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Refrigeration, Diets and Human Health: Evidence from Ghana

Enoch Ntsiful and François Cohen

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Abstract

Little is known about household-level interventions to strengthen household resilience to food insecurity. Rapid electrification could enable refrigeration and transform how food is stored, prepared, and consumed. We provide the first causal evidence on how access to refrigeration affects food insecurity and dietary quality in a low-income country. Our identification exploits appliance breakdowns, comparing households with functioning and broken refrigerators purchased at the same time and similar prices. Losing access increases food insecurity by one third and reduces consumption of animal-sourced foods, lowering intake of vitamin B12. Refrigeration is an overlooked lever to improve diets and reduce micronutrient deficiencies.

JEL Classification: I14, I15, Q49, O13

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Authors:

Enoch Ntsiful, Chair of Energy Sustainability, Institute of Economics of Barcelona; and Department of Economics, University of Barcelona. enoch.ntsiful@ub.edu

François Cohen, Chair of Energy Sustainability, Institute of Economics of Barcelona; and Department of Economics, University of Barcelona.

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Many families around the world struggle to provide or access food for their families. Shocks to agriculture, food prices, and distribution systems are well-established drivers of hunger (D'Souza & Jolliffe, 2014; Hadley et al., 2023; Headey & Martin, 2016). Yet households differ widely in their ability to cope. Even small shocks can have large mortality effects when they strike already malnourished populations living near survival thresholds (Ravallion, 1997).

Little is known about how access to infrastructure and basic household technologies can enhance resilience to shocks affecting food security. Rapid electrification offers an opportunity: it enables refrigeration and could transform how food is stored, prepared, and consumed among vulnerable populations. In sub-Saharan Africa (SSA), household grid connections have doubled, from about 25% in 2000 to over 50% today (IEA et al., 2023). Because refrigerators are among the first appliances households acquire (Lee et al., 2016; McNeil & Letschert, 2010), an estimated 800 million people are expected to gain access to refrigeration in the next decade (IEA, 2022).

We provide the first causal evidence on how access to refrigeration affects food insecurity and dietary quality in low-income country contexts. Economic research on the welfare gains from reliable cold chains is only beginning to emerge. Recent works (Barrett et al., 2022; Macchiavello et al., 2022) show that cold storage and logistical infrastructure are central to modernizing agri-food systems, particularly by enabling the distribution of perishable and animal-sourced foods. We extend this literature by documenting nutritional and food-security gains from refrigeration.

This paper also contributes to the broader literature on the welfare effects of electrification in low- and middle-income countries (LMICs). Contrary to conventional expectations, a large-scale RCT in rural Kenya by Lee et al. (2020b) found no meaningful medium-run effects on health or education, largely because electricity use remained limited and few households acquired appliances such as refrigerators. Our findings highlight the importance of distinguishing between grid access and energy services, and of analysing all relevant outcomes.

In particular, our results show that evaluating energy access requires going beyond conventional welfare indicators. For refrigeration, this requires examining food insecurity, food quantities, and the nutritional composition of diets. Nutritional outcomes related to vitamin and mineral intake are rarely studied in applied economics (Berry et al., 2020; von Grafenstein et al., 2023; Wong et al., 2014). We are, to our knowledge, the first to trace disaggregated nutritional effects in the context of electrification and energy services. By moving beyond standard outcomes such as income or educational attainment, we recover health-relevant welfare gains that would otherwise remain invisible.

We use data from Ghana, an early adopter of grid connection in SSA, where refrigerator ownership rose from 9.1 percent in 1993 to 41.9 percent in 2022 (ICF, 1993, 2022). We find that lacking access to a functioning refrigerator increases the probability of food insecurity by 33 percent. A key mechanism is reduced dietary diversity: households without refrigeration acquire 21 percent less meat, 18 percent less dairy, 39 percent fewer eggs, and 10 percent less fish. Total energy and macronutrient availability (e.g., calories or total protein) change little, consistent with substitution toward plant-based foods such as tubers, pulses, and plantain when refrigeration is unavailable. However, refrigeration materially increases intakes of key micronutrients concentrated in animal-sourced foods, especially vitamin B12 and retinol. Widespread deficiencies in these nutrients have serious health consequences in low-income settings, underscoring the role refrigeration and cold chains should play as integral components of nutrition and public health policy.

Our identification strategy exploits the fact that households do not choose when appliances break. In the Ghana Living Standards Surveys (GLSS), refrigerators are recorded as either functional or broken (i.e. dysfunctional) at the time of interview. We use this feature to define treatment and control groups: all households in our sample purchased a refrigerator, but some report a functioning unit (control), while others report a broken one (treatment, that is, a loss of refrigeration) at the time of the survey. This improves comparability by reducing concerns about selection into treatment.

We further use information on purchase year and price, alongside household characteristics such as geographical location, household size, and income, to balance the probability of belonging to either group. This ensures comparability in refrigerator quality, durability, and use since acquisition. Estimation relies on an augmented inverse probability weighting (AIPW) estimator with LASSO-based covariate selection, which is among the set of machine learning estimators for causal inference as described by Chernozhukov et al. (2018), allowing comparisons across similar households in the same location who acquired refrigerators at the same time and at comparable prices. This approach is analogous to a matching estimator that adjusts for the main determinants of treatment assignment.

The main identification risk is hidden bias. We address this concern with Rosenbaum's sensitivity analysis (Rosenbaum, 2002a, 2002b, 2005), which tests how much unobserved heterogeneity in the odds of treatment would be required to overturn the results. Our estimates remain statistically significant at the 5 percent level even under substantial hidden bias. We also demonstrate robustness to alternative specifications and matching estimators. Placebo tests furthermore confirm that the dietary impacts are specific to refrigeration, as no effects arise when comparing households with unrelated broken appliances, such as radios. Importantly, results also hold when focusing on households that received refrigerators as a gift, showing omitted variable biases linked to appliance selection are not driving our findings.

In section I, we highlight our core contributions from a brief review of the relevant literature. In section II, we provide relevant context about food insecurity and refrigerator ownership in Ghana. Section III presents the food insecurity data, the estimation method and the corresponding results. Section IV presents the food basket data and the corresponding impacts of refrigeration on basket composition. Section V presents additional data on nutrient intakes and the corresponding impact of refrigeration on nutrition. Section VI concludes.

I. Review of related literature

While much of the agricultural and development economics literature has focused on farm-level production, few studies have paid attention to the role of value chains and intermediaries in shaping household food access in LMICs (Barrett et al., 2022; Macchiavello et al., 2022). In contexts with high transport costs and poor storage, intermediaries have been shown to extract significant rents (Bergquist et al., 2020), reducing affordability for consumers. Suri & Udry (2022) also point to substantial heterogeneity in the returns to agricultural technologies in SSA, which post-harvest bottlenecks may partly drive. Improving cold chains could help address these inefficiencies both upstream in the value chain and at the point of final consumption.

Our finding that refrigerators reduce food insecurity by one third underscores that refrigeration could play a complementary role alongside existing interventions such as food fortification, supplementation, nutrition education, and direct food provision (Allen & Gillespie, 2001; De

Marchis et al., 2019), as well as demand-side efforts like cash transfers aimed at improving food affordability (Bhalla et al., 2018; Burchi & Strupat, 2016; Debela et al., 2021; Tiwari et al., 2016). By improving access to micronutrient-rich foods, cold chains may help close persistent nutrition gaps that traditional interventions have struggled to fully address. This aligns with the Global Cooling Pledge, endorsed by over 70 countries at the 2023 UN Climate Change Conference, which calls for National Cooling Adaptation Plans that incorporate access to cooling and a strengthening of cold chains to foster sustainable development.

Our research furthermore highlights the importance of studying specific energy services, not just electricity access. At the national level, electrification has been linked to gains in employment and productivity in countries like South Africa, India, Ghana, and Brazil (Dinkelman, 2011; Lipscomb et al., 2013; Ntsiful et al., 2024; Rud, 2012). However, Lee et al. (2020a) show that these gains are far from automatic and hinge on actual energy use. More recent work (Burlig & Preonas, 2024) finds that impacts depend on factors like community size and service demand, pointing to the importance of how electricity is used, and not just whether it is available. Barriers include low energy affordability (Dube & Ikhupuleng, 2003; C. C. Lee & Yuan, 2024; Nchofoung, 2024), supply-side constraints (Burgess et al., 2020), and, as this paper underscores, appliance uptake. Prior work reinforces this perspective. Lee et al. (2016) show that home solar systems cannot substitute for grid power in rural Kenya, primarily because they cannot support high-wattage appliances like refrigerators. Follow-up work by the same authors (Lee et al., 2020b) shows that households willing to pay for connections benefit more than those who connect only when subsidised, highlighting the importance of complementary inputs.

Targeting energy poverty more effectively may require shifting focus from grid access to the specific services that households need to improve welfare. Climate-related research shows that access to heating in winter and cooling in summer can significantly reduce mortality (Barreca et al., 2016; Chirakijja et al., 2024). Households respond to temperature risk by investing in energy-intensive home adaptations (Cohen et al., 2025; Deschênes & Greenstone, 2011). We show that refrigeration plays a similar protective role for nutrition. By enabling safe storage and greater intake of micronutrient-rich foods, refrigerators help households adapt to dietary risk, just as air conditioners and heaters help them adapt to climate risk. This suggests that a broader set of domestic appliances may have underappreciated health and welfare benefits.

Prior to our study, evidence on refrigeration was largely descriptive. Most work compared households *with* and *without* refrigerators, and no study effectively addressed selection bias (Heard et al., 2020; Karlsson & Subramanian, 2023; Martinez et al., 2021; Jo et al., 2024; Karlsson et al., 2020; Visram & Brown, 2020). Several of these studies were conducted outside Africa, where dietary patterns and energy infrastructure differ considerably (Craig et al., 2004; Heard et al., 2020; Karlsson et al., 2020). Moreover, some contributions had focused narrowly on children under five, potentially underestimating broader population-level effects (Grantham-McGregor et al., 2007; Karlsson & Subramanian, 2023; Martinez et al., 2021; Steyn et al., 2006). Even research on food waste, where refrigeration might be expected to play a central role, overlooked the role played by cooling technologies: a systematic review of 54 interventions targeting food waste did not include any analysis of household refrigeration (Liechti et al., 2024).

By exploiting the GLSS measure of *broken versus functioning refrigerators* and purchase information, we implement a within-adopter design that can be replicated to study other technologies such as air conditioners and water pumps. Random allocation of appliances is rarely feasible, but nationally representative surveys can record ownership and functionality at relatively low cost, which could enable similar analyses of the effect of appliance take-up and functionality.

Likewise, only a handful of economic studies have examined health-relevant nutritional indicators such as vitamin and mineral intakes (Berry et al., 2020; von Grafenstein et al., 2023; Wong et al., 2014). Our findings highlight that economic research can uncover the nutritional impacts of non-health-related interventions, thereby broadening the scope of economic research on nutrition and human capital development.

II. Institutional context of Ghana: food insecurity and refrigeration

Food insecurity, whether moderate or severe, remains a critical global challenge. Nearly 900 million people face hunger and malnutrition worldwide (FAO et al., 2024), with SSA particularly affected. In Ghana, surveys show deteriorating conditions: in 2022, almost half of the population experienced moderate to severe food insecurity (Ghana Statistical Service, 2022).

LMICs often have more vulnerable cold chains, which exacerbate food insecurity in warmer climates, leading to higher levels of food loss and waste. Downstream, food waste from Ghanaian households, at 84 kg per person per year, is estimated to exceed the global average of 79 kg (UNEP, 2024), despite having lower-than-average food access.[1]

Better cold chains could make a significant difference (Friedman-Heiman & Miller, 2024). Refrigeration extends the shelf life of perishable foods and enhances food safety (Ballantine et al., 2008; Faber et al., 2009; Karlsson & Subramanian, 2023; Martinez et al., 2021). At the household level, it also enables bulk purchases with lower unit costs, while reducing transportation expenses and providing time savings (Craig et al., 2004; Karlsson & Subramanian, 2023; Martinez et al., 2021).

In Ghana, the gains from refrigeration are now within reach because the national electrification rate has doubled since 2000, reaching 88.5% in 2024.[2] Improved electricity access facilitates appliance adoption, with refrigerators being one of the first significant investments for many families after electricity access (McNeil & Letschert, 2010). Between 1993 and 2022, the proportion of Ghanaian households owning functioning refrigerators rose markedly, from 1.2% to 22.4% in rural areas and from 23.4% to 56.3% in urban areas. Similar trends can be observed in many LMICs where refrigeration is currently being adopted at pace (ICF, 2022).[3]

Nonetheless, one-fifth of the world's population still lacks a refrigerator (IEA, 2022). Households without refrigerators sometimes rent freezer spaces. The cost reported by Afriyie et al. (2023) in their community study is 2 to 5 Ghanaian Cedis[4] per day, which is equivalent

[1] Post-harvest losses alone are estimated to be about 30% in Ghana (Ehrlich, 2025; Ghanaian Times, 2022) despite efforts from the National Food Buffer Stock Company (NAFCO), which manages surplus cereals during glut and lean periods (Afriyie et al., 2023; Armah et al., 2019). Rich-nutrient foods, such as fruits, vegetables, eggs, and dairy, are often handled by individual consumers; however, no national policy currently addresses household-level food waste. In fact, such consumer-focused policies remain largely absent across many developing countries (Aulakh et al., 2013; Majumder et al., 2016).

[2] **Appendix A1** shows the progress of electrification since 2000. Ghana has a higher electrification rate than many countries in sub-Saharan Africa, where the average rose from about 30% in 2000 to more than 50% in 2024 (World Bank, 2025).

[3] However, economic disparities have remained a barrier to refrigeration adoption. The ownership rate of functioning refrigerators among the wealthiest households (fifth quintile of income) increased from 43.1% in 1993 to 93.8% in 2022, but ownership rates remain minimal among poor households (0.7% and 8.2% for the first and second quintiles, respectively) (ICF, 1993, 2022). Other factors, like frequent power outages and unstable electricity supply, also affect appliance functionality and sustainability. Illegal or substandard electrical connections further exacerbate these issues, increasing the risk of appliance damage.

[4] This is equivalent to \$0.34 to \$0.86 at the time of their study, using the Bank of Ghana exchange rate (Bank of Ghana, 2024)

to 13% to 34% of Ghana's 2023 daily minimum wage of 14.88 Ghanaian Cedis. This economic burden excludes many households from the benefits of refrigeration.

As for those who own a refrigerator, not all appliances are of the same quality. Ghana (and for that matter Africa) has persistently been a dumping ground for inefficient and obsolete refrigerators imported from other regions, such as Europe, China or North America. Aside from being near or over their life-usage capacity, these imported obsolete appliances are often not designed for tropical climates and are therefore prone to frequent breakdowns, reducing their remaining useful life upon arrival in Ghana (Agyarko et al., 2021; Tamakloe, 2022).[5]

When refrigerators break down, repairs are often costly, and there are few qualified technicians available to perform them (FAO-UN, 2016). Many households hold on to broken refrigerators for extended periods, hoping to repair them in the future, since the appliance typically represents a significant investment. Many households also retain non-functional refrigerators even when they have no intention of repairing them, using them for storage, for instance (Obeng-Odoom & Amedzro, 2011).[6,7]

Ghanaian households without adequate refrigeration typically rely on unconventional food preservation methods (Afriyie et al., 2023). These include placing half-used canned milk in cold water, mixing onions with lime, applying wood ash to sliced yams, and adding charcoal to soups before storage. Smoking is another common practice for preserving fish, meats,

[5] In 2000, more than 200,000 obsolete refrigerators were imported to Ghana, and over 400,000 second-hand refrigerators were imported into Ghana between 2008 and 2012. In 2014 alone, about 9,500 of such refrigerators were illegally imported (Agyarko et al., 2021; Tamakloe, 2022).

[6] The disposal of large electronic appliances is rare. While the country prohibits improper disposal of bulky electronic waste, it lacks accessible and complementary systems for proper disposal or recycling (FAO-UN, 2016). Both economic and practical constraints (particularly the cost and difficulty of moving heavy, bulky appliances) significantly limit households' options for responsible disposal. Instead, broken refrigerators are frequently repurposed for non-perishable storage, thus preserving some utility even in a non-functional state (Obeng-Odoom & Amedzro, 2011). In lower-income households, a broken refrigerator may also serve as a source of spare parts for other appliances. Moreover, refrigerator ownership is sometimes viewed as a status symbol in certain communities; displaying a refrigerator, whether functional or not, can convey social standing and pride in possession. Some families may also attach sentimental value to their refrigerators (especially when they were gifts or inherited items), which further discourages disposal, even when the appliance is broken (Obeng-Odoom & Amedzro, 2011). The problem of poor maintenance culture with regards to assets is very common among Ghanaian households.

[7] Also, the problem of maintenance plagues all African countries. In Ghana, for instance, the family house is not for sale, and hence maintenance of the dwelling and its assets – which enhances market value, but not necessarily sentimental value – is not usually a major concern (Tipple, 1987; Van Der Geest, 1998; Willis & Tipple, 1991). Pellow (1988) and Pellow (2001) have shown that some Ghanaian ethnic groups that believe homes are of sentimental value instead of market value consider the maintenance of the dwelling and assets as secondary. This "*poor maintenance culture*" emanating from a set of apathetic attitudes and beliefs has been found to explain why occupants do not have a responsible attitude toward maintaining or repairing their buildings and appliances (Obeng-Odoom & Amedzro, 2011).

poultry, and snails. While these methods are culturally rooted, they often result in food poisoning and can pose significant health risks.[8]

Adequate food storage could increase resilience to food shocks, particularly where diets are fragile. Annan et al. (2022) found that most Ghanaian households consume unbalanced diets with adverse nutritional outcomes. Coomson & Aryeetey (2022) find a high prevalence of underweight and wasting among young children, who often suffer from anaemia and vitamin A deficiency.[9]

Ensuring access to affordable, functional refrigeration, while strengthening cold chain infrastructure and addressing appliance quality and disposal, could play a key role in improving both food security and nutrition outcomes in Ghana and similar contexts.

III. Impact of refrigeration on food insecurity

We turn to estimating the impact of refrigeration on food insecurity.

Data. This paper uses the last two waves of the Ghana Living Standards Surveys (GLSS VI and VII) (GSS, 2014, 2018).[10] Those surveys provide information from 16,772 households in 2012-2013 and 14,009 households in 2016-2017, respectively. We extract several variables on appliance ownership, food insecurity, and food expenditure. We also extract several

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[8] For instance, high levels of toxic polycyclic aromatic hydrocarbons (PAHs) have been detected in traditionally smoked fish (Moorthy et al., 2015). PAHs are toxic and carcinogenic. Among other health risks, chronic exposure is associated with lung cancer (Moorthy et al., 2015). Besides, high salt concentrations in preserved meats can increase hypertension risk (Dzikunoo et al., 2021; Plahar & Lu, 1989).

[9] They also found that 6.8% of children under 5 suffer from wasting, and 17.5% from stunting and almost half of all deaths in children under 5 are attributable to malnutrition. Meanwhile, unhealthy weight gain is also on the rise. Rousham et al. (2020), focusing on Ghana and Uganda, show a consistently lower consumption of fruits and vegetables but a high consumption of sugar-sweetened beverages, which contribute to overweight and obesity. This issue is now affecting adult women with increasing concern, with overweight rates rising from 13% in 1993 to 43% in 2022 (ICF, 1993, 2022).

[10] The Ghana Statistical Service (GSS) used a two-stage stratified sampling design. In the first stage, a nationally representative sample consisting of 1000-1200 enumeration areas was selected from all over the country to form the primary sampling units (PSUs), which were allocated into the 10 administrative regions of the country using a probability proportional to population size (PPS). At the time of both surveys, there were 10 administrative regions in Ghana. The PSUs were divided into rural and urban areas, followed by a complete listing of all households in the identified PSUs. This formed the secondary sampling units (SSUs). At the second stage, 15 households were systematically selected from each PSU for the survey. This yielded a nationwide sample size of 18,000 households in GLSS VI and 15,000 households in GLSS VII. The response rates for GLSS VI and VII were 93.2% and 93.3%, respectively. Each survey was spread over 12 months in order to ensure a continuous recording of household consumption and expenditures and changes occurring thereof.

socioeconomic and demographic characteristics. Since we are interested in households with a refrigerator, the study focuses on households with access to reliable electricity.[11]

Depending on data availability for specific outcomes, analyses either use both waves or GLSS VII only, which is more comprehensive. For food insecurity, we use GLSS VII only, which is when the GSS adopted the Food Insecurity Experience Scale (FIES) developed by the FAO. The scale covers 8 binary questions that require respondents to self-report on their ability to access food of sufficient quality and quantity in the last 12 months. For instance, the questions include whether the household was worried about not having enough food to eat, or whether the respondent did not eat for a whole day. Each response is assigned the value of 1 if the household reports experiencing food insecurity (and zero, if otherwise).

With these 8 questions, we create two main food insecurity indicators. The first is a food insecurity risk indicator which takes the value of 1 if a household responds "yes" to at least 1 of the eight questions (and zero, if otherwise). The second is a count measure indicating the intensity of food insecurity experienced by the household. It is obtained from summing up all 8 indicators; hence, it ranges from 0 to 8, and higher values represent higher food insecurity intensity.

Table 1 provides summary statistics on the food insecurity responses, separately for households with a functioning or a broken refrigerator. On average, households with broken refrigerators are at much higher risk of food insecurity and are more likely to answer yes to several food insecurity questions.

The differences reported in **Table 1** are not causal due to substantial differences between the groups. For instance, households with broken refrigerators bought lower-quality appliances. In addition to appliance ownership and functionality, the GLSS includes the purchase price and the year of acquisition of appliances.[12] For some households, refrigerators were received as gifts and, therefore, a price was not reported. **Table 2** provides summary statistics for these main variables, separately for functioning and broken refrigerators. To reduce risks of

[11] Households that depend solely on crop residue, firewood, flashlights, and candles for electricity power were excluded (that is, 3% of the households owning refrigerators), leaving only those who depend on the national grid, mini-grid, and or solar power.

[12] The prices of the appliances for a few households were reported in foreign currencies (USD, Euros, Pounds, CFA, Naira, etc.). We converted all prices to Ghanaian Cedis (GHS) using historical end-of-year average exchange rates from FRED (2024), the Bank of Ghana (2024) and the World Currency Exchange Rates and Currency Exchange Rate History (2024). We furthermore converted all prices to 2017 real prices, adjusting for inflation using Ghana's 2017 CPI deflator provided by the World Bank (2025).

measurement error and recall bias, we have winsorized the 1st and 99th percentiles of the price and age of refrigerators. Broken refrigerators were usually older and bought at lower prices. Those offered as gifts were also more likely to break down.

The GLSS include many variables related to household characteristics, such as household size or income, as well as the educational attainment or marital status of the household members. **Table 3** shows that the sociodemographic characteristics of those with broken refrigerators also differ – predominantly male-headed, with large household sizes, low formal education, and low income. Notably, urban areas host more households with both broken and functioning appliances (See **Tables B1 and B2** in **Appendix B** for the full set of control variables).

Table 1: Mean statistics for food insecurity indicators

Food insecurity indicators	**(1) Functioning fridges (N=3,388)**	**(2) Broken fridges (N=252)**	**(3) Diff.**	**(4) SE**
Panel A: Constructed food insecurity indices				
A1: At risk of food insecurity (0/1)	0.37	0.65	-0.27***	0.03
A2: Intensity of food insecurity (0 to 8)	1.52	3.01	-1.49***	0.16
Panel B: Disaggregated binary food insecurity indicators				
B1: Worried about not having enough food to eat	0.29	0.52	-0.23***	0.03
B2: Unable to eat healthy and nutritious food	0.23	0.44	-0.21***	0.03
B3: Ate only a few kinds of foods	0.27	0.53	-0.27***	0.03
B4: Had to skip a meal	0.21	0.42	-0.21***	0.03
B5: Ate less than expected	0.22	0.47	-0.26***	0.03
B6: Ran out of food	0.17	0.35	-0.18***	0.03
B7: Hungry but did not eat	0.11	0.20	-0.09***	0.02
B8: Did not eat for a whole day	0.03	0.07	-0.04***	0.01

Note: Data from GLSS VII only. N = total number of households in the sample category. Diff. = the mean difference. SE = Standard Error of the mean difference. *** p<0.01, ** p<0.05, * p<0.1.

Table 2: Mean statistics for refrigerators

Refrigerator information	**(1) Functioning fridges (N=7,639)**	**(2) Broken fridges (N=490)**	**(3) Diff.**	**(4) SE**
Real purchase price (2017 GHS)	800	658	+142***	35
Age (in years)	4.59	6.87	-2.28***	0.16
Gift (=1)	0.07	0.14	-0.07***	0.01

Note: Data from GLSS VI and GLSS VII, pooled. N = total number of households in the sample category. Prices are deflated to 2017 real local currency values.[13] Diff. = the mean difference. SE = Standard Error of the mean difference. *** p<0.01, ** p<0.05, * p<0.1.

[13] In 2017, GHS 1 = $0.23 on average (Bank of Ghana, 2024).

Table 3: Mean statistics of selected baseline covariates

Baseline covariates	(1) Functioning refrigerator (N=7639)	(2) Broken refrigerator (N=490)	(3) Diff.	(4) SE
Male household head (=1)	0.72	0.65	+0.07***	0.02
Age of household head (in years)	44.25	49.07	-4.82***	0.64
Real gross household income (per AE/year)	11,221	7,917	+3,304***	798
Household size	3.90	4.51	-0.61***	0.11
Urban (=1)	0.77	0.66	+0.11***	0.02

Notes: Data from GLSS VI and GLSS VII, pooled. N = total number of households in the sample category. Diff. = the mean difference. SE = Standard Error of the mean difference. AE = adult equivalence. Income is measured in real 2017 Ghanaian Cedis and is winsorised at the 1st and 99th percentiles. *** p<0.01, ** p<0.05, * p<0.1

Estimation. Our empirical strategy employs a LASSO-based Augmented Inverse Probability Weighting (AIPW) estimator, which is among the set of machine learning estimators for causal inference described in Chernozhukov et al. (2018). The objective is to estimate the average treatment effect on the treated (ATT) of having a broken refrigerator at the time of interview. The treatment group consists of households reporting a dysfunctional (broken) unit at the time of interview, while the control group comprises those with a functioning refrigerator. This choice of treatment and control groups is an important methodological contribution that avoids the conventional comparison between households *with* and *without* refrigerators, which would confound treatment with appliance ownership.[14]

To ensure credible identification, we construct a rich set of pre-treatment covariates capturing appliance characteristics, household sociodemographic, and contextual factors. Rather than relying on an ad-hoc specification, we follow a systematic but intertwined two-stage approach. First, we pre-select a minimal set of variables that economic theory, existing literature, and the Ghanaian institutional context identify as core determinants of refrigerator quality, durability, and usage. Namely, purchase price, year of acquisition, gift status, region, urban/rural location, household size, and the age and gender of the household head, along with interview month and year to ensure temporal comparability. These variables constitute very good proxies for appliance quality and purchasing power and help ensure spatiotemporal and compositional balance between the treated and control groups.

[14] In **Appendix F**, we show that our choice to focus on people with broken vs. functioning appliances increases the comparability of the control and treatment groups. With our data, results looking at the composition of food baskets while comparing households with and without refrigerators would not be robust to hidden bias.

Second, we allow LASSO to select any additional relevant covariates from the pool of available socioeconomic variables. In short, standard LASSO is a common machine learning technique that allows refining the pool of potential covariates and identifying the variables that have a significant correlation with the probability of being treated. It refines the candidate set by penalizing the absolute size of coefficients, ensuring parsimony and mitigating concerns of overfitting, overlap violations, and avoiding a "*throw in the kitchen sink*" approach in covariate selection, which could bias estimates (Shortreed & Ertefaie, 2017). All continuous variables are standardised prior to selection. Across all specifications, household income consistently emerges as the only additional predictor retained by the standard LASSO algorithm. The pre-selected and LASSO-selected variables are summarised in **Table 3** (full list in **Table B1** in **Appendix B**, while **Table B2** reports the remaining set of covariates available for selection).

Following the recommendations of Belloni et al. (2014), we jointly perform the covariate selection with standard LASSO and the estimation of treatment effects using `telasso` command in STATA (Hastie et al., 2015; Koch et al., 2017; Shortreed & Ertefaie, 2017; StataCorp, 2023; Tibshirani, 1996). The `telasso` estimation is specifically designed to estimate treatment effects using AIPW while incorporating LASSO-based covariate selection simultaneously. Joint estimation is essential: performing LASSO selection and causal estimation separately would compromise inference, producing biased estimates, understated standard errors, and inflated type I error rates (Leeb & Pötscher, 2005, 2006, 2008; StataCorp, 2021). `telasso` is doubly robust (i.e. either the outcome model or the treatment model can be misspecified) and Neyman orthogonal (i.e. robust to minor model selection errors).[15]

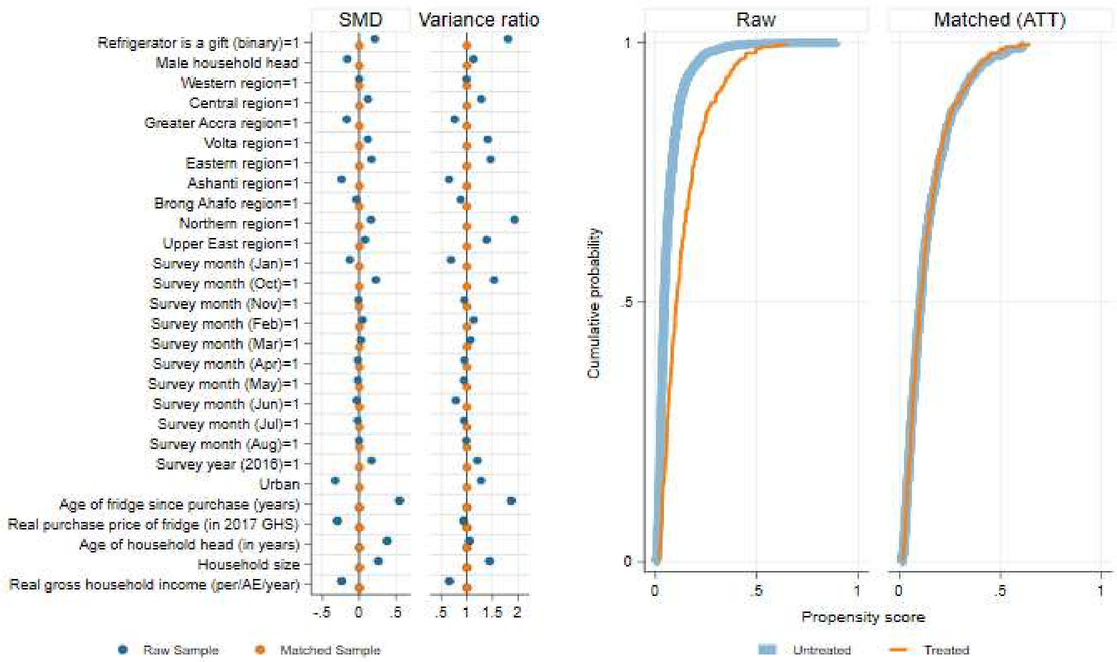
For each food insecurity outcome, we estimate the ATT by comparing households that are observationally similar across all covariates in **Tables 2** and **B1**. The core assumption of the model is that, conditional on these observed covariates, households in the treatment and control groups should have had similar probabilities of experiencing a refrigerator breakdown, making treatment assignment plausibly as good as random. This ensures valid identification under the standard conditional independence and overlap assumptions.

[15] See **Appendix B** for more discussions on LASSO and `telasso`. `telasso` implements an AIPW estimator, using LASSO to select appropriate covariates from a pool of potential covariates. By jointly estimating variable selection and treatment effects, `telasso` ensures consistent causal inference. Furthermore, it is more resilient to minor machine learning errors than traditional matching techniques, such as regression adjustment (RA), inverse probability weighting (IPW), or combined methods like IPWRA. To select the optimal value of the LASSO penalty parameter, we employed the cross-validation (CV) method in all our baseline estimations. We use the `telasso` command in STATA17 with the default setup and a random-number seed of 777 for reproducibility.

Finally, standard errors were clustered at the Enumeration Area (EA) level to adjust for intra-cluster correlation arising from the surveys' two-stage sampling design (as described in *footnote **10***).

Food insecurity results. We begin by assessing standardized bias between treated and control groups before and after conditioning on covariates. **Figure 1** presents standardized mean differences (SMD), variance ratios, and cumulative probability graphs. Standard benchmarks (Rosenbaum & Rubin, 1985) recommend mean differences below 20% and variance ratios between 0.5 and 2, ideally close to 1. Therefore, our sample appears well-balanced with SMD close to zero and variance ratios close to 1. The cumulative probability graphs further confirm good overlap and balance in propensity scores within the common support region after conditioning. Overall, **Figure 1** suggests that the treated and control groups are comparable.

Figure 1: Model diagnostics for the food insecurity model



Notes: Diagnostic tests when running our model on food insecurity outcomes, using GLSS VII data only. The left panel presents the covariate balance using the standardized mean difference (SMD) and variance ratio. In the raw sample, we observe large disparities, even beyond 20% in the SMD and outside the recommended range in the variance ratio. However, in the matched sample and under the common support, the SMD is zero (0) and the variance ratio is one (1) for all covariates. The right panel presents the cumulative probability plots of the propensity scores before matching (Raw) and after matching (Matched) under the common support. The vertical axis of the right panel reports the probability that the score is less than or equal to a given propensity score.[16]

[16] Given that we have 10 food insecurity outcomes, it would be ideal to present 10 covariate balance graphs. However, since the same covariates were selected in all models and the figures were exactly the same, we report only one figure to save space. All the other figures can be made available upon request.

In **Table 4**, we move on to showing our baseline treatment effects of broken refrigerators on food insecurity. Each row corresponds to a different food insecurity outcome and, therefore, a different estimation. Column (1) shows the ATT from the `telasso` estimator. The positive signs imply that having a broken refrigerator worsens food insecurity. Thus, on average, we find that households with a broken refrigerator are 16 percentage points more likely to be at risk of food insecurity (see **Panel A**, outcome A1). Column (2) displays the treated group mean for comparison. In relative terms, losing access to refrigeration increases risk of food insecurity by 33 percent relative to what the risk would have been if the refrigerator were functioning.[17]

We also find that households without a refrigerator are more likely to answer yes to several questions: having a broken refrigerator raises the intensity of food insecurity by 0.92 points, which is about a 44% increase relative to what the intensity would have been had the refrigerator been functioning (outcome A2).

In **Panel B**, disaggregated results by question are statistically significant for 7 out of 8 questions. Refrigeration appears to reduce households' concerns about whether they will have enough food and might help them avoid running out of food. In addition, refrigeration seems to support greater dietary diversity: households with functioning refrigerators are more likely to eat healthy and nutritious foods and less likely to rely on a limited variety of foods. These households may also skip meals less frequently. Finally, functioning refrigerators might help some households avoid running out of food, going without food for an entire day, or being hungry but unable to eat.

We check whether all these results are robust to hidden bias in Column (3) by reporting the results of the Rosenbaum bounds tests. As already explained, the core assumption of the model is that the control and treatment groups are virtually identical after conditioning on covariates. Nonetheless, in practice, controls are often imperfect, and we could expect that households in both groups might not have had exactly the same probability of belonging to the treatment and control groups due to unobserved confounders such as household preferences and habits affecting appliance life spans (or simply because of slight differences in propensity scores). Differences in probabilities of treatment due to unobservables could create a hidden bias in the estimates (Caliendo & Kopeinig, 2008).

[17] This is: $\frac{ATT}{(treated\ group\ mean - ATT)} = \frac{0.16}{0.65-0.16} \approx 0.33$.

We use the bounds test developed by Rosenbaum (2002a) to assess the sensitivity of our estimates to possibly remaining differences between treatment and control groups. The test relies on a sensitivity parameter Γ, which denotes the difference in the probability of treatment between the observations in the treated group vs. the control group. The bounds test assesses whether the treatment effect would remain of the same sign even if the odds ratio of belonging to the treatment versus the control group were as large as Γ. Results should ideally remain valid even for large values of Γ, as this would indicate that they are robust to the potential presence of unobserved confounding factors (Becker & Caliendo, 2007; Diprete & Gangl, 2004; Liu et al., 2013; Rosenbaum, 2002b, 2002a).[18]

Column (3) of **Table 4** shows the maximum Γ value from the sensitivity analysis, which represents the largest tolerable difference in the odds of treatment between the groups for the results to remain statistically significant at the 5% level.[19] A maximum Γ of 370% (as shown in **Table 4**) implies that the odds of belonging to one group would have to differ by a factor of 1 to 4.7 for the results to become statistically insignificant, confirming the robustness of our main result to hidden bias. Results for other entries are also generally robust to hidden bias with a maximum Γ above 40%. Disaggregated results by question remain robust for five out of the seven statistically significant items.

[18] To implement this bounds test, we re-estimate treatment effects with entropy balancing (Hainmueller 2012), using the same pre-selected and LASSO-selected baseline covariates to ensure full comparability with the `telasso` estimates. This is because we cannot use `telasso` to formally perform sensitivity tests for hidden bias. We report in **Appendix C1** the ATTs obtained from entropy balancing. They are very similar to the `telasso` estimates. Our entropy balancing estimations are done in STATA17 using the default settings of the `kmatch` command developed by Jann (2020). We set the entropy balance constraint to the 2nd-order moment. Other forms of matching algorithms are nearest neighbor, caliper, and radius, stratification and interval, and inverse probability weighting. Our choice presents two advantages considering our sample size and the number of LASSO-selected covariates to control for. Because kernel methods are non-parametric, they do not require specific functional form specifications and, therefore, are not subject to misspecification biases. Furthermore, control households with propensity scores that are closer to the scores of the treated households are assigned more weight than those with far-away scores. This allows us to reduce the biases that distant matches could create, considering that, with a relatively small sample size and a high number of controls, matches could be imperfect. Moreover, to match households on the selected covariates, we use a kernel method (Heckman et al., 1998). There are many kernel-based algorithms to choose from. We adopt an Epanechnikov kernel pair-matching algorithm since it is the most frequently used in the literature. The smoothing parameter is automatically determined through the pair-matching approach as discussed in Huber et al. (2013). Frölich (2004) provides details on other algorithms.

[19] For example, a Γ of 10% means that unobserved factors would need to increase the odds of being in the treatment group by more than 10% (relative to similar control households) in order to overturn our results. In this example, results would be barely robust to hidden bias since a 10% difference in odds is small.

Table 4: Causal impacts of having a broken refrigerator on food insecurity

Food insecurity indicators	(1) ATT	(2) Treatment group mean	(3) Max. Γ
Panel A: Food insecurity indices			
A1: Risk of food insecurity	0.16***	0.65	370%
	(0.04)		
A2: Intensity of food insecurity	0.92***	3.01	40%
	(0.20)		
Panel B: Disaggregated binary food insecurity indicators			
B1: Worried about not having enough food to eat	0.14***	0.52	150%
	(0.04)		
B2: Unable to eat healthy and nutritious foods	0.13***	0.44	70%
	(0.04)		
B3: Ate only a few kinds of foods	0.16***	0.53	160%
	(0.04)		
B4: Had to skip a meal	0.15***	0.42	50%
	(0.04)		
B5: Ate less than the respondent's expectation	0.14***	0.47	90%
	(0.04)		
B6: Ran out of food	0.13***	0.35	<10%
	(0.04)		
B7: Went without eating for a whole day	0.05	0.20	<5%
	(0.03)		
B8: Hungry but did not eat	0.04***	0.07	<5%
	(0.02)		

Note: N=3,615. Standard errors are in parentheses. Panel A focuses on the 2 main indicators that we constructed from the data, while Panel B focuses on the 8 original indicators from GLSS VII. Column (1) reports the ATT, Column (2) reports the mean of the treated group; and Column (3) reports the maximum Γ value (in %) from the Rosenbaum bounds sensitivity analysis beyond which our estimates would be sensitive to hidden bias, at 5% critical level. *** p<0.01, ** p<0.05, * p<0.1

Robustness. We first assess the stability of the AIPW estimates (**Appendix C2**). Results are similar when adding additional household controls (education and employment status of the household head; materials used for the roof, walls, and floor of the dwelling; and ownership of any other broken appliance) and when excluding households who received their refrigerator as a gift. Estimates are also unchanged when using the adaptive LASSO rather than the cross-validation method for covariate selection. Replacing AIPW with inverse probability weighting, propensity score matching, or Mahalanobis distance matching yields similar effects. Finally, the GLSS includes survey weights, which we have not used in the main estimations since our sample, by construction, cannot be representative of the Ghanaian population. We use those weights as importance weights in **Appendix C2**, which has no substantial effect on our findings. Taken together, these checks show that the main findings do not depend on estimator choice or covariate specification.

We then assess whether omitted variable bias could be driving the results. Already, the high maximum Γ values of the Rosenbaum bounds tests in **Table 4** give us strong confidence in the direction of the effects. Furthermore, since we control for appliance price and time of purchase, and households have little control over whether a refrigerator of a given age and price breaks down, the remaining heterogeneity due to unobserved factors, such as household "*savviness*" or maintenance behaviour, is likely to play only a small role. Matching and AIPW estimators are appropriate when treatment assignment is exogenous (i.e. appliance breakdown is not a choice) and the covariate set is rich enough to balance treated and control groups. However, we cannot fully rule out the existence of unobserved factors that may influence both refrigerator durability and food insecurity. Results could therefore still be biased even if the critical value for Γ is high (Becker & Caliendo, 2007). A high Γ only gives us strong evidence that the main results are robust to hidden bias, even though bounding tests cannot directly confirm the unconfoundedness assumption.

To evaluate potential selection concerns, we run two complementary analyses that rule out two potential sources of omitted variable bias: first, using the sample of households that received their refrigerators as a gift, and second, with placebo tests focusing on other broken appliances.

Sample of households with refrigerators as a gift. We estimate fixed-effects models using only households that received a refrigerator as a gift. This "*gift*" sample is less prone to selection bias as appliance ownership in this group is only indirectly related to household characteristics or preferences. Comparability is further enhanced since all households received their appliances from an external source. We run linear regressions weighted by the survey weights to assess the impact of refrigerator breakdowns on food insecurity within this subsample.

Table 5 presents the results for the "*gift*" sample. The estimates are remarkably consistent with those from the main quasi-experimental design in **Table 3**. In both samples, refrigerator breakdowns are associated with higher food insecurity by about 0.15 points for the risk score and 0.8–0.9 points for the intensity score. The magnitude of the coefficients closely matches the baseline estimates despite the smaller sample size and wider confidence intervals, suggesting that the main results are not driven by appliance selection or unobserved heterogeneity.

Table 5 furthermore reports six specifications used to test the stability of results to the inclusion of additional control variables. If appliance breakdowns are exogenous for households that received a refrigerator as a gift, the coefficients should remain stable despite the inclusion of controls. Results are stable across specifications despite a loss of precision due to small sample sizes and the inclusion of many controls, providing further evidence that our results are not driven by omitted variable biases.

Table 5: Impact of refrigerator breakdowns on food insecurity among households that received the appliance as a gift

Food insecurity outcomes	(1)	(2)	(3)	(4)	(5)	(6)
A. Food security indices						
A1: At risk of food	0.153	0.166	0.163	0.135	0.117	0.087
insecurity (0/1)	(0.108)	(0.111)	(0.125)	(0.118)	(0.120)	(0.124)
A2: Intensity of food	0.786*	0.871*	0.889*	0.735	0.704	0.644
insecurity (0 to 8)	(0.471)	(0.475)	(0.470)	(0.464)	(0.464)	(0.477)
B. Disaggregated indicators						
B1: Worried about not	0.132	0.151	0.160	0.131	0.129	0.131
having enough food	(0.096)	(0.097)	(0.104)	(0.102)	(0.099)	(0.111)
B2: Unable to eat nutritious	0.135	0.149	0.160*	0.149	0.160*	0.177*
foods	(0.093)	(0.094)	(0.091)	(0.093)	(0.096)	(0.103)
B3: Ate only a few kinds of	0.205**	0.206**	0.232**	0.177*	0.164*	0.119
foods	(0.102)	(0.102)	(0.109)	(0.097)	(0.090)	(0.091)
B4: Had to skip a meal	0.153	0.182*	0.161*	0.127	0.107	0.082
	(0.096)	(0.097)	(0.093)	(0.084)	(0.082)	(0.091)
B5: Ate less than the	0.096	0.085	0.081	0.051	0.059	0.015
respondent's expectation	(0.087)	(0.086)	(0.079)	(0.075)	(0.079)	(0.092)
B6: Ran out of food	0.012	0.026	0.019	0.001	0.010	0.039
	(0.063)	(0.062)	(0.062)	(0.064)	(0.065)	(0.081)
B7: Went without eating for	0.013	0.032	0.027	0.040	0.010	0.024
a whole day	(0.058)	(0.061)	(0.059)	(0.065)	(0.069)	(0.078)
B8: Hungry but did not eat	0.040	0.040	0.048	0.057	0.066	0.057
	(0.052)	(0.052)	(0.051)	(0.053)	(0.049)	(0.043)
Controls						
Age of appliance		✓	✓	✓	✓	✓
Region			✓	✓	✓	✓
Rural/urban				✓	✓	✓
Household var.					✓	✓
Community var.						✓
Observations	268	268	267	267	267	198

Notes: All specifications include interview year and month fixed effects. Food insecurity uses GLSS VII only. Household variables include (i) age and (ii) sex of householder; (iii) whether ever attended school; (iv) their employment status (employed or not); (v) the household size; and whether the (vi) floor, (vii) roof and (walls) of the dwelling are permeable. Community variables are not available for all observations and include access to a market, a financial institution, a road, living conditions of the area, and the community's main activity (fishing, trading, handicraft, or other). Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Placebo tests. Refrigerator breakdowns may proxy for household characteristics such as care, "*savviness*," or maintenance ability, in which case food insecurity would respond to appliance failures generally rather than to the loss of refrigeration specifically. Breakdown rates could also reflect unobserved home conditions, such as indoor heat or humidity. Finally, appliance breakdowns could influence spending patterns if households save to replace appliances, which could act as a negative income shock. To assess the role of these mechanisms, we estimate placebo effects using the same identification strategy as in the main analysis but applied to other household appliances.

The GLSS records functional status, purchase year, and price for 14 additional appliance categories (see **Appendices A2** and **A3**). However, many of these categories contain too few broken units to support estimation. The two appliances with sufficient variation in functionality in GLSS VII are radios and sewing machines. We therefore construct placebo treatments that consist of having a broken radio or a broken sewing machine, with the corresponding control groups defined as households with functional units of the same appliance.

Table 6 displays the placebo results. We find no effects of these placebo treatments on food insecurity or dietary composition. This indicates that the estimated impacts are specific to refrigeration rather than to general appliance failure, unobserved household characteristics linked to failures, or income-related replacement behaviour.

Table 6: Placebo tests - Causal impacts of other broken appliances on food insecurity

Household food insecurity outcomes	**(1) Broken radio (N=1467)**	**(2) Broken sewing machine (N=588)**
Panel A: Food insecurity indices		
A1: Risk of food insecurity	0.04	-0.04
	(0.07)	(0.09)
A2: Intensity of food insecurity	0.21	-0.28
	(0.36)	(0.49)
Panel B: Disaggregated binary food insecurity indicators		
B1: Worried about not having enough food to eat	0.05	-0.03
	(0.07)	(0.10)
B2: Unable to eat healthy and nutritious foods	0.04	-0.12
	(0.07)	(0.08)
B3: Ate only a few kinds of foods	0.09	-0.12
	(0.07)	(0.09)
B4: Had to skip a meal	0.05	-0.06
	(0.06)	(0.09)
B5: Ate less than the respondent's expectation	0.04	0.01
	(0.07)	(0.09)

B6: Ran out of food	-0.02	-0.02
	(0.06)	(0.07)
B7: Went without eating for a whole day	-0.03	0.05
	(0.05)	(0.08)
B8: Hungry but did not eat	0.0006	0.02
	(0.02)	(0.04)

Note: N = number of observations in the sample category. Columns (1) and (2) report the ATT of having a broken radio and sewing machine on food insecurity, respectively. Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Overall, we find that refrigeration significantly reduces food insecurity. It alleviates concerns about food shortages and supports greater food diversification. Covariate balance diagnostics confirm that the treated and control groups are well-matched. The results are also robust to hidden bias, changes in control variables, and alternative estimation strategies. Placebo tests further emphasize that the observed effects are specific to refrigeration.

IV. Impact of refrigeration on food baskets

We next examine whether refrigeration fosters food diversity. We focus on acquired quantities, which we derive from purchases and own consumption by the household. We report technical details on how we compute food expenditure and food quantities in **Appendix D1**.

In short, food expenditure data is available in GLSS VI and GLSS VII. Enumerators visited each household seven times at five-day intervals. During these visits, a diary was used to record daily consumption and market value of own produce, as well as food expenditures. On the first visit, a literate household member was identified and trained to record all household expenditures daily, submitting the diary during the next visit for data entry. If no literate person was present in the household, the enumerator would make daily visits to record expenditures. The daily values were then aggregated. Both methods led to the computation of 30-day expenditure by food item for each household after either seven visits at 5-day intervals, or daily visits for 30 days in the case of illiterate households.

We compute quantities by dividing the value of own consumption and food expenditures by local market prices. To collect information for computing food and non-food CPIs, the Ghana Statistical Service also required enumerators to visit three randomly selected local markets in each community. GLSS VI and VII, therefore, professionally collected consistent price information from local markets for each food item. For every food item, enumerators either observed or weighed the item using standard scales and recorded both the quantity and the corresponding retail price. Reported prices are highly reliable: in over 98% of cases, the three item-specific recorded prices are similar within a community.

Summary statistics. Summary statistics for food quantities are reported in **Table 7**, distinguishing households with functioning versus broken refrigerators. Total food acquisition amounts to about 1.7 kg per person per day, roughly half of which consists of vegetables (high in water content). The distribution across food groups is also consistent with expectations: Ghanaian households rely primarily on vegetables and cereals, complemented by smaller amounts of meat, dairy, eggs, and fish. Sweetened beverages are rarely purchased, consistent with evidence that they are treated as an occasional luxury rather than a daily staple.[20] On average, households with a broken refrigerator acquire less meat, milk and dairy, eggs and fish. They also acquire more of roots, tubers and plantain, and less of leafy vegetables and fruit. Finally, they acquire non-alcoholic beverages (e.g. sweetened drinks) less often. This is consistent with households being predominantly of lower income status. Summary statistics for food expenditure are provided in **Appendix D3**.[21]

Table 7: Summary statistics of food quantities demanded

	(1)	(2)	(3)	(4)
Food group (in kg/day/AE)	**Functioning refrigerator (7639)**	**Broken refrigerator (490)**	**Diff.**	**SE**
Total at home (excl. alcohol)	1.659	1.576	0.083	0.086
All Meats	0.044	0.030	0.015***	0.003
Milk & dairy products	0.015	0.009	0.005***	0.001
Eggs	0.038	0.021	0.018***	0.004
Fish	0.084	0.072	0.013***	0.005
All vegetables	0.783	0.827	-0.044	0.053
Roots, tubers, & plantain	0.530	0.615	-0.085**	0.042
Other leafy vegetables	0.228	0.202	0.026*	0.015
Fruits	0.127	0.103	0.024***	0.009
Cereals, flour & bread	0.290	0.298	-0.009	0.018
Pulse, nuts, & seeds	0.056	0.057	0.000	0.005

[20] Observed acquired quantities are close to daily recommendations. For animal-sourced products, the National Food-Based Dietary Guidelines by Ghana's Ministry of Food and Agriculture (2023) recommend 0.144kg per day, which is higher than our sample averages (of 0.181kg and 0.132g for people with a functioning or broken refrigerator, respectively). Quantities for leafy vegetables also align with recommendations of 0.227kg per day, but households may not eat enough fruit, and pulse, nuts and seeds, with the recommendation being twice higher for fruit, at 0.226kg per day, and four times higher for pulse, nuts and seeds, at 0.198kg per day.

[21] With the GSS, we can track food expenditure outside the home, such as in canteens, restaurants, and hotels. However, we are unable to disaggregate such expenditure into item-specific values or to estimate their calorie contents (see **Appendix D1**).

Oil & fats	0.038	0.040	-0.001	0.003
Spices	0.017	0.016	0.001	0.002
Sugar & sweets	0.018	0.018	0.000	0.002
Alcoholic beverages	0.015	0.013	0.003	0.003
Non-alcoholic beverages	0.042	0.027	0.015***	0.003

Notes: Data from GLSS VI and GLSS VII, pooled. N = total number of households in the sample category. SE = Standard Error of the mean difference. *** p<0.01, ** p<0.05, * p<0.1

Impact of refrigeration on food quantities. We estimate average treatment effects on the treated for food quantities using the same LASSO-based AIPW estimator (Chernozhukov et al., 2018), as for food insecurity in the previous section. The baseline model is strictly identical, and the results are reported in **Table 8**.

We find sizeable statistically significant reductions in animal-sourced foods. The effects are statistically significant at the 1% level for all meats, milk and dairy products, and eggs, and at the 10% level for fish. In relative terms, having a broken refrigerator reduces meat acquisition by about 21%, milk and dairy by 17%, eggs by 39%, and possibly fish by 10% relative to how much would have been demanded if the refrigerator were functioning.

Column (3) further shows that reductions in animal-sourced foods are robust to hidden bias. Model diagnostics, robustness checks, and placebo tests are reported in **Appendix D2.** These mirror those for food insecurity: results are consistent and stable across specifications, and the effect is specific to refrigeration and not to other appliances. In the sample of refrigerators received as a gift, we again find similar effects for animal-sourced products, with no meaningful changes for non-animal foods. Furthermore, we report ATTs for food expenditure instead of food quantities in **Appendix D3**, confirming that refrigeration has an impact on access to animal-based food items.

Table 8: Average treatment effect on the treated for food quantities demanded

Food category	**(1) ATT**	**(2) Treatment group mean**	**(3) Max. Γ**
Total at home (excl. alcohol)	-0.052	1.576	70%
	(0.096)		
All Meats	-0.008***	0.030	160%
	(0.003)		
Milk & dairy products	-0.002***	0.009	110%
	(0.001)		
Eggs	-0.013***	0.021	390%

	(0.003)		
Fish	-0.008*	0.072	80%
	(0.005)		
All vegetables	-0.010	0.827	70%
	(0.062)		
Roots, tubers, & plantain	0.014	0.615	<5%
	(0.052)		
Other leafy vegetables	-0.010	0.202	120%
	(0.013)		
Fruits	-0.003	0.103	80%
	(0.009)		
Cereals, flour & bread	0.010	0.298	<5%
	(0.020)		
Pulse, nuts, & seeds	0.004	0.057	<5%
	(0.006)		
Oil & fats	0.003	0.040	<5%
	(0.003)		
Spices	0.001	0.016	<5%
	(0.001)		
Sugar & sweets	0.002	0.018	<5%
	(0.002)		
Alcoholic beverages	0.001	0.013	<5%
	(0.002)		
Non-alcoholic beverages	-0.003	0.027	140%
	(0.003)		

Notes: N=8,072. Standard errors are in parentheses. Column (1) reports the ATT, Column (2) reports the mean of the treatment group; Column (3) reports the maximum Γ value (in %) from the Rosenbaum bounds sensitivity analysis beyond which our estimates would be sensitive to hidden bias, at 5% critical level. *** p<0.01, ** p<0.05, * p<0.1.

The results in this section confirm our prior results for food insecurity, which suggested that refrigeration may allow for higher food diversity. They are also consistent with the fact that refrigeration can durably extend the shelf life of perishable products such as meat and dairy, which is particularly important in a tropical country with hot weather like Ghana (Ballantine et al., 2008; Faber et al., 2009; Karlsson & Subramanian, 2023; Martinez et al., 2021). Furthermore, we find no effect on the products that rarely go to the refrigerator, such as pulses or cereals.

V. Impact on nutritional availability

We compute the caloric and nutrient content of all food quantities using the *West Africa Food Composition Table* by Vincent et al. (2020). This database reports macronutrient and micronutrient values per 100 grams of the edible portion of each food item. We merge this item-level nutritional database with our food quantity data to compute the nutritional composition of foods acquired, including caloric content, carbohydrates, proteins, fats, vitamins, and minerals. The data can be further disaggregated to analyse the origin of nutrients (e.g., animal-sourced versus plant-based) or specific nutrient types such as fat subcategories, vitamins, or minerals.

This procedure allows us to estimate nutritional availability at the point of acquisition. Our approach represents a significant contribution to the literature: to our knowledge, no previous study has estimated the causal impact of household refrigeration on nutrition using item-level quantity-to-nutrient conversion.

Table 9 reports the average per-capita, adult-equivalent daily intakes computed using this method. Both total caloric intake and the distribution across carbohydrates, fats, and proteins are consistent with physiological norms and with existing evidence for Ghana (Ministry of Food and Agriculture, 2023; UNDP, 2013). On average, animal-sourced foods account for about 11% of total caloric intake but provide roughly half of protein intake, approximately 20% of fat intake, 16% of mineral intake, and about 7% of vitamin intake. This aligns with the composition of typical Ghanaian dishes, which are primarily based on cereals, pulses, nuts and seeds, and vegetables (especially roots, tubers, and plantain).[22]

Importantly, these summary statistics do not account for food waste at the household level, which was not recorded in GLSS and is notoriously difficult to measure.[23] Because food waste is likely lower among households with refrigeration, our estimated treatment effects on food intake may understate the true nutritional benefits of refrigeration. The reported estimates

[22] In **Appendix E1**, we compare summary statistics of average intakes between the treated and control groups, distinguishing animal sources (columns 1–4) from plant sources (columns 5–8). We find significant differences in nutrient intakes from animal origin, and some differences too for a few plant-based nutrients (iron, zinc, fibre and some vitamins).

[23] Existing studies either rely on self-reported waste (which tends to underestimate true levels because households are reluctant to report wasting food) or on weighing household waste (UNEP, 2024). They are field studies which are limited in scope (e.g. to a few households). In practice, because organic waste is often mixed with other materials, and because some discarded items (such as bones or vegetable peels) are inedible in any case, accurate estimates of edible food are difficult to gather.

should therefore be interpreted as conservative. In future versions of this paper, we will provide alternative estimates under the assumption of 10% food waste for households without refrigeration and 5% for those with refrigeration, to illustrate how differential waste levels could affect our findings. These values of 5 and 10 percent are consistent with the available evidence on food waste and preservation potential in sub-Saharan Africa.[24]

Table 9: Mean caloric intake corresponding to the quantities of food acquired

Nutrient intake (unit/day/AE)	Animal origin	Plant based	Total
Metabolizable energy (kcal)	277	2321	2599
Carbohydrate (g)	3	392	394
Protein (g)	36	39	76
Fat (g)	14	63	76
Saturated fat (g)	5.1	25.3	30.4
Monounsaturated fat (g)	5.1	14.2	19.7
Polyunsaturated fat (g)	1.6	11.4	13.0
Cholesterol (g)	0.29	-	0.29
Minerals (g)	1.7	8.9	10.6
Iron (mg)	3.5	24.4	27.9
Zinc (mg)	3.2	12.6	15.6
Calcium (mg)	350	324	674
Phosphorous (g)	0.57	0.96	1.53
Potassium (g)	0.50	3.55	4.05
Magnesium (mg)	54.5	400	455
Copper (mg)	0.19	2.68	2.88
Vitamins (mg)	17.76	256	273
Vitamin A (RAE) (mg)	0.08	0.93	1.02
Retinol (mcg)	82.6	-	82.6
Beta-carotene equivalents (provitamin A) (mg)	-	10.96	10.96
Alpha-carotene (provitamin A) (mg)	-	0.86	0.86
Beta-carotene (provitamin A) (mg)	-	10.03	10.03
Vitamin B1 (mg)	162	1682	1844
Vitamin B2 (mg)	0.27	2.02	2.28
Vitamin B3 (mg)	13.3	17.3	30.6
Vitamin B6 (mg)	0.49	2.34	2.83
Vitamin B9 (mg)	0.03	0.38	0.41
Vitamin B12 (mcg)	7.99	-	7.99
Vitamin C (mg)	0.5	223	223.5

[24] Existing research suggests that household food waste in Sub-Saharan Africa is relatively low. Estimates place it at around 10% of total food expenditure in Nigeria (Sunday et al., 2022). Higher-value foods such as meat are typically wasted less often than cheaper, more perishable items. For Ghana, UNEP (2024) estimates per-capita household food waste at 84 kg per year, including non-edible components. In our dataset, the average annualized per-capita food acquisition is 481 kg, implying that total food waste (including non-edible portions) represents roughly 18% of total acquisition. This estimate is broadly consistent with an edible waste share of about 10% as found in Nigeria. Households frequently report that limited storage contributes to spoilage, suggesting that refrigeration reduces food waste (e.g., Sunday et al. (2022)). Empirical evidence from China supports this view: households with refrigerators waste less food after controlling for demographic characteristics (Zhang et al., 2025).

Vitamin D (mcg)	4.94	0.68	5.62
Vitamin E (mg)	2.89	8.31	11.2
Fibre (g)	-	53.1	53.1

Notes: N= 8129. Animal origin comprises all meat, eggs, milk and dairy products, and fish. Plant-based refers to the main remaining food groups, as described in the data section. Vitamin A (RAE) is the retinol activity equivalent of vitamin A. It comprises the factional sum of beta-carotene equivalent and retinol, whereas beta-carotene equivalent is the fractional sum of beta-carotene, alpha-carotene, and beta-cryptoxanthin. Hence, total Vitamins is the sum of Vitamin A (RAE), Vitamin B1, Vitamin B2, Vitamin B3, Vitamin B6, Vitamin B9, Vitamin B12, Vitamin C, Vitamin D, & Vitamin E. See Vincent et al. (2020) for more details on the definition of each nutrient.

Nutritional impact of refrigeration. For now, **Table 10** reports the ATT of refrigeration on nutritional availability, estimated with the LASSO-based AIPW estimator described above. We also report Rosenbaum bounds tests to assess the sensitivity of our estimates to hidden bias.

Results for main nutrients are disaggregated by source (animal vs. plant-based) and then aggregated to compute overall ATTs. We find that households with broken refrigerators obtain significantly fewer nutrients from animal-sourced foods. The overall reduction of 47 calories corresponds to a 19-percent decline in animal protein intake, and this estimate is robust to hidden bias.[25] By contrast, we find no statistically significant effect of losing access to refrigeration on plant-based nutritional values. Point estimates are positive and suggest that households without refrigeration may partly offset losses in animal-sourced foods by consuming easier-to-store, plant-based alternatives. Taken together, the results indicate no statistically significant effect on total nutritional intake once animal- and plant-based sources are summed, consistent with the possibility that households adapt by substituting toward plant-based options when refrigeration is unavailable.

In **Table 10**, we aggregated vitamins and minerals. Results for each vitamin type and mineral are provided in **Appendix E2**. For vitamins that are available from both animal and plant sources, we find no statistically significant differences in total intake once both sources are combined. However, some micronutrients are only available in animal-sourced products. This is the case for cholesterol, vitamin B12 and retinol, whose results are reported in **Table 11**.

[25] The mean of the treatment group is 195 kcal/day/AE. The impact of refrigeration loss is equal to: $-47/(196 + 47) \approx 19\%$.

The added cholesterol for those with functioning refrigerators has, most likely, no implications for human health. This is because saturated fats, which are associated with an increase in low-density lipoprotein in blood (bad cholesterol levels) do not increase (see **Table 9**).

Table 10: ATT of refrigeration on home-based nutrient intake (excl. alcohol)

Nutrient intake	Animal origin		Plant based		Total (excl. alcohol)	
	ATT	Max. Γ	ATT	Max. Γ	ATT	Max. Γ
Metabolizable energy (kcal)	-47.1***	110%	140.0	<5%	94.46	<5%
	(12.6)		(124.2)		(130.13)	
Carbohydrate (g)	-0.37***	110%	23.23	<5%	22.85	<5%
	(0.14)		(22.47)		(22.50)	
Protein (g)	-5.37***	100%	3.36	<5%	-2.218	40%
	(1.66)		(2.46)		(3.40)	
Fat (g)	-2.68***	160%	4.29	<5%	1.61	<5%
	(0.69)		(3.62)		(3.95)	
Saturated (g)	-0.99***	150%	1.35	<5%	0.28	<5%
	(0.25)		(1.72)		(1.84)	
Monounsaturated (g)	-1.02***	170%	1.51	<5%	0.45	<5%
	(0.28)		(0.96)		(1.10)	
Polyunsaturated (g)	-0.30***	140%	0.95	<5%	0.65	<5%
	(0.09)		(0.73)		(0.75)	
Minerals (g)	-0.28***	110%	0.35	<5%	0.09	<5%
	(0.08)		(0.46)		(0.50)	
Vitamins (mg)	-2.51***	110%	9.497	<5%	6.94	<5%
	(0.79)		(16.512)		(16.87)	
Fibre (g)	-	-	4.00	<5%	4.00	<5%
	-		(3.54)		(3.54)	

Notes: N= 8072. Standard errors are in parentheses

The lower retinol and vitamin B12 intakes reported in **Table 11** are particularly concerning for households with a broken refrigerator, especially given that this group includes a large share of food-insecure households likely to experience vitamin deficiencies.

Vitamin deficiency in sub-Saharan Africa is difficult to quantify because it requires collecting biological samples. Deficiencies were, however, often observed at high prevalence, especially for vitamin B12 (e.g., Adu-Afarwuah et al. (2025); Sakyi et al. (2021)). Using quantitative dietary intake data of young children in rural Northern Ghana, De Jager et al. (2018) estimated that food intakes were likely insufficient to cover vitamin A and vitamin B12. A similar analysis of the diets of 400 pregnant women in Ghana found that over 50 percent obtained less than two-thirds of the recommended daily amounts of vitamin B12 (Saaka & Oladele, 2020). For individuals experiencing such deficiencies, refrigeration could have positive health impacts that further field research could directly quantify.

Vitamin A can be obtained directly from retinol (active vitamin A) or synthesized by the body from plant-based provitamin A. Active vitamin A not only provides direct absorption but also enhances the conversion of provitamin A, playing a dual protective role against vitamin A deficiency. The health consequences of vitamin A deficiency can be severe, including an increased risk of mortality (e.g., Baye et al. (2022)). Vitamin A deficiency impairs immune function, increases susceptibility to infections, and is a leading cause of preventable blindness, particularly among children.

Vitamin B12, by contrast, can only be obtained through the consumption of animal products. Deficiency is associated with megaloblastic anaemia, impaired neurological development, and cognitive decline. Among women of reproductive age, low vitamin B12 status has been linked to adverse pregnancy outcomes and an increased risk of neural tube defects in infants (e.g., Dhume et al. (2023)), particularly given the higher vitamin B12 requirements during pregnancy.

Table 11: Impact of refrigeration on nutrients strictly from animal-sourced foods

Nutrient intake (unit/day/AE)	**Total (all are of animal origin)**	
	ATT	**Max. Γ**
Retinol	-16.49*** (4.35)	120%
Vitamin B12	-1.47*** (0.58)	110%
Cholesterol	-0.06*** (0.02)	150%

Note: N=8072. Retinol and Vitamin B12 are measured in micrograms/day/AE. Cholesterol is measured in grams/day/AE. Standard errors are in open parentheses (). *** p<0.01, ** p<0.05, * p<0.1

Hence, animal-sourced micronutrients can play a crucial role in combating severe vitamin deficiencies. Additional health benefits from refrigeration may also arise from increased mineral bioavailability. Even if total mineral intake remains stable, as shown in **Table 10**, minerals are not absorbed equally by the human body. For instance, heme iron from meat is absorbed far more efficiently than non-heme iron from plant sources, and meat consumption also enhances the absorption of non-heme iron. Similarly, zinc and calcium from animal-sourced foods are generally more bioavailable than their plant-based equivalents.

Below, we report exploratory findings for the average treatment effects on the treated of broken refrigerators on iron intake, accounting for bioavailability. In future research, we intend to leverage data from micronutrient surveys in Ghana and other African countries to determine whether refrigeration could have a causal impact on ferritin concentrations in blood samples. For now, we follow the reference values of Carpenter & Mahoney (1992) to distinguish absorption rates from animal and plant sources. These values vary with physiological iron stores (typically low, at around 0–250 mg, among anaemic individuals) and with the dietary availability of iron, which increases with meat intake but tends to be low in plant-based diets. For individuals with near-zero iron stores and low dietary availability, reference absorption rates are 35% for heme iron and 5% for non-heme iron.

Table 12: Impact of broken refrigerator on bioavailability-corrected estimates for iron

Physiological iron stores (mg)	Dietary availability	Total	Heme iron	Nonheme iron
0 – 250	Low	-9.76	-19.60***	9.99
		(10.77)	(6.12)	(7.02)
	Medium	2.14	-19.60***	21.97
		(18.43)	(6.12)	(15.44)
250 – 500	Low	-7.81	-15.68***	7.99
		(8.62)	(4.90)	(5.61)
	Medium	-1.79	-15.68***	13.98
		(12.38)	(4.90)	(9.82)
500 – 1000	Low	-6.95	-12.88***	5.99
		(6.74)	(4.02)	(4.21)
	Medium	-2.98	-12.88***	9.99
		(9.20)	(4.02)	(7.02)
Above 1000	Low	-4.47	-8.40***	3.99
		(4.45)	(2.62)	(2.81)
	Medium	-2.47	-8.40***	5.99
		(5.67)	(2.62)	(4.21)

Note: Bioavailability reference rates were taken from Carpenter & Mahoney (1992). Standard errors are in open parentheses. *** p<0.01, ** p<0.05, * p<0.1

As shown in **Table 12**, results suggest a potential reduction in total iron absorption for anaemic individuals with low iron stores and low dietary availability, although confidence intervals remain wide. These estimates are conservative, as they imperfectly account for the fact that heme iron enhances dietary availability for all iron, especially non-heme iron. With the data at hand, considerable uncertainty remains, as reductions in heme iron intake may be offset by increases in non-heme iron. Moreover, substantial heterogeneity across individuals is plausible, given that bioavailability depends on numerous factors, including enhancers and inhibitors of iron absorption, individual nutritional requirements (which are substantially higher for pregnant women, as discussed earlier), and variation in iron content and bioavailability across vegetables and meats. For instance, if some households substitute meat with plant-based foods that are low in iron or inhibit its absorption, refrigeration could, in some cases, protect against anaemia.

VI. Conclusion

With rapid electrification across LMICs, an estimated 800 million people are expected to gain access to a refrigerator in the next decade (IEA, 2022). The consequences could be profound for the global fight against hunger.

This paper provides the first causal evaluation of refrigeration's effects on food insecurity, diets and welfare using quasi-experimental variation in appliance functionality at the time of interview. Conditioning on location, purchase price, acquisition year, and other observable determinants of breakdown, we compare otherwise similar Ghanaian households with functional versus broken refrigerators, estimating causal effects with a machine learning algorithm (i.e. LASSO-based AIPW design).

We find that refrigeration can provide serious health benefits by reducing food insecurity and enhancing diets. First, access to a functional refrigerator reduces household food insecurity risk by 33 percent and makes households less likely to report food-insecurity experiences (e.g., running out of food, skipping meals, or reducing meal size) and show lower intensity on summary indices. These effects are robust to hidden bias, consistent across several alternate specifications and specific to refrigerators (using placebos). Second, refrigeration shapes the composition of food demand: households with broken refrigerators demand 10-40% less of animal-sourced items (meat, dairy, eggs, fish). Third, the primary nutritional margin could be quality rather than quantity: loss of refrigeration is associated with a 19-percent decline in access to animal-source protein. While total calories remain stable, households with lost access to refrigeration are at higher risk of vitamin B12 deficiency. Vitamin A absorption may also be impaired without refrigeration, which enhances retinol intake. Mineral deficiencies, such as iron deficiency, might also concern more Ghanaian households without access to refrigeration, even though confidence intervals are large and iron absorption is context dependent.

Overall, our results highlight that refrigeration is an overlooked but essential channel through which households can become more resilient to shocks to food security, and a key mechanism linking electrification to improved welfare. Future research could analyse impacts on health markers to better capture nutritional and health outcomes at a micro level. The environmental implications of the above will also require special scrutiny, since refrigeration can be expected to trigger higher meat consumption and higher energy usage. Likewise, the diffusion of appliances should probably be accompanied by information policies, for instance, on how to best use refrigeration to enhance diets. Finally, our identification strategy could be used to study other technological transitions in low- and middle-income countries.

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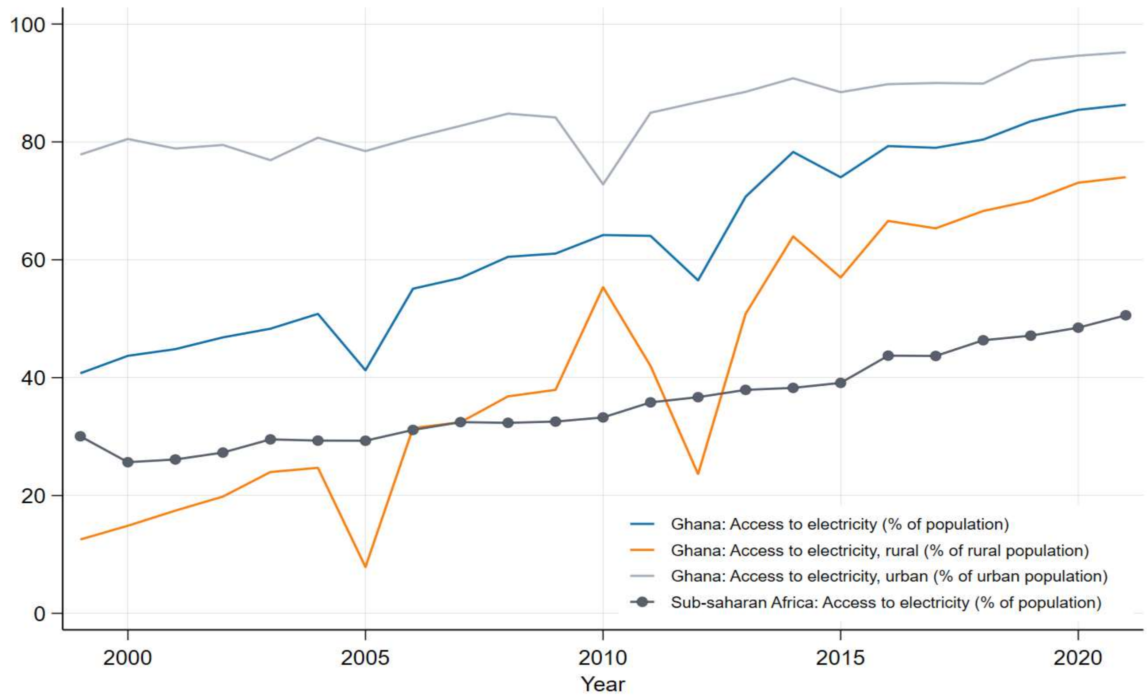
Appendices

A. Electricity access rate and ownership of other household appliances



Appendix A1: Electricity access rate in Ghana and sub-Saharan Africa
Source: Authors' construction with data from World Bank (2025)

Appendix A2: Mean statistics of appliance ownership (only GLSS VII sample)

Appliance information	(1)	(2)	(3)	(4)	(5)	(6)
	Broken asset		Functioning asset			
	N	Mean	N	Mean	Diff.	SE
Real price of radio	64	128	1406	134	6.28	28.9
Age of radio	64	5.67	1406	3.72	-1.95***	0.4
Real price of sewing machine	88	387	3383	1016	629***	163
Age of sewing machine	88	6.63	3383	4.99	-1.6***	0.38
Real price of fan	58	187	3168	191	3.78	25.9
Age of fan	58	5.6	3168	4.33	-1.3***	0.43
Real price of electric iron	57	116	2977	121	4.69	17.6
Age of electric iron	57	5.04	2977	3.59	-1.4***	0.36
Real price of blender	42	211	1024	270	58.90	50.2
Age of blender	42	4.02	1024	3.28	-0.74**	0.33
Real price of gas stove	37	345	2205	463	117	110
Age of gas stove	37	5.95	2205	4.54	-1.41**	0.48
Real price of television	35	134	553	474	340*	185
Age of television	35	17.8	553	11.3	-6.5***	1.61
Real price of mobile phone	3	280	3556	514	235	422
Age of mobile phone	3	2.33	3556	2.17	-0.17	0.82
Real price of kerosene stove	5	79.4	19	50.1	-29.3	38.4
Age of kerosene stove	5	16.8	19	15.37	-1.43	5.94
Real price of electric stove	1	598	45	1277	679	.
Age of electric stove	1	7	45	5.60	-1.40	.
Real price of freezer	15	616	306	2584	1967***	843
Age of freezer	15	7.6	306	5.21	-2.39**	1.18
Real price of air conditioner	5	1152	93	1972	820	939
Age of air conditioner	5	5.4	93	5	-0.51	2.56
Real price of washing machine	7	415	99	1895	1480	954
Age of washing machine	7	5.43	99	4.1	-1.35	1.12
Real price of microwave	6	328	372	502	174	201
Age of microwave	6	6.5	372	3.62	-2.88***	.79

Notes: Data from GLSS VII only. N = number of households owning each asset and provides information on the price and age of the appliance. All prices are deflated to 2017 real GHS, and all ages are in years.

Appendix A3: Mean statistics of appliance ownership (GLSS VI & VII pooled sample)

Appliance information	(1)	(2)	(3)	(4)	(5)	(6)
	Broken asset		Functioning asset			
	N	Mean	N	Mean	Diff.	SE
Real price of radio	139	106	3486	122	15.5	20.1
Age of radio	139	4.98	3486	3.58	-1.4***	0.28
Real price of fan	142	174	6963	172	-1.9	16.7
Age of fan	142	5.22	6963	3.98	-1.2***	0.28
Real price of sewing machine	112	232	1493	415	183*	105
Age of sewing machine	112	15.9	1493	11.5	-4.42***	0.92
Real price of electric iron	92	103	6707	111	7.80	12.6
Age of electric iron	92	4.52	6707	3.23	-1.3***	0.22
Real price of blender	96	158	2371	240	81.6**	31.3
Age of blender	96	3.47	2371	2.95	-0.52**	0.21
Real price of television	102	396	7602	827	431***	105
Age of television	102	5.95	7602	4.49	-1.5***	0.26
Real price of mobile phone	36	164	7778	431	267**	115
Age of mobile phone	36	2.28	7778	1.88	-0.40	0.25
Real price of gas stove	63	361	4864	410	48.4	82.4
Age of gas stove	63	5.68	4864	4.15	-1.54***	0.38
Real price of kerosene stove	33	431	133	314	-118	301
Age of kerosene stove	33	9.42	133	8.35	-1.07	1.51
Real price of electric stove	9	344	149	1296	951	1360
Age of electric stove	9	5.11	149	5.13	0.02	1.64
Real price of freezer	39	732	827	1937	12052**	449
Age of freezer	39	7.67	827	4.83	-2.84***	0.68
Real price of air conditioner	7	1003	202	1681	678	626
Age of air conditioner	7	5.29	202	4.16	-1.13	1.78
Real price of washing machine	14	2084	188	1652	-432	710
Age of washing machine	14	5.5	188	3.78	-1.72*	0.88
Real price of microwave	31	372	975	433	60.71	88.7
Age of microwave	31	3.71	975	3.08	-0.63*	0.36

Notes: Data from GLSS VI and GLSS VII, pooled. N = number of households owning each asset and provides information on the price and age of the appliance. All prices are deflated to 2017 real GHS, and all ages are in years.

B. Technical description of LASSO and covariate selection process

Our baseline strategy compares households with dysfunctional refrigerators (treated) to those with functional units (control). We condition on locality, refrigerator price, and age of purchase to ensure treated and control households are drawn from similar markets and acquisition periods. Conditional on these variables and basic demographics (age and gender of household head, and household size), the treatment assignment should approximate randomness. However, matching in observational data rarely yields a perfect balance, and the core assumption may fail.

To strengthen identification, we incorporate additional socioeconomic indicators that one may think their omission could arguably confound our estimates. Including more covariates improved the plausibility of the conditional independence assumption,[26] but indiscriminate inclusion can violate the overlap assumption and reduce both bias and statistical efficiency of propensity scores (Shortreed & Ertefaie, 2017). Two broad covariate selection strategies are common: (i) a theory-driven or institutional approach, which selects variables based on prior literature or contextual knowledge (Caliendo & Kopeinig, 2008), and (ii) data-driven selection using model selection tools such as LASSO.

Because purely theory-driven selection lacks objectivity and purely data-driven selection may omit contextually important variables, we combine both. We first define a comprehensive set of potential covariates guided by economic theory, Ghana's institutional set-up, and previous empirical works. We then apply LASSO to this pool to algorithmically refine the set.

LASSO for covariate selection

LASSO refines a large set of candidate predictors by shrinking coefficients via a penalised penalty or regularization parameter (λ). Compared with standard regression, LASSO (i) enhances interpretability by eliminating irrelevant variables that may lead to overfitting, (ii) can reduce variance and improve prediction accuracy with minimal bias increase, and (iii) handles high-dimensional settings. Although it allows the inclusion of many variables, it selects a parsimonious subset relevant to both treatment and outcome.

Formally, LASSO minimizes the residual sum of squares through λ, where $\lambda \geq 0$ controls the regularisation strength. Larger λ values induce greater sparsity, potentially shrinking even

[26] The conditional independence assumption is that dependent on a set of control variables, the potential outcome is independent of the treatment assignment. The overlap assumption is that there is always a positive probability that any given unit is treated or untreated.

relevant coefficients to zero; too small a λ produces little shrinkage. Because the choice of λ critically affects the model performance (Schneider & Wagner, 2012), it should be selected objectively. Information criteria such as cross-validation (CV), Akaike Information Criterion (AIC), and Bayesian Information Criterion (BIC) are common guides (R. J. Tibshirani & Taylor, 2012). In small samples, AIC and BIC are computationally cumbersome and volatile than CV (Zou et al., 2007), but CV directly minimizes out-of-sample prediction error[27]. In all our baseline estimations, we adopt a 10-fold CV, which is the default in STATA17.

Tables B1 and B2 present the full set of covariates which we used in this study. **Table B1** displays the pre-selected variables and the only variable that LASSO selected (income), which we used in the baseline estimation. In **Table B1**, we present the remaining list of covariates that were fed into the model but were not selected by LASSO.

The choice of all these variables was inspired by theory, Ghana's cultural setting, and recent empirical studies (Agedew et al., 2023; Heard et al., 2020; Katoch, 2022; Martinez et al., 2021). To avoid scale effects and unintended penalties in the LASSO regression, all continuous covariates are standardized to a zero mean and a unit standard deviation.

Brief notes on TELASSO. Standard practices often apply LASSO for selection, then conduct inference as if there is no model selection, or assume the selected model is correct (StataCorp, 2023). This is problematic. Ignoring model selection inflates type I errors, biases estimated treatment effects, and understates standard errors (Leeb & Pötscher, 2005, 2006, 2008; StataCorp, 2021). Belloni et al. (2014) introduced approaches that integrate LASSO selection with valid post-selection inference and the making of causal interpretations.

We therefore employ TELASSO, a machine learning implementation of the Augmented Inverse Probability Weighting (AIPW) estimator. TELASSO simultaneously estimates treatment effects while using LASSO to select relevant covariates from our pre-specified pool in addition to preselected covariates. Its main advantages include (i) the joint selection of relevant covariate and estimation of causal impact, (ii) doubly robustness, (iii) Neyman orthogonality, and (iv) greater resilience since it is less sensitive to machine-learning imperfections than single-equation estimators such as regression adjustment (RA), inverse probability weighting (IPW), or IPW with regression adjustment (IPWRA). This integrated

[27] More detailed information on LASSO is provided by StataCorp (2023), Shortreed & Ertefaie (2017), Hastie et al. (2015), and R. Tibshirani (1996).

approach allows us to exploit high-dimensional control while maintaining valid inference for the average treatment effect on the treated (ATT).

Table B1: Mean statistics of baseline covariates

Baseline covariates	**(1) Functioning refrigerator (N=7639)**	**(2) Broken refrigerator (N=490)**	**(3) Diff.**	**(4) SE**
Male household head (=1)	0.72	0.65	+0.07***	0.02
Age of household head (in years)	44.25	49.07	-4.82***	0.64
Real gross household income (per AE/year)	11,221	7,917	+3,304***	798
Household size	3.90	4.51	-0.61***	0.11
Urban (=1)	0.77	0.66	+0.11***	0.02
Region				
Western	0.11	0.11	0.00	0.01
Central	0.10	0.10	0.00	0.01
Greater Accra	0.24	0.19	+0.05**	0.02
Volta	0.06	0.11	-0.05***	0.01
Eastern	0.10	0.12	-0.02	0.01
Ashanti	0.21	0.16	+0.04**	0.02
Brong Ahafo	0.08	0.07	+0.01	0.01
Northern	0.03	0.06	-0.02**	0.01
Upper East	0.04	0.06	-0.02**	0.01
Upper West	0.03	0.02	+0.01	0.01
Survey year				
2012	0.12	0.11	+0.01	0.01
2013	0.44	0.37	+0.07***	0.02
2016	0.10	0.15	-0.05***	0.01
2017	0.35	0.37	-0.02	0.02
Survey month				
January	0.10	0.11	-0.01	0.01
February	0.10	0.10	0.00	0.01
March	0.10	0.10	-0.01	0.01
April	0.10	0.09	+0.01	0.01
May	0.09	0.09	+0.01	0.01
June	0.01	0.01	0.00	0.00
July	0.10	0.09	+0.01	0.01
August	0.09	0.08	+0.01	0.01
September	0.10	0.07	+0.03**	0.01
October	0.11	0.18	-0.07***	0.01
November	0.08	0.06	+0.02	0.01
December	0.03	0.03	0.00	0.01

Notes: Data from GLSS VI and GLSS VII, pooled. N = total number of households in the sample category. SE = Standard Error of the mean difference. AE = adult equivalence. Income is measured in real 2017 Ghanaian Cedis and is winsorised at the 1st and 99th percentiles. *** p<0.01, ** p<0.05, * p<0.1

Table B2: Mean statistics for potential covariates (those that LASSO did not select)

Potential covariates	Functioning refrigerators (N=7,639)	Broken refrigerators (N=490)	Diff.	SE
Household head information				
Ever attended school (=1)	0.92	0.88	0.04***	0.01
Employed (=1)	0.87	0.83	0.04**	0.02
Marital status				
Never married before	0.13	0.05	0.08***	0.02
Married	0.69	0.69	0.01	0.02
Divorced/separated/widowed	0.18	0.27	-0.09***	0.02
Religion:				
No religion	0.03	0.05	-0.02*	0.01
Christian	0.82	0.79	0.03	0.02
Islamic	0.14	0.16	-0.01	0.02
Other religion	0.01	0.00	0.00	0.00
Ethnicity:				
Akan	0.57	0.53	0.04	0.02
Ga-Dangme	0.09	0.06	0.03**	0.01
Ewe	0.12	0.18	-0.05***	0.02
Guan	0.03	0.04	-0.01	0.01
Gurma	0.01	0.01	0.00	0.01
Mole-Dagbani	0.11	0.12	-0.02	0.01
Grusi	0.02	0.01	0.01	0.01
Mande	0.01	0.01	0.00	0.00
Other	0.04	0.03	0.01	0.01
Household-level information				
Owns other broken appliances (=1)	0.07	0.28	-0.21***	0.01
Impermeable roof material (=1)	0.97	0.96	0.00	0.01
Impermeable floor material (=1)	0.98	0.98	0.01	0.01
Impermeable wall material (=1)	0.88	0.80	0.09***	0.01
Dwelling ownership:				
Owning	0.36	0.44	-0.07***	0.02
Renting	0.39	0.31	0.07***	0.02
Rent-free	0.25	0.25	0.00	0.02
Perching	0.00	0.00	0.00	0.00
Squatting	0.00	0.00	0.00	0.00

Notes: Data from GLSS VI and GLSS VII, pooled. N = total number of households in the sample category. SE = Standard Error of the mean difference. Ownership of other broken appliances is binary (= 1 if the household owns at least one of the following appliances and is broken: freezer, washing machine, air conditioner, television, radio, fan, sewing machine, and iron; and = 0 if otherwise). Roof material is impermeable if it is a metal sheet, slate/asbestos, cement/concrete, or roofing tiles; otherwise, it is permeable to rain or sunlight. Floor material is impermeable if it is cement/concrete, stone, burnt brick, vinyl tiles, ceramic/porcelain/granite/marble tiles, or terrazzo/terrazzo tiles; otherwise, it is permeable to water. Wall material is impermeable if it is concrete/cement/brick/stone; otherwise, it is permeable to rain or water. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

C. **Food insecurity estimates from entropy balance estimation**

Appendix C1: TELASSO vs. Entropy balance estimates from the food insecurity analyses

Food insecurity outcomes	**(1)**	**(2)**
	TELASSO	**Entropy balance**
Panel A: Food insecurity indices		
A1: Risk of food insecurity	0.16***	0.18***
	(0.04)	(0.03)
A2: Intensity of food insecurity	0.92***	1.01***
	(0.20)	(0.22)
Panel B: Disaggregated binary food insecurity indicators		
B1: Worried about not having enough food to eat	0.14***	0.15***
	(0.04)	(0.04)
B2: Unable to eat healthy and nutritious foods	0.13***	0.14***
	(0.04)	(0.04)
B3: Ate only a few kinds of foods	0.16***	0.18***
	(0.04)	(0.04)
B4: Had to skip a meal	0.15***	0.15***
	(0.04)	(0.04)
B5: Ate less than the respondent's expectation	0.14***	0.17***
	(0.04)	(0.04)
B6: Ran out of food	0.13***	0.12***
	(0.04)	(0.04)
B7: Went without eating for a whole day	0.05	0.06*
	(0.03)	(0.03)
B8: Hungry but did not eat	0.04***	0.03*
	(0.02)	(0.02)

Note: N=3,615. Standard errors are in parentheses. Each cell is a separate estimation. Column (1) provides the ATT from TELASSO as found in the baseline. Column (2) provides the corresponding ATT from entropy balance estimation which uses the same preselected and LASSO-selected covariates employed in the baseline. Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Appendix C2: Robustness of AIPW estimation on food insecurity indicators

We assess the sensitivity of our baseline results to specification changes. Key sensitivity checks on the AIPW model are reported in **Table C2**. Each cell represents an estimate from a unique AIPW estimation, and each row is a separate food insecurity outcome. Results are robust to the selection of control variables. In Column (1), we pre-select additional covariates that were not LASSO-selected in the baseline model: the education and employment status of the household head, the materials used in making the roof, wall, and floor of the dwelling, and whether the household owns a broken appliance other than a refrigerator. We observe impacts similar to the baseline estimates. Results are not impacted by the context of refrigerator acquisition either. In column (2), we exclude households that reported having their refrigerators as gifts. Furthermore, results do not depend on the chosen estimator. In column (3), we estimate the baseline model using the adaptive selection method in the LASSO process instead of the cross-validation method. In columns (4) to (6), we provide results with alternative matching estimation techniques: inverse probability weighting (IPW), propensity score matching (PSM), and Mahalanobis distance (MD) matching. Finally, the GLSS includes survey weights, which we have not used in the main estimations since our sample, by construction, cannot be representative of the Ghanaian population. Furthermore, weights are treated as importance weights rather than frequency weights by `telasso`. Column (7) provides the results where we use the survey weights. Results are consistent with the baseline estimates.

Table C2: Robustness – Alternative specifications of the food insecurity models

Food insecurity outcomes	(1) Extra covariates	(2) Excluding gifts	(3) Adaptive LASSO	(4) IPW	(5) PSM	(6) MD	(7) Survey weights
A1:	0.16***	0.16***	0.16***	0.19***	0.21***	0.25***	0.16***
	(0.04)	(0.03)	(0.04)	(0.03)	(0.04)	(0.03)	(0.04)
	[390%]	[390%]	[390%]	[390%]	[110%]	[230%]	[390%]
A2:	0.89***	0.91***	0.92***	1.10***	1.13***	1.38***	1.01***
	(0.20)	(0.21)	(0.20)	(0.22)	(0.22)	(0.21)	(0.23)
	[40%]	[50%]	[80%]	[80%]	[60%]	[110%]	[80%]
B1:	0.14***	0.14***	0.14***	0.17***	0.19***	0.22***	0.13***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)	(0.05)
	[140%]	[150%]	[150%]	[150%]	[90%]	[130%]	[150%]
B2:	0.12***	0.11***	0.13***	0.16***	0.16***	0.19***	0.12***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)	(0.05)
	[60%]	[70%]	[70%]	[70%]	[40%]	[60%]	[70%]
B3:	0.15***	0.16***	0.16***	0.20***	0.19***	0.25***	0.19***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)	(0.05)
	[160%]	[170%]	[160%]	[160%]	[80%]	[140%]	[160%]
B4:	0.14***	0.14***	0.15***	0.16***	0.16***	0.20***	0.14***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)
	[50%]	[60%]	[50%]	[50%]	[30%]	[50%]	[50%]
B5:	0.13***	0.14***	0.14***	0.18***	0.17***	0.23***	0.15***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)	(0.04)
	[90%]	[100%]	[90%]	[90%]	[50%]	[80%]	[90%]
B6:	0.12***	0.13***	0.13***	0.13***	0.14***	0.17***	0.17***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
	[<10%]	[10%]	[<10%]	[<10%]	[<5%]	[<5%]	[<10%]
B7:	0.04	0.05	0.05	0.07*	0.07*	0.08***	0.05
	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)
	[<5%]	[<5%]	[<5%]	[<5%]	[<5%]	[<5%]	[<5%]
B8:	0.04***	0.05***	0.04***	0.04***	0.05***	0.04***	0.05***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)
	[<5%]	[<5%]	[<5%]	[<5%]	[<5%]	[<5%]	[<5%]
N	3615	3354	3615	3640	3640	3640	3615

Notes: N = number of observations. Standard errors are in parentheses (), and the maximum Γ is reported in []. For the food insecurity outcomes: A1 = risk of food insecurity; A2 = Intensity of food insecurity; B1 = Worried about not having enough food to eat; B2 = Unable to eat healthy and nutritious foods; B3 = Ate only a few kinds of foods; B4 = Ate only a few kinds of foods; B5 = Ate less than the respondent's expectation; B6 = Ran out of food; B7 = Went without eating for a whole day; and B8 = Hungry but did not eat. In column (1), we preselected other covariates that seemed relevant to have been selected by LASSO in the baseline (that is, education and employment status of the household head, type of dwelling (roof, wall, and floor) materials, and whether the household owns any other appliance. See Appendix B2 on how these variables are measured. In Column (2), we exclude all households that reported that their refrigerator was a gift and hence no price was reported. In Column (3), we used the adaptive LASSO to select the tuning parameter since the CV method has been criticised to be (i) inconsistent as features grow rapidly, and (ii) unable to perform hypothesis tests and confidence intervals. In columns (4) to (6), we used the traditional matching estimators of IPW, PSM, and MD. In column (7), we used the survey weights. The weights are treated as importance weights since TELASSO doesn't allow the use of frequency weights. *** p<0.01, ** p<0.05, * p<0.1.

D. Food basket analysis

Appendix D1: Computing food expenditure and quantity

Food expenditure data. Food expenditure data is available in GLSS VI and GLSS VII. Enumerators visited each household seven times at five-day intervals. During these visits, a diary was used to record daily consumption of own produce and expenditures. On the first visit, a literate household member was identified and trained to record all household expenditures daily, submitting the diary during the next visit for data entry. If no literate person was present in the household, the enumerator would make daily visits to record expenditures. The daily values were then aggregated. Both methods led to the computation of 30-day expenditure by food item for each household after either seven visits at 5-day intervals, or daily visits for 30 days in the case of illiterate households.

Food items were classified in thirteen main categories: (1) All meats; (2) Fish; (3) Eggs; (4) Milk and dairy products; (5) Oil and fats; (6) Fruits; (7) All vegetables (including potatoes and other tubers); (8) Cereals, flour, and bread; (9) Pulses, nuts, and seeds; (10) Spices and condiments; (11) Sugars and sweets; (12) Non-alcoholic drinks; and (13) Alcoholic drinks. GLSS VII used a more comprehensive list of 305 food items, against 118 in GLSS VI. However, both nomenclatures are similar. Both waves covered the main food types, but GLSS VII provided more specific breakdowns. We use the 13 broad categories from both waves to assess overall food expenditure. We also compute total food expenditure, excluding alcoholic beverages. Furthermore, we disaggregate the all-vegetables category into two finer subcategories: roots, tubers and plantains vs. other vegetables.

The GSS recommends harmonizing the raw data on food expenditure to account for: (a) the consumption of own food production, which is very common in rural areas; (b) substantial local price differences; and (c) caloric needs based on household age and sex composition. Therefore, we harmonize the food expenditure data following the standard Survey-based Harmonized Indicator Program (SHIP) Manual of GSS (GSS, 2014, 2018). For own consumption, the surveys cover food items that can be classified following the same typologies as the expenditure section. Enumerators asked for quantities and their overall monetary value, asking farmers to provide the farmgate price of the units they consumed. A 30-day item-specific expenditure was computed by summing own consumption values and purchases for each household. To account for cost-of-living variations, we adjust those values based on the GSS regional cost-of-living food indices.[28] To account for household size, sex and age compositions, we apply the equivalence scale used by GSS, which is derived from the 10th Edition of the National Research Council's Recommended Dietary Allowances (GSS, 2014, 2018; Washington D.C.: National Academy Press, 1989).[29] All values are deflated to 2017 real values using food deflators from the Ghana Statistical Service (2018) and then expressed in daily values (i.e., divided by 30). This results in daily per capita adult equivalent food expenditure values, expressed in 2017 local currency.

Food quantities. We derive food quantity from the food expenditure data. Technically, GLSS VI reports quantities consumed from own production, but only expenditures for purchased items. In contrast, GLSS VII records both expenditures and quantities (including purchased quantities) at each household visit, along with units of measurement. However, only about 6% of these quantities were reported in standard units. This reflects local practices in Ghana, where food is often measured in traditional units such as *olonkas* (a volume measure that varies across regions) or by containers such as cans, which also differ in weight or volume. Converting these non-standard units into consistent measures would require detailed region- and item-specific conversion factors for each traditional unit, which are not available.

Instead, we convert the 30-day item-specific expenditures into quantities using detailed market price information. To collect information for computing food and non-food CPIs, the Ghana Statistical Service requires enumerators to visit three randomly selected local markets in each community. Both surveys professionally collect consistent price information from local markets for each food item. For every food item listed in the expenditure section, enumerators either observe or weigh the item using standard scales and record both the quantity and the corresponding retail price. Reported prices are highly reliable: in over 98% of cases, prices are consistent across the three markets for a given item within a community. In GLSS VI, all market prices were collected in kilograms or litres, while in GLSS VII, about 95% were expressed in standard units (e.g., kg, g, mg, litres). We converted all reported mass units into kilograms, and

[28] The index is based on regional monthly food and non-food consumer price indexes (CPIs) weighted by region and urban-rural shares. The base value of this spatiotemporal index is normalised to 1 for January in Accra.
[29] Though a simple way of doing this would be to divide the adjusted annualised expenditures by the nominal household size to obtain the per capita component, this does not allow for the fact that different households have different calorie needs (GSS, 2014, 2018).

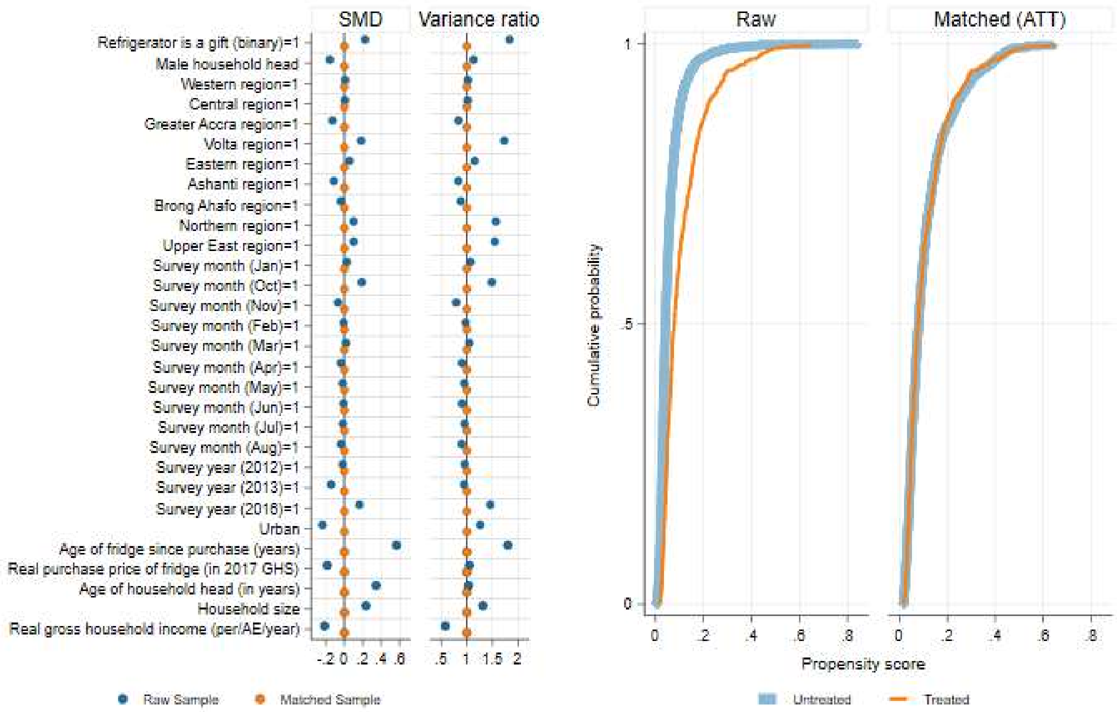
for items recorded in volume (e.g., litres or millilitres), we used food-specific density estimates from Charrondiere et al. (2012) to convert them into kilograms.

We then compute item-specific average local market prices per kilogram. When a specific food item lacked a recorded local market price, we imputed its price using the average per-kilogram price of the same item within the relevant rural/urban community (defined by region and rural/urban status). In the few cases where no such price was available, we used the average price for the broader food group (e.g., all cereals) within the same rural/urban community. Items labelled as "other foods" (e.g., other cereals, other fruits) were excluded from this procedure to avoid misclassification.

To proxy food quantities, we use the pre-harmonised 30-day item-specific expenditure data (i.e., before adjusting for cost of living and household composition). We divide those by the corresponding average local market price per kilogram per item. This method yields food quantities (in kilograms) for about 96% of all reported food items. We then express them in daily values and scale them to account for household composition by applying the adult-equivalence scale used by GSS (GSS, 2014, 2018; National Academy of Sciences - National Research Council, 1989). Finally, we winsorize food quantities at the 1st and 99th percentiles to reduce the influence of outliers.

Appendix D2: Model diagnostics and robustness checks for the food quantity model

Figure D2.1: Model diagnostics



Notes: This is based on the pooled data from GLSS VI and GLSS VII data for food quantity analysis. The left panel presents the covariate balance using the standardized mean difference (SMD) and variance ratio. In the raw sample, we observe large disparities, even beyond 20% in the SMD and outside the recommended range in the variance ratio. However, in the matched sample and under the common support, the SMD is zero (0) and the variance ratio is one (1) for all covariates. The right panel presents the cumulative probability plots of the propensity scores before matching (Raw) and after matching (Matched) under the common support. ATT = Average Treated effect on the Treated. The vertical axis of the right panel reports the probability that the score is less than or equal to a given propensity score. These graphs depict perfect covariate balance, indicating that, conditional on these observables, the treatment is as good as random. Given that we run 16 different models, it is ideal to present the covariate balance for all 16 models. We observe that the same covariates are selected in all models, and the covariate balance is the same in all cases; thus, we present just one. The remaining 15 are available upon request.

Table D2.1: TELASSO vs. Entropy balance estimates from the food quantity analyses

Food expenditure category	(1) TELASSO	(2) Entropy balance
Total at home (excl. alcohol)	-0.052	-0.025
	(0.096)	(0.092)
All Meats	-0.008***	-0.008***
	(0.003)	(0.002)
Milk & dairy products	-0.002***	-0.002***
	(0.001)	(0.001)
Eggs	-0.013***	-0.011***
	(0.003)	(0.003)
Fish	-0.008*	-0.005
	(0.005)	(0.005)
All vegetables	-0.010	0.009
	(0.062)	(0.060)
Roots, tubers, & plantain	0.014	0.041
	(0.052)	(0.049)
Other leafy vegetables	-0.010	-0.014
	(0.013)	(0.014)
Fruits	-0.003	0.004
	(0.009)	(0.009)
Cereals, flour & bread	0.010	0.009
	(0.020)	(0.021)
Pulse, nuts, & seeds	0.004	0.005
	(0.006)	(0.005)
Oil & fats	0.003	0.004
	(0.003)	(0.003)
Spices	0.001	0.001
	(0.001)	(0.002)
Sugar & sweets	0.002	0.002
	(0.002)	(0.002)
Alcoholic beverages	0.001	0.001
	(0.002)	(0.002)
Non-alcoholic beverages	-0.003	-0.002
	(0.003)	(0.003)
N	8072	8129

Notes: N = number of observations in the sample category. Each cell is a separate estimation. Column (1) provides the ATT from TELASSO as found in the baseline. Column (2) provides the corresponding ATT from entropy balance estimation which uses the same preselected and LASSO-selected covariates employed in the baseline. Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table D2.2: Alternative specifications for food quantities

Food category	(1) Extra covariates	(2) Excluding gifts	(3) Adaptive LASSO	(4) IPW	(5) PSM	(6) MD	(7) Survey weight
Total at home (excl. alcohol)	-0.055	-0.078	-0.052	-0.100	-0.108	-0.012	-0.086
	(0.095)	(0.088)	(0.096)	(0.105)	(0.110)	(0.089)	(0.103)
	[60%]	[70%]	[60%]	[70%]	[40%]	[40%]	[60%]
All meat	-0.008***	-0.006***	-0.008***	-0.008***	-0.009***	-0.010***	-0.008***
	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.002)	(0.002)
	[140%]	[140%]	[160%]	[160%]	[110%]	[160%]	[140%]
Milk and dairy	-0.002***	-0.002***	-0.002***	-0.002***	-0.003***	-0.004***	-0.001*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
	[100%]	[100%]	[110%]	[110%]	[90%]	[140%]	[100%]
Eggs	-0.012***	-0.014***	-0.013***	-0.013***	-0.012***	-0.016***	-0.010***
	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)
	[370%]	[400%]	[390%]	[390%]	[240%]	[290%]	[310%]
Fish	-0.008*	-0.009*	-0.008*	-0.007	-0.006	-0.007	-0.004
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
	[80%]	[90%]	[80%]	[80%]	[50%]	[60%]	[80%]
All vegetables	-0.007	-0.019	-0.007	-0.036	-0.001	0.088	-0.044
	(0.060)	(0.061)	(0.062)	(0.071)	(0.066)	(0.057)	(0.068)
	[70%]	[70%]	[<5%]	[80%]	[30%]	[<5%]	[70%]
Roots, tubers, & plantain	0.016	0.004	0.016	0.004	0.034	0.111***	-0.021
	(0.051)	(0.050)	(0.052)	(0.059)	(0.055)	(0.047)	(0.057)
	[<5%]	[<5%]	[<5%]	[<5%]	[<5%]	[<5%]	[<5%]
Other leafy vegetables	-0.012	-0.010	-0.010	-0.017	-0.017	-0.012	-0.011
	(0.014)	(0.014)	(0.013)	(0.015)	(0.015)	(0.014)	(0.012)
	[110%]	[130%]	[120%]	[120%]	[80%]	[80%]	[110%]
Fruits	-0.002	-0.002	-0.002	-0.000	-0.000	-0.011	0.005
	(0.009)	(0.009)	(0.009)	(0.009)	(0.010)	(0.009)	(0.009)

	[80%]	[80%]	[80%]	[70%]	[50%]	[80%]	[80%]
Cereals, flour & bread	0.012	0.012	0.010	0.007	-0.002	-0.010	-0.010
	(0.020)	(0.019)	(0.020)	(0.020)	(0.024)	(0.021)	(0.014)
	[<5%]	[60%]	[<5%]	[<5%]	[30%]	[50%]	[<5%]
Pulse, nuts, & seeds	0.004	-0.002	0.004	0.004	0.002	0.000	0.005
	(0.006)	(0.005)	(0.006)	(0.005)	(0.006)	(0.006)	(0.005)
	[<5%]	[70%]	[<5%]	[<5%]	[<5%]	[<5%]	[<5%]
Oil and fat	0.003	0.004	0.003	0.004	0.003	0.002	0.006*
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
	[<5%]	[<5%]	[<5%]	[<5%]	[<5%]	[<5%]	[<5%]
Spices	0.001	0.000	0.001	0.000	-0.001	-0.000	0.000
	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
	[<5%]	[70%]	[<5%]	[<5%]	[60%]	[60%]	[<5%]
Sugars and sweets	0.002	0.002	0.002	0.001	0.001	0.000	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
	[<5%]	[<5%]	[<5%]	[<5%]	[<5%]	[<5%]	[<5%]
Alcohol beverages	0.001	0.001	0.001	0.001	0.001	-0.002	-0.001
	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.001)
	[<5%]	[<5%]	[<5%]	[<5%]	[<5%]	[190%]	[<5%]
Nonalcoholic beverages	-0.003	-0.004	-0.003	-0.004	-0.005	-0.009***	-0.000
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
	[130%]	[150%]	[140%]	[140%]	[100%]	[170%]	[130%]
N	8072	7477	8072	8129	8129	8129	8072

Note: N = number of observations. Standard errors are in parentheses, and the maximum Γ is reported in block brackets. In column (1), we preselected other covariates that seemed relevant to have been selected by LASSO in the baseline (that is, education and employment status of the household head, type of dwelling (roof, wall, and floor) materials, and whether the household owns any other appliance. See Appendix B2 on how these variables are measured. In Column (2), we exclude all households that reported that their refrigerator was a gift and hence no price was reported. In Column (3), we used the adaptive LASSO to select the tuning parameter since the CV method has been criticised to be (i) inconsistent as features grow rapidly, and (ii) unable to perform hypothesis tests and confidence intervals. In columns (4) to (6), we used the traditional matching estimators of IPW, PSM, and MD. In column (7), we used the survey weights. The weights are treated as importance weights since TELASSO doesn't allow the use of frequency weights. *** p<0.01, ** p<0.05, * p<0.1

Table D2.2: Placebo tests – Causal impacts of other broken appliances on food quantity

Food category	(1) Broken fan (N=7105)	(2) Broken radio (N=3625)	(3) Broken sewing machine (N=1605)
Total at home (excl. alcohol)	-0.098	-0.248*	0.147
	(0.149)	(0.142)	(0.182)
All Meats	-0.008*	0.006	-0.004
	(0.004)	(0.006)	(0.005)
Milk & dairy products	-0.002	0.000	-0.001
	(0.001)	(0.002)	(0.002)
Eggs	-0.009	0.001	-0.003
	(0.006)	(0.008)	(0.008)
Fish	-0.000	0.001	0.013
	(0.009)	(0.007)	(0.011)
All vegetables	-0.029	-0.096	0.133
	(0.101)	(0.099)	(0.140)
Roots, tubers, & plantain	-0.019	-0.054	0.117
	(0.077)	(0.082)	(0.123)
Other leafy vegetables	0.005	-0.009	0.033
	(0.031)	(0.022)	(0.030)
Fruits	0.006	-0.010	0.002
	(0.019)	(0.013)	(0.016)
Cereals, flour & bread	0.012	-0.060***	-0.008
	(0.031)	(0.027)	(0.031)
Pulse, nuts, & seeds	-0.007	-0.006	0.007
	(0.008)	(0.009)	(0.013)
Oil & fats	0.011*	-0.005	0.007
	(0.006)	(0.004)	(0.006)
Spices	0.000	-0.001	0.000
	(0.003)	(0.002)	(0.003)
Sugar & sweets	-0.001	-0.001	-0.002
	(0.003)	(0.003)	(0.003)
Alcoholic beverages	0.004	-0.001	0.001
	(0.005)	(0.003)	(0.005)
Non-alcoholic beverages	-0.004	-0.003	-0.001
	(0.005)	(0.003)	(0.005)

Notes: N = number of observations in the sample category. Columns (1), (2), and (3) report the ATT of having a broken fan, radio, and sewing machine on food expenditure, respectively. Standard errors are in parentheses. As already explained in the main text and can be observed in **Appendix A2 and A3** regarding the number of observations with broken fans, TELASSO was only able to converge with the pooled sample possibly due to the large sample size. That is why we include fan as a placebo in the pooled sample, but not in the food insecurity analysis, which uses only GLSS VII. *** p<0.01, ** p<0.05, * p<0.1

Table D2.3: Gift sample – Impact of refrigerator breakdowns on food quantities among households that received the appliance as a gift

	(1)	(2)	(3)	(4)	(5)	(6)
Total at home (excl. alcohol)	0.105	0.084	0.086	0.027	0.044	0.004
	(0.307)	(0.303)	(0.286)	(0.285)	(0.295)	(0.516)
All Meats	-0.026***	-0.025***	-0.021***	-0.019***	-0.019***	-0.018***
	(0.005)	(0.004)	(0.005)	(0.004)	(0.004)	(0.006)
Milk & dairy products	-0.007***	-0.006***	-0.006***	-0.004**	-0.003	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Eggs	-0.017*	-0.017*	-0.016	-0.015	-0.012	-0.028
	(0.010)	(0.010)	(0.011)	(0.011)	(0.011)	(0.018)
Fish	-0.024***	-0.023**	-0.021**	-0.017*	-0.015	-0.022*
	(0.009)	(0.009)	(0.010)	(0.010)	(0.010)	(0.013)
All vegetables	0.138	0.104	0.129	0.058	0.051	0.042
	(0.184)	(0.192)	(0.169)	(0.165)	(0.174)	(0.284)
Roots, tubers & plantain	0.160	0.134	0.166	0.102	0.098	0.075
	(0.178)	(0.185)	(0.162)	(0.156)	(0.166)	(0.276)
Other leafy vegetables	-0.011	-0.015	-0.015	-0.018	-0.021	-0.020
	(0.026)	(0.027)	(0.029)	(0.033)	(0.031)	(0.050)
Fruits	-0.016	-0.014	-0.009	-0.008	-0.007	-0.013
	(0.019)	(0.019)	(0.018)	(0.019)	(0.018)	(0.024)
Cereals, flour & bread	-0.008	-0.005	-0.032	-0.036	-0.030	-0.093
	(0.071)	(0.069)	(0.064)	(0.064)	(0.065)	(0.120)
Pulse, nuts, & seeds	0.017	0.017	0.014	0.015	0.014	0.023
	(0.022)	(0.022)	(0.020)	(0.020)	(0.021)	(0.035)
Oil & fats	-0.003	-0.003	-0.003	-0.001	-0.000	-0.003
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.007)
Spices	-0.001	-0.001	-0.002	-0.002	-0.002	-0.001
	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.004)
Sugar & sweets	0.000	0.001	0.000	0.000	-0.000	-0.002
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)
Alcoholic beverages	-0.003*	-0.002	-0.002	-0.002	-0.002	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)
Non-alcoholic beverages	-0.007	-0.007	-0.005	-0.004	-0.004	-0.004
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)
Controls						
Age of appliance		✓	✓	✓	✓	✓
Region			✓	✓	✓	✓
Rural/urban				✓	✓	✓
Household var.					✓	✓
Community var.						✓
Observations	626	626	626	626	626	299

Notes: All specifications include interview year and interview month fixed effects. Observations include only households that received the refrigerator as a gift. Here, both GLSS VI and GLSS VII samples were used. Household variables include (i) age and (ii) sex of householder; (iii) whether ever attended school; (iv) their employment status (employed or not); (v) the household size; and whether the (vi) floor, (vii) roof and (walls) of the dwelling are permeable. Community variables are not available for all observations and include access to a market, a financial institution, a road, living conditions of the area, and the community's main activity (fishing, trading, handicraft, or other). Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

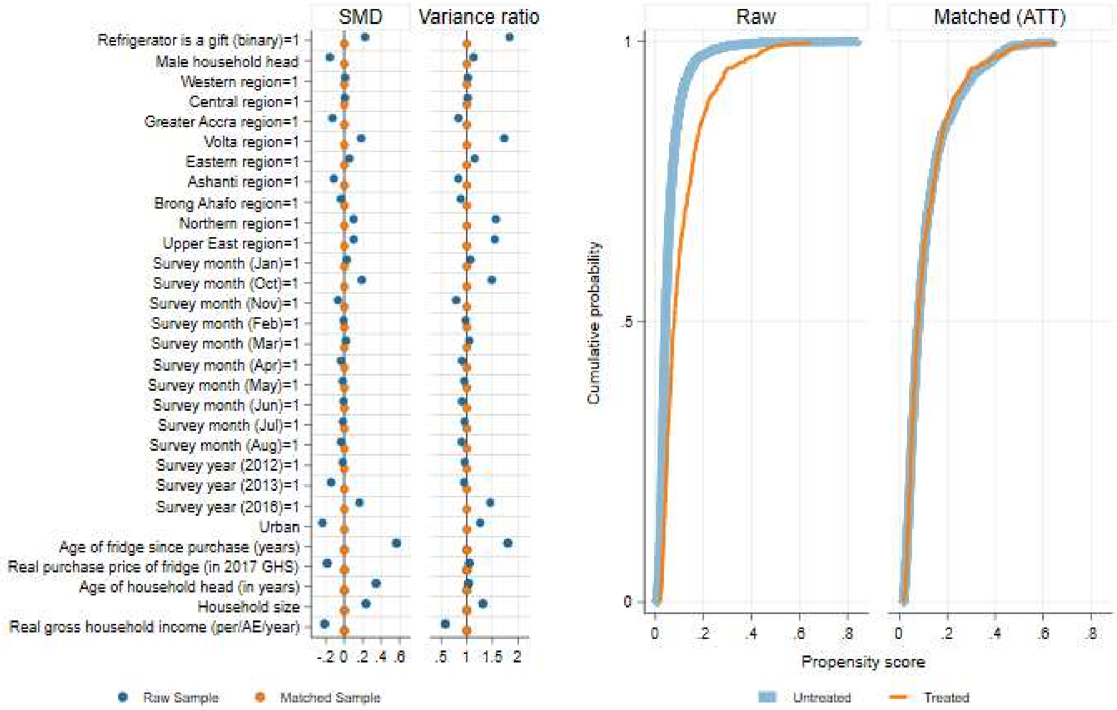
Appendix D3: Food expenditure outcomes

Table D3.1: Summary statistics of food expenditure outcomes

Food category	**(1) Functioning refrigerator (7639)**	**(2) Broken refrigerator (490)**	**(3) Diff.**	**(4) SE**
Total at home (excl. alcohol)	7.61	6.95	0.66**	0.27
All Meats	0.76	0.52	0.25***	0.04
Milk & dairy products	0.22	0.15	0.07***	0.01
Eggs	0.13	0.09	0.04***	0.01
Fish	1.35	1.23	0.12**	0.06
All vegetables	2.00	2.13	-0.13	0.09
Roots, tubers, & plantain	1.00	1.21	-0.21***	0.06
Other leafy vegetables	0.98	0.90	0.08**	0.04
Fruits	0.30	0.23	0.07***	0.02
Cereals, flour & bread	1.53	1.44	0.09	0.06
Pulse, nuts, & seeds	0.16	0.18	-0.03**	0.01
Oil & fats	0.26	0.26	0.00	0.01
Spices	0.10	0.11	-0.01*	0.01
Sugar & sweets	0.16	0.13	0.03**	0.01
Alcoholic beverages	0.11	0.11	0.00	0.02
Non-alcoholic beverages	0.43	0.30	0.13***	0.03
Total out of home	1.56	1.25	0.32***	0.11
Hotels, cafes, restaurants	0.39	0.25	0.14***	0.05
Canteens	1.12	0.97	0.14	0.10

Notes: Data from GLSS VI and GLSS VII, pooled. N = total number of households in the sample category. Outcomes are reported in real expenditure per day per adult equivalence (in 2017 GHS). In 2017, GHS 1 = $0.23 on average (Bank of Ghana, 2024). SE = Standard Error of the mean difference. *** p<0.01, ** p<0.05, * p<0.1

Figure D3.1: Model diagnostics for the food expenditure model



Notes: This is based on the pooled data from GLSS VI and GLSS VII data for food expenditure analysis. The left panel presents the covariate balance using the standardized mean difference (SMD) and variance ratio. In the raw sample, we observe large disparities, even beyond 20% in the SMD and outside the recommended range in the variance ratio. However, in the matched sample and under the common support, the SMD is zero (0) and the variance ratio is one (1) for all covariates. The right panel presents the cumulative probability plots of the propensity scores before matching (Raw) and after matching (Matched) under the common support. ATT = Average Treated effect on the Treated. The vertical axis of the right panel reports the probability that the score is less than or equal to a given propensity score. These graphs depict perfect covariate balance, indicating that, conditional on these observables, the treatment is as good as random. Given that we run 19 different models, it is ideal to present the covariate balance for all 19 models. We observe that the same covariates are selected in all models, and the covariate balance is the same in all cases; thus, we present just one. The remaining 18 are available upon request.

Table D3.2: Causal impacts of having a broken refrigerator on food expenditure outcomes

Food category (in 2017 real GHS)	(1) ATT	(2) Treated group mean	(3) Max. Γ	(4) Entropy balance
Total at home (excl. alcohol)	-0.065	6.95	50%	-0.107
	(0.285)			(0.284)
All Meats	-0.141***	0.52	180%	-0.139***
	(0.044)			(0.039)
Milk & dairy products	-0.023***	0.15	100%	-0.032***
	(0.011)			(0.011)
Eggs	-0.019***	0.09	120%	-0.021***
	(0.007)			(0.007)
Fish	-0.053	1.23	70%	-0.064
	(0.055)			(0.059)
All vegetables	0.101	2.13	<5%	0.115
	(0.109)			(0.109)
Roots, tubers, & plantain	0.144*	1.21	<5%	0.153*
	(0.082)			(0.082)
Other leafy vegetables	-0.039	0.90	70%	-0.034
	(0.044)			(0.041)
Fruits	-0.004	0.23	<5%	-0.000
	(0.018)			(0.018)
Cereals, flour & bread	0.031	1.44	<5%	0.005
	(0.063)			(0.065)
Pulse, nuts, & seeds	0.024	0.18	<5%	0.024
	(0.016)			(0.015)
Oil & fats	0.012	0.26	<5%	0.011
	(0.015)			(0.014)
Spices	0.010*	0.11	<5%	0.008
	(0.006)			(0.006)
Sugar & sweets	-0.007	0.13	90%	-0.004
	(0.010)			(0.009)
Alcoholic beverages	0.027*	0.11	<5%	0.024
	(0.016)			(0.016)
Non-alcoholic beverages	-0.025	0.30	90%	-0.027
	(0.022)			(0.021)
Total out of home	0.172*	1.25	<5%	0.134
	(0.091)			(0.103)
Hotels, cafes, & restaurants	0.010	0.25	130%	0.003
	(0.031)			(0.032)
Canteens	0.159*	0.97	<5%	0.130
	(0.088)			(0.098)
N	8072			8129

Notes: N = total number of households in the sample category. Standard errors are in parentheses. Column (1) reports the ATT from the TELASSO, and Column (2) reports the mean of the treated group. Column (3) reports the maximum Γ value (in %) from the Rosenbaum bounds sensitivity test beyond which our estimates would be sensitive to hidden bias, at 5% critical level, and Column (4) provides the corresponding ATT from entropy balance estimation which uses the same preselected and LASSO-selected covariates employed in the baseline. *** p<0.01, ** p<0.05, * p<0.1.

Table D3.3: Alternative specifications for food expenditure models

Food expenditure category	**(1)** **Extra covariates**	**(2)** **Excluding gifts**	**(3)** **Adaptive LASSO**	**(4)** **IPW**	**(5)** **PSM**	**(6)** **MD**	**(7)** **Survey weight**
Total at home (excl. alcohol)	-0.047	-0.220	-0.062	-0.136	-0.262	-0.351	-0.031
	(0.334)	(0.327)	(0.331)	(0.333)	(0.341)	(0.345)	(0.294)
	[<5%]	[50%]	[50%]	[50%]	[40%]	[60%	[<5%]
All meat	-0.176***	-0.146***	-0.172***	-0.192***	-0.236***	-0.222***	-0.146***
	(0.058)	(0.059)	(0.058)	[(0.053)	(0.066)	(0.050)	(0.048)
	[150%]	[160%]	[180%]	[190%]	[130%]	[190%	[110%]
Milk and dairy	-0.027***	-0.025*	-0.027***	-0.034***	-0.052***	-0.065***	-0.018
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.012)
	[90%]	[100%]	[100%]	[100%]	[100%]	[150%	[<5%]
Eggs	-0.022***	-0.020***	-0.021***	-0.027***	-0.022***	-0.041***	-0.018***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.007)
	[120%]	[120%]	[120%]	[130%]	[100%]	[160%	[60%]
Fish	-0.086	-0.137***	-0.085	-0.100	-0.108	-0.085	-0.046
	(0.066)	(0.065)	(0.065)	(0.069)	(0.067)	(0.069)	(0.055)
	[60%]	[60%]	[70%]	[70%]	[40%]	[60%	[<5%]
All vegetables	0.199	0.169	0.183	0.187	0.181	0.328***	0.124
	(0.156)	(0.163)	(0.156)	(0.155)	(0.158)	(0.155)	(0.166)
	[<5%]	[<5%]	[<5%]	[<5%]	[<5%]	[<5%	[<5%]
Roots, tubers, & plantain	0.247*	0.187	0.233*	0.232*	0.228*	0.361***	0.167
	(0.129)	(0.136)	(0.129)	(0.129)	(0.129)	(0.129)	(0.153)
	[<5%]	[<5%]	[<5%]	[<5%]	[<5%]	[<5%	[<5%]
Other leafy vegetables	-0.044	-0.023	-0.042	-0.045	-0.047	-0.033	-0.042
	(0.056)	(0.056)	(0.055)	(0.055)	(0.057)	(0.053)	(0.042)
	[60%]	[60%]	[70%]	[70%]	[40%]	[50%	[<5%]
Fruits	-0.003	-0.010	-0.003	0.001	0.002	-0.031	0.035
	(0.029)	(0.034)	(0.029)	(0.028)	(0.030)	(0.029)	(0.043)
	[<5%]	[90%]	[<5%]	[<5%]	[<5%]	[100%	[<5%]
Cereals, flour & bread	0.041	-0.005	0.040	0.015	-0.013	-0.167	0.000
	(0.086)	(0.067)	(0.085)	(0.087)	(0.092)	(0.116)	(0.058)
	[<5%]	[40%]	[<5%]	[<5%]	[20%]	[60%	[<5%]

Pulse, nuts, & seeds	0.070	0.005	0.070	0.074	0.068	0.067	0.041*
	(0.056)	(0.017)	(0.056)	(0.056)	(0.059)	(0.056)	(0.025)
	[<5%]	[<5%]	[<5%]	[<5%]	[<5%]	[<5%	[<5%]
Oil and fat	0.006	0.008	0.004	0.005	0.004	-0.004	0.022
	(0.016)	(0.016)	(0.016)	(0.015)	(0.016)	(0.015)	(0.016)
	[<5%]	[<5%]	[<5%]	[<5%]	[<5%]	[30%	[<5%]
Spices	0.011	0.014	0.010	0.006	0.002	0.006	0.004
	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.008)	(0.007)
	[<5%]	[<5%]	[<5%]	[<5%]	[<5%]	[<5%	[<5%]
Sugars and sweets	-0.014	-0.011	-0.014	-0.014	-0.022*	-0.028***	-0.002
	(0.012)	(0.013)	(0.012)	(0.011)	(0.013)	(0.011)	(0.010)
	[80%]	[80%]	[90%]	[90%]	[60%]	[90%	[<5%]
Alcohol beverages	0.037	0.047	0.036	0.030	0.049	0.001	0.000
	(0.040)	(0.047)	(0.040)	(0.039)	(0.039)	(0.044)	(0.031)
	[<5%]	[<5%]	[<5%]	[<5%]	[<5%]	[<5%	[<5%]
Nonalcoholic beverages	-0.052***	-0.060***	-0.051***	-0.057***	-0.068***	-0.109***	-0.018
	(0.024)	(0.025)	(0.023)	(0.023)	(0.027)	(0.023)	(0.021)
	[90%]	[90%]	[100%]	[100%]	[60%]	[130%	[<5%]
Total out of home	0.197*	0.183	0.190*	0.162	0.193	-0.149	0.082
	(0.106)	(0.111)	(0.106)	(0.117)	(0.125)	(0.123)	(0.083)
	[<5%]	[<5%]	[<5%]	[<5%]	[<5%]	[110%	[<5%]
Hotels, cafes, & restaurants	-0.025	-0.039	-0.027	-0.026	-0.012	-0.111***	-0.026
	(0.040)	(0.045)	(0.040)	(0.039)	(0.042)	(0.041)	(0.028)
	[130%]	[150%]	[130%]	[130%]	[80%]	[170%	[<5%]
Canteens	0.213***	0.207*	0.218***	0.189	0.205*	-0.038	0.109
	(0.108)	(0.111)	(0.105)	(0.115)	(0.123)	(0.121)	(0.079)
	[<5%]	[<5%]	[<5%]	[<5%]	[<5%]	[100%	[<5%]
N	8072	7477	8072	8129	8129	8129	8072

Note: N = total number of households in the sample category. Standard errors are in parentheses, and the maximum Γ is reported in block brackets. In column (1), we preselected other covariates that seemed relevant to have been selected by LASSO in the baseline (that is, education and employment status of the household head, type of dwelling (roof, wall, and floor) materials, and whether the household owns any other appliance. See Appendix B2 on how these variables are measured. In Column (2), we exclude all households that reported that their refrigerator was a gift and hence no price was reported. In Column (3), we used the adaptive LASSO to select the tuning parameter since the CV method has been criticised to be (i) inconsistent as features grow rapidly, and (ii) unable to perform hypothesis tests and confidence intervals. In columns (4) to (6), we used the traditional matching estimators of IPW, PSM, and MD. In column (7), we used the survey weights. The weights are treated as importance weights since TELASSO doesn't allow the use of frequency weights. *** p<0.01, ** p<0.05, * p<0.1

Table D3.4: Placebo – Causal impacts of other broken appliances on food expenditure

Food expenditure category	(1) Broken fan (N=7105)	(2) Broken radio (N=3625)	(3) Broken sewing machine (N=1605)
Total at home (excl. alcohol)	0.12	0.19	0.55
	(0.57)	(0.46)	(0.57)
All Meats	-0.07	0.05	0.06
	(0.08)	(0.08)	(0.10)
Milk & dairy products	-0.02	0.02	0.00
	(0.02)	(0.02)	(0.03)
Eggs	-0.00	-0.01	-0.01
	(0.01)	(0.01)	(0.01)
Fish	-0.05	0.03	0.12
	(0.10)	(0.09)	(0.11)
All vegetables	0.17	0.07	0.38*
	(0.23)	(0.18)	(0.22)
Roots, tubers, & plantain	0.06	0.07	0.26
	(0.14)	(0.14)	(0.17)
Other leafy vegetables	0.06	0.03	0.12
	(0.08)	(0.06)	(0.08)
Fruits	0.01	-0.00	0.05
	(0.04)	(0.03)	(0.04)
Cereals, flour & bread	0.01	-0.07	0.05
	(0.11)	(0.10)	(0.12)
Pulse, nuts, & seeds	-0.02	0.03	0.01
	(0.02)	(0.03)	(0.04)
Oil & fats	0.03	-0.03	-0.01
	(0.03)	(0.02)	(0.02)
Spices	0.01	0.01	0.00
	(0.01)	(0.01)	(0.01)
Sugar & sweets	-0.01	0.00	-0.01
	(0.02)	(0.02)	(0.02)
Alcoholic beverages	0.06*	0.02	0.01
	(0.04)	(0.03)	(0.02)
Non-alcoholic beverages	-0.05	0.01	0.01
	(0.04)	(0.03)	(0.04)
Total out of home	-0.23***	0.15	-0.11
	(0.11)	(0.15)	(0.08)
Hotels, cafes, restaurants	0.06	-0.03	0.00
	(0.08)	(0.05)	(0.05)
Canteens	-0.28***	0.15	-0.11
	(0.08)	(0.14)	(0.07)

Notes: N = total number of households in the sample category. Columns (1), (2), and (3) report the ATT of having a broken fan, radio, and sewing machine on food expenditure, respectively. Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

E. Nutrient intake analysis

Appendix E1: Mean statistics of all essential nutrients by refrigerator functionality status

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Animal sources				Plant sources			
Nutrient intake (unit/day/AE)	**Functioning fridge (7639)**	**Broken fridge (490)**	**Diff.**	**SE**	**Functioning fridge (7639)**	**Broken fridge (490)**	**Diff.**	**SE**
Metabolizable energy (kcal)	282	196	86.9***	15.0	2313	2448	-134	113
Carbohydrate (g)	2.78	1.78	1.00***	0.17	390	418	-28.5	20.3
Protein (g)	36.9	27.2	9.66***	1.97	39.0	42.7	-3.66*	2.13
Fat (g)	13.7	8.73	4.94***	0.81	62.7	64.8	-2.12	3.22
Saturated fat (g)	5.23	3.35	1.88***	0.29	25.3	24.8	0.53	1.71
Monounsaturated fat (g)	5.17	3.29	1.88***	0.32	14.1	15.4	-1.24	0.82
Polyunsaturated fat (g)	1.60	1.07	0.53***	0.11	11.3	12.6	-1.23*	0.67
Cholesterol (g)	0.30	0.19	0.10***	0.02	-	-	-	-
Minerals (g)	1.74	1.24	0.50***	0.10	8.91	9.0	-0.08	0.46
Iron (mg)	3.55	2.54	1.01***	0.22	24.3	27.2	-2.99***	1.15
Zinc (mg)	3.27	2.24	1.03***	0.19	12.2	14.5	-2.33***	0.78
Calcium (mg)	356	257	99.1***	28.2	323	343	-20.0	17.7
Phosphorous (g)	0.58	0.41	0.17***	0.04	0.96	1.03	-0.07	0.05
Potassium (g)	0.51	0.37	0.14***	0.03	3.55	3.7	-0.11	0.19
Magnesium (mg)	55.3	41.7	13.6***	2.77	398	433	-35.0	21.3
Copper (mg)	0.20	0.15	0.05***	0.01	2.64	3.40	-0.75***	0.28
Vitamins	18.1	13.3	4.73***	0.93	255	269	-14.6	14.6
Vitamin A (RAE) (mg)	0.09	0.06	0.03***	0.01	0.93	0.95	-0.02	0.07
Retinol (mcg)	84.5	54.0	30.5***	5.77	-	-	-	-
Beta-carotene equivalents (provitamin A) (mg)	-	-	-	-	10.9	11.3	-0.33	0.81
Alpha-carotene (provitamin A) (mg)	-	-	-	-	0.87	0.83	0.04	0.08
Beta-carotene (provitamin A) (mg)	-	-	-	-	10.0	10.5	-0.45	0.78
Vitamin B1 (mcg)	166	106	59.5***	10.6	1634	2429	-795***	257

Vitamin B2 (mg)	0.27	0.19	0.08***	0.01	1.96	2.81	-0.85***	0.27
Vitamin B3 (mg)	13.6	9.95	3.60***	0.70	17.2	18.6	-1.38	0.88
Vitamin B6 (mg)	0.49	0.35	0.14***	0.03	2.30	3.04	-0.74**	0.27
Vitamin B9 (mg)	0.03	0.02	0.01***	0.00	0.38	0.42	-0.04**	0.02
Vitamin B12 (mcg)	8.13	5.84	2.28***	0.79	-	-	-	-
Vitamin C (mg)	0.51	0.42	0.09*	0.05	222	232	-10.00	13.3
Vitamin D (mcg)	5.04	3.40	1.64***	0.35	0.63	1.35	-0.72***	0.25
Vitamin E (mg)	2.93	2.21	0.72***	0.18	8.26	9.12	-0.87*	0.47
Fibre (g)	-	-	-	-	52.7	58.9	-6.19**	2.96

Notes: Pooled Data from GLSS VI and GLSS VII and matched with the West Africa Food Composition Table. N = total sample in each category. SE = Standard Error of the mean difference. Animal sources comprise all meats, eggs, fish and milk & dairy products. Plant sources include all remaining food groups, as described in the data section. Vitamin A (RAE) is the retinol activity equivalent of vitamin A. It comprises the factional sum of beta-carotene equivalent and retinol, whereas beta-carotene equivalent is the fractional sum of beta-carotene, alpha-carotene, and beta-cryptoxanthin. Hence, total Vitamins = Vitamin A (RAE) + Vitamin B1 + Vitamin B2 + Vitamin B3 + Vitamin B6 + Vitamin B9 + Vitamin B12 + Vitamin C + Vitamin D + Vitamin E, considering all the varying units of measurement. See Vincent et al. (2020) for more details on the computational definitions of each nutrient. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Appendix E2: ATT of refrigeration on home-based Micronutrient intake (excl. alcohol)

Nutrient intake	Animal origin		Plant based		Total (excl. alcohol)	
	ATT	Max. Γ	ATT	Max. Γ	ATT	Max. Γ
Minerals						
Iron	-0.56***	100%	1.997	<5%	1.433	<5%
	(0.175)		(1.403)		(1.472)	
Zinc	-0.589***	160%	1.125	<5%	0.526	<5%
	(0.153)		(0.961)		(1.014)	
Calcium	-57.36***	150%	13.605	<5%	-43.774	<5%
	(20.211)		(19.404)		(31.556)	
Phosphorous	-0.09***	170%	0.069	<5%	-0.027	<5%
	(0.027)		(0.058)		(0.072)	
Potassium	-0.08***	140%	0.084	<5%	0.000	<5%
	(0.022)		(0.200)		(0.211)	
Magnesium	-6.57***	110%	29.875	<5%	22.691	<5%
	(2.377)		(24.514)		(25.644)	
Copper	-0.02	110%	0.328	<5%	0.312	<5%
	(0.013)		(0.383)		(0.384)	
Vitamins						
Vitamin A (RAE)	-0.017***	150%	0.046	<5%	0.029	<5%
	(0.005)		(0.076)		(0.078)	
Retinol (mcg)	-16.5***	150%	-	-	-16.49***	150%
	(4.354)		-		(4.354)	
Beta-carotene equiv. (mg)	-	-	0.689	<5%	0.689	<5%
	-		(0.900)		(0.900)	
Alpha-carotene (mg)	-	-	-0.041	70%	-0.041	70%
	-		(0.081)		(0.081)	
Beta-carotene (mg)	-	-	0.733	<5%	0.733	<5%
	-		(0.878)		(0.878)	
Vitamin B1 (mg)	-31.91***	170%	318.373	<5%	286.42	<5%
	(8.396)		(364.840)		(365.58)	
Vitamin B2	-0.042***	110%	0.340	<5%	0.299	<5%
	(0.011)		(0.367)		(0.368)	
Vitamin B3	-1.975***	100%	1.112	<5%	-0.909	50%
	(0.594)		(0.998)		(1.351)	
Vitamin B6 (mg)	-0.077***	110%	0.281	<5%	0.204	<5%
	(0.022)		(0.376)		(0.380)	
Vitamin B9	-0.007***	310%	0.031	<5%	0.024	<5%
	(0.002)		(0.024)		(0.025)	
Vitamin B12 (mcg)	-1.474***	150%	-	-	-1.47***	150%
	(0.583)		-		(0.583)	
Vitamin C (mg)	0.017	<5%	6.507	<5%	6.526	<5%
	(0.050)		(15.013)		(15.017)	
Vitamin D (mcg)	-0.982***	150%	0.254	<5%	-0.715	130%
	(0.272)		(0.355)		(0.444)	
Vitamin E (mg)	-0.383***	120%	0.703	<5%	0.318	<5%
	(0.160)		(0.551)		(0.627)	

Notes: N= 8072. Standard errors are in parentheses. Beta-carotene and alpha-carotene are provitamin A. *** p<0.01, ** p<0.05, * p<0.1.

F. Comparing households with vs. without refrigerators

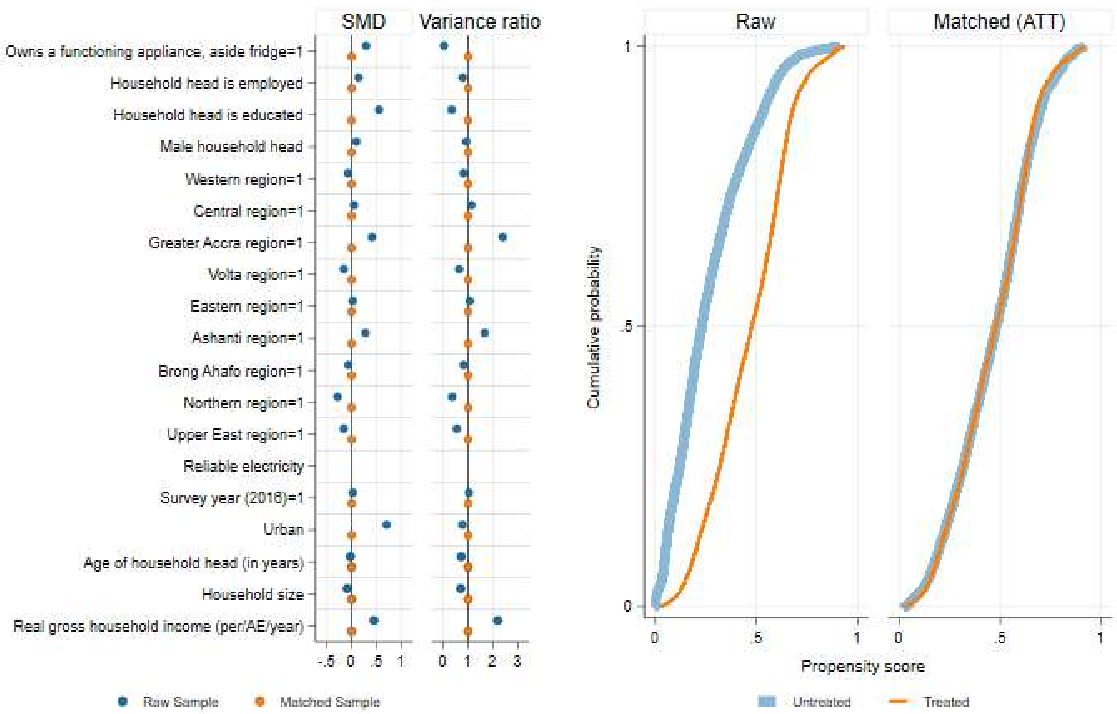
Prior analyses have compared households that own a refrigerator with households that do not own one. Here, we provide the results obtained when running the same model as the baseline model but changing the treatment variable to compare households with a functioning refrigerator (treatment) to households without a refrigerator or with broken refrigerators (control).

Our primary aim in this section is to analyse the possible existence of hidden bias in the conventional practice of comparing households with refrigerators and those without refrigerators, using Rosenbaum's sensitivity test. We argue that since such households are largely different, attributing causality to estimates from such analysis is to be done with caution. In this sense, if a low Γ value is observed post estimation, it would mean that the resulting ATT is not robust to hidden bias, and hence estimates should be considered with a grain of salt in terms of causality.

In this approach, we employ the TELASSO estimation technique as used in the baseline analysis in the text. However, refrigerator information in **Table 2** of the text is not used since that will lead to missing information for households without refrigerators. We use the set of potential covariates described in **Tables B1 and B2**. Similar to the baseline model, locality of the household (i.e. region and rural/urban), household size, and gender and age of the household head are preselected. In their recent work on analysing refrigeration and the health of children, Karlsson & Subramanian (2023) identify key socioeconomic variables whose omissions can confound estimates. They include education, income, and dwelling conditions. Thus, these variables are preselected in addition to the employment status of the head, the household's access to reliable electricity, and whether the household owns any other functioning electric appliance other than a refrigerator. Survey year and month dummies are also included. Among the set of potential covariates that we allow LASSO to select from in this case, include the head's marital status, religion, ethnicity, and the dwelling's (roof, wall, and floor) materials.

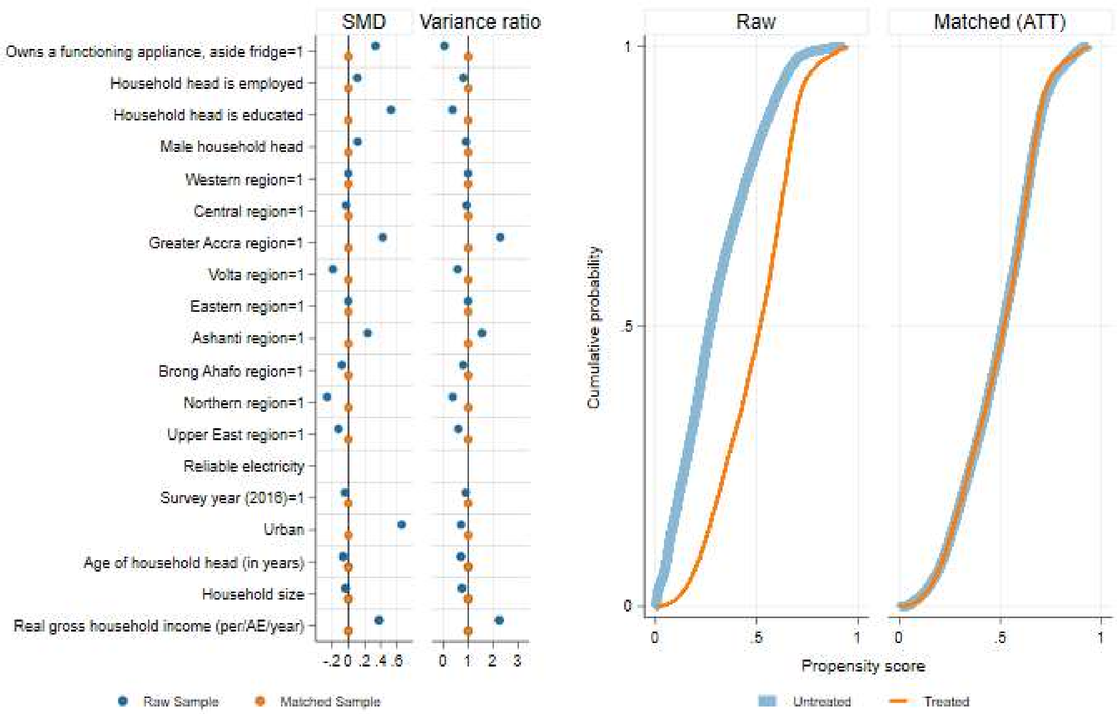
We present the model diagnostics for food insecurity and food basket (quantity and expenditure) below. These show groups are comparable based on observables.

Figure F1.1: Model diagnostics for the food insecurity model



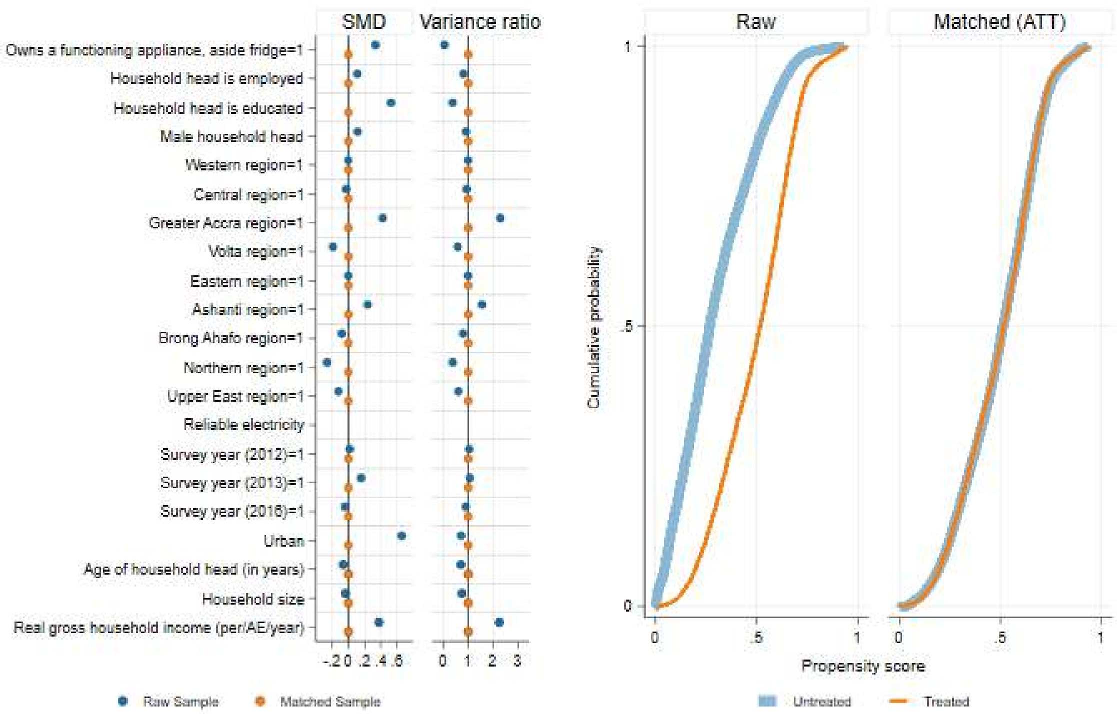
Notes: This is Model diagnostics for the food insecurity model comparing those with vs without refrigerators. This is based on the pooled data from GLSS VII data for food insecurity analysis. The left panel presents the covariate balance using the standardized mean difference (SMD) and variance ratio. In the raw sample, we observe large disparities, even beyond 20% in the SMD and outside the recommended range in the variance ratio. However, in the matched sample and under the common support, the SMD is zero (0) and the variance ratio is one (1) for all covariates. The right panel presents the cumulative probability plots of the propensity scores before matching (Raw) and after matching (Matched) under the common support. The vertical axis of the right panel reports the probability that the score is less than or equal to a given propensity score. These graphs portray a perfect covariate balance.

Figure F1.2: Model diagnostics for the food quantity model



Notes: This is Model diagnostics for the food quantity model comparing those with vs without refrigerators. This is based on the pooled data from GLSS VI and GLSS VII data for food expenditure analysis. The left panel presents the covariate balance using the standardized mean difference (SMD) and variance ratio. In the raw sample, we observe large disparities, even beyond 20% in the SMD and outside the recommended range in the variance ratio. However, in the matched sample and under the common support, the SMD is zero (0) and the variance ratio is one (1) for all covariates. The right panel presents the cumulative probability plots of the propensity scores before matching (Raw) and after matching (Matched) under the common support. The vertical axis of the right panel reports the probability that the score is less than or equal to a given propensity score. These graphs portray a perfect covariate balance.

Figure F1.3: Model diagnostics for the food expenditure model



Notes: This is Model diagnostics for the food expenditure model comparing those with vs. without refrigerators. This is based on the pooled data from GLSS VI and GLSS VII data. The left panel presents the covariate balance using the standardized mean difference (SMD) and variance ratio. In the raw sample, we observe large disparities, even beyond 20% in the SMD and outside the recommended range in the variance ratio. However, in the matched sample and under the common support, the SMD is zero (0) and the variance ratio is one (1) for all covariates. The right panel presents the cumulative probability plots of the propensity scores before matching (Raw) and after matching (Matched) under the common support. The vertical axis of the right panel reports the probability that the score is less than or equal to a given propensity score. These graphs portray a perfect covariate balance.

The resulting ATTs are presented in **Tables F1 to F3**. In this case, we do observe that refrigeration improves food security. In terms of the food basket, the results show increases in food demand for people who own a functioning refrigerator. However, the estimates are not robust to hidden bias, i.e. all those estimates are not statistically significant when we account for possible violations of the identification strategy stemming from unobserved differences between groups, especially for the food quantity and expenditure outcomes, which multiple studies have focused on.

The latter suggests that this identification strategy is likely to provide biased results and highlight the strong advantage in comparing households with functional vs. broken refrigerators instead, as comparability is strongly improved, especially after controlling for the age of the refrigerator and its purchase price.

Table F1: Impacts of having a functioning refrigerator on food insecurity

Food insecurity outcomes	ATT	Treated group mean	Max. Γ
Risk of food insecurity	-0.17*** (0.02)	0.38	>400%
Food Insecurity Intensity	-1.05*** (0.08)	1.55	160%
Worried about not having enough food to eat	-0.16*** (0.01)	0.29	<5%
Unable to eat healthy and nutritious foods	-0.17*** (0.01)	0.24	30%
Ate only a few kinds of foods	-0.18*** (0.01)	0.27	<10%
Had to skip a meal	-0.15*** (0.01)	0.21	50%
Ate less than the respondent's expectation	-0.16*** (0.01)	0.22	40%
Ran out of food	-0.13*** (0.01)	0.18	100%
Went without eating for a whole day	-0.10*** (0.01)	0.11	260%
Hungry but did not eat	-0.03*** (0.01)	0.03	>400%

Notes: N=13774. The treated group comprises of 3455 households. Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table F2: Testing for hidden bias: Impacts of having a functioning refrigerator on food quantity

Food expenditure category	(1) ATT	(2) Treatment group mean	(3) Max. Γ
Total at home (excl. alcohol)	0.206*** (0.037)	1.69	<5%
All Meats	0.017*** (0.001)	0.04	10%
Milk & dairy products	0.006*** (0.000)	0.01	10%
Eggs	0.016*** (0.002)	0.04	<5%
Fish	0.020*** (0.002)	0.08	<5%
All vegetables	0.029 (0.023)	0.80	<5%
Roots, tubers, & plantain	-0.013 (0.018)	0.54	<5%
Other leafy vegetables	0.036*** (0.007)	0.23	<5%
Fruits	0.036*** (0.004)	0.13	<5%
Cereals, flour & bread	0.028*** (0.007)	0.29	<5%
Pulse, nuts, & seeds	0.003 (0.003)	0.06	<5%
Oil & fats	0.008*** (0.001)	0.04	<5%
Spices	0.003*** (0.001)	0.02	<5%
Sugar & sweets	0.004*** (0.001)	0.02	<5%
Alcoholic beverages	0.002* (0.001)	0.02	<5%
Non-alcoholic beverages	0.016*** (0.001)	0.04	<5%

Notes: N = 30589. The treated group comprises 7859 households. Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table F3: Testing for hidden bias: Impacts of having a functioning refrigerator on food expenditure

Food expenditure category	(1) ATT	(2) Treatment group mean	(3) Max. Γ
Total at home (excl. alcohol)	1.65*** (0.12)	7.63	10%
All Meats	0.30*** (0.02)	0.76	20%
Milk & dairy products	0.09*** (0.01)	0.22	20%
Eggs	0.04*** (0.00)	0.13	<5%
Fish	0.27*** (0.02)	1.35	<5%
All vegetables	0.19*** (0.04)	2.02	<5%
Roots, tubers, & plantain	0.01 (0.03)	1.01	<5%
Other leafy vegetables	0.18*** (0.02)	0.98	<5%
Fruits	0.09*** (0.01)	0.30	<5%
Cereals, flour & bread	0.28*** (0.03)	1.53	<5%
Pulse, nuts, & seeds	0.01*** (0.01)	0.16	<5%
Oil & fats	0.06*** (0.01)	0.26	<5%
Spices	0.02*** (0.00)	0.10	<5%
Sugar & sweets	0.05*** (0.00)	0.16	<5%
Alcoholic beverages	0.01 (0.01)	0.11	<5%
Non-alcoholic beverages	0.14*** (0.01)	0.43	<5%
Total out of home	-0.08 (0.05)	1.55	100%
Hotels, cafes, restaurants	0.04*** (0.02)	0.39	<5%
Canteens	-0.14*** (0.05)	1.10	150%

Notes: N = 30,589. The treated group comprises 7859 households. Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

UBIREA
Institut de Recerca en Economia Aplicada Regional i Pública
Research Institute of Applied Economics
Universitat de Barcelona
Av. Diagonal, 690 • 08034 Barcelona

WEBSITE: www.ub.edu/irea/ • **CONTACT:** irea@ub.edu