Heat or Eat: How Food and Energy Subsidies Shape Household Trade-offs

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Motivation

- Access to food and energy is fundamental to household welfare.
- Price shocks in either domain can force trade-offs for low-income households known as 'Heat-or-Eat-Dilemma'.
- Univariate poverty analysis misses interactions of essential needs within constrained budgets.
- Joint analysis of food and energy expenditure shares is needed to understand co-movements and material hardship.
- Prior work documents energy and food hardship in multiple settings and motivates joint perspectives (Snell et al., 2018; National Energy Assistance Directors' Association (NEADA), 2018; Alkire et al., 2021; Bednar and Reames, 2020).

Conceptual background

- At lower incomes, households devote large budget shares to both food and energy, producing positive dependence between these expenditures.
- Dependence tends to weaken with rising income as basic needs are satisfied and flexibility increases (Engel's Law for food expenditure) (Meyer and Sullivan, 2012; Aguiar and Hurst, 2013).
- Strong co-movement indicates joint deprivation and tight budget constraints.
- Joint distribution matters to identify hardship (Sen, 1976).

Policy context in the US

- In the United States, food and energy needs are supported by separate programs.
  - Supplemental Nutrition Assistance Program (SNAP) focuses on food resources;
  - Low-Income Home Energy Assistance Program addresses (LIHEAP) energy affordability.

- Eligible populations overlap, but programs are rarely evaluated together (Hoynes and Schanzenbach, 2009; Hanna and Oliva, 2015).

- Coordinated support should relax joint constraints and reduce the dependence of food and energy shares (Alkire et al., 2021).

Analytical approach

- Modelling the joint distribution of food and energy expenditure shares using distributional copula methods (Decancq, 2014; Gu, 2023).
  $\rightarrow$ nonlinear and asymmetric dependence while conditioning on income, demographics, housing, and region.
- Overlap weighting to balance recipients and non-recipients for reducing composition bias.
  - Demographics like race and gender may influence access and receiving subsidies (Dogan et al., 2021)
- Study whether participation in assistance programs weakens the dependence of energy and food expenditure (reduced deprivation).
- Prior studies, for example Fry et al. (2023), estimate food-energy trade-offs using SUR models focused on mean effects.
  - SUR: correlated residuals but not nonlinearities or asymmetries.
  - Copula-based quantiles: entire joint distribution of expenditure shares, heterogeneity and tail behavior relevant for joint deprivation.

Expected contributions

- Evidence on how food and energy subsidies shape household trade-offs and the joint distribution of essential expenditures.
- Clarification of whether programs act as complements or substitutes in stabilizing budgets.
- A multidimensional perspective that avoids collapsing information into a single index and focuses on dependence structures (Sen, 1976).
- Policy guidance for coordinating assistance to address overlapping vulnerabilities within budget constraints and ecological limits (Alkire et al., 2021; Bednar and Reames, 2020).

Energy subsidies in the US

Major energy subsidy program in/before 2019: Low Income Home Energy Assistance Program (LIHEAP) and Weatherization Assistance Program (WAP).

- Effect of LIHEAP on energy insecurity (Murray and Mills, 2014).
- LIHEAP as a response to energy poverty (Bednar and Reames, 2020).
- Eligibility to LIHEAP:
  - being at or below 150% of the federal poverty level (FPL) income guidelines; or
  - 60 percent of the state median income.

Statistical strategy in a nutshell

Data: US Panel Study of Income Dynamics (PSID), 2003-2019

1. **Full bivariate conditional distribution** through distributional copula models.
   1.1 Overlap weighting to control for 'self-selection into treatment' combined with population weights.
   1.2 Model calibration: covariate selection, choice of copula and marginals.
   1.3 Conditional copula prediction and dependence parameter.

2. **Conditional directional quantiles:** Derivation from the bivariate conditional distribution via line search algorithm.

3. **Effect of energy subsidies:** Event-study-like comparison of pre- and post-treatment quantiles for food and energy expenditures.

Exemplary quantiles from the upper right

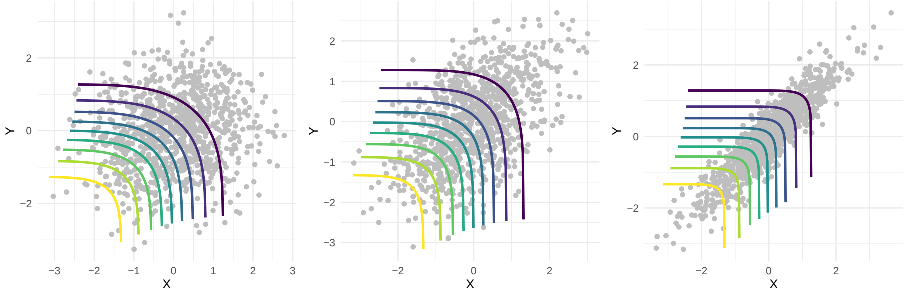


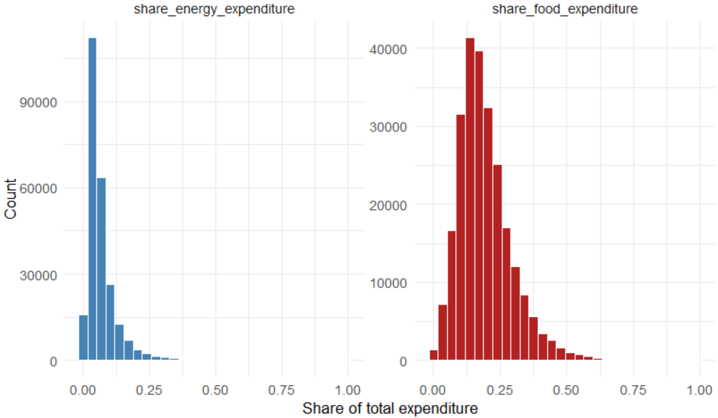
Figure 1: Simulated standard normally distributed data with $n = 1000$ and dependence parameters $\rho = 0.1, 0.5, 0.9$ (from left to right) and the calculated 10% to 90% upper-right quantiles obtained by the described method when regressing on a constant.

Data

2003-2019 US Panel Study of Income Dynamics (PSID)

- Couple and single adult households: 334,071 observations.
- Households with no energy costs are excluded, but otherwise, all with reported income and energy expenditures are included.
- Top 1% expenditures are dropped.
- No restrictions on household composition.
- Bivariate dependent vector variables
  - Share of household food expenditure in household expenditures.
  - Share of household expenditure on electricity and gas or other types of fuel in household expenditures.

Expenditure share of food and energy

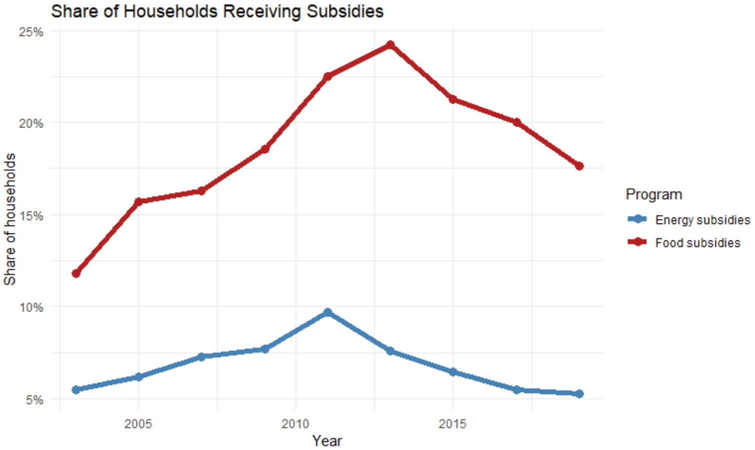


The covariates

- $black$: the household is defined as black if the response person (hh head) is black.
- $gender$: dummy for gender of household head.
- $govsubd$: dummy for government subsidy for energy expenditure
- $foodsubd$: dummy for government subsidy for food expenditure
- edu_yr: measures the years of education of household head
- age: the years of life of household head
- $hhsize$: represents the number of household members
- $hhtype$: the building type in seven categories
- $hhinc$: household income
- $state\_res$: US state of residency
- $partner$: dummy indicating whether partner lives in the household
- $nchild$: number of children
- $below60$ and $below130$: Dummy indicating whether person is eligible for energy or food subsidies, respectively
- $year$: observation period

Energy and food subsidies

- Increased volume of subsidies in (post-)crisis years (Bednar and Reames, 2020)



- For instance, 6,497 households receive energy subsidies for the first time in the sample period

Distributional copula regression

Systematically choose between alternative copulas based on AIC, QQ-plots.

$\Rightarrow$ DAGUM distribution and normal copula.

Bivariate response distribution $D = F_{1,2}$ is defined by

$$\begin{pmatrix} share\ of\ energy \\ share\ of\ food \end{pmatrix} \sim D(\theta_1, \theta_2, \theta_3, \theta_4, \theta_5, \theta_6, \theta_7)$$

with parameter θ_j defined by a predictor $\theta_j(\mathbf{z}) = h_j(\eta^{\theta_j})$ with a GAMLSS model for mean and copula parameters

$$\begin{aligned} \eta^{\theta_j} = \beta_0^{\theta_j} + \beta_1^{\theta_j} event\_time + \beta_2^{\theta_j} black + \beta_3^{\theta_j} gender + \beta_4^{\theta_j} nchild \\ + \beta_5^{\theta_j} state\_res + \beta_6^{\theta_j} educ\_yr + \beta_7^{\theta_j} hhsize + \beta_8^{\theta_j} partner \\ + \beta_9^{\theta_j} age + \beta_{10}^{\theta_j} hhtype + \beta_{11}^{\theta_j} heat\ type \\ + \beta_{12}^{\theta_j} s(hhinc\_pre) + \beta_{13}^{\theta_j} below60\_pre + \beta_{14}^{\theta_j} s(year) \end{aligned}$$

Variance and skewness parameter are regressed on the income spline only.

Bivariate copula-based conditional quantiles

- Bivariate quantiles are not uniquely defined, e.g., via statistical depths, calculating vector-based or spatial quantiles (see, e.g., Hallin et al., 2010; Carlier et al., 2017; Abdous and Theodorescu, 1992).

- We are primarily interested in the upper-right or the lower-left corner.

- Our approach is similar to Tepegjozova and Czado (2022):
  - Relate bivariate distribution to covariates via distributional copula regression.
  - Define quantiles for conditional copula $C_{V_1,V_2|\boldsymbol{X}}(v_1, v_2|\mathbf{x})$ by

$$Q_\alpha^{Y|X}(x) = \{(F_{Y_1}(y_1), F_{Y_2}(y_2)) \in [0,1]^2; C_{V_1,V_2|\boldsymbol{X}}(v_1, v_2|\mathbf{x}) = \alpha\},$$

  - Determine $Q_\alpha^{Y|X}(x)$ by line search algorithm.

An event study like comparison

Focus on the treated: Compare the quantiles conditioned on fixed covariate values before and after treatment (energy, food or both subsidies).

1. Estimate distributional copula model based on the whole data set.
2. Fix covariate values and $event\_time = -2, 0$ (and 2).
3. Derive conditional quantiles at $event\_time = -2, 0$.
4. Run stratified bootstrap to derive confidence sets for conditional quantiles.
5. Compare the quantiles based on, e.g., Hausdorff metric and visually.

Household profiles & scenario analysis

12 representative household profiles vary by:

- Income: 10%, 20% and 50% quantile of pre-treatment income
- Subsidies: SNAP / LIHEAP participation pre-treatment
- Housing & Heating: dwelling type (house/apt/mobile), energy source (gas/electric/oil)
- Demographics: elderly single, larger families, owner-occupiers, single mother etc.

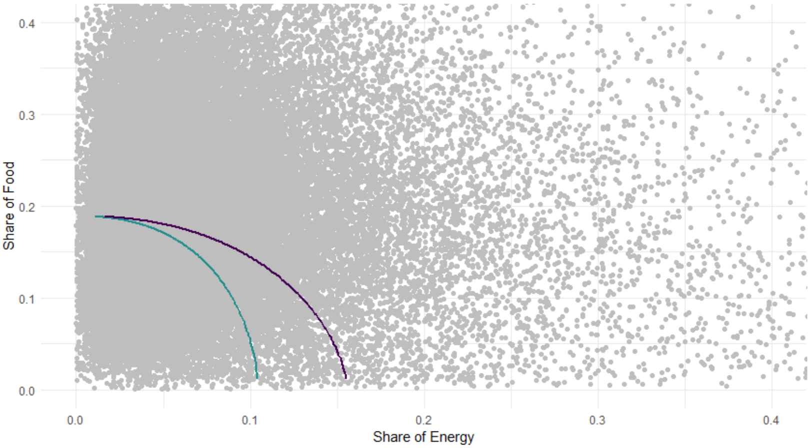
States analyzed:

- Mississippi – Low-income South, hot, low coverage of food stamps
- Massachusetts – High-cost Northeast, cold, heat AND eat policy

Next slides: quantiles for single mothers in Mississippi, i.e.,
$below60 = 1$; $below130 = 1$; $black = 0$; $sex = 2$; $log(hhinc) = 9.21$; $govsubd = 1$; $nchild = 2$; $food\_stamp = 1$; $age = 40$; $hhsize = 3$; $partner = 0$; $state\_red = 23$; $ed\_yr = 12$; $hhtype = 3$; $heattype = 2$, $year = 2009$

The effect of energy subsidies

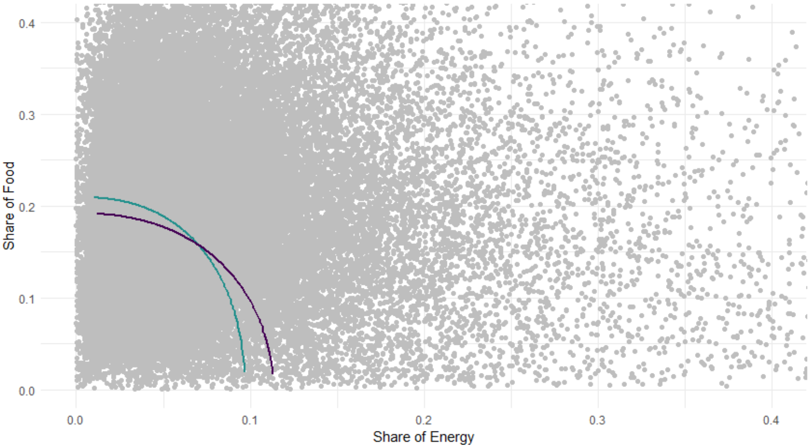
- Quantiles before and after treatment ($event\_time == -2$ (light blue) and 0 (dark blue)), 50% quantile.



- Kendall's tau: pre 0.0543, post -0.0459

The effect of food subsidies

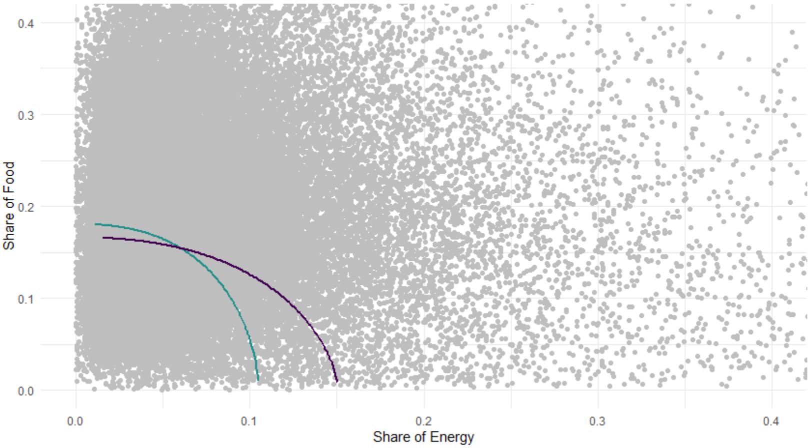
- Quantiles before and after treatment ($event\_time == -2$ (light blue) and 0 (dark blue)), 50% quantile.



- Kendall's tau: pre 0.0679, post 0.0080

The effect of both subsidies

- Quantiles before and after treatment ($event\_time == -2$ (light blue) and 0 (dark blue)), 50% quantile.



- Kendall's tau: pre 0.0713, post -0.0004

Conclusions I

- Question when using threshold lines: How does relaxing one part of the budget constraint reshape expenditure pressure in another part?

- Asymmetry within the multidimensional expenditure space
  - The impact of food stamps and energy subsidies is asymmetric.
  - The heterogeneous effects across energy levels illustrate why a multidimensional, dependence-based perspective is necessary.
  - Co-allocation of household resources and movements across dependence structure, not just average budget pressure and marginal effects.

- Effect largely robust across household profiles, but differences in size and the location of quantiles wrt, e.g., state of residence or income.

Conclusions II

- In relation to household budget studies:
  - Energy subsidies: added income raises energy spending rather than freeing resources; energy needs are rigid.
  - Food subsidies: support frees income that can ease energy pressure $\rightarrow$ food consumption is often inframarginal.

- Policy setting:
  Food subsidy recipients: freed-up budget, possible spillover to energy.
  Energy subsidy recipients: still constrained, little spillover to food.
  $\rightarrow$ Coordinated programs are needed to relieve both constraints.

Outlook

- Bootstrap for all settings and improved reasoning of household profiles.
- Comparison to univariate quantile regression and Seemingly Unrelated Regression.
- Verify parallel trends assumption and document all pre-checks.
- Work out consequences for policy set-up.
- Overall: policy effects at the upper end of the income distribution.

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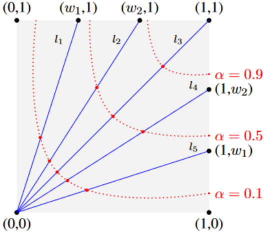
Derivation of the conditional quantiles $Q_\alpha^{Y|X}(x)$

1. Choose a combination of covariates $\boldsymbol{x}_0 \in \mathbb{R}^K$ and store conditional distribution parameters $\hat{\theta}_1(\boldsymbol{x}_0), \ldots, \hat{\theta}_7(\boldsymbol{x}_0)$.
2. We determine values $(v_1^*, v_2^*) \in [0,1]^2$ for which the condition $C_{V_1,V_2|X_0}(v_1, v_2|\boldsymbol{x}_0) = \alpha$ holds with $C_{V_1,V_2|X_0}$ defined by $\hat{\theta}_7(\boldsymbol{x}_0)$. Follow a line search algorithm to determine $(v_1^*, v_2^*) \in [0,1]^2$.



3. Values (v_1^*, v_2^*) are transformed to the original data space by the inverse conditional distributions $F^{-1}_{Y_1|\mathbf{x}_0}(v_1^*)$ and $F^{-1}_{Y_2|\mathbf{x}_0}(v_2^*)$. We obtain $Y^* = (y_1^*, y_2^*)$ which are on the quantile line $Q_\alpha^{Y|X}(\boldsymbol{x}_0)$.