjt} + \sum_{k=1}^{K} \gamma_k z_{hkt} + \epsilon_{ht}
\end{aligned}
\tag{2.4}
$$

$$
\begin{aligned}
y_{ht} \times P_{hjt} = \delta_0 + \delta_1 \mathrm{AS}_{ht} + \delta_2 \mathrm{MS}_{ht} + \delta_3 \mathrm{MS}_{ht} \times P^{IV}_{h1t} + \delta_4 \mathrm{MG}_{ht} + \delta_4 \mathrm{MG}_{ht} \times P^{IV}_{h1t} \\
+ \sum_{j=1}^{J} \rho_j \mathrm{AS}_{ht} \times P^{IV}_{hjt} + \sum_{j=1}^{J} \Gamma_j P^{IV}_{hjt} + \sum_{k=1}^{K} \Delta_k z_{hkt} + e_{ht}
\end{aligned}
\tag{2.5}
$$

$$
\begin{aligned}
P_{hjt} = \phi_0 + \phi_1 \mathrm{AS}_{ht} + \phi_2 \mathrm{MS}_{ht} + \phi_3 \mathrm{MS}_{ht} \times P^{IV}_{h1t} + \phi_4 \mathrm{MG}_{ht} + \phi_5 \mathrm{MG}_{ht} \times P^{IV}_{h1t} \\
+ \sum_{j=1}^{J} \sigma_j \mathrm{AS}_{ht} \times P^{IV}_{hjt} + \sum_{j=1}^{J} \eta_j P^{IV}_{hjt} + \sum_{k=1}^{K} \zeta_k z_{hkt} + w_{ht}
\end{aligned}
\tag{2.6}
$$

where P^{IV}_j is the instrumental variable for food group j discussed in the previous section with $j = 1$ as the instrumental variable for maize. ϵ_{ht}, e_{ht} and w_{ht} are the error terms.

Figure 2.1 plots the local polynomial regression of the predicted real expenditure (y_hat) on log maize price $(ln_P 1)$ by household type. As expected, for net sellers (blue), $\hat{y}$ rises monotonically with the maize price and higher than that for net buyers, consistent with the profit effect channel: higher prices raise sales revenue and total household expenditure. For net buyers (red), the curve is nonlinear: $\hat{y}$ falls as maize prices move from low levels, then increases strongly as prices rise further. Over most of the observed range the slope for net buyers is positive, suggesting that additional income gains associated with higher maize price (for example, increase in demand for farm labor or higher wages in local agriculture) offset the decline in real expenditure. In sum, my setup allows maize price to affect food demand in two ways: indirectly through the first stage, where it shifts real total expenditure, and directly as a regressor in the food demand equation.

I decompose the impact of a maize price increase into the three channels and estimate them within Ag–EASI. First, the substitution effect is the compensated price response in budget shares, given by $h_{i1} = \partial w_i / \partial P_1$ (see the mathematical appendix for the derivation of food demand elasticities). Second, the

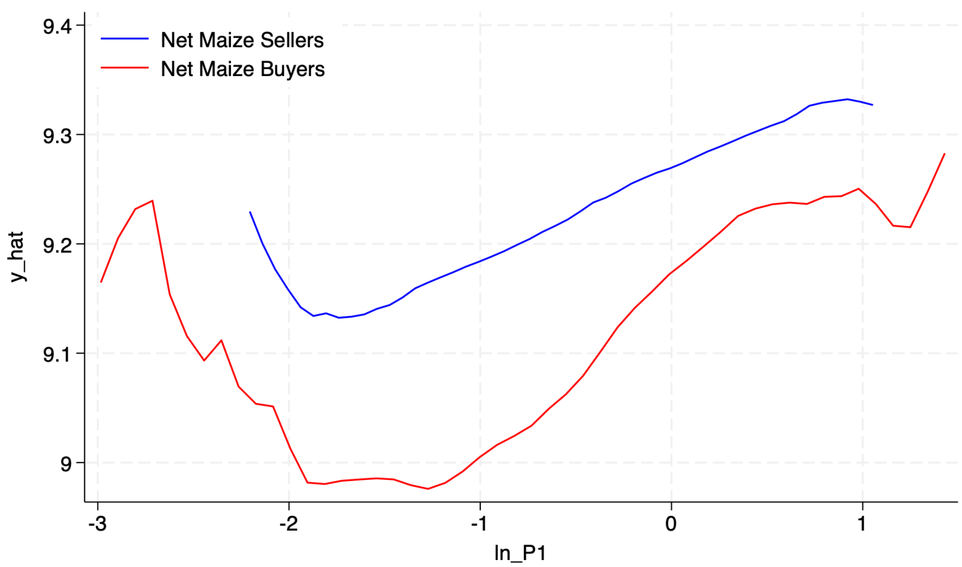


Figure 2.1: Local polynomial regression of fitted real expenditure on maize price by maize market position

income effect from a maize price increase is $-\xi_i, w_1$, the negative of the product of total expenditure elasticity of good i and the maize budget share. Third, Ag–EASI adds the profit effect, an indirect channel in which a higher maize price increases households' total expenditure—through crop revenue or farm-related earnings—and this changes demand for all goods in the system holding prices in the demand system constant. The net effect also accounts for maize price increase in the demand equation, keeping the total expenditure constant. This is expressed as;

$$\frac{\partial w_i}{\partial y}\frac{\partial y}{\partial P_1} = \frac{\partial w_i}{\partial y}\frac{\partial y}{\partial P_1^{IV}}\frac{\partial P_1^{IV}}{\partial P_1} \tag{2.7}$$

Table 2.3 summarizes these channels, shows how the profit term maps to first–stage parameters, and contrasts the Ag–EASI decomposition with the standard EASI case where the profit channel is absent. In Ag–EASI, the profit effect is obtained by combining the total expenditure elasticity for good i ($\partial w_i/\partial y \equiv \xi_i$) with the empirically identified response of total expenditure to maize price ($\partial y/\partial P_1$), which I recover from the first–stage using the maize price instrument and its interactions. In the standard EASI model this channel is absent, so the total effect includes only substitution and income terms (a+b), whereas Ag–EASI adds the profit term (a+b+c).

Table 2.3: Decomposition of Effect of Maize Price Increase under Ag–EASI and EASI Models

	Ag–EASI	**EASI**
Substitution Effect (a)	$h_{1j} = \dfrac{\partial \log q_i}{\partial P_1}$	$h_{i1} = \dfrac{\partial w_i}{\partial P_1}$
Income Effect (b)	$-\xi_i\, w_1$	$-\xi_i\, w_1$
Profit Effect (c)	$\dfrac{\partial \log q_i}{\partial y}\,\dfrac{\partial y}{\partial P_1} = \dfrac{\partial \log q_i}{\partial y}\,\dfrac{\partial y}{\partial P_1^{IV}}\,\dfrac{\partial P_1^{IV}}{\partial P_1}$ $= \xi_i \left[\dfrac{\lambda_3\,\mathrm{MS} + \lambda_5\,\mathrm{MG} + \theta_1\,\mathrm{AS} + \tau_1}{\phi_3\,\mathrm{MS} + \phi_5\,\mathrm{MG} + \rho_1\,\mathrm{AS} + \eta_1} \right]$	—
Total Effect	a+b+c	a+b

Note: This table shows the welfare effect of a maize price increase across models using notations from equations 2.1, 2.4 and 2.6 in the main text.

2.5 Results

I present and compare the median total expenditure and Marshallian price elasticities across household types and models. To show how production status shapes demand responses, I report elasticities separately for net maize buyers who grow maize and for net maize buyers who do not.

Across all model specifications, I use a third-order polynomial in real total expenditure for the Engel curve (r = 3), chosen based on instrument strength. I start with a quadratic (r = 2) and confirm that the first-stage F-statistic of the excluded instruments exceeds 10 (Staiger & Stock, 1997). Adding the cubic term (r = 3), the F-statistic remains comfortably above 10 (12.57), indicating adequate strength. Moving to a fourth-order polynomial (r = 4) lowers the statistic below 10 (4.54), signaling weak instruments. I therefore select r = 3 as the optimal degree which provides flexible Engel curvature relative to QUAIDS without sacrificing identification.[4] Table C.10 reports the first-stage coefficients for the endogenous variables and the corresponding F-statistics.

2.5.1 Expenditure elasticities

Table 2.4 reports the median total expenditure elasticities for maize, pulses and nuts, and fruits and vegetables by households type and models. In line with evidence from studies from low-income settings, food quantities respond strongly to changes in total expenditure (E. McCullough et al., 2022; E. B. McCullough et al., 2024), but the magnitudes differs across models.

Among net buyers who do not grow maize, EASI and FI-EASI yield nearly identical expenditure elasticities and classify all three food groups as normal goods: about 0.55–0.57 for maize, 0.79–0.80 for pulses and nuts, and 0.67–0.68 for fruits and vegetables. Under Ag-EASI, the pattern shifts. Maize becomes an inferior good: a 1% increase in total expenditure is associated with a 0.72% decrease in maize consumption. Pulses and nuts remain normal but are far less responsive (0.16), while fruits and vegetables are close to the EASI benchmarks (0.78). For net buyers who grow maize, all models indicate that higher expenditure increases consumption across food groups; the difference lies in the Ag-EASI magnitudes. The elasticity for maize is relatively small (0.19), pulses and nuts behave like a luxury (1.04), and fruits and vegetables are similar across models at roughly 0.66–0.68.

For net maize sellers, EASI and FI-EASI classify all three groups as normal goods, with elasticities of about 0.45–0.56 for maize, 0.84–0.87 for pulses and nuts, and 0.68–0.70 for fruits and vegetables. Ag-EASI changes the maize result: the elasticity becomes negative (−0.26), suggesting that as overall resources rise, these households shift away from maize and toward other foods. In this specification, pulses and nuts are more responsive (0.92), while fruits and vegetables are somewhat less so (0.59). Unsurprisingly, the EASI and FI-EASI elasticities align with prior Malawian estimates (Ecker & Qaim, 2011; Maganga et al., 2014; E. B. McCullough et al., 2024); by contrast, Ag-EASI mostly differs from those studies. Whereas

[4] Unlike many EASI applications that estimate a full demand system and choose the shape of the Engel curve via joint significance tests on the real-expenditure coefficients, for example as in E. McCullough et al., 2022, I estimate each food group in a single-equation model and choose the optimal polynomial degree of the Engel curve using the strength of my instruments.

the literature generally finds maize to be a normal good across households, my Ag-EASI results indicate that maize is inferior for net sellers and for net buyers who do not grow maize. A plausible reason is that, for net sellers, maize is mainly a cash crop. As total expenditure rises, they reallocate spending toward higher-value foods such as animal products. Likewise, net buyers who do not grow maize shift toward more diverse, nutrient-dense foods like fruits and vegetables as expenditure increases, consistent with Bennett's Law.

Table 2.4: Total expenditure elasticities

	Net Buyers (Non Maize Growers)			Net Buyers (Maize Growers)			Net Sellers		
Food group	EASI	FI-EASI	Ag-EASI	EASI	FI-EASI	Ag-EASI	EASI	FI-EASI	Ag-EASI
Maize	0.55***	0.57***	-0.72***	0.61***	0.62***	0.19***	0.56***	0.45***	-0.26***
	(0.00)	(0.00)	(0.03)	(0.00)	(0.00)	(0.03)	(0.00)	(0.00)	(0.06)
Pulses and nuts	0.79***	0.80***	0.16***	0.89***	0.89***	1.04***	0.87***	0.84***	0.92***
	(0.00)	(0.00)	(0.04)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.02)
Fruits and vegetables	0.68***	0.67***	0.78***	0.68***	0.68***	0.66***	0.68***	0.70***	0.59***
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)

Notes: This table shows median elasticity of food demand (quantity consumed) with respect to total household expenditure by household type. Bootstrapped standard errors are in parenthesis (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$).

2.5.2 Price elasticities

I report the median Marshallian price elasticities of maize, pulses and nuts, and fruits and vegetables across household type and models in Tables 2.5, 2.6 and 2.7 respectively.

Own-price elasticity

For maize (Table 2.5), demand is own-price sensitive across all household types and models, but Ag–EASI slightly shifts the pattern. Except for non-maize growing net buyers, Ag–EASI yields smaller own-price responses for maize than EASI and FI–EASI. For pulses and nuts (Table 2.6), own-price elasticities are negative across all models and groups, and Ag–EASI generally shows greater price sensitivity, except among net buyers of maize growing, where FI-EASI is the largest. Own-price elasticities for fruits and vegetables (Table 2.7) are strongly elastic in every model and household type. Ag–EASI is slightly less elastic for non-maize growing net buyers (-1.42 vs. -1.51 and -1.49), but more elastic for maize-growing net buyers (−1.68 vs. −1.54 in both EASI and FI–EASI) and for net sellers (−1.63 vs. −1.55 in EASI and −1.36 in FI–EASI).

My own-price elasticities for these food groups (across all models) differ from Ecker and Qaim, 2011, who use a conditional demand system to compute food demand elasticities in Malawi. My maize own-price elasticity is much smaller in magnitude than theirs, while the own-price elasticities for pulses and nuts and for fruits and vegetables are somewhat closer to their sample-wide means. In general, own-price elasticities for these food groups are relatively similar across models within household type, with the Ag–EASI model producing slightly higher or lower magnitudes depending on the household type.

Cross-price elasticity

Across household types, cross-price patterns are similar in EASI and FI–EASI, but Ag–EASI often amplifies or flips the signs. For maize demand (Table 2.5), non–maize growing net buyers substitute toward maize when prices of close staples rise under Ag–EASI: the elasticity with respect to cereals and grains (P_2) shifts from −0.01 (EASI) to 0.31 (Ag–EASI), and with respect to roots and tubers (P_5) from −0.05 (EASI) to 0.48 (Ag–EASI). By contrast, when the price of meat, fish, and animal products (P_4) increases, maize demand falls more sharply under Ag–EASI: −0.20 vs. −0.06/−0.04 (EASI/FI–EASI) for non–maize growing buyers, −0.49 vs. −0.17/−0.15 for maize growing net buyers, and −0.38 vs. −0.14/−0.19 for net sellers. In short, whereas EASI and FI–EASI generally portray close starches as complements to maize and proteins as substitutes, Ag–EASI implies the opposite: close starches behave as substitutes and proteins behave more like complements to maize.

The pattern extends to the other food groups. For pulses and nuts (Table 2.6), Ag–EASI often reverses the starch response: among non-maize growing buyers, a rise in the price of roots and tubers (P_5) reduces consumption under EASI (−0.62) but increases it under Ag–EASI (0.43); for maize growing net buyers, the sign also flips from −0.54/−0.62 (EASI/FI–EASI) to 0.18 (Ag–EASI). For fruits and vegetables (Table 2.7), substitution away from other staples remains positive across models but is stronger in Ag–EASI model. For example, maize growing net buyers show a 0.51% increase in consumption when the price of roots and tubers (P_5) increases by 1% versus 0.47%/0.50% increment in EASI/FI–EASI, and non-maize growing net buyers' response to price of "other food" (P_7) is much larger in Ag–EASI (0.61 vs. 0.21/0.24). Overall, Ag–EASI implies bigger shifts toward cheaper staples and stronger cutbacks on costlier categories, especially for maize growing net buyers and net sellers.

Table 2.5: Marshallian price elasticities of maize with respect to food prices

	Net Buyers (Non–Maize Growers)			Net Buyers (Maize Growers)			Net Sellers		
Price of food group	EASI	FI–EASI	Ag–EASI	EASI	FI–EASI	Ag–EASI	EASI	FI–EASI	Ag–EASI
Maize (P_1)	-0.14***	-0.13***	-0.18***	-0.20***	-0.18***	-0.14***	-0.18***	-0.28***	-0.11***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
Cereals and grains (P_2)	-0.01***	0.03***	0.31***	-0.01***	0.01***	0.16***	-0.01***	-0.07***	0.22***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Pulses and nuts (P_3)	0.23***	0.24***	0.20***	0.15***	0.16***	-0.04***	0.17***	0.10***	0.05***
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
Meat, fish and animal products (P_4)	-0.06***	-0.04***	-0.20***	-0.17***	-0.15***	-0.49***	-0.14***	-0.19***	-0.38***
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
Roots, tubers and starches (P_5)	-0.05***	-0.10***	0.48***	-0.08***	-0.13***	0.18***	-0.07***	0.12***	0.28***
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
Fruits and vegetables (P_6)	-0.01***	-0.01***	0.25***	-0.01***	0.00***	0.25***	-0.01***	-0.05***	0.26***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Other food (P_7)	0.16***	0.19***	0.54***	0.17***	0.20***	0.37***	0.17***	0.05***	0.45***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Notes: Entries are median Marshallian price elasticities of demand with respect to the maize price. Bootstrapped standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 2.6: Marshallian price elasticities of pulses and nuts with respect to food prices

	Net Buyers (Non–Maize Growers)			Net Buyers (Maize Growers)			Net Sellers		
Price of food group	EASI	FI–EASI	Ag–EASI	EASI	FI–EASI	Ag–EASI	EASI	FI–EASI	Ag–EASI
Maize (P_1)	-0.27***	-0.29***	-0.19***	-0.28***	-0.29***	-0.20***	-0.26***	-0.13***	-0.21***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Cereals and grains (P_2)	-0.05***	-0.02***	0.02***	0.02***	0.05***	0.01***	0.01	-0.10***	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Pulses and nuts (P_3)	-0.53***	-0.49***	-0.57***	-0.57***	-0.54***	-0.68***	-0.59***	-0.92***	-0.69***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Meat, fish, animal products (P_4)	0.15***	0.15***	-0.05***	0.18***	0.18***	0.22***	0.16***	0.00	0.11***
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
Roots, tubers, starches (P_5)	-0.62***	-0.72***	0.43***	-0.54***	-0.62***	0.18***	-0.53***	-0.03***	0.39***
	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Fruits and vegetables (P_6)	0.23***	0.24***	0.22***	0.21***	0.21***	0.49***	0.20***	0.17***	0.35***
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)
Other food (P_6)	-0.51***	-0.55***	-0.38***	-0.45***	-0.48***	-0.36***	-0.44***	-0.11***	-0.35***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Notes: Entries are median Marshallian price elasticities of demand with respect to the price of pulses and nuts. Bootstrapped standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 2.7: Marshallian price elasticities of fruits and vegetables with respect to food prices

	Net Buyers (Non–Maize Growers)			Net Buyers (Maize Growers)			Net Sellers		
Price of food group	EASI	FI–EASI	Ag–EASI	EASI	FI–EASI	Ag–EASI	EASI	FI–EASI	Ag–EASI
Maize (P_1)	-0.09***	-0.12***	-0.01	-0.12***	-0.14***	-0.16***	-0.12***	0.01***	-0.13***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
Cereals and grains (P_2)	0.29***	0.31***	0.22***	0.20***	0.21***	0.22***	0.24***	0.17***	0.24***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Pulses and nuts (P_3)	0.20***	0.11***	0.16***	0.07***	0.01***	0.13***	0.11***	0.59***	0.15***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)
Meat, fish and animal products (P_4)	0.28***	0.30***	0.02***	0.30***	0.32***	0.15***	0.29***	0.19***	0.12***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Roots, tubers and starches (P_5)	0.45***	0.48***	0.41***	0.47***	0.50***	0.51***	0.47***	0.12***	0.51***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Fruits and vegetables (P_6)	-1.51***	-1.49***	-1.42***	-1.54***	-1.54***	-1.68***	-1.55***	-1.36***	-1.63***
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)
Other food (P_7)	0.21***	0.24***	0.61***	0.20***	0.24***	0.44***	0.20***	0.07***	0.52***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)

Notes: Entries are median Marshallian price elasticities of demand with respect to the price of fruits and vegetables. Bootstrapped standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

2.6 Maize Price Simulation

To move beyond reporting own- and cross-price elasticities, I simulate how a 10% increase in the maize price, the main staple in Malawi, affects demand for maize, pulses and nuts, and fruits and vegetables. In the EASI and FI-EASI models, the price change operates only through substitution and income effects, which are summarized by the Marshallian elasticities. The Ag-EASI model introduces a third channel, the profit effect, where higher maize prices raise household income, especially for net sellers, and this additional income shifts demand. I describe the simulated effects for each food group in detail.

Figure 2.2 shows that a 10% maize-price increase lowers maize demand across all household types in every model, but the channels differ. Under EASI and FI-EASI, treating households as pure consumers yields a small negative substitution effect plus a larger negative income effect, producing clear declines for all groups (e.g., non-maize growing net buyers: -1.27% in EASI; -1.15% in FI-EASI), with FI-EASI largely mirroring EASI except for net sellers, where a larger negative substitution (-1.75%) drives a bigger total drop (-2.73%). Allowing additional income from the price increase in the Ag-EASI model changes the picture. For net buyers who do not grow maize, total demand still falls and is similar in size to EASI/FI-

EASI (−1.48%), but the mechanism shifts: a large negative substitution effect (−3.15%) is partly offset by a positive income effect (1.57%) and a negligible profit term (0.10%), consistent with maize being inferior. For net buyers who grow maize, demand decreases modestly (−0.70%), much less than in EASI (−1.85%) or FI-EASI (−1.69%), with small negative substitution (−0.27%) and income (−0.42%) effects and essentially no profit effect (−0.01%). For net sellers, the negative substitution effect (−1.15%) is offset by a positive income effect (0.58%) and a positive profit effect (0.26%), yielding a small net decline (−0.31%)—far smaller than in EASI (−1.76%) or FI-EASI (−2.73%).

A 10% maize price increase lowers consumption of pulses and nuts (Figure 2.3) for every household type in all three models, but the sources of the decline differs. Under EASI and FI-EASI, households are considered as pure consumers, so a negative substitution effect plus a sizeable negative income effect drives the fall. For example, for non-maize growing net buyers, the increase leads to a reduction in maize demand in EASI (−2.78%) and FI-EASI (−2.93%), with a negative substitution effect that reinforces a negative income effect. Under Ag-EASI, net buyers who do not grow maize experience a slightly smaller total decline (−2.42%) in demand for pulses and nuts because the more negative substitution effect (−2.09%) is partly offset by a weaker income effect (−0.31%) and a near-zero profit term (−0.02%). For maize growing net buyers, Ag-EASI again yields a smaller decline (−2.37%) than EASI (−2.92%) or FI-EASI (−3.06%): the substitution effect is close to zero (−0.09%), the income effect is more negative (−2.20%), and the profit term remains tiny (−0.08%). The sharpest contrast is among net sellers: Ag-EASI produces the largest reduction (−3.17%) in demand for pulses and nuts because a negative profit effect (−0.95%) and a negative substitution effect (−0.44%) reinforce the negative income effect (−1.78%). By comparison, FI-EASI shows a much smaller total decline (−1.32%) for sellers due to a positive substitution effect (0.45%) that offsets part of the income loss, while EASI sits in between at −2.81%.

For fruits and vegetables (Figure 2.4), a 10% maize price increase generally reduces consumption for net buyers because the income effect dominates any substitution toward this category. Among non-maize growing net buyers, total demand for fruits and vegetables falls by 0.84% in EASI and 1.13% in FI-EASI; under Ag-EASI demand still declines (0.69%) as a stronger pull toward fruits and vegetables is more than offset by a larger negative income effect and a small negative profit effect. For maize growing net buyers, all models show declines—1.22% in EASI, 1.48% in FI-EASI, and 2.17% in Ag-EASI—with the larger drop in Ag-EASI arising because substitution effect turns negative and the income effect remains strongly negative, compounded by a small negative profit effect. For net sellers, the models diverge: EASI shows a 1.21% decline because the negative income effect outweighs modest substitution toward fruits and vegetables; FI-EASI shows a slight increase of 0.49% as strong substitution more than offsets the income loss; Ag-EASI shows a 2.15% decline because the substitution, income, and profit effect become negative.

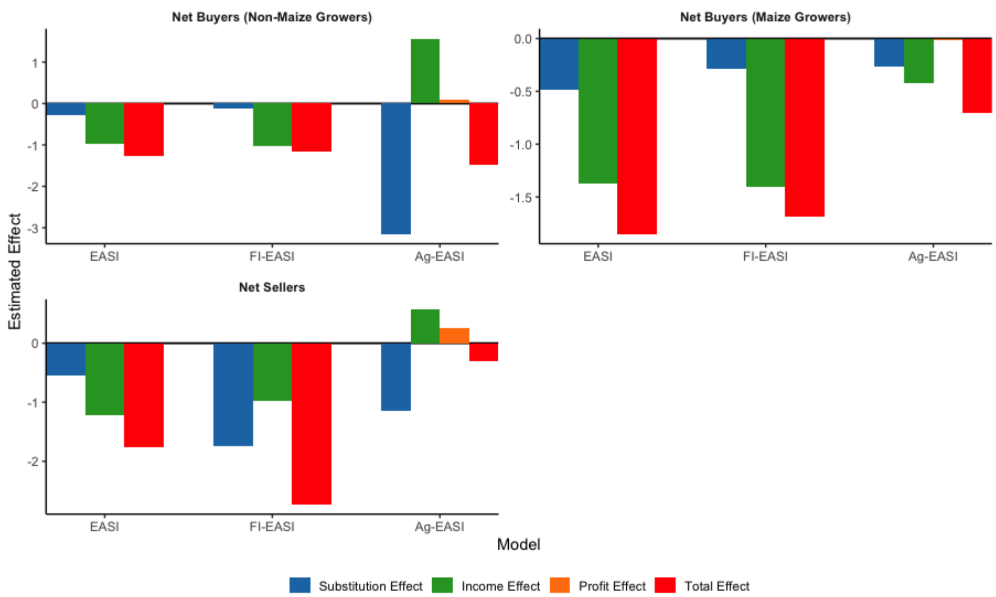


Figure 2.2: The simulated effects of a 10% increase in maize price on the consumption of maize by household type and across models

2.7 Conclusion and Policy Implications

This study examines what is lost when households that both produce and consume staples are modeled as pure consumers, thereby omitting the income gains from higher staple prices (the profit effect). Using nationally representative panel data from Malawi, I estimate demand for three major food groups—maize, pulses and nuts, and fruits and vegetables—under three Exact Affine Stone Index (EASI) specifications. First, I follow the literature with a standard EASI model that includes a net-maize seller indicator as a

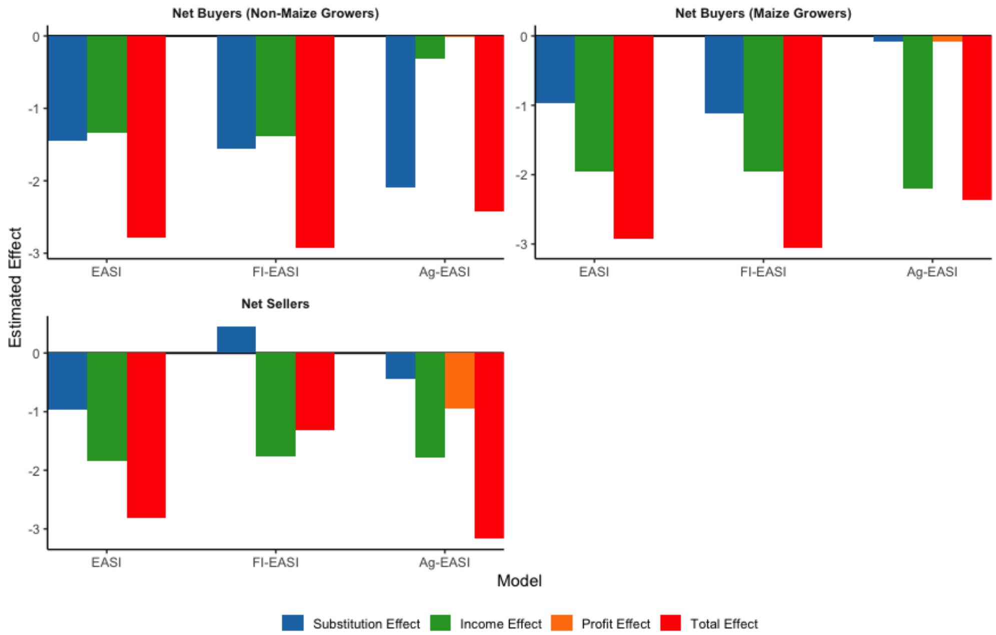


Figure 2.3: The simulated effects of a 10% increase in maize price on the consumption of pulses and nuts by household type and across models

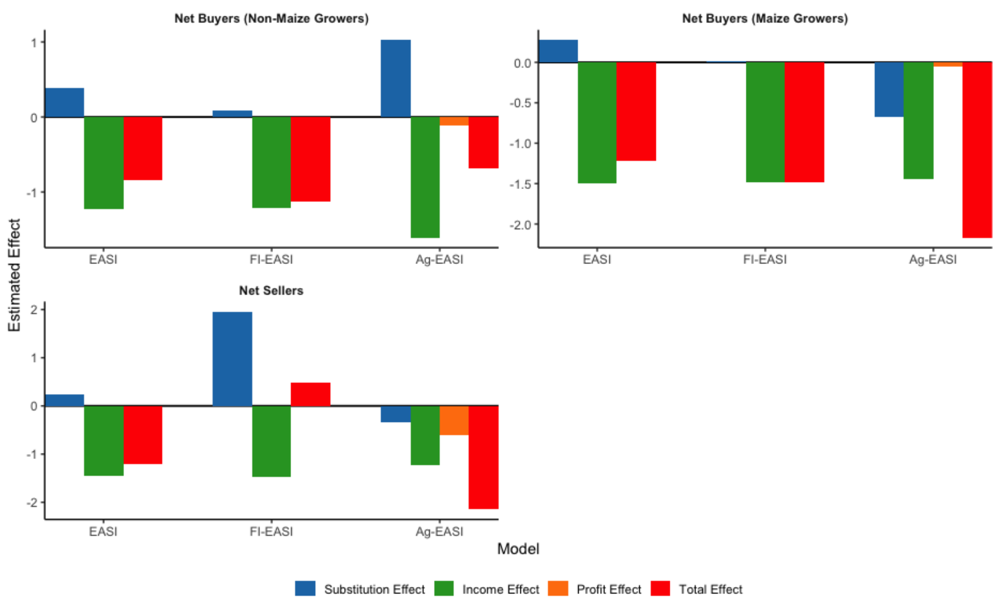


Figure 2.4: The simulated effects of a 10% increase in maize price on the consumption of fruits and vegetables by household type and across models

demand shifter. Second, I estimate a fully interacted EASI that allows prices and real expenditure to vary with household's maize market position, capturing preference differences by household type. Third, I introduce an agricultural-household EASI (Ag-EASI) that endogenizes total expenditure so staple price changes can affect household income through production, implemented via a two-stage instrumental variables (2SLS) framework. I then compare demand elasticities and simulate the effect of a 10% maize price increase on food demand to assess whether models that ignore the profit effect yield biased estimates across household types.

These simulation results reveal several important implications for policy tools that rely on food demand elasticities in developing countries where households are both producers and consumers. Ag-EASI often delivers different total effects than EASI and FI-EASI, while the two consumer-only models largely agree. This matters for policy because EASI and FI-EASI treat all households as pure consumers, whereas Ag-EASI allows producer income to change with the maize price and can materially alter the results. Net sellers in the maize model show the issue clearly: EASI and FI-EASI imply a large fall in maize consumption after a 10% maize price increase, which could push policymakers toward broad consumer subsidies for these households. Ag-EASI, however, shows a much smaller decline once producer income is allowed to rise with the maize price, because higher profits partly offset the negative substitution effect. A policy based on Ag-EASI would therefore de-prioritize broad consumer subsidies for net sellers and focus scarce resources on net buyers. In short, when Ag-EASI diverges from EASI and FI-EASI, policies that ignore producer income responses to staple price changes may over-subsidize net sellers and under-support the households that bear the largest welfare losses.

In cases where the total effect of the 10% increase in maize price simulation is similar across models, the decomposition differs across models. In several instances, Ag–EASI indicates a dominant substitution or income effect, while EASI and FI–EASI suggest the opposite. Even when a profit effect is present, it generally moves in the same direction as the income effect, which means analysts relying on EASI or FI–EASI may attribute the impact of the profit effect to the income effect when designing policy tools. This distinction is important for policy design. For example, EASI might point to a reduction in consumption driven mainly by substitution effect and, in turn, motivate tax reductions for all household types, whereas Ag–EASI may attribute the response to both income and profit effects and therefore support a different mix, such as cash vouchers for net buyers and producer-side interventions for net sellers.

We gain additional insights when I examine food demand elasticities across these models and household types. The main departures for expenditure elasticities arise under Ag–EASI. For non-maize growing net buyers, Ag–EASI flips maize from a normal to an inferior good and sharply dampens the expenditure responsiveness of pulses and nuts, while leaving fruits and vegetables close to EASI and FI-EASI. For net sellers, Ag–EASI again makes maize inferior (negative expenditure elasticity) and indicates a stronger shift toward pulses and nuts with a slightly weaker response for fruits and vegetables. By contrast, for maize growing net buyers, Ag–EASI broadly preserves the EASI/FI-EASI signs.

Own-price elasticities under the Ag–EASI sometimes changes the conclusion reached by EASI and FI–EASI. In particular, it tends to dampen maize's own-price elasticity for net sellers and amplify own-price elasticities for pulses and nuts, and fruits and vegetables. Similarly, cross-price elasticity under Ag–EASI often reverses or amplifies the relationships seen in EASI and FI–EASI models. For maize demand, EASI and FI–EASI typically treat close starches (cereals, roots, tubers) as complements and proteins as substitutes, whereas Ag–EASI flips this: close starches behave as substitutes for maize and proteins look more like complements. Across food groups, the Ag–EASI's magnitudes are more elastic, indicating stronger reallocation when other prices move especially for maize-growing net buyers and net sellers.

Overall, the results indicate that treating households as pure consumers and ignoring the profit effect leads to different and potentially misleading policy conclusions. Simply adding producer status as a demand shifter does not capture the profit channel, and fully interacting that status with prices and expenditures also falls short; in practice, the interacted EASI often mirrors the standard EASI and yields similar takeaways. Given the systematic differences I observe when producer income moves with prices, the clear implication is to use a model that endogenizes total expenditure to staple price changes (Ag-

EASI) in settings where households both produce and consume staples; otherwise, policy risks being mis-targeted or mis-scaled.

Despite the key insights from this study, some limitations must be acknowledged. First, I estimate each food group in a single-equation framework rather than a full demand system that imposes standard theoretical restrictions such as adding-up, homogeneity, and symmetry. Second, focusing on three broad groups in Malawi may mask category-specific responses for important food items (e.g., meats and poultry), as highlighted in prior work Ecker and Qaim, 2011; E. B. McCullough et al., 2024. These limitations point to clear avenues for future research to estimate a full, theoretically consistent demand system with disaggregated food groups and assess how ignoring the profit effect alters results at that granular level.

Chapter 3

The Impacts of Child Health Conditions on Maternal Employment Outcomes[1]

3.1 Introduction

Understanding the short-term and long-term consequences of early child health and nutrition is important for many reasons. Early child health and nutrition issues negatively affect a child's educational and economic outcomes as an adult (Black et al., 2022; Currie & Goodman, 2020; Hoddinott et al., 2013; Mwene-Batu et al., 2021; Smith, 2009). Severe malnutrition especially in impoverished conditions is a significant risk factor of child mortality globally (Black et al., 2008; Guerrant et al., 2013; Pelletier & Frongillo, 2003). Poor childhood health conditions may also affect a mother's labor supply (Corcnan et al., 2005; Gould, 2004; Powers, 2003; Salkever, 1982). However, it is poorly understood how child health affects economic activities.

Maternal labor supply disruptions could be particularly relevant in rural agricultural contexts in Africa where men and women differ in their access to agricultural factors of production, including labor, land, farm inputs, and technologies and where gender roles are prevalent (Palacios-López & López, 2015; Udry, 1996b). Women and men also differ in their time allocated to household work, providing

[1]With Yawotse Nouve, Nicholas Magnan and Ellen McCullough

more time to caring for children. For these women, an expansion of household labor requirements due to child illness could curtail women's participation in the labor force and their labor productivity (Aguilar et al., 2014; D. Ali et al., 2015; Backiny-Yetna & McGee, 2015; C. R. Doss, 2018; Kilic et al., 2015). Besides the labor force participation effect, poor child health could also influence the mother's occupational choice and the mother's efficiency in the allocation of time across productive activities (Brummund & Merfeld, 2021), which has implications for household welfare. We use incidence of child sickness to examine the effect of child health on maternal labor supply. We ask: does a mother's labor supply change when her child is sicker? does a mother allocate her time to less efficient and sub-optimal activities when her child is sicker?

Using three waves of nationally representative panel household data from the Malawi Integrated Household Surveys (IHS), this paper therefore provides new evidence on the impacts of child health status on mothers' employment. We conduct this analysis in Malawi because it has one of the highest prevalences of child stunting under 5 in sub-Saharan Africa (Akombi et al., 2017), and hence offers the opportunity to explore the nexus of child nutrition and health, and mother's employment. We retain households that include a mother and a child under the age of 3. The child health variable is the child stunting, based on the child's Height-for-Age z-score (HAZ). The use of stunting as a measure of child health health is supported by a vast literature in the fields of nutrition and health, documenting the association between child stunting and frequent child sickness, especially in developing countries (Black et al., 2008). Our maternal employment outcomes include labor supply to four separate economic activities – farm self-employment (family plots), seasonal farm wage (called ganyu in Malawi), non-farm self-employment (off-farm business), and non-farm wage (salary job). We estimate both the extensive margin of labor supply (participation) and the intensive margin of labor supply (average labor days per week).

To address the endogeneity issue caused by the reverse causality and simultaneity of child health and mother's employment outcomes, we use a novel instrument, the child's in-utero exposure to extreme temperature (measured by the average degree days over 29°C), to generate exogenous variation in child stunting (Andalón et al., 2016; Banerjee & Maharaj, 2020; X. Chen et al., 2020; Davenport et al., 2020; Grace et al., 2015; Ha et al., 2017). The exclusion restriction relies on the assumption that in-utero temperature shocks only affect maternal labor supply through child stunting and not through any other channel. Our approach is similar to that of Frijters et al., 2009 who relied on the Instrumental Variables (IV) approach to address the econometric challenge of studying the child health-mother labor supply relationship. We address potential threats to the validity of this method and provide appropriate robustness checks that rule out these threats.

Our main findings reveal that poor child health significantly reduces the mother's participation in casual agricultural wage employment (ganyu). More specifically, our findings show that child stunting reduces mother's time allocated to agricultural wage employment by about 1.3 labor days per week. We find this result to be more pronounced when the child is a boy. Nonetheless, we do not find enough evidence of the impact of child health on the mother's participation in the other types of labor (farm self-employment, non-farm self-employment, and non-farm wage employment). This finding could be explained by the fact that agricultural wage employment is less flexible and more energy-demanding as opposed to for instance self-employment in family farms or own farms. In that regard, although agricultural wage employment offers cash opportunities, it might be less appealing to mothers dealing with issues of child health.

Besides the child health effects on mother's farm wage labor, we also find that mother's education and household landholdings are good predictors of maternal labor force participation. Results reveal that mothers with no education have a higher chance of participating in farm activities (paid labor to other farms or farm self-employment) while mothers with some education are more likely to participate in non-agricultural activities. Similarly, we find that the probability of mothers participating in family farm labor augments with household landholdings. At the same time, an increase in household landholdings decreases the probability of mothers engaging in non-farm labor.

These findings hold after correcting for potential bias from the mother's self-selection into the labor market, using the Heckman two-step sample selection method (J. J. Heckman, 1976, 1979) and ivtobit method. Our results also hold after using a continuous measure of stunting (rather than a binary measure) and after using alternative temperature thresholds to calculate the in-utero average degree days.

The results provide insights on the importance of child health for mother's participation in the labor force. For instance, in sub-Saharan Africa, women provide about half the agricultural labor (Palacios-Lopez et al., 2017). Poor child health could therefore reduce this contribution to the labor force. In addition, because different activities are associated with different returns to participation (E. B. McCullough, 2017), time allocation across different activities could have important implications for overall labor productivity (Brummund & Merfeld, 2021). Our findings support the rationale behind designing interventions that reduce early childhood stunting and poor health conditions, thereby enhancing children's human capital in developing countries.

Improving a child's health is an important aspect of fostering his human capital (Currie, 2009, 2020). There is a vast literature that has showed that various investments in early childhood including parental investments have positive effects on the child's human capital development (Attanasio, Cattan, et al., 2020; Attanasio, Meghir, & Nix, 2020; J. Heckman et al., 2013). Evidence has also showed that early childcare has benefits for the child's development (Araujo et al., 2019) and the mother's employment outcomes (Clark et al., 2019; Connelly et al., 1996; Dang et al., 2022; Kimmel, 1998). In a context of rural agricultural contexts where there might be a competition in the allocation of resources between parents' investments on children and investments on household's needs such as farm or off-farm businesses, early childhood interventions aiming at improving child health and the child's human capital will particularly be beneficial for both the child's development and the mother's employment outcomes. However, as noted by Bernal and Ramírez, 2019 and Blimpo et al., 2022, these interventions should include nutrition and health components to be fully effective.

Our paper contributes to the literature in two major ways. First, to the best of our knowledge, there is little to no evidence in developing countries that explains the links between child health, and parents' labor force participation. There is an extensive body of literature on the relationship between child health and maternal employment from developed countries. Most of these studies address the impact of child illness on maternal labor force participation and earnings in a wage employment setting (Eriksen et al., 2021; Fleche et al., 2019; Frijters et al., 2009; Gallen, 2018; Gould, 2004; Kuhlthau & Perrin, 2001; Salkever, 1982; Wasi et al., 2012). The study most similar to ours is that of Frijters et al., 2009, which finds that poor child development decreases maternal labor force participation, using a sample of non-agricultural households from Australia.

Second, unlike many studies that consider child health as an outcome of interest, our study considers child health as a potential determinant of mother's employment. Often, child health is considered a consequence or outcome of household economic activities. We show that child health could also explain household choice of economic activities, especially mother's labor allocation. Most of the interventions to improve child nutrition usually target improvements in women's health or economic empowerment (Abreha & Zereyesus, 2021; Allendorf, 2007; Chilinda et al., 2021; Duflo, 2012; Essilfie et al., 2020; Heckert et al., 2019; Komatsu et al., 2018; Melesse, 2021; Santoso et al., 2019). Our findings suggest that interventions that target child nutrition and health might also improve women's economic empowerment and overall welfare, by raising their labor productivity.

The remainder of the paper is structured as follows. After describing our data and variable construction in section 3.2, we explain the empirical strategy in section 3.3. Section 3.4 discusses the results, followed by heterogeneity analysis and robustness checks. Finally, the conclusion and the policy implications are presented in section 3.7.

3.2 Data

We form a district-level panel with three waves of nationally representative household panel data, the 2010/11 Integrated Household Survey (IHS3), the 2013 Integrated Household Panel Survey (IHPS) 2013, and the 2016 IHPS.[2] Our dataset is part of the World Bank Living Standards Measurement Study-Integrated Surveys on Agriculture (LSMS-ISA). We test our hypothesis in Malawi because it has one of

[2]The data collection for the first wave was conducted between March 2010 and March 2011, for the second wave between April and December 2013, and for the third wave between April 2016 and April 2017

the highest prevalences of child stunting under 5 (Akombi et al., 2017). Our primary sample is composed of households that include at least one mother-child pair with the child between 6 months and 3 years of age. We restrict our sample of study to these households so that we can compute the child anthropometric indicator height-for-age Z score (HAZ). Our sample is also about 78% rural, and the labor market in rural Malawi is often characterized by seasonal employments (Guiteras & Jack, 2018).

Table 3.1: Summary Statistics of Key Variables

	Obs.	Mean	Std. dev.	Min	Max
Mother's Labor participation					
Labor participation=1	3201	0.79	0.41	0	1
Family farm labor=1	3201	0.63	0.48	0	1
Farm wage labor (ganyu) =1	3201	0.31	0.46	0	1
Non-farm wage labor=1	3201	0.04	0.20	0	1
Non-farm self-employment=1	3201	0.15	0.35	0	1
Number of labor days (unconditional)					
Family farm labor per week (days)	3201	1.6	1.89	0	7
Farm wage labor (ganyu) per week (days)	3201	0.27	0.68	0	6.46
Non-farm wage labor per week (days)	3201	0.16	0.96	0	7
Non-farm self-employment per week (days)	3201	0.56	1.61	0	7
Child health					
Height-for-age (HAZ)	3201	-0.52	1.78	-4.99	4.96
Stunted=1	3201	0.20	0.40	0	1
Instrumental Variable					
Gestational Average degree days >29°C	3201	0.08	0.23	0	1.34
Demographics					
Male child=1	3201	0.50	0.50	0	1
Child has siblings under five=1	3201	0.33	0.47	0	1
Mother's age in years	3201	27.62	6.50	15	48
Mother has some education=1	3201	0.23	0.42	0	1
Mother has a chronic disease=1	3201	0.05	0.22	0	1
Father's age in years	3201	33.28	7.13	18	58
Father labor participation=1	3201	0.73	0.44	0	1
Ratio dependent to active	3201	1.37	0.84	0	7
Household landholdings (ha)	3201	0.66	0.55	0	3.48

Notes: This table reports the summary statistics of regression variables.

Our final sample of study has a total of 2815 households with 1078 households in wave 1, 1147 households in wave 2, and 590 households in wave 3. As shown in Table C.1 in the Appendix, for all three waves, we have a total of 2920 mothers, of which 1393 have boys only, 1401 have girls only and 126 have both boys and girls aged 0 - 3. The sample has 3201 children, of which 20.3% is stunted, with a height-for-age below -2 standard deviations. The sample is also balanced in terms of child gender, with 50% male. Table 3.1 shows the descriptive statistics of the sample and as illustrated in the table, the average height-for-age (HAZ) is -0.52. Table 3.1 also shows that the average age of mothers is about 28 while the average age of fathers is 33. On average, households have 0.6 hectares of land.

3.2.1 Construction of Labor Outcomes and Stunting Variables

For each mother, we construct several labor supply outcome variables. For farm labor supply, we aggregate the mother's labor on all plots (family and own plots) during the agricultural seasons but also the mother's casual labor supplied to other farms for wage (ganyu). For non-farm labor, we consider salary employment but also self-employment in activities such as manufacturing, trade, restaurants, etc.

To ensure comparability between different labor types, the total number of workdays for both farm and non-farm activities was calculated over a 12-month period and then converted into a standardized per-week measure. Respondents were asked the number of months they worked, the number of weeks they worked per month, and the number of days they worked per week in the preceding 12 months. For non-farm labor, a more direct approach was used. Respondents were asked for the total number of days they worked in their most recent month of activity within the last year. On average during a week, women in our sample spent about 1.6 labor days on family plots, 0.27 days of work on remunerated farm work (ganyu), 0.56 days of work on self-employment activities, and 0.16 days on wage employment (Table 3.1). [3]

Table 3.1 shows that about 79% of mothers in the sample have participated in any form of labor in the 12 months prior to the data collection. The table corroborates that the sample is mainly rural agricultural

[3] We consider in this study that a labor day is equivalent to 6 hours of work in a day.

given that 63% of mothers have worked on family plots while 31% have participated in paid agricultural labor during agricultural seasons. Also, 15% of the mothers have run an off-farm self-business at least once in the last month prior to the survey but only about 4% have done a salary job.

Child stunting occurs when the value of the child's height-for-age (HAZ) is below -2 standard deviations (SD). Hence, we construct the treatment variable, dummy variable for child stunting, as 1 if a child's height-for-age (HAZ) is below -2 and 0 otherwise. The mean stunting in our sample is 0.26.

3.2.2 Temperature Data and IV construction

The temperature data used to construct our instrumental variable (IV) come from the Climate Hazards InfraRed Temperature with Stations (CHIRTS) database (Funk et al., 2019). The CHIRTS dataset provides daily maximum and minimum temperatures at a high spatial resolution of 0.05-degree from 2006 through 2015, coinciding with the birth years (2007 to 2015) of the children in our sample. We extract the daily maximum and minimum temperature at the district level[4] and merge it with our household level data base on the district and wave-year identifiers.

Our IV measures temperature exposure during the critical developmental period of gestation. Specifically, we construct the in-utero average degree days above a threshold temperature of 29°C for each child. In the absence of reliable child's date of birth (day-month-year), we follow Banerjee and Maharaj, 2020 to estimate each child's gestational period as nine months preceding their month and year of birth. For example, a child born in October 2006 is assigned a gestational period from January to September 2006, while a child born in May 2015 has a gestational period spanning from September 2014 through April 2015. For each day within a child's gestational period, we compute the daily degree days above 29°C (DD_{29}) as follows:

$$\mathrm{DD}_{29} = \max\left(\frac{T_{\max} + T_{\min}}{2} - 29,\ 0\right) \tag{3.1}$$

[4]We extract the temperature data at the district level rather than at the household cluster level to reduce measurement errors caused by intra-district migration immediately following childbirth. To further mitigate concerns related to inter-district migration, our analysis includes only households that did not migrate into or out of their district during the study period, ensuring an accurate estimation of maternal temperature exposure during gestation.

where T_{max} and T_{min} represent the daily maximum and minimum temperatures, respectively. If the daily average temperature is at or below 29°C, DD_{29} is set to zero; otherwise, DD_{29} measures how many degrees the average temperature exceeds 29°C. The final IV for each child is calculated as the average of daily DD_{29} values during the gestational period.

We selected 29°C as our temperature threshold in a data-driven way to overcome the problem of weak instruments discussed in Angrist and Pischke, 2009 and Cunningham, 2021. To do this, we examined alternate temperature thresholds (28°C, 29°C, 30°C, and 31°C) by running first-stage regressions to evaluate the relationship between average degree days during gestation and child stunting. Although all considered thresholds produced statistically significant first-stage relationships, the 29°C threshold provided the highest first-stage IV F-statistic, indicating a strong IV and thus circumventing the problems of weak instrument. First-stage regression results comparing the alternative thresholds are provided in Table C.10.

Figure 3.1 presents the distribution of the average degree days above 29°C during gestation in our sample, highlighting the skewness in the exposure distribution. We discuss in detail the validity of average degree days above 29°C as an instrument for child stunting in Section 3.3.2.

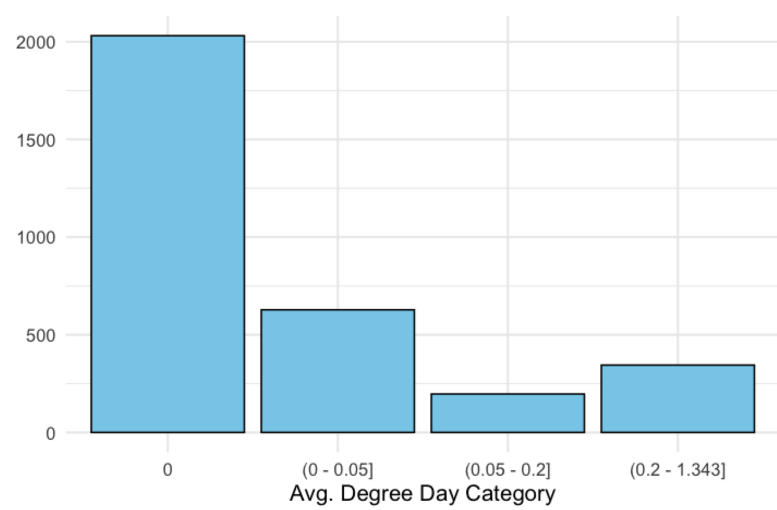


Figure 3.1: Distribution of Average Degree Days > 29°C during Gestation

3.2.3 Child Stunting and Health Conditions

In the absence of reliable health conditions variables in our data, we assume that a child stunting can reflect the child's health conditions as a whole. According to the Word Health Organization (Organization et al., 2012), stunting is part of the three impact indicators of child health. Moreover, several studies have used child anthropometric measures as child health variables. For example, Tanaka, 2014 studied the child health effects of removing user fees in South Africa using primarily the child weight-for-age (WAZ) as the child health variable. The author also used the child weight-for-height (WHZ) and height-for-age (HAZ) as additional continuous measures of child health. The author suggests that while WAZ and WHZ are more likely to reflect short-term health effects, HAZ is more appropriate to capture the long-term cumulative effects. Since stunting is a good indicator of the child past nutrition status but also a predictor of the child future development, it is generally used as a long-term indicator of health conditions. Thus, stunting is a good proxy for the child overall health since it depicts the accumulated child nutrition and health capital from birth. Aslam and Kingdon, 2012 also used child WAZ and HAZ as the child health variables to study the effects of parental education on child health in Pakistan while F. R. M. Ali and Elsayed, 2018 used dichotomous measures of WHZ and HAZ as the child health variables to study the same causal relationship in Egypt. Moreover, Minoiu and Shemyakina, 2012 used a difference-in-differences methodology to investigate the causal link between armed conflicts and child health, where the child health is evaluated using the child HAZ. Furthermore, Y. Chen et al., 2017 used HAZ and WAZ as the child health indicator variables to explore whether an increase in family income will improve child health in China.

Earlier works such as Duflo, 2000 also utilized the child anthropometric height-for-age z-score as an indicator of child health. In addition, Blau et al., 1996 investigates the relationship between child health and mother labor supply using direct measures of child height and weight (instead of height-for-age or weight-for age) as an indicator of long-term and short-term child health measures. The paper however acknowledged that while these variables may not comprehensively reflect the child health, they are commonly used in developing countries as health indicators given the correlation between the child nutrition and the child health in these countries. Even though most of the aforementioned studies used the child anthropometric measures as an outcome variable instead of as a treatment variable, we find enough support in the literature in using the child stunting as an indicator of child health.

Child stunting is often caused by undernutrition, infections, and diseases such as malaria and diarrhea, which results in an unhealthy growth (Checkley et al., 2008; Danaei et al., 2016; Gari et al., 2018; Guerrant et al., 2013; Kang et al., 2013; Keats et al., 2022). The reverse relationship is also possible; stunting can be a risk factor for diseases (Deen et al., 2002). In general, stunted children are likely to fall sick more frequently.

3.3 Empirical Strategy

To examine the relationship between child health and maternal labor outcomes, we are interested in the following linear model:

$$L_{idt} = \alpha S_{idt} + \mathbf{X'_{idt}}\gamma + \delta_{\mathbf{d}} + \lambda_{\mathbf{t}} + \epsilon_{\mathbf{it}} \tag{3.2}$$

where L_{idt} is the labor supply outcome of interest of mother i in district d and survey wave t. S_{idt} is the treatment variable, dummy variable for whether mother i's child is stunted or not – our proxy for child health. $\mathbf{X'_{it}}$ is a matrix of controls that includes child siblings (whether the child has siblings under 5), mother's age, age squared, mother's education, child gender, mother's health (whether the mother has a chronic disease), father's age, father labor participation, ratio of household dependent (members older than 65 or younger than 15) to active members, and household landholdings. District fixed-effect, δ_d, sweeps out any time invariant characteristics of the districts in our sample, while λ_t captures common shocks over time; ϵ_{idt} is the idiosyncratic error term. Standard errors are clustered at the household level.

We investigate the impacts of child health on the mother's supply of farm labor (paid and non-paid) and non-farm labor (salary and self-employment) separately. In each case, we investigate the effects of child health on maternal labor participation (extensive margin of labor supply) and on the number of days worked (intensive margin of labor supply). For the intensive margin of labor supply, the four outcomes of interest are (i) the average weekly days of work in own and family farms, (ii) the average weekly days of ganyu work (casual farm wage labor), (iii) the average weekly days of non-farm employment, and (iv) the average weekly days of non-farm self-employment. We do not condition the intensive margin of labor supply estimations on labor participation. The corresponding extensive margin of labor of supply indicates whether the mother has participated in the employment.

3.3.1 Addressing Endogeneity

We face two major concerns in identifying the causal effects of child health condition on maternal labor supply outcomes. The first concern is the reverse causality or the simultaneity of the relationship. Maternal labor supply can affect child health. For instance, in the case of farm labor, an increase in the farm labor supply of mothers for instance could result in good agricultural yields which will increase the household food supply and will have nutritional benefits for children. On the other hand, a child who is often sick may prevent the mother from working on her plots or on her non-farm activities, and may prevent the mother from being fully effective in her work, which may lead to both a decrease in the time allocated to work by the mother or a decrease in the total productivity. In the case of seasonal paid farm labor (ganyu) and non-farm labor, a child with health issues could prevent the mother from working but at the same time, it could also make the mother prefer to work more for the purpose of getting cash more quickly to contribute to household food supply and improve the child health condition. We expect poor child health conditions to have negative effects on maternal farm labor outcomes, but in the presence of reverse causality, these negative effects could be underestimated due to the fact that mother's income from paid employment or mother's agricultural productivity are likely to have positive effects on child health, thereby leading to upward biased estimates.

Second, we are concerned about the omitted variable bias issue due to the fact that unobserved factors such as genetic factors, mother's health conditions during pregnancy, that affect child health will also affect maternal health, and thereby affect maternal labor supply outcomes. The omitted variable bias can also emanate from sample selection bias due to mothers' self-selection into labor force. In all cases, we would have in equation 3.2, the error term correlated with the treatment variable (S_{idt}) such that $Cov(S_{idt}, \epsilon_{idt}) \neq 0$, and implementing the standard OLS will result in biased estimates (Angrist & Pischke, 2009; Wooldridge, 2010).

To address these concerns, we employ an identification strategy using an Instrumental Variables (IV) method, where we use the average degree days above 29°C during the child's gestational period ($\text{ADD}^{29^\circ\text{C}}$) to instrument for child stunting. The IV method requires that our choice of instrument, $\text{ADD}^{29^\circ\text{C}}$, is strongly correlated with child stunting (relevance condition) but affects mother's labor supply outcomes only through the endogenous variable (child stunting). While prior evidence shows that in-utero exposure to extreme temperatures affects birth outcomes and child health—supporting the relevance of our instrument (Andalón et al., 2016; X. Chen et al., 2020; Davenport et al., 2020; Deschênes et al., 2009; Grace et al., 2015; Ha et al., 2017)—the exclusion restriction remains obscure because it cannot be directly tested. In the next subsection, we discuss in detail the relevance and the plausibility of the exclusion restriction of our IV in detail. In an experimental setting, our IV would work as an assignment variable, determined exogenously from potential outcomes, on which the treatment is assigned. Thus, our IV method will identify the Local Average Treatment Effects (LATE) among the compliers to the treatment, that is, the fraction of children that are exposed to extreme temperature in-utero that react to the treatment.

For a mother i in survey wave t, the first stage equation of the IV estimation is:

$$S_{idt} \;=\; \theta \, \text{ADD}^{29^\circ\text{C}}_{idt} \;+\; \mathbf{X}'_{idt}\, \Gamma \;+\; \rho_d \;+\; \mu_t \;+\; v_{idt}, \tag{3.3}$$

where $\text{ADD}^{29^\circ\text{C}}$ is mother i's child in-utero average degree days above 29°C, v_{idt} is the error term and the rest of variables follow same definition as in equation (3.2).

The second stage is specified as follows.

$$L_{idt} = \beta \hat{S}_{idt} + \mathbf{X'_{idt}} + \tau_\mathbf{d} + \phi_\mathbf{t} + \mathbf{e_{idt}} \tag{3.4}$$

3.3.2 In-utero exposure to extreme heat as Instrument: Validity and Robustness

The first assumption required for the validity of our instrumental variable (average in-utero degree days above 29°C) is its strong correlation with child stunting. A substantial and growing literature has documented the adverse impacts of prenatal exposure to extreme temperatures on child birth outcomes in developing countries (Andalón et al., 2016; Banerjee & Maharaj, 2020; X. Chen et al., 2020; Davenport et al., 2020; Grace et al., 2015; Ha et al., 2017). For instance, X. Chen et al., 2020, examining data from rural China, found that in-utero exposure to temperatures above 28°C significantly reduced birth weight. Specifically, each additional gestational day spent above 28°C, compared to cooler conditions (0–4°C), resulted in a birth weight decrease of approximately 1.66 grams. Similar findings have been observed in sub-Saharan Africa. Grace et al., 2015 and Davenport et al., 2020, using data from the Demographic and Health Surveys combined with climatic information, investigated how extreme temperature exposure during pregnancy affects multiple birth outcomes, including child birth weight. Both studies reported significant negative impacts, establishing a robust relationship between prenatal heat exposure and adverse birth outcomes.

Our empirical analysis further supports these findings. The local polynomial regression plot in Figure 3.2 visually illustrates a clear nonlinear relationship between in-utero exposure to temperatures exceeding 29°C and child stunting outcomes. Initially, the plot indicates a slight reduction in stunting rates at lower levels of exposure; however, beyond approximately 0.5 degree days above the threshold, the rate of stunting sharply increases, underscoring the adverse impact of higher temperature exposure during gestation. This graphical evidence reinforces the relevance of our instrumental variable, demonstrating that prolonged and severe exposure to extreme heat conditions during pregnancy is strongly correlated with higher rates of child stunting.

Several mechanisms may explain these observed impacts. One prominent explanation is the limited availability of adaptive technologies, such as air conditioning, that can mitigate heat exposure during pregnancy (X. Chen et al., 2020). In the context of sub-Saharan Africa specifically, evidence indicates that although food security does not strongly mediate this relationship, improved access to prenatal healthcare services could significantly attenuate the negative impacts of prenatal heat exposure on child health outcomes (Davenport et al., 2020).

Next, we argue that both the exogeneity condition and exclusion restriction are satisfied for our instrument. Although this assumption is not directly testable, we argue that in our case this assumption is plausibly met. First, temperature variability during pregnancy is as-good-as-random conditional on the set of control variables, district and year fixed effects (Banerjee & Maharaj, 2020; Dell et al., 2014; Deschênes et al., 2009; Miguel et al., 2004). Thus, extreme temperature during pregnancy is not correlated with the error term. Second, while exogeneity ensures that the instrument is unrelated to confounders, we must argue that the only channel by which gestational heat shocks influence the mother's later labor supply is through child's health (stunting). We consider potential violations and present evidence that other channels are negligible in our context, especially given the timing of events.

A potential concern regarding the exclusion restriction is that prenatal exposure to extreme temperatures could directly impact maternal labor supply, independently of child health outcomes. For example, prolonged or severe maternal health impairments resulting from heat exposure could directly reduce a mother's capacity to participate in the labor market. Although existing literature documents that extreme heat during pregnancy increases the risk of acute conditions such as gestational diabetes, pregnancy-induced hypertension, eclampsia, and pre-eclampsia (Cil & Cameron, 2017; Kim et al., 2021; Shashar et al., 2020; Xiong et al., 2020), these conditions usually resolve at or shortly after delivery (Neiger, 2017). However, women who experience such complications may face an increased risk of recurrence in subsequent pregnancies, which could affect their long-term health (Neiger, 2017). To address this concern empirically, we conduct robustness checks in which we explicitly examine whether prenatal heat exposure affects mothers' long-term health indicators. A significant relationship in this analysis would suggest a violation of our exclusion restriction, while the absence of such a relationship would reinforce our claim that extreme temperature exposure during pregnancy affects maternal labor outcomes exclusively through its impact on child health (stunting).

Another potential challenge to our exclusion restriction could arise if extreme heat episodes during gestation coincide with agricultural shocks—such as reduced crop yields due to unusually high temperatures during critical growing periods. Such shocks could reduce household income and food consumption, potentially causing maternal malnutrition and consequent long-term health impacts, thus independently influencing maternal labor supply. However, we argue that such agricultural shocks tend to be transitory rather than persistent, limiting their long-term health implications. Furthermore, the inclusion of district and year fixed effects in our analysis controls for these location-specific and temporal shocks. Nevertheless, as an additional robustness check, we explicitly test whether extreme heat exposure during pregnancy correlates with household asset holdings and farm sizes, proxies for agricultural shocks, to validate that these shocks do not independently affect maternal labor supply outcomes in our context.

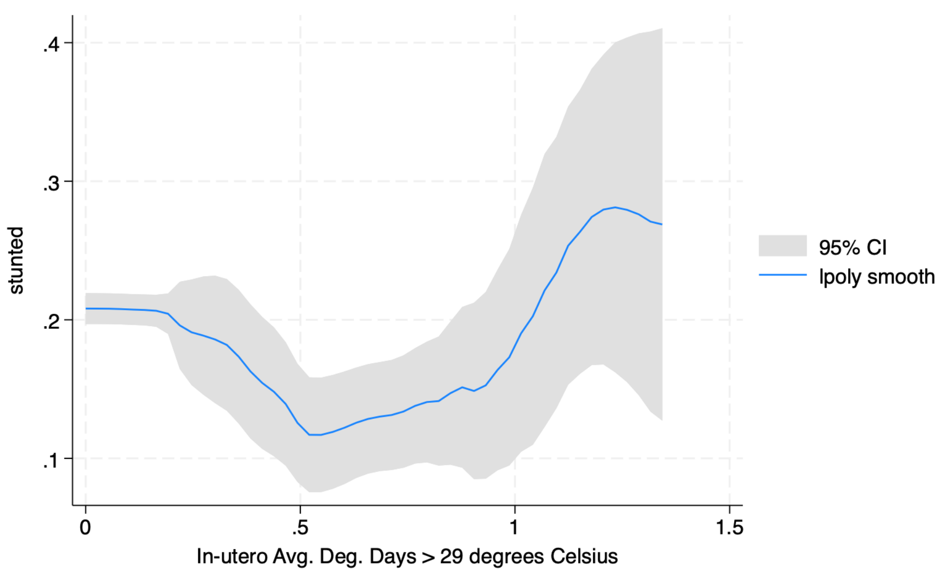


Figure 3.2: Local polynomial regression of child stunting and in-utero Average Degree Days > 29°C

Notes: kernel = epanechnikov, degree = 0, bandwidth = 0.09, pwidth = 0.14

3.4 Results

This section presents the results of poor child health effects on maternal employment. We first present the pooled IV estimation results of the impacts of child health on the mother's overall labor participation. We then show the effects separately for each type of labor, looking at the extensive margin of labor (labor participation) and the intensive margin of labor (average weekly labor days).

The value of the F-statistics testing the null hypothesis that the IV is equal to zero in the first stage is always greater than 10 in our 2SLS models, so we are not concerned about the problem of weak instrument (Staiger & Stock, 1997). Consistent with prior research, we find that in-utero exposure to temperature shocks (hereby proxied as the average degree days exceeding 29°C) is significantly associated with stunting in children (X. Chen et al., 2020; Davenport et al., 2020; Grace et al., 2015).

3.4.1 Child Health Effects on Maternal Labor Force Participation

The first set of results, in Table 3.2, shows the impacts of child health on mother's employment. The IV results (column 4) indicate that child stunting negatively affects the mother's overall employment. In other words, child sickness will decrease the likelihood of the mother's employment or increase the likelihood of the mother opting out of the labor market. Although our results are consistent with previous literature on the relationship between child health and mother's labor supply, the findings are not statistically significant.

3.4.2 Effects on Family Farm Labor

Table 3.3 reports the results of the pooled estimates of the impacts of child health on the mother's time spent on household's plots. Though we find a positive child health effect on the mother's likelihood of employment (column 4) and number of days of employment (column 7), the results indicate no statistical significance in neither cases. Nonetheless, results reveal that the mother's education has a statistically negative effect on mother's farm labor supply while household landholdings are positively associated with

Table 3.2: Labor Participation Estimates

		(Extensive Margin)		
	First Stage	Reduced Form	OLS	2nd Stage
	(1)	(2)	(3)	(4)
Stunted=1			0.0001	-0.1897
			(0.0175)	(0.3270)
In-utero Avg. Deg. Days >29°C	0.2478***	-0.0470		
	(0.0748)	(0.0817)		
Male Child=1	0.0222	0.0042	0.0041	0.0084
	(0.0140)	(0.0133)	(0.0133)	(0.0158)
Mother's age in years	-0.004	-0.0184**	-0.0184**	-0.0191**
	(0.0089)	(0.0082)	(0.0082)	(0.0084)
Mother's age squared	0.0001	0.0004***	0.0004***	0.0004***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Mother has some education=1	-0.0396**	0.0018	0.0015	-0.0056
	(0.0178)	(0.0192)	(0.0192)	(0.0228)
Mother has a chronic Disease=1	0.0113	0.0556*	0.0556*	0.0577*
	(0.0349)	(0.0293)	(0.0293)	(0.0308)
Father's age in years	0.0010	-0.0033**	-0.0033**	-0.0032**
	(0.00146)	(0.0013)	(0.0013)	(0.0014)
Fatther's labor participation=1	0.0131	0.1832***	0.1831***	0.1857***
	(0.0168)	(0.0189)	(0.0189)	(0.0198)
Child has siblings under five=1	-0.0053	0.0065	0.0066	0.0054
	(0.0160)	(0.0161)	(0.0161)	(0.0163)
Ratio of dependent to active	0.0207**	0.0643***	0.0641***	0.0683***
	(0.0101)	(0.0099)	(0.0099)	(0.0120)
Household landholdings (Ha)	-0.0182	0.0070	0.0070	0.0036
	(0.0124)	(0.0124)	(0.0124)	(0.0139)
F-statistic for IV in First Stage	10.976			
Wave FE	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
R-squared	0.0604	0.1716	0.1716	0.1387
N	3201	3201	3201	3201

Notes: This table reports the iv estimates of child stunting on maternal labor participation The dependent variable in columns 2-4 is binary and equals 1 if positive number of labor days. The first column reports the first stage results. Reduced form estimates are shown in column 2, and iv estimates are shown in column 4 Robust standard errors in parentheses are clustered at the household level. *, **, *** indicate the statistical significance at the 10%, 5%, and 1% level, respectively.

mother's family farm labor supply. Across all specifications, we also find that the father's employment is a significant predictor of maternal farm labor supply.

Table 3.3: Farm Labor Estimates

		Labor Participation (Extensive Margin)			Nber of Labor days (Intensive Margin)		
	First Stage	Reduced Form	OLS	2nd Stage	Reduced Form	OLS	2nd Stage
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Stunted=1			-0.0198	0.0360		-0.0292	0.1530
			(0.0185)	(0.3810)		(0.0714)	(1.6770)
In-utero Avg. Deg. Days >29	0.2478***	0.0089			0.0379		
	(0.0748)	(0.0948)			(0.4170)		
Male Child=1	0.0222	0.0035	0.0040	0.0027	-0.0243	-0.0235	-0.0277
	(0.0140)	(0.0141)	(0.0141)	(0.0170)	(0.0559)	(0.0558)	(0.0676)
Mother's age in years	-0.0040	-0.0297***	-0.0298***	-0.0296***	-0.0614*	-0.0615*	-0.0608*
	(0.0089)	(0.0086)	(0.0086)	(0.0088)	(0.0349)	(0.0349)	(0.0356)
Mother's age squared	0.0001	0.0006***	0.0006***	0.0006***	0.0014**	0.0014**	0.0013**
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0006)	(0.0006)	(0.0006)
Mother has some education=1	-0.0396**	-0.0843***	-0.0850***	-0.0828***	-0.1870**	-0.1880**	-0.1810*
	(0.0178)	(0.0196)	(0.0196)	(0.0240)	(0.0739)	(0.0740)	(0.0957)
Mother has a chronic Disease=1	0.0113	-0.0146	-0.0144	-0.0151	0.1100	0.1110	0.1090
	(0.0349)	(0.0347)	(0.0347)	(0.0348)	(0.1420)	(0.1420)	(0.1420)
Father's age in years	0.0010	-0.0035**	-0.0035**	-0.0036**	-0.0067	-0.0067	-0.0069
	(0.0015)	(0.0016)	(0.0016)	(0.0016)	(0.0066)	(0.0065)	(0.0066)
Fatther's labor participation=1	0.0131	0.2050***	0.2050***	0.2050***	0.5800***	0.5800***	0.5780***
	(0.0168)	(0.0193)	(0.0193)	(0.0202)	(0.0697)	(0.0698)	(0.0736)
Child has siblings under five=1	-0.0053	0.0198	0.0197	0.0200	0.0633	0.0631	0.0641
	(0.0160)	(0.0172)	(0.0171)	(0.0173)	(0.0705)	(0.0705)	(0.0712)
Ratio of dependent to active	0.0207**	0.0731***	0.0735***	0.0723***	0.2470***	0.2480***	0.2440***
	(0.0101)	(0.0106)	(0.0105)	(0.0135)	(0.0459)	(0.0459)	(0.0594)
Household landholdings (Ha)	-0.0182	0.0355**	0.0351**	0.0361**	0.8060***	0.8050***	0.8090***
	(0.0124)	(0.0148)	(0.0148)	(0.0163)	(0.0776)	(0.0776)	(0.0818)
F-statistic for IV in First Stage	10.9760						
Wave FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3201	3201	3201	3201	3201	3201	3201

Notes: This table reports the iv estimates of child stunting on maternal on-farm labor supply. The dependent variable in columns 2-4 is binary and equals 1 if positive number of labor days. The dependent variable in columns 5-7 is the weekly average number of labor days. The first column reports the first stage results. Reduced form estimates are shown in columns 2 and 5, and iv estimates are shown in columns 4 and 7. Robust standard errors in parentheses are clustered at the household level. *, **, *** indicate the statistical significance at the 10%, 5%, and 1% level, respectively.

3.4.3 Effects on Ganyu Labor

Table 3.4 shows the impacts of child health on maternal agricultural wage labor supply (ganyu). We find that female farmers facing issues of poor child health are less likely to allocate their time to casual agricultural labor (column 4). This finding is corroborated by the intensive margin specification where we find that child stunting significantly decreases the mother's supply of casual agricultural labor by about 1.3 days of work per week on average (column 7). This implies that although ganyu labor could be appealing to families looking for cash payments, women are less likely to allocate their time to that type of labor when facing poor child health problems.

These results could be explained by the fact that poor child health adds additional burdens to childcare that prevent mothers from working or from being fully efficient in farm work, given that paid farm work or contract farm work is physically demanding due to the limited use of agricultural technology. Additionally, findings reveal that women with some level of formal school education and women in households with large landholdings are less likely to engage in paid agricultural labor.

3.4.4 Effects on Non-Agricultural Wage Employment

Table 3.5 reports the effects of child health on the mother's time allocation to salary jobs. For both intensive and extensive margin estimations, we find a positive association between child stunting and mother's employment in non-agricultural wage jobs including paid labor from private or government employments in sectors such as education, health, food service, sales, etc. However, these findings are not statistically significant. These findings contrast with cases often observed in developed countries where mothers significantly decreases their labor force participation in salary jobs as a result of having a child with poor health or disability (Eriksen et al., 2021; Frijters et al., 2009; Gould, 2004).

Furthermore, we find that the mother's age and education, and the household ratio of dependent to active members are statistically significant indicators of the mother's labor supply. We find that while mother's age and formal education are positively associated with agricultural wage jobs, the number of dependents in the household is negatively associated with non-farm wage labor force participation.

Table 3.4: Ganyu Labor Estimates

		Labor Participation (Extensive Margin)			Nber of Labor days (Intensive Margin)		
	First Stage	Reduced Form	OLS	2nd Stage	Reduced Form	OLS	2nd Stage
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Stunted=1			0.0073	-0.7870*		0.0419	-1.2960*
			(0.0204)	(0.4480)		(0.0347)	(0.7540)
In-utero Avg. Deg. Days >29	0.2478***	-0.1950*			-0.3210**		
	(0.0748)	(0.1060)			(0.1640)		
Male Child=1	0.0222	0.0064	0.0058	0.0238	0.0031	0.0015	0.0318
	(0.0140)	(0.0155)	(0.0155)	(0.0215)	(0.0228)	(0.0229)	(0.0358)
Mother's age in years	-0.0040	-0.0228**	-0.0229**	-0.0261**	-0.0114	-0.0115	-0.0167
	(0.0089)	(0.0094)	(0.0094)	(0.0113)	(0.0128)	(0.0129)	(0.0170)
Mother's age squared	0.0001	0.0004**	0.0004**	0.0004**	0.0002	0.0002	0.0003
	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0003)
Mother has some education=1	-0.0396**	-0.1230***	-0.1240***	-0.1540***	-0.1630***	-0.1630***	-0.2140***
	(0.0178)	(0.0189)	(0.0189)	(0.0292)	(0.0238)	(0.0237)	(0.0442)
Mother has a chronic Disease=1	0.0113	0.1020***	0.1020***	0.1100**	0.0808	0.0806	0.0954
	(0.0349)	(0.0386)	(0.0385)	(0.0481)	(0.0687)	(0.0685)	(0.0837)
Father's age in years	0.0010	-0.0041**	-0.0040**	-0.0033	-0.0018	-0.0017	-0.0005
	(0.0015)	(0.0018)	(0.0018)	(0.0021)	(0.0024)	(0.0025)	(0.0032)
Fatther's labor participation=1	0.0131	-0.0159	-0.0163	-0.0056	-0.0735**	-0.0746**	-0.0566
	(0.0168)	(0.0188)	(0.0189)	(0.0238)	(0.0317)	(0.0318)	(0.0400)
Child has siblings under five=1	-0.0053	0.0376**	0.0381**	0.0335	0.0114	0.0124	0.0046
	(0.0160)	(0.0191)	(0.0191)	(0.0228)	(0.0299)	(0.0300)	(0.0360)
Ratio of dependent to active	0.0207**	0.0517***	0.0507***	0.0680***	0.0589***	0.0567***	0.0857***
	(0.0101)	(0.0118)	(0.0119)	(0.0173)	(0.0188)	(0.0188)	(0.0290)
Household landholdings (Ha)	-0.0182	-0.0715***	-0.0716***	-0.0858***	-0.0695**	-0.0692**	-0.0930***
	(0.0124)	(0.0160)	(0.0159)	(0.0195)	(0.0276)	(0.0277)	(0.0339)
F-statistic for IV in First Stage	10.9760						
Wave FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3201	3201	3201	3201	3201	3201	3201

Notes: This table reports the iv estimates of child stunting on maternal ganyu labor supply. The dependent variable in columns 2-4 is binary and equals 1 if positive number of labor days. The dependent variable in columns 5-7 is the weekly average number of casual paid farm labor days. The first column reports the first stage results. Reduced form estimates are shown in columns 2 and 5, and iv estimates are shown in columns 4 and 7. Robust standard errors in parentheses are clustered at the household level. *, **, *** indicate the statistical significance at the 10%, 5%, and 1% level, respectively.

Table 3.5: Non-Farm Wage Labor Estimates

		Labor Participation (Extensive Margin)			Nber of Labor days (Intensive Margin)		
	First Stage	Reduced Form	OLS	2nd Stage	Reduced Form	OLS	2nd Stage
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Stunted=1			-0.0036	0.1400		-0.0720*	0.2390
			(0.0088)	(0.1220)		(0.0375)	(0.3700)
In-utero Avg. Deg. Days >29°C	0.2478***	0.0347			0.0591		
	(0.0748)	(0.0283)			(0.0898)		
Male Child=1	0.0222	-0.0095	-0.0093	-0.0126	-0.0323	-0.0306	-0.0376
	(0.0140)	(0.0070)	(0.0070)	(0.0079)	(0.0333)	(0.0334)	(0.0332)
Mother's age in years	-0.0040	0.0148***	0.0148***	0.0154***	0.0910***	0.0907***	0.0919***
	(0.0089)	(0.0036)	(0.0036)	(0.0038)	(0.0163)	(0.0163)	(0.0165)
Mother's age squared	0.0001	-0.0001***	-0.0002***	-0.0002***	-0.0012***	-0.0012***	-0.0013***
	(0.0001)	(0.0000)	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0002)
Mother has some education=1	-0.0396**	0.0893***	0.0894***	0.0949***	0.4250***	0.4230***	0.4350***
	(0.0178)	(0.0125)	(0.0125)	(0.0142)	(0.0611)	(0.0611)	(0.0636)
Mother has a chronic Disease=1	0.0113	0.0014	0.0014	-0.0001	-0.0663	-0.0655	-0.0690
	(0.0349)	(0.0164)	(0.0164)	(0.0171)	(0.0662)	(0.0662)	(0.0670)
Father's age in years	0.0010	-0.0004	-0.0005	-0.0006	-0.0045*	-0.0044*	-0.0047*
	(0.0014)	(0.0007)	(0.0007)	(0.0007)	(0.0025)	(0.0025)	(0.0026)
Fatther's labor participation=1	0.0131	-0.0149*	-0.0148*	-0.0167*	-0.0422	-0.0412	-0.0454
	(0.0168)	(0.0086)	(0.0086)	(0.0091)	(0.0412)	(0.0411)	(0.0414)
Child has siblings under five=1	-0.0053	-0.0156**	-0.0157**	-0.0149**	-0.0750***	-0.0756***	-0.0738***
	(0.0160)	(0.0061)	(0.0061)	(0.0065)	(0.0246)	(0.0246)	(0.0248)
Ratio of dependent to active	0.0207**	-0.0140***	-0.0138***	-0.0169***	-0.0583**	-0.0565**	-0.0633**
	(0.0101)	(0.0045)	(0.0045)	(0.0057)	(0.0234)	(0.0232)	(0.0258)
Household landholdings (Ha)	-0.0182	-0.0152***	-0.0152***	-0.0126**	-0.0443*	-0.0455*	-0.0400
	(0.0124)	(0.0053)	(0.0053)	(0.0056)	(0.0260)	(0.0262)	(0.0266)
F-statistic for IV in First Stage	10.9760						
Wave FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3201	3201	3201	3201	3201	3201	3201

Notes: This table reports the iv estimates of child stunting on maternal non-farm wage labor supply. The dependent variable in columns 2-4 is binary and equals 1 if positive number of labor days. The dependent variable in columns 5-7 is the weekly average number of non-farm labor days. The first column reports the first stage results. Reduced form estimates are shown in columns 2 and 5, and iv estimates are shown in columns 4 and 7. Robust standard errors in parentheses are clustered at the household level. *, **, *** indicate the statistical significance at the 10%, 5%, and 1% level, respectively.

3.4.5 Effects on Non-Agricultural Self-Employment

Table 3.6 indicates the estimation results when the mother is self-employed. We find that a mother is less likely to engage in self-employment, mostly informal (restaurant, manufacturing, trade, etc.) if her child is sick. For both the intensive (column 4) and extensive margin (column 7) of labor supply, child stunting decreases the mother's labor participation in self-employment. However, we find that these findings are not statistically significant.

The finding that child health has no significant effects on mother's self-employment is similar to Dessy and Bago, 2022 who found no significant effects of motherhood on mothers' self-employment though the focus in their paper is on motherhood rather than child health. Additionally, similarly to the other employment types, education has a positive effect on mother's labor supply. This result is surprising as formal education might not be a necessary requirement to engage in this type of activities giving its informal nature.

Except for ganyu labor, we do not find enough statistical evidence to support the effects of child stunting on mother's employment. Nonetheless, the child health effects on ganyu labor reveal the role of child care burden on mothers' participation in productive activities, especially in developing countries. This finding underscores the importance of addressing child stunting given its welfare implications (Hoddinott et al., 2013). Our findings also reveal that other key factors such as the mother's level of education might play a bigger role in the mother's decision to select into a particular employment or work for a certain amount of time.

3.5 Heterogeneity Analysis

To better understand the findings, we explore how the child health effects vary by gender and age groups. We first focus on those two dimensions because previous research has shown that infant boys are more likely to be stunted than girls(Bork & Diallo, 2017; Elsmén et al., 2004; Thurstans et al., 2020, 2022; Townsel et al., 2017; Wamani et al., 2007). Moreover, while research has shown that stunting is preva-

Table 3.6: Self-Employment Labor Estimates

		Labor Participation (Extensive Margin)			Nber of Labor days (Intensive Margin)		
	First Stage	Reduced Form	OLS	2nd Stage	Reduced Form	OLS	2nd Stage
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Stunted=1			0.0204	-0.0599		0.0502	-0.7920
			(0.0163)	(0.2510)		(0.0755)	(0.8130)
In-utero Avg. Deg. Days >29	0.2478***	-0.0148			-0.1960		
	(0.0748)	(0.0623)			(0.1920)		
Male Child=1	0.0222	-0.0073	-0.0078	-0.0060	-0.0488	-0.0504	-0.0313
	(0.0140)	(0.0120)	(0.0119)	(0.0130)	(0.0530)	(0.0530)	(0.0579)
Mother's age in years	-0.0040	0.0125*	0.0126*	0.0123*	0.0364	0.0365	0.0331
	(0.0089)	(0.0070)	(0.0070)	(0.0071)	(0.0314)	(0.0314)	(0.0319)
Mother's age squared	0.0001	-0.0001	-0.0001	-0.0001	-0.0004	-0.0004	-0.0003
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0005)	(0.0005)	(0.0005)
Mother has some education=1	-0.0396**	0.0669***	0.0676***	0.0645***	0.3350***	0.3360***	0.3040***
	(0.0178)	(0.0182)	(0.0182)	(0.0204)	(0.0879)	(0.0879)	(0.0922)
Mother has a chronic Disease=1	0.0113	0.0178	0.0176	0.0185	0.0691	0.0687	0.0780
	(0.0349)	(0.0304)	(0.0304)	(0.0304)	(0.1430)	(0.1420)	(0.1470)
Father's age in years	0.0010	-0.0014	-0.0014	-0.0013	-0.0007	-0.0007	0.0001
	(0.0015)	(0.0013)	(0.0013)	(0.0013)	(0.0059)	(0.0059)	(0.0061)
Fatther's labor participation=1	0.0131	0.0192	0.0189	0.0199	0.1210*	0.1200*	0.1310*
	(0.0168)	(0.0148)	(0.0148)	(0.0153)	(0.0644)	(0.0644)	(0.0680)
Child has siblings under five=1	-0.0053	-0.0065	-0.0063	-0.0068	0.0136	0.0143	0.0094
	(0.0160)	(0.0145)	(0.0145)	(0.0144)	(0.0650)	(0.0650)	(0.0653)
Ratio of dependent to active	0.0207**	0.0148*	0.0143*	0.0160	0.0604	0.0585	0.0768*
	(0.0101)	(0.0084)	(0.0083)	(0.0102)	(0.0391)	(0.0391)	(0.0451)
Household landholdings (Ha)	-0.0182	-0.0069	-0.0065	-0.0080	-0.0554	-0.0548	-0.0698
	(0.0124)	(0.0113)	(0.0113)	(0.0119)	(0.0481)	(0.0481)	(0.0501)
F-statistic for IV in First Stage	10.9760						
Wave FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3201	3201	3201	3201	3201	3201	3201

Notes: This table reports the iv estimates of child stunting on maternal self-employment labor. The dependent variable in columns 2-4 is binary and equals 1 if positive number of labor days. The dependent variable in columns 5-7 is the weekly average number of non-farm labor days. The first column reports the first stage results. Reduced form estimates are shown in columns 2 and 5, and iv estimates are shown in columns 4 and 7. Robust standard errors in parentheses are clustered at the household level. *, **, *** indicate the statistical significance at the 10%, 5%, and 1% level, respectively.

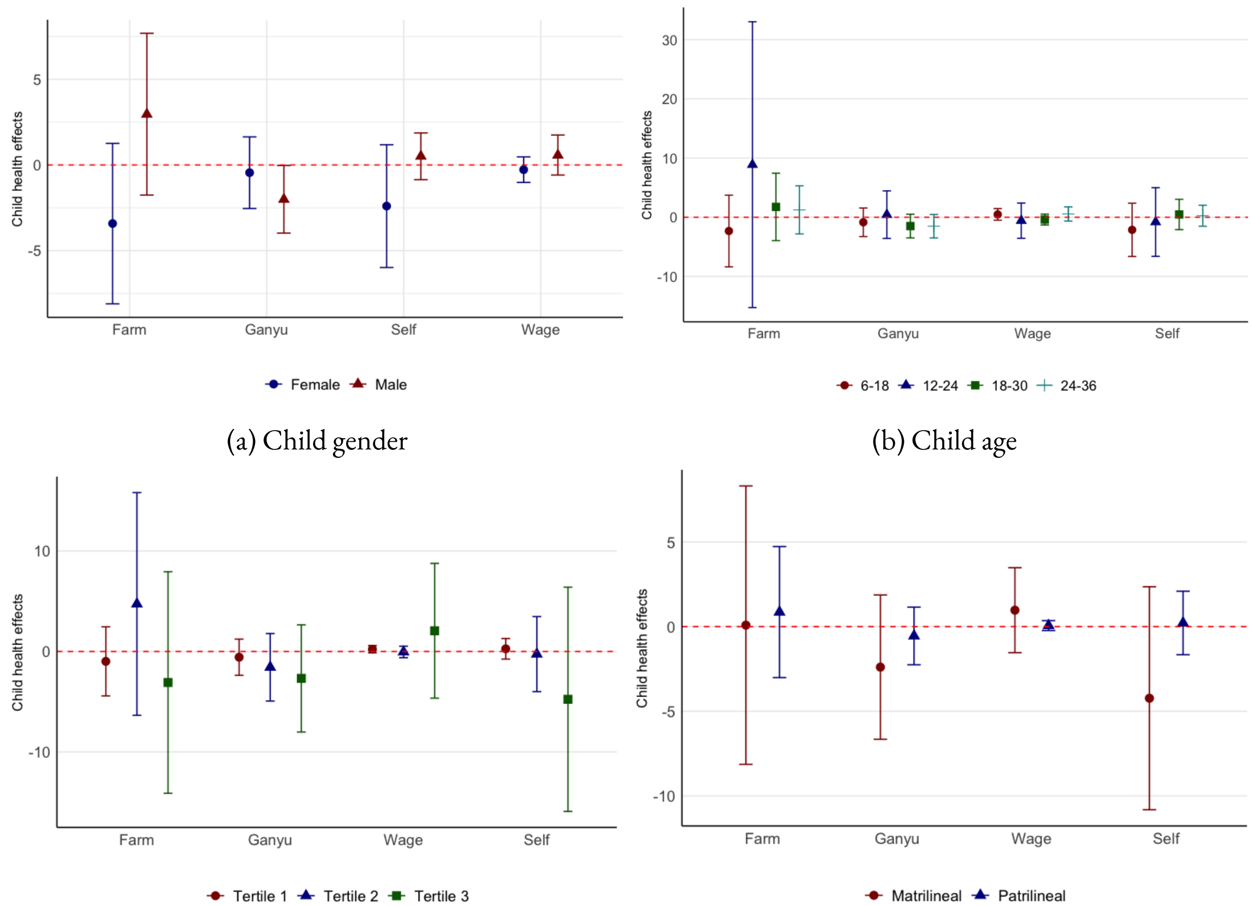
lent among younger children (Bork & Diallo, 2017), other studies have shown that older children have a higher likelihood of stunting (Darteh et al., 2014; Sultana et al., 2019).

The results by the child gender, illustrated in Figure 3.3a, shows no significant effects across different types of employment except for ganyu labor where we find that having a stunted infant boy significantly decreases the mother's employment than having a stunted infant girl. The results by the child age group, as illustrated in Figure 3.3b, report the effects for the age groups 6-18 months, 12-24 months, 18-30 months, and 24-36 months. Similarly to the child gender case, we find no statistically significant effects by age group across all types of employment.

Moreover, we further investigate the role of household economic status in worsening or mitigating the negative effects of poor child health on mother's employment. To do that, we approximate household wealth using household assets and create three household wealth tertiles, from the poorest (tertile 1) to the wealthiest (tertile 3) households. We then estimate separately the effects of poor child health on mother's labor allocation for each of the three wealth tertile sub-samples (Figure 3.3c). However, as per the figure, we find no particular patterns of child health effects by wealth tertiles.

Furthermore, some studies have suggested that maternal autonomy is negatively associated with child stunting (Chilinda et al., 2021; Shroff et al., 2009). If this is the case, we would expect the effects of poor child health to be less severe with women's empowerment. Hence, we explore the role of women empowerment in mitigating the negative effects of poor child health. We do this by looking at the mother's employment effects of poor child health separately for mothers living in matrilineal communities and for mothers in patrilineal communities. In a matrilineal system, land and other family assets are inherited by women from their parents instead of men. Malawi as some other countries in Africa have the unique feature of having the coexistence of both types of inheritance systems. Also, previous literature suggests that women in matrilineal families are more likely to have more power than their counterparts who live in patrilineal families (Gneezy et al., 2009; Rink et al., 2021). In our data, respondents were asked the following question: *Do individual here trace their descent through their father, mother or both?*. We use the responses to this question to identify patrilineal and matrilineal households.

The results of the estimations for patrilineal vs matrilineal communities are summarized in Figure 3.3d and show that in most cases, the effects of poor child health on mother's employment is not statistically significant. Hence, we do not find enough evidence of women's empowerment in explaining our main findings.



(a) Child gender

(b) Child age

(c) Household wealth

(d) Household kinship

Figure 3.3: Heterogeneous effects with 95% Confidence Interval

3.6 Robustness Checks

In this section, we address the threats to the identification strategy. Specifically, we address the concern of violations of the exclusion restriction of the IV, and the concern of sample selection. We also investigate the robustness of the findings using alternative measures of the treatment variable.

3.6.1 Addressing Threats to the Exclusion Restriction

As discussed in section 3.3.2, our exclusion restriction assumption could be undermined by two major threats. First, in-utero exposure to extreme heat could directly impact mother's employment, independently of child health outcomes. To address this concern, we investigate the relationship between in-utero extreme temperature and mother's long-term health conditions. The results are shown in Table C.2. As per the table, we find no statistically significant effect of pregnancy exposure to extreme heat on the mother's health outcomes.

Second, extreme heat during pregnancy can lead to agricultural shocks, thus reducing household food availability, which may cause maternal malnutrition and negatively impact a mother's long-term health and labor supply. We evaluate this potential threat in Table C.3 by investigating the correlation between exposure to extreme temperature during pregnancy and some measures of household exposure to agricultural shocks such as household wealth and farm size. As shown in the table, we do not find enough evidence of extreme heat during pregnancy significantly affecting mother's nutrition and hence potentially her employment outcomes. Thus, these findings reinforce the validity of our instrumental variable and suggest that in-utero exposure to extreme temperature significantly affect the child's long term health but not necessarily that of the mother.

3.6.2 Robustness to Correcting for Sample Selection

In this section, instead of estimating separately the extensive and the intensive margins of labor supply, we address the issue of sample selection bias, that is, the bias arising from the mother's non-random decision to participate into any specific type of labor. To correct for the self-selection bias, we use the Heckman two-step sample selection correction approach (J. J. Heckman, 1976, 1979), which is common in the labor economics literature. Given that our main explanatory variable (child stunting) is also endogenous, we address jointly the selection bias issue and the endogenous treatment issue.

To do this, we estimate in the first stage the selection equation, a probit model where the dependent variable indicates whether the mother participates in the labor type. We then conduct an IV estimation in the second stage where the dependent variable is now the number of work days while including the inverse Mills' ratio obtained from the first stage. We exclude some exogenous variables in this latter stage, as discussed in (Wooldridge, 2010). The Heckman second stage standard errors are bootstrapped.

Table C.4 reports the Heckman-type correction estimates. After correcting for selection bias, the results do not significantly differ from the IV estimation findings in section 3.4.1. We find no significant negative effects of child health on mother's number of work days. Although the magnitudes of the estimates are slightly different from the IV results, we find no statistically significant effects. However, for self-employment and family farm labor types, we find that the first stage results are statistically significant as opposed to the second stage results.

In addition to the Heckman sample selection correction method, we use Tobit estimation with instrumental variables, where we assume the number of work days is censored at 0. Table C.5 reports the ivtobit correction estimates. The second stage results are consistent with previous findings and show no statistically significant effects of poor child health on mother's employment except for ganyu employment. Instead, the results support the findings that education is a better predictor of women's labor supply, and that the more educated women tend to select into non-farm employment while the least educated women choose to work in farm activities. Similarly, the results suggest that as the household landholdings increase, the mother is more likely to select into family farm activities and less likely to do non-farm activities.

Overall, consistent with our IV results, the Heckman and the ivtobit models confirm that poor child health significantly decreases the mother's casual agricultural wage labor (ganyu). However, we found no evidence of child health on the other types of employment. Instead, we find that mother's education on the other hand might be a more important predictor of mother's employment than child health.

3.6.3 Robustness to Using Alternative Thresholds of Average Degree Days and Alternative Measures of Stunting

Instead of a binary treatment variable, we use a continuous measure of stunting, the child height-for-age (HAZ). The findings are presented in Tables C.6 to C.9. The results are similar to our main findings using the binary stunting variable. We find that a one standard deviation increase in the child's height-for-age increases the mother's likelihood of ganyu employment by 0.18% and the number of ganyu days by 0.3 days. In other words, better child health is associated with higher likelihood of mother's ganyu employment. Nonetheless, we find no significant effects of child HAZ on other types of mother's employment.

We also use alternatives measures of instrumental variables for our first stage regression. We compare our main specification using a 29°C cutoff with specifications using average degree days based on 28°C, 29°C, and 31°C cutoffs. The results are presented in Table C.10. The table reveals that our main specification with the 29°C threshold results in the better first-stage F-statistic, hence suggesting that our first-stage main specification is robust to other threshold values of average degree days.

3.7 Conclusion

With prevailing gender norms in developing countries, the employment of mothers with younger children and their occupational choices oftentimes depends on childcare requirements. This is especially the case when the child has a medical condition or specific health issues. Hence, there is a tradeoff between the mother's time allocation to caring for a sick child and her time allocation for paid labor or productive activity.

Using a novel instrumental variable, the child in-utero exposure to extreme heat, to address the endogeneity of the relationship between child health (hereby proxied by child stunting) and mother's employment, we estimate the extent to which poor child health affects mother's employment in Malawi. We exploit the fact that stunting is prevalent in developing countries to construct a measure of child health using the child anthropometric indicator height-for-age, and assuming stunting is associated with poor child health. We also exploit the randomness of having the pregnancy coinciding with a period of extreme heat to isolate the causal impacts of the child's health on mother's employment. The choice of the instrument is motivated by the fact that child exposure to extreme heat in-utero is likely to affect child stunting at early age, as widely evidenced in the literature.

We use IV estimations on a three-wave household panel data and show that children exposed to extreme heat in-utero are more likely to be more stunted than children that were not. The validity of our identification strategy relies on the assumption that the child exposure to extreme heat will most likely affect the mother's employment outcomes only through the effects on the child stunting or health conditions and not through any other effects.

We find no statistically significant effects of child health on mother's employment, except for labor supplied to paid agricultural work. We find that poor child health reduces mother's casual agricultural wage labor in Malawi. We find similar results even after correcting for the selection bias potentially emanating from the mother's self-selection into the labor market. From a policy perspective, interventions that could improve child nutrition and health such as programs promoting diet improvement solutions or programs enhancing the quality of child care in general will have the double benefits of improving child and maternal nutrition and health, and maternal employment outcomes, thereby contributing to improving household welfare. The lack of statistical significance for most types of employment could be due to the child health variable used in the paper. Future research can for instance rely on quasi-natural experiment settings to better capture the child health impacts on maternal labor supply in developing countries.

Results also show that education and household landholdings are key predictors of mother's labor force participation but their effects differ depending on the type of labor. Agriculture related employments are negatively affected by mother's education and positively affected by landholdings. Non-farm related employments indicate the opposite effects. Although the child health effects show no statistical significance in most cases, the results suggest that poor child health to some degree plays a role in explaining maternal employment in Malawi.

Appendix A

Chapter 1

A.1 Supplementary Figure

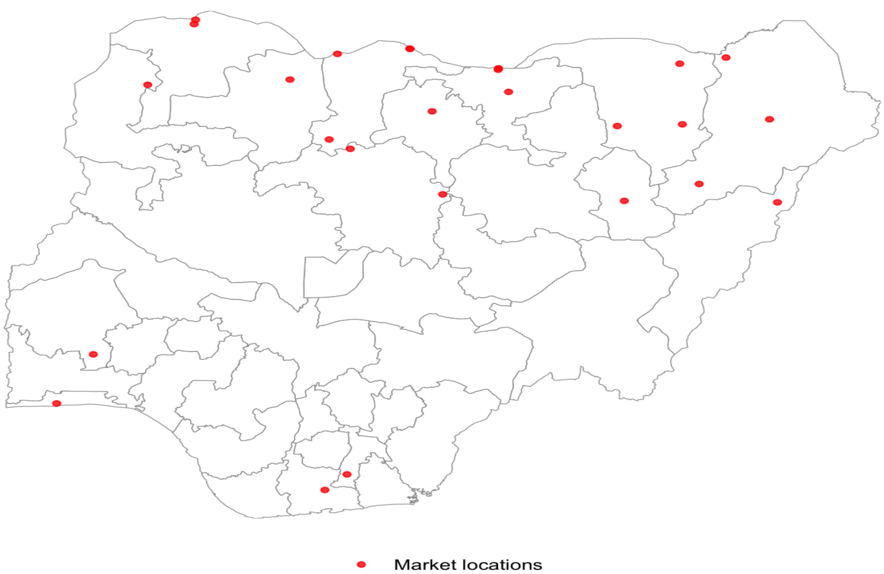


Figure A.1: Spatial coverage of maize market locations in the World Bank data

A.2 Supplementary Tables

Table A.1: Spatial data sources for the maize price prediction model

Spatial data	**Source**
Travel in time (hrs) to nearest port	Nelson et al., 2019
Travel in time (hrs) to the nearest town with over 20,000 to 250,000 inhabitants	Nelson et al., 2019
Population density (persons per km^2)	Rose et al., 2020
Cropland (ha)	International Food Policy Research Institute, 2020
Annual precipitation (mm)	Fick and Hijmans, 2017
Maize price data	Cedrez et al., 2020

Table A.2: Robustness to the definition of Rainfall Shock Dummies

	Percentile Cut-off for Positive/Negative Shocks				
	75/25	80/20	80/25	80/30	70/30
	(1)	(2)	(3)	(4)	(5)
	Panel A– Dependent Variable: Fertilizer Adoption (1/0)				
Positive Shock (t-1)	-0.043	-0.067	-0.103	-0.118	-0.036
	(0.088)	(0.097)	(0.095)	(0.097)	(0.091)
Negative Shock (t-1)	-0.093**	-0.094**	-0.097**	-0.108**	-0.096**
	(0.040)	(0.046)	(0.039)	(0.042)	(0.044)
	Panel B– Dependent Variable: Fertilizer Use Rate (kg/acre)				
Positive Shock (t-1)	-20.789	-29.090	-40.429**	-39.804**	-13.876
	(18.820)	(20.720)	(19.013)	(19.040)	(18.901)
Negative Shock (t-1)	-28.094***	-21.00**	-29.490***	-22.494**	-19.250*
	(9.308)	(8.858)	(9.383)	(11.261)	(11.302)

Note: This tables examines robustness of the results to alternate cut-offs for positive and negative rainfall shocks. Panel A reports estimates from the OLS regression, while Panel B presents results from the Tobit model with coefficients representing the average marginal effects calculated using the *margins* command in STATA. In each column, positive and negative shocks are defined under different cut-offs, as labeled at the top of each column. E.g., in Column (1), a positive (negative) shock is defined as rainfall above (below) the 75th (25th) percentile of the historical distribution. This correspond to the definition of shocks in the main specification in the paper. Similarly, in Column (2), a positive (negative) shock is defined as rainfall above (below) the 80th (20th) percentile of the historical distribution, and so on. All regressions include proxies for past profit: livestock accumulation and prior season's maize price. Additional Controls include household head age and education, household size, average plot slope, plot elevation, soil nutrient retention and nutrient availability, potential wetness index, distance to the nearest market, log asset value, log maize plot area, and current maize and fertilizer prices. Standard errors are clustered at the enumeration area level. *, **, *** indicate the statistical significance at the 10%, 5%, and 1% level, respectively.

Appendix B

Chapter 2

B.1 Supplementary Tables

Table B.1: Food items contained in each food group

Food Group	Food Items Included
Maize	Maize ufa mgaiwa (normal flour); maize ufa refined (fine flour); maize ufa madeya (bran flour); maize grain (not as ufa); green maize
Cereals, Grains and Cereal Products	Rice; finger millet (mawere); sorghum (mapira); pearl millet (mchewere); wheat flour; bread; buns; scones; biscuits; spaghetti; macaroni; pasta
Pulses and Nuts	Beans (white); beans (brown); pigeonpea (nandolo); groundnut; groundnut flour; soybean flour; ground bean (nzama); cowpea (khobwe)
Meat, Fish and Animal Products	Eggs; dried fish (large variety); dried fish (small variety); fresh fish (large variety); fresh fish (small variety); beef; goat; pork; mutton; chicken; powdered milk; margarine
Roots, Tubers and Other Starches	Cassava tubers and flours; white sweet potato; orange sweet potato; irish potato; plantain;cooking banana
Fruits and Vegetables	Onion; cabbage; nkhwani; chinese cabbage; tomato; cucumber; pumpkin; okra (therere); mango; banana; papaya; guava; avocado; wild fruit
Other Foods	Sugar; sugar cane; cooking oil; tea; squash (sobo drink concentrate); fruit juice; freezes (flavored ice); soft drinks (coca-cola, Fanta, Sprite, etc.); Salt; spices; yeast, baking powder and bicarbonate of soda

Note: This table shows how individual food items listed in the Malawi IHS are mapped onto food groups. Food items are separated by semicolons.

Table B.2: Results from first stage instrumental variable regressions

	y	y^2	y^3	P_1	P_2	P_3	P_4	P_5	P_6	P_7	y x P_1	y x P_2	y x P_3	y x P_4	y x P_5	y x P_6	y x P_7
P_1^{IV}	0.0010	0.1840	5.2120	1.0420***	-0.0289	0.0585	0.0287	-0.0358	-0.0128	-0.0613	9.3620***	-0.1000	0.6240	0.3630	-0.1350	0.1010	-0.3540
	(0.0583)	(1.0630)	(14.9800)	(0.0397)	(0.0450)	(0.0451)	(0.0451)	(0.0398)	(0.0430)	(0.0375)	(0.3700)	(0.4140)	(0.4210)	(0.4230)	(0.3650)	(0.3940)	(0.3400)
P_2^{IV}	-0.1530**	-2.5880**	-32.7400**	0.0029	1.0140***	-0.0601	0.0522	0.0309	0.0092	0.0067	0.1610	8.8910***	-0.3350	0.5090	0.4690	0.3040	0.2700
	(0.0635)	(1.1240)	(15.1900)	(0.0406)	(0.0470)	(0.0474)	(0.0486)	(0.0370)	(0.0399)	(0.0442)	(0.3680)	(0.4160)	(0.4280)	(0.4560)	(0.3350)	(0.3610)	(0.3910)
P_3^{IV}	0.0966	1.8180	25.7600	0.0304	-0.1350***	0.9620***	-0.0450	0.0533	0.0295	-0.0278	0.4520	-0.9450**	8.8720***	-0.0412	0.7810*	0.5580	0.1010
	(0.0738)	(1.3260)	(18.2300)	(0.0483)	(0.0504)	(0.0548)	(0.0667)	(0.0459)	(0.0487)	(0.0508)	(0.4430)	(0.4620)	(0.5040)	(0.6190)	(0.4220)	(0.4390)	(0.4570)
P_4^{IV}	0.1050	1.6230	19.1200	0.0147	-0.0677	0.0217	0.8260***	-0.0304	0.0361	-0.0476	0.0273	-0.7170	0.0988	7.2700***	-0.4180	0.1220	-0.4150
	(0.0770)	(1.4030)	(19.6100)	(0.0516)	(0.0563)	(0.0596)	(0.0649)	(0.0495)	(0.0514)	(0.0515)	(0.4730)	(0.5140)	(0.5530)	(0.6090)	(0.4510)	(0.4680)	(0.4670)
P_5^{IV}	0.0801	1.6820	26.3400	0.0402	0.0250	-0.0139	0.0354	1.0010***	0.0109	0.0974*	0.3070	0.1750	-0.1760	0.1690	8.7520***	-0.0442	0.7580*
	(0.0768)	(1.3610)	(18.5500)	(0.0498)	(0.0502)	(0.0564)	(0.0563)	(0.0465)	(0.0510)	(0.0510)	(0.4520)	(0.4570)	(0.5070)	(0.5220)	(0.4220)	(0.4580)	(0.4580)
P_6^{IV}	-0.1740*	-3.1160*	-42.2600*	-0.0158	-0.0792	0.0672	-0.0482	-0.1110**	1.0500***	0.0748	-0.4700	-1.0460*	0.1680	-0.8740	-1.6230***	8.9950***	0.3950
	(0.0977)	(1.7730)	(24.6200)	(0.0599)	(0.0620)	(0.0684)	(0.0728)	(0.0560)	(0.0656)	(0.0613)	(0.5530)	(0.5690)	(0.6320)	(0.6770)	(0.5200)	(0.6000)	(0.5530)
P_7^{IV}	-0.1740**	-3.2150**	-45.4200**	-0.0538	0.0560	-0.0431	0.0904	0.0368	0.0178	0.9060***	-0.7890*	0.2990	-0.5950	0.7820	0.1160	-0.0636	7.7210***
	(0.0805)	(1.4410)	(19.7700)	(0.0493)	(0.0520)	(0.0588)	(0.0638)	(0.0466)	(0.0528)	(0.0513)	(0.4500)	(0.4730)	(0.5320)	(0.5900)	(0.4220)	(0.4780)	(0.4610)
$Numeraire^{IV}$	0.3720***	6.5620***	87.3300***	-0.0190	0.2140***	0.0594	0.0565	0.0618	-0.1130	0.0441	0.4130	2.3930***	0.9860	0.8150	1.2020*	-0.7260	0.4820
	(0.1320)	(2.3610)	(32.2200)	(0.0812)	(0.0827)	(0.0927)	(0.0984)	(0.0759)	(0.0903)	(0.0873)	(0.7440)	(0.7600)	(0.8530)	(0.9140)	(0.7030)	(0.8170)	(0.7740)
Assets	0.0000*	0.0000	0.0003	0.0000**	-0.0000	-0.0000	-0.0000**	-0.0000	0.0000	-0.0000	0.0000	-0.0000	-0.0000*	-0.0000**	-0.0000*	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0002)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Maize Seller (1/0)	0.0900***	1.6030***	21.4500***	-0.0166	-0.0335*	-0.0304	-0.0223	-0.0141	0.0115	-0.0077	-0.1080	-0.2940*	-0.2180	-0.1920	-0.0876	0.1420	-0.0381
	(0.0258)	(0.4730)	(6.5910)	(0.0172)	(0.0184)	(0.0197)	(0.0239)	(0.0164)	(0.0179)	(0.0169)	(0.1590)	(0.1710)	(0.1820)	(0.2250)	(0.1520)	(0.1650)	(0.1550)
Maize Grower (1/0)	-0.0382	-0.7930	-12.2700	-0.0245	-0.0121	0.0123	-0.0105	0.0121	-0.0154	-0.0021	-0.2660	-0.1030	0.0958	-0.1080	0.0853	-0.1400	-0.0148
	(0.0298)	(0.5540)	(7.9270)	(0.0190)	(0.0200)	(0.0206)	(0.0229)	(0.0169)	(0.0196)	(0.0175)	(0.1790)	(0.1900)	(0.1940)	(0.2190)	(0.1610)	(0.1850)	(0.1610)
Assets $\times P_1^{IV}$	0.0000	0.0000	-0.0000	-0.0000	0.0000	-0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	-0.0000	0.0000	0.0000	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0005)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Assets $\times P_2^{IV}$	0.0000	0.0000	0.0007	-0.0000	-0.0000	0.0000	-0.0000	-0.0000	-0.0000	0.0000	-0.0000	-0.0000	0.0000	-0.0000	-0.0000	-0.0000	0.0000
	(0.0000)	(0.0000)	(0.0005)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Assets $\times P_3^{IV}$	-0.0000	-0.0000	-0.0005	-0.0000	0.0000	-0.0000	0.0000	-0.0000	-0.0000	-0.0000	-0.0000	0.0000	-0.0000	0.0000	-0.0000	-0.0000	-0.0000
	(0.0000)	(0.0000)	(0.0006)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Assets $\times P_4^{IV}$	0.0000**	0.0001**	0.0014**	0.0000	-0.0000	0.0000	0.0000	0.0000*	-0.0000**	0.0000**	0.0000	-0.0000	0.0000	0.0000	0.0000**	-0.0000*	0.0000*
	(0.0000)	(0.0000)	(0.0006)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Assets $\times P_5^{IV}$	-0.0000*	-0.0001*	-0.0010*	-0.0000	0.0000	0.0000	0.0000	-0.0000	-0.0000	-0.0000	-0.0000	0.0000	0.0000	0.0000	-0.0000	-0.0000	-0.0000
	(0.0000)	(0.0000)	(0.0006)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Assets $\times P_6^{IV}$	0.0000	0.0000	0.0001	0.0000	0.0000	0.0000	0.0000	0.0000***	-0.0000	-0.0000	0.0000	0.0000	0.0000	0.0000	0.0000***	-0.0000	-0.0000
	(0.0000)	(0.0000)	(0.0007)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Assets $\times P_7^{IV}$	-0.0000***	-0.0001***	-0.0017***	0.0000	0.0000	-0.0000	-0.0000	-0.0000	0.0000**	-0.0000	0.0000	0.0000	-0.0000	-0.0000	0.0000**	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0006)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Assets $\times Numeraire^{IV}$	0.0000	0.0001	0.0012	0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000*	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000
	(0.0000)	(0.0001)	(0.0008)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Maize Seller $\times P_1^{IV}$	-0.0977**	-1.7300**	-23.2100**	-0.0012	0.0323	-0.0099	0.0770**	-0.0186	0.0066	0.0115	0.0216	0.3560	-0.0120	0.7720**	-0.1050	0.1470	0.2160
	(0.0420)	(0.7640)	(10.5700)	(0.0279)	(0.0278)	(0.0324)	(0.0371)	(0.0266)	(0.0280)	(0.0261)	(0.2580)	(0.2590)	(0.2980)	(0.3490)	(0.2450)	(0.2580)	(0.2440)
Maize Grower $\times P_1^{IV}$	0.0094	-0.0858	-5.0660	0.0054	0.0055	-0.0514**	-0.0069	0.0180	0.0124	0.0279	-0.2540	-0.1630	-0.8000***	-0.2670	-0.0936	-0.1320	0.0035
	(0.0343)	(0.6510)	(9.5480)	(0.0267)	(0.0258)	(0.0261)	(0.0283)	(0.0240)	(0.0250)	(0.0193)	(0.2550)	(0.2450)	(0.2520)	(0.2700)	(0.2280)	(0.2340)	(0.1820)
F-Stats	14.0600	13.4600	12.5700	727.7300	386.7300	462.2100	318.6300	588.1200	527.8700	660.4600	693.8800	370.3200	442.0700	301.3600	554.5300	504.9500	628.3100
N	7,702	7,702	7,702	7,702	7,702	7,702	7,702	7,702	7,702	7,702	7,702	7,702	7,702	7,702	7,702	7,702	7,702

Note: P_j denotes the price of food group j, and P_j^{IV} denotes the instrument for P_j which is based on the average price index for neighboring households. Due to space limits, we report the coefficients on price instrument only and omit the demand shifters and columns for the numeraire good and its interaction with y. The demand shifters are age, marital status and gender of household head, ratio of dependent (younger than 14 years old or older than 65 years old) to adults and three wave dummies. We report standard errors in parentheses (* $p < 0.1$, *** $p < 0.05$, *** $p < 0.01$).

Table B.3: Hicksian (Compensated) Price Elasticities with respect to the Maize Price

	Net Buyers (Non–Maize Growers)			Net Buyers (Maize Growers)			Net Sellers		
Food group	EASI	FI–EASI	Ag–EASI	EASI	FI–EASI	Ag–EASI	EASI	FI–EASI	Ag–EASI
Maize	-0.02***	-0.01**	-0.31***	-0.04***	-0.02***	0.02***	-0.05***	-0.17***	-0.11***
	(0.00)	(0.00)	(0.02)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
Cereals and grains	0.02***	0.06***	0.28***	0.01***	0.03***	0.17***	0.01***	-0.06***	0.21***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Pulses and nuts	0.26***	0.27***	0.17***	0.19***	0.20***	-0.03***	0.21***	0.13***	0.04***
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
Meat, fish and animal products	0.00	0.01***	-0.25***	-0.14***	-0.11***	-0.47***	-0.10***	-0.16***	-0.40***
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
Roots, tubers and starches	-0.03***	-0.08***	0.46***	-0.06***	-0.10***	0.19***	-0.05***	0.15***	0.27***
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
Fruits and vegetables	0.02***	0.02***	0.20***	0.03***	0.04***	0.29***	0.03***	-0.02***	0.26***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Other food	0.24***	0.27***	0.43***	0.27***	0.29***	0.39***	0.25***	0.11***	0.42***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Notes: Entries are Hicksian (compensated) own- and cross-price elasticities with respect to the maize price; standard errors in parentheses. (* $p < 0.1$, *** $p < 0.05$, *** $p < 0.01$).

Table B.4: Hicksian (Compensated) Price Elasticities: Pulses and Nuts

	Net Buyers (Non–Maize Growers)			Net Buyers (Maize Growers)			Net Sellers		
Food group	EASI	FI–EASI	Ag–EASI	EASI	FI–EASI	Ag–EASI	EASI	FI–EASI	Ag–EASI
Maize	-0.14***	-0.15***	-0.20***	-0.09***	-0.11***	0.01***	-0.09***	0.04***	-0.04***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Cereals and grains	-0.01**	0.01*	0.02***	0.06***	0.08***	0.04***	0.03***	-0.07***	0.04***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Pulses and nuts	-0.50***	-0.45***	-0.57***	-0.52***	-0.48***	-0.63***	-0.53***	-0.87***	-0.64***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Meat, fish and animal products	0.22***	0.22***	-0.03	0.24***	0.24***	0.31***	0.23***	0.06***	0.20***
	(0.00)	(0.00)	(0.02)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
Roots, tubers and starches	-0.58***	-0.70***	-0.43***	-0.50***	-0.58***	-0.38***	-0.49***	0.00***	-0.36***
	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Fruits and vegetables	0.29***	0.30***	0.23***	0.28***	0.28***	0.59***	0.27***	0.23***	0.43***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)
Other food	-0.40***	-0.44***	-0.39***	-0.31***	-0.34***	-0.22***	-0.31***	0.00***	-0.23***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Notes: Entries are Hicksian (compensated) own- and cross-price elasticities with respect to the price of pulses and nuts; standard errors in parentheses. (* $p < 0.1$, *** $p < 0.05$, *** $p < 0.01$).

Table B.5: Hicksian (Compensated) Price Elasticities: Fruits and Vegetables

	Net Buyers (Non–Maize Growers)			Net Buyers (Maize Growers)			Net Sellers		
Food group	EASI	FI–EASI	Ag–EASI	EASI	FI–EASI	Ag–EASI	EASI	FI–EASI	Ag–EASI
Maize	0.03***	0.00***	0.10***	0.02***	0.00	-0.06***	0.02***	0.19***	-0.03***
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
Cereals and grains	0.34***	0.35***	0.26***	0.23***	0.24***	0.24***	0.27***	0.19***	0.27***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Pulses and nuts	0.24***	0.14***	0.19***	0.12***	0.05***	0.16***	0.16***	0.66***	0.18***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)
Meat, fish and animal products	0.33***	0.37***	0.06***	0.34***	0.37***	0.19***	0.34***	0.23***	0.15***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Roots, tubers and starches	0.48***	0.51***	0.44***	0.51***	0.54***	0.54***	0.51***	0.14***	0.53***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Fruits and vegetables	-1.46***	-1.44***	-1.36***	-1.49***	-1.48***	-1.64***	-1.50***	-1.30***	-1.60***
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)
Other food	0.31***	0.35***	0.69***	0.32***	0.35***	0.51***	0.32***	0.17***	0.59***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)

Notes: Entries are Hicksian (compensated) own- and cross-price elasticities of fruits and vegetables with respect to prices of food groups; standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

B.2 Derivation of Food Demand Elasticities

This appendix derives Hicksian (compensated) price elasticities and total expenditure elasticities for the standard EASI specification; the other models follow the same steps. Marshallian (uncompensated) price elasticities then follow from the Slutsky equation. For clarity, I display the EASI share equation and drop the household and time subscripts:

$$w_i = \mu_i + \sum_{j=1}^{J} \alpha_{ij} \log p_j + \sum_{r=1}^{L} \beta_{ir} y^r + \sum_{j=1}^{J} \alpha_{ijy}(y \times \log p_j) + \sum_{k=1}^{K} \gamma_k z_k + u_i \tag{B.1}$$

Recall that $w_i = \frac{q_i^h p_i}{x^h}$, where h subscript emphasizes that the variable is compensated. Taking logs and re-arranging terms, we have

$$\log w_i = \log q_i^h + \log p_i - \log x^h \tag{B.2}$$

The Hicksian price elasticity (h_{ij}) can be derived as;

$$\begin{aligned} h_{ij} = \frac{\partial \log q_i^h}{\partial \log p_j} &= \frac{\partial \log w_i}{\partial \log p_j} + \frac{\partial \log x^h}{\partial \log p_j} - \frac{\partial \log p_i}{\partial \log p_j} \\ &= \frac{\partial w_i}{\partial \log p_j}\frac{1}{w_i} + \frac{\partial x^h}{\partial p_j}\frac{p_j}{x^h} - \mathbb{1}(i=j) \end{aligned} \tag{B.3}$$

From the Shepherd's Lemma $\frac{\partial x^h}{\partial p_j} = q_j^h$, therefore we have that

$$\begin{aligned} h_{ij} = \frac{\partial \log q_i^h}{\partial \log p_j} &= \frac{\partial w_i}{\partial \log p_j}\frac{1}{w_i} + q_j^h \frac{p_j}{x^h} - \mathbb{1}(i=j) \\ &= \frac{\partial w_i}{\partial \log p_j}\frac{1}{w_i} + w_j - \mathbb{1}(i=j) \\ &= \frac{\alpha_{ij} + \alpha_{ijy}}{\partial w_i} + w_j - \mathbb{1}(i=j) \end{aligned} \tag{B.4}$$

Therefore the when $i = j$, the Hicksian price elasticity is $h_{ij} = \frac{\alpha_{ij}+\alpha_{ijy}}{\partial w_i} + w_j - 1$ and $h_{ij} = \frac{\alpha_{ij}+\alpha_{ijy}}{\partial w_i} + w_j$ when $i \neq j$.

The expenditure elasticity (ξ_i), we can also derived as;

$$\begin{aligned} \xi_i = \frac{\partial \log q_i}{\partial y} &= 1 + \frac{1}{w_i}\left[\frac{\partial w_i}{\partial y}\right] \\ &= 1 + \frac{1}{w_i}\left[\sum_{j=1}^{J} \alpha_{ijy} + \sum_{r=1}^{L} \beta_{ir} y^{r-1} r\right] \end{aligned} \tag{B.5}$$

Once I have the Hicksian (compensated) price and total expenditure elasticities, the Marshallian (uncompensated) price elasticity can be calculated from the Slutsky's equation as:

$$M_{ij} = h_{ij} - w_j \xi_i \tag{B.6}$$

I calculate predicted budget shares (conditional means of observed budget shares) and replace the observed budget shares with the predicted in the above equations to obtain expected demand elasticities.

Appendix C

Chapter 3

C.1 Supplementary Tables

Table C.1: Sample description by wave

	Wave 1	Wave 2	Wave 3	Total
Nber of households	1078	1147	590	2815
Nber of mothers	1095	1196	629	2920
Mothers with boys only	552	563	278	1393
Mothers with girls only	507	581	313	1401
Mothers with both	36	52	38	126
Nber of children	1161	1299	741	3201

Table C.2: Extreme Temperature during Gestation and Mother's Long-term Health Outcomes

	Any Chronic Disease=1		Diabetes=1		Mental Health=1	
	(1)	(2)	(3)	(4)	(5)	(6)
In-utero ADD>29	-0.0135	-0.00571	-0.000937	-0.000902	0.00938	0.00962
	(0.0424)	(0.0427)	(0.000710)	(0.000849)	(0.00758)	(0.00758)
Controls	No	Yes	No	Yes	No	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes	Yes	Yes
R squared	0.024	0.028	0.006	0.008	0.018	0.019
N	3201	3201	3201	3201	3201	3201

Notes: This table reports the relationship between extreme temperature during gestation and mother's long-term health outcomes. Robust standard errors in parentheses are clustered at the household level. *, **, *** indicate the statistical significance at the 10%, 5%, and 1% level, respectively.

Table C.3: Extreme Temperature during Gestation and Household Agricultural Shocks

	Farm Size		Wealth Index	
	(1)	(2)	(3)	(4)
In-utero ADD>29	-0.0115	0.00438	0.0625	0.0521
	(0.151)	(0.187)	(0.0805)	(0.0774)
Controls	No	Yes	No	Yes
District FE	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes
R squared	0.139	0.192	0.180	0.306
N	3201	3201	3201	3201

Notes: This table reports the relationship between extreme temperature during gestation and household agricultural shocks. Robust standard errors in parentheses are clustered at the household level. *, **, *** indicate the statistical significance at the 10%, 5%, and 1% level, respectively.

Table C.4: Labor supply estimates correcting for selection bias and treatment endogeneity

	Farm Labor		Ganyu Labor		Wage Labor		Self-employment	
	Participation	Labor days	Participation	Labor days	Participation	Labor days	Participation	Labor days
	Ist Stage	2nd Stage	Ist Stage	2nd Stage	Ist Stage	2nd Stage	Ist Stage	2nd Stage
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Stunted=1	-0.1010*	-0.7120	0.0497	-0.0345	0.0327	0.0924	0.1680**	-0.0464
	(0.0593)	(1.2990)	(0.0593)	(0.1160)	(0.1130)	(18.4700)	(0.0669)	(0.1740)
In-utero Avg. Deg. Days >29	0.3420***		0.3090***		0.0527		-0.2510*	
	(0.1210)		(0.1040)		(0.2110)		(0.1480)	
Male Child=1	0.0180	-0.0484	0.0104	-0.0019	-0.1100	-0.0164	-0.0642	-0.0032
	(0.0475)	(0.0658)	(0.0479)	(0.0248)	(0.0891)	(0.4810)	(0.0556)	(0.0668)
Mother's age in years	-0.1600***	0.9530**	-0.0897***	0.1040	0.1980***	0.3870	0.0944***	0.0837
	(0.0309)	(0.4340)	(0.0280)	(0.1280)	(0.0618)	(2.3650)	(0.0345)	(0.1630)
Mother's age squared	0.0028***	0.2360**	0.0015***	0.0256	-0.0027***	0.0769	-0.0012**	-0.0276
	(0.0005)	(0.1150)	(0.0005)	(0.0226)	(0.0010)	(0.5650)	(0.0006)	(0.0581)
Mother has some education=1	-0.5320***	-0.0040**	-0.5920***	-0.0004	0.9110***	-0.0011	0.3920***	0.0003
	(0.0572)	(0.0020)	(0.0651)	(0.0004)	(0.0904)	(0.0074)	(0.0639)	(0.0008)
Mother has a chronic Disease=1	-0.0950	0.3200	0.3080***	-0.0562	0.0780	-0.0521	0.1680	0.0083
	(0.1100)	(0.2020)	(0.1050)	(0.0959)	(0.1950)	(0.9620)	(0.1210)	(0.1590)
Father's age in years	-0.0158***	0.0292***	-0.0168***	0.0053	-0.0035	-0.0040	-0.0034	0.0060
	(0.0050)	(0.0109)	(0.0051)	(0.0042)	(0.0103)	(0.0517)	(0.0057)	(0.0055)
Fatther's labor participation=1	0.6530***	-0.9890**	0.0119	-0.0666**	-0.2400**	-0.0264	0.0911	0.0198
	(0.0553)	(0.5030)	(0.0554)	(0.0281)	(0.0953)	(1.2200)	(0.0659)	(0.0613)
Child has siblings under five=1	0.0675	-0.0838	0.1060**	-0.0454	-0.2640**	-0.0456	-0.0540	0.0480
	(0.0535)	(0.0959)	(0.0535)	(0.0306)	(0.1110)	(0.3390)	(0.0624)	(0.0692)
Ratio of dependent to active	0.3040***	-0.3830*	0.1830***	-0.0216	-0.1870**	-0.0534	0.0320	-0.0128
	(0.0370)	(0.2330)	(0.0324)	(0.0415)	(0.0766)	(0.9810)	(0.0366)	(0.0393)
Household landholdings (Ha)	0.3330***		-0.1080**		-0.4660***		-0.1290**	
	(0.0492)		(0.0459)		(0.1150)		(0.0536)	
Inverse Mills Ratio		-4.4800***		-0.6650**		-0.1420		-1.2720***
		(1.2350)		(0.2750)		(2.8830)		(0.4680)
Wage FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R-squared	0.1077		0.0683		0.1826		0.0371	
Wald chi2	387.1100		252.1000		160.6100		93.8100	
N	3201	3201	3201	3201	3201	3201	3201	3201

Notes: This table reports the Heckman estimates of child stunting on maternal labor supply, correcting for both the treatment endogeneity and the sample selection bias. Columns 1, 3, 5, 7 show the probit estimates for participation into labor. Columns 2, 4, 6, 8 report IV estimates for the corresponding intensive margin of labor supply. The standard errors in parentheses in columns 2, 4, 6, and 8 are corrected using bootstrapping. *, **, *** indicate the statistical significance at the 10%, 5%, and 1% level, respectively.

Table C.5: Labor supply estimates using ivtobit model with continuous endogenous treatment

		Intensive margin of labor supply			
		Farm Labor	Ganyu Labor	Wage Labor	Self-employment
	Ist Stage	2nd Stage	2nd Stage	2nd Stage	2nd Stage
	(1)	(2)	(3)	(4)	(5)
Stunted=1		0.0802	-3.3730*	10.8000	-1.6910
		(2.0080)	(1.9000)	(52.1600)	(9.8600)
In-utero Avg. Deg. Days >29	0.2478***				
	(0.0748)				
Male Child=1	0.0222	-0.0241	0.0920	-0.9430	-0.1890
	(0.0140)	(0.0976)	(0.0930)	(1.1300)	(0.4150)
Mother's age in years	-0.0040	-0.1310**	-0.0930*	1.6890***	0.3200
	(0.0089)	(0.0526)	(0.0502)	(0.4780)	(0.2240)
Mother's age squared	0.0001	0.0027***	0.0016*	-0.0233***	-0.0033
	(0.0001)	(0.0009)	(0.0008)	(0.0078)	(0.0036)
Mother has some education=1	-0.0396**	-0.4370***	-0.8350***	7.1610***	1.8010***
	(0.0178)	(0.1380)	(0.1360)	(1.5140)	(0.5630)
Mother has a chronic Disease=1	0.0113	0.0955	0.4040**	-0.1560	0.4470
	(0.0349)	(0.2020)	(0.1840)	(2.6280)	(0.7560)
Father's age in years	0.0010	-0.0141	-0.0077	-0.0422	-0.0218
	(0.0015)	(0.0092)	(0.0088)	(0.0730)	(0.0385)
Fatther's labor participation=1	0.0131	1.1140***	-0.0978	-1.9730	0.7000
	(0.0168)	(0.1090)	(0.1000)	(1.4080)	(0.4340)
Child has siblings under five=1	-0.0053	0.0966	0.0981	-1.9040*	-0.1100
	(0.0160)	(0.0965)	(0.0921)	(1.1210)	(0.4000)
Ratio of dependent to active	0.0207**	0.4420***	0.2720***	-1.5920	0.4530
	(0.0101)	(0.0736)	(0.0691)	(1.2800)	(0.3190)
Household landholdings (Ha)	-0.0182	0.8930***	-0.3480***	-3.1740*	-0.3520
	(0.0124)	(0.0880)	(0.0901)	(1.6860)	(0.4100)
First stage F-stats	10.9760				
Wage FE	Yes	Yes	Yes	Yes	Yes
Distict FE	Yes	Yes	Yes	Yes	Yes
R-squared	0.0604				
Wald chi2		1207.0000	245.1000	101.2300	178.3800
N	3201	3201	3201	3201	3201

Notes: This table reports the ivtobit estimates of the intensive margin of labor supply. Standard errors in parentheses. *, **, *** indicate the statistical significance at the 10%, 5%, and 1% level, respectively.

Table C.6: Farm Labor Estimates with HAZ as Treatment Variable

		Labor Participation (Extensive Margin)			Number of Labor Days (Intensive Margin)		
	First Stage	Reduced Form	OLS	2nd Stage	Reduced Form	OLS	2nd Stage
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
HAZ			0.0026	-0.0082		-0.0012	-0.0350
			(0.0043)	(0.0873)		(0.0165)	(0.3840)
In-utero Avg. Deg. Days >29	-1.0840***	0.0089			0.0379		
	(0.3060)	(0.0948)			(0.4170)		
Male Child=1	-0.0844	0.0035	0.0037	0.0028	-0.0243	-0.0243	-0.0272
	(0.0610)	(0.0141)	(0.0141)	(0.0164)	(0.0559)	(0.0558)	(0.0650)
Mother's age in years	-0.0307	-0.0297***	-0.0296***	-0.0300***	-0.0614*	-0.0614*	-0.0625*
	(0.0383)	(0.0086)	(0.0086)	(0.0088)	(0.0349)	(0.0349)	(0.0361)
Mother's age squared	0.0005	0.0006***	0.0006***	0.0006***	0.0014**	0.0014**	0.0014**
	(0.0006)	(0.0001)	(0.0001)	(0.0001)	(0.0006)	(0.0006)	(0.0006)
Mother has some education=1	0.2510***	-0.0843***	-0.0849***	-0.0822***	-0.1870**	-0.1870**	-0.1790
	(0.0819)	(0.0196)	(0.0196)	(0.0286)	(0.0739)	(0.0741)	(0.1170)
Mother has chronic Disease=1	-0.0889	-0.0146	-0.0144	-0.0154	0.1100	0.1100	0.1070
	(0.1550)	(0.0347)	(0.0347)	(0.0351)	(0.1420)	(0.1420)	(0.1450)
Father's age in years	-0.0071	-0.0035**	-0.0035**	-0.0036**	-0.0067	-0.0068	-0.0070
	(0.0065)	(0.0016)	(0.0016)	(0.0017)	(0.0066)	(0.0065)	(0.0069)
Father's labor participation=1	0.0316	0.2050***	0.2050***	0.2050***	0.5800***	0.5800***	0.5810***
	(0.0715)	(0.0193)	(0.0193)	(0.0192)	(0.0697)	(0.0697)	(0.0698)
Child has siblings under five=1	0.0091	0.0198	0.0198	0.0199	0.0633	0.0632	0.0636
	(0.0714)	(0.0172)	(0.0171)	(0.0171)	(0.0705)	(0.0705)	(0.0704)
Ratio of dependent to active	-0.0416	0.0731***	0.0732***	0.0727***	0.2470***	0.2470***	0.2460***
	(0.0427)	(0.0106)	(0.0105)	(0.0113)	(0.0459)	(0.0459)	(0.0496)
Household landholdings (Ha)	0.1750***	0.0355**	0.0350**	0.0369*	0.8060***	0.8060***	0.8120***
	(0.0592)	(0.0148)	(0.0148)	(0.0213)	(0.0776)	(0.0776)	(0.1000)
F-statistic for IV in First Stage	12.5690						
Wave FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3201	3201	3201	3201	3201	3201	3201

Notes: This table reports the iv estimates of child stunting on maternal on-farm labor supply. The dependent variable in columns 2-4 is binary and equals 1 if positive number of labor days. The dependent variable in columns 5-7 is the weekly average number of labor days. The first column reports the first stage results. Reduced form estimates are shown in columns 2 and 5, and iv estimates are shown in columns 4 and 7. Robust standard errors in parentheses are clustered at the household level. *, **, *** indicate the statistical significance at the 10%, 5%, and 1% level, respectively.

Table C.7: Ganyu Labor Estimates with HAZ as Treatment Variable

		Labor Participation (Extensive Margin)			Number of Labor Days (Intensive Margin)		
	First Stage	Reduced Form	OLS	2nd Stage	Reduced Form	OLS	2nd Stage
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
HAZ			0.0005	0.1800*		-0.0034	0.2960*
			(0.0046)	(0.1060)		(0.0075)	(0.1730)
In-utero Avg. Deg. Days >29	-1.0840***	-0.1950*			-0.3210**		
	(0.3060)	(0.1060)			(0.1640)		
Male Child=1	-0.0844	0.0064	0.0060	0.0216	0.0031	0.0021	0.0281
	(0.0610)	(0.0155)	(0.0155)	(0.0206)	(0.0228)	(0.0229)	(0.0343)
Mother's age in years	-0.0307	-0.0228**	-0.0230**	-0.0173	-0.0114	-0.0117	-0.0023
	(0.0383)	(0.0095)	(0.0094)	(0.0119)	(0.0128)	(0.0128)	(0.0175)
Mother's age squared	0.0005	0.0004**	0.0004**	0.0003	0.0002	0.0002	0.0001
	(0.0006)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0003)
Mother has some education=1	0.2510***	-0.1230***	-0.1240***	-0.1680***	-0.1630***	-0.1640***	-0.2370***
	(0.0819)	(0.0189)	(0.0190)	(0.0348)	(0.0238)	(0.0236)	(0.0538)
Mother has chronic Disease=1	-0.0889	0.1020***	0.1020***	0.1180**	0.0808	0.0807	0.1070
	(0.1550)	(0.0386)	(0.0385)	(0.0481)	(0.0687)	(0.0685)	(0.0855)
Father's age in years	-0.0071	-0.0041**	-0.0040**	-0.0028	-0.0018	-0.0017	0.0003
	(0.0065)	(0.0018)	(0.0018)	(0.0022)	(0.0025)	(0.0025)	(0.0034)
Father's labor participation=1	0.0316	-0.0159	-0.0162	-0.0216	-0.0735**	-0.0739**	-0.0829**
	(0.0715)	(0.0188)	(0.0189)	(0.0227)	(0.0317)	(0.0317)	(0.0389)
Child has siblings under five=1	0.0091	0.0376**	0.0381**	0.0360	0.0114	0.0122	0.0087
	(0.0714)	(0.0191)	(0.0191)	(0.0228)	(0.0299)	(0.0300)	(0.0367)
Ratio of dependent to active	-0.0416	0.0517***	0.0509***	0.0592***	0.0589***	0.0575***	0.0713***
	(0.0427)	(0.0118)	(0.0119)	(0.0145)	(0.0188)	(0.0188)	(0.0245)
Household landholdings (Ha)	0.1750***	-0.0715***	-0.0718***	-0.1030***	-0.0695**	-0.0693**	-0.1210***
	(0.0592)	(0.0160)	(0.0160)	(0.0000)	(0.0276)	(0.0278)	(0.0455)
F-statistic for IV in First Stage	12.5690						
Wave FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3201	3201	3201	3201	3201	3201	3201

Notes: This table reports the iv estimates of child stunting on maternal ganyu labor supply. The dependent variable in columns 2-4 is binary and equals 1 if positive number of labor days. The dependent variable in columns 5-7 is the weekly average number of casual paid farm labor days. The first column reports the first stage results. Reduced form estimates are shown in columns 2 and 5, and iv estimates are shown in columns 4 and 7. Robust standard errors in parentheses are clustered at the household level. *, **, *** indicate the statistical significance at the 10%, 5%, and 1% level, respectively.

Table C.8: Self-Employment Labor Estimates with HAZ as Treatment Variable

		Labor Participation (Extensive Margin)			Nber of Labor Days (Intensive Margin)		
	First Stage	Reduced Form	OLS	2nd Stage	Reduced Form	OLS	2nd Stage
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Height-for-Age Zscore (HAZ)			-0.0005	0.0137		0.0120	0.1810
			(0.0037)	(0.0574)		(0.0172)	(0.1870)
In-utero Avg. Deg. Days >29	-1.0840***	-0.0148			-0.1960		
	(0.3060)	(0.0623)			(0.1920)		
Male Child=1	-0.0844	-0.0074	-0.0074	-0.0062	-0.0488	-0.0482	-0.0336
	(0.0610)	(0.0120)	(0.0120)	(0.0127)	(0.0530)	(0.0530)	(0.0567)
Mother's age in years	-0.0307	0.0125*	0.0125*	0.0130*	0.0364	0.0366	0.0419
	(0.0383)	(0.0070)	(0.0070)	(0.0071)	(0.0314)	(0.0314)	(0.0327)
Mother's age squared	0.0005	-0.0001	-0.0001	-0.0001	-0.0004	-0.0004	-0.0005
	(0.0006)	(0.0001)	(0.0001)	(0.0001)	(0.0005)	(0.0005)	(0.0005)
Mother has some education=1	0.2510***	0.0669***	0.0669***	0.0635***	0.3350***	0.3310***	0.2900***
	(0.0819)	(0.0182)	(0.0182)	(0.0227)	(0.0879)	(0.0875)	(0.0967)
Mother has a chronic Disease=1	-0.0889	0.0178	0.0178	0.0191	0.0691	0.0703	0.0852
	(0.1550)	(0.0304)	(0.0304)	(0.0306)	(0.1430)	(0.1430)	(0.1480)
Father's age in years	-0.0071	-0.0014	-0.0014	-0.0013	-0.0007	-0.0006	0.0006
	(0.0065)	(0.0013)	(0.0013)	(0.0013)	(0.0059)	(0.0059)	(0.0060)
Father's labor participation=1	0.0316	0.0192	0.0191	0.0187	0.1210*	0.1200*	0.1150*
	(0.0715)	(0.0148)	(0.0148)	(0.0148)	(0.0644)	(0.0644)	(0.0644)
Child has siblings under five=1	0.0091	-0.0065	-0.0064	-0.0066	0.0136	0.0139	0.0119
	(0.0714)	(0.0145)	(0.0145)	(0.0144)	(0.0650)	(0.0650)	(0.0653)
Ratio of dependent to active	-0.0416	0.0148*	0.0147*	0.0154*	0.0604	0.0601	0.0679
	(0.0427)	(0.0084)	(0.0083)	(0.0089)	(0.0391)	(0.0390)	(0.0414)
Household landholdings (Ha)	0.1750***	-0.0069	-0.0068	-0.0093	-0.0554	-0.0578	-0.0871
	(0.0592)	(0.0113)	(0.0113)	(0.0147)	(0.0481)	(0.0485)	(0.0578)
F-statistic for IV in First Stage	12.5690						
Wave FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3201	3201	3201	3201	3201	3201	3201

Notes: This table reports the iv estimates of child HAZ on maternal self-employment labor. The dependent variable in columns 2-4 is binary and equals 1 if positive number of labor days. The dependent variable in columns 5-7 is the weekly average number of non-farm labor days. The first column reports the first stage results. Reduced form estimates are shown in columns 2 and 5, and iv estimates are shown in columns 4 and75. Robust standard errors in parentheses are clustered at the household level. *, **, *** indicate the statistical significance at the 10%, 5%, and 1% level, respectively.

Table C.9: Non-Farm Wage Labor Estimates with HAZ as Treatment Variable

		Labor Participation (Extensive Margin)			Number of Labor Days (Intensive Margin)		
	First Stage	Reduced Form	OLS	2nd Stage	Reduced Form	OLS	2nd Stage
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
HAZ			0.2960*	-0.0321		0.0221*	-0.0546
			(0.1730)	(0.0271)		(0.0117)	(0.0839)
In-utero Avg. Deg. Days >29	-1.0840***	0.0347			0.0591		
	(0.3060)	(0.0283)			(0.0898)		
Male Child=1	-0.0844	-0.0095	0.0281	-0.0122	-0.0323	-0.0303	-0.0369
	(0.0610)	(0.0070)	(0.0343)	(0.0078)	(0.0333)	(0.0333)	(0.0331)
Mother's age in years	-0.0307	0.0148***	-0.0023	0.0138***	0.0910***	0.0917***	0.0893***
	(0.0383)	(0.0036)	(0.0175)	(0.0038)	(0.0163)	(0.0164)	(0.0166)
Mother's age squared	0.0005	-0.0002***	0.0001	-0.0002***	-0.0013***	-0.0013***	-0.0013***
	(0.0006)	(0.0001)	(0.0003)	(0.0001)	(0.0002)	(0.0002)	(0.0002)
Mother has some education=1	0.2510***	0.0893***	-0.2370***	0.0974***	0.4250***	0.4200***	0.4390***
	(0.0819)	(0.0125)	(0.0538)	(0.0152)	(0.0611)	(0.0611)	(0.0657)
Mother has chronic Disease=1	-0.0889	0.0015	0.1070	-0.0014	-0.0663	-0.0644	-0.0711
	(0.1550)	(0.0164)	(0.0855)	(0.0174)	(0.0662)	(0.0660)	(0.0683)
Father's age in years	-0.0071	-0.0005	0.0003	-0.0007	-0.0045*	-0.0044*	-0.0049*
	(0.0065)	(0.0007)	(0.0034)	(0.0008)	(0.0025)	(0.0025)	(0.0026)
Father's labor participation=1	0.0316	-0.0149*	-0.0829**	-0.0139	-0.0422	-0.0428	-0.0405
	(0.0715)	(0.0086)	(0.0389)	(0.0089)	(0.0412)	(0.0411)	(0.0414)
Child has siblings under five=1	0.0091	-0.0156**	0.0087	-0.0153**	-0.0750***	-0.0754***	-0.0745***
	(0.0714)	(0.0061)	(0.0367)	(0.0066)	(0.0246)	(0.0245)	(0.0250)
Ratio of dependent to active	-0.0416	-0.0140***	0.0713***	-0.0154***	-0.0583**	-0.0571**	-0.0606**
	(0.0427)	(0.0045)	(0.0245)	(0.0050)	(0.0234)	(0.0233)	(0.0242)
Household landholdings (Ha)	0.1750***	-0.0152***	-0.1210***	-0.0095	-0.0443*	-0.0481*	-0.0348
	(0.0592)	(0.0054)	(0.0455)	(0.0068)	(0.0260)	(0.0264)	(0.0295)
F-statistic for IV in First Stage	12.5690						
Wave FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3201	3201	3201	3201	3201	3201	3201

Notes: This table reports the iv estimates of child stunting on maternal non-farm wage labor supply. The dependent variable in columns 2-4 is binary and equals 1 if positive number of labor days. The dependent variable in columns 5-7 is the weekly average number of non-farm labor days. The first column reports the first stage results. Reduced form estimates are shown in columns 2 and 5, and iv estimates are shown in columns 4 and 7. Robust standard errors in parentheses are clustered at the household level. *, **, *** indicate the statistical significance at the 10%, 5%, and 1% level, respectively.

Table C.10: First Stage Regression with Different Temperature Thresholds

	Dependent Variable: Stunted=1			
	(1)	(2)	(3)	(4)
In-utero Avg. Deg. Days >28°C	0.155***			
	(0.0510)			
In-utero Avg. Deg. Days >29°C		0.248***		
		(0.0748)		
In-utero Avg. Deg. Days >30°C			0.412***	
			(0.124)	
In-utero Avg. Deg. Days >31°C				0.700***
				(0.243)
Male Child=1	0.0223	0.0222	0.0220	0.0219
	(0.0140)	(0.0140)	(0.0140)	(0.0140)
Mother's age in years	-0.00405	-0.00409	-0.00404	-0.00402
	(0.00896)	(0.00896)	(0.00896)	(0.00896)
Mother's age squared	5.17e-05	5.32e-05	5.34e-05	5.36e-05
	(0.000146)	(0.000147)	(0.000146)	(0.000146)
Mother has some education=1	-0.0395**	-0.0396**	-0.0396**	-0.0394**
	(0.0178)	(0.0178)	(0.0178)	(0.0178)
Mother has a chronic Disease=1	0.0119	0.0113	0.0108	0.0106
	(0.0349)	(0.0349)	(0.0349)	(0.0349)
Father's age in years	0.00102	0.000995	0.000946	0.000874
	(0.00146)	(0.00146)	(0.00146)	(0.00146)
Fatther's labor participation=1	0.0133	0.0131	0.0129	0.0129
	(0.0168)	(0.0168)	(0.0168)	(0.0168)
Child has siblings under five=1	-0.00541	-0.00530	-0.00512	-0.00502
	(0.0160)	(0.0160)	(0.0160)	(0.0160)
Ratio of dependent to active	0.0210**	0.0207**	0.0205**	0.0205**
	(0.0101)	(0.0101)	(0.0101)	(0.0101)
Household landholdings (Ha)	-0.0177	-0.0182	-0.0187	-0.0190
	(0.0124)	(0.0124)	(0.0124)	(0.0124)
First Stage IV F-statistic	9.280	10.98	10.97	8.31
Wave FE	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
R-squared	0.060	0.060	0.061	0.061
N	3201	3201	3201	3201

Notes: This table reports the iv estimates of child stunting on maternal ganyu labor supply. The dependent variable in columns 2-4 is binary and equals 1 if positive number of labor days. The dependent variable in columns 5-7 is the weekly average number of casual paid farm labor days. The first column reports the first stage results. Reduced form estimates are shown in columns 2 and 5, and iv estimates are shown in columns 4 and 7. Robust standard errors in parentheses are clustered at the household level. *, **, *** indicate the statistical significance at the 10%, 5%, and 1% level, respectively.

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