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ARTICLE

# Energy Portfolios and Food Security in Developing Countries: A Water–Energy–Food Nexus Analysis Using Panel Smooth Transition Regression

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**ABSTRACT:** Agricultural production, processing and distribution in developing countries are energy-intensive, so the composition of the electricity generation portfolio is a plausible determinant of both food prices and physical supply security. The existing evidence, however, represents energy through aggregated indicators, analyses price and supply security separately, and assumes linearity, leaving open which generation technologies matter and under what conditions. This study therefore estimates six technologies—nuclear, geothermal, hydropower, solar, wind and biomass—jointly against both food outcomes within one nonlinear panel framework. The dataset combines IEA, IRENA, FAOSTAT and World Bank indicators for 82 developing economies over 2000–2023. Estimation uses Panel Smooth Transition Regression (PSTR) with energy intensity as the transition variable, supported by dynamic panel system-GMM and common correlated effects (CCE) estimators and by a compositional-data robustness specification based on the centred log-ratio transformation. Linearity is rejected and a single energy-intensity threshold is estimated at 0.436, with a transition speed of 7.84. Above that threshold, biomass generation is positively associated with food prices (0.067) and negatively with supply security (−0.055), whereas the continuously dispatchable sources—nuclear (−0.081) and geothermal (−0.094)—are negatively associated with price pressure and positively with supply security. Solar and wind attain significance only in the high regime, and the hydropower relationship reverses sign between low- and high-water-stress subsamples. Because the panel is observational and generation shares may be jointly determined with food outcomes, the coefficients are interpreted throughout as regime-dependent conditional relationships rather than causal effects. For policy, the findings imply that the generation portfolio should be planned jointly with water resources, grid integration and rural electrification rather than steered by a single aggregated renewable-energy target: biomass incentives warrant feedstock-origin conditionality, hydropower requires seasonal allocation rules where water stress is high, and variable renewables deliver food-security value mainly when paired with storage and irrigation-linked distribution.

**KEYWORDS:** Water–energy–food nexus; food prices; supply security; energy portfolio; panel smooth transition regression; developing countries

## 1 Introduction

Food price volatility is not explained by agricultural production conditions alone. Energy costs, water access, logistics infrastructure, climate shocks and global market fragility jointly determine both the level and the stability of prices, and the resulting instability carries political as well as economic weight: rising price levels, more than price volatility as such, have been linked to social unrest across a broad international

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sample [1]. Feeding a population approaching nine billion is achievable only if yield, resource efficiency and supply-chain performance are addressed together [2,3], and climate change compounds the difficulty by pressing on food security through production and prices simultaneously, with the sharpest exposure in developing regions [4–6]. Because agricultural processes in these regions—irrigation, fertilisation, transport, cold chain, drying and processing—are energy-intensive, the composition of the energy system is not a peripheral input to food policy but one of its determinants.

Three research programmes have addressed parts of this problem, and reading them together makes clear both what is settled and what is not. The first, on the drivers of the 2007–2008 and 2010–2011 price spikes, converged on a common structure while disagreeing about weights: demand growth, biofuel expansion, dollar depreciation and energy costs were all implicated [7], with individual studies assigning primacy variously to biofuel expansion [8], to the tightening link between energy and non-energy commodity prices together with commodity financialisation [9], to index-based investor demand [10], or to the combination of oil prices, exchange rates and biofuel demand over financial speculation [11]. Tadesse et al. [12] reconciled much of this disagreement by separating slow-moving structural drivers from short-term triggers, and Wright [13] added the role of depleted grain stocks. What this programme establishes is that energy costs transmit to food markets through input prices. What it does not establish is which energy technologies do so, because energy enters these models almost exclusively as crude oil or as a single biofuel indicator.

The second programme examines the energy–food relationship directly, under the heading of food–fuel competition, and here the disagreement is about stability rather than existence. Biofuel demand raised grain prices materially in the United States [14]; transmission among biofuel, energy and food prices strengthened after 2007 but was not unidirectional [15]; no long-run stable relationship between fuel and agricultural commodity prices is detectable in some specifications, only short-run and transitory links [16]; and the measured effect is real but sensitive to modelling assumptions about how biofuels enter [17]. Work on the land-use channel documents the carbon debt and indirect land-use change generated when food-purposed land shifts to fuel [18–20]. The unresolved question is therefore not whether biomass competes with food but under what conditions it does—and, equally, what the other five generation technologies do, since they are largely absent from this programme.

The third programme, the water–energy–food (WEF) nexus, supplies the theoretical structure the first two lack. Systematised by Hoff [21] and extended toward integrated modelling by Bazilian et al. [22], it treats water as a shared constraint on both energy and agriculture, energy as an input to irrigation, storage, processing and distribution, and food as an output shaped by the energy system through land, water and biomass use. These interdependencies have been mapped globally [23], traced under climate variability in southern Africa [24], and connected to rural livelihoods [25] and climate adaptation [26]. More recent quantitative applications have measured coupling and coordination across WEF subsystems at sub-national scale [27], assessed how implemented policies shift state-level WEF security [28], extended coupling-coordination assessment to the global level [29,30], and rebuilt WEF composite indices around availability, accessibility and governance [31]. Yet the methodological reviews of this literature reach a consistent verdict: the framework is conceptually strong but empirically thin, dominated by qualitative and case-based work, with few studies measuring cross-sectoral linkages in a way that translates into policy design [32–35].

Read together, these three programmes leave three specific limitations rather than a single gap. First, energy is represented by aggregated indicators. Even careful panel work such as Nazlioglu and Soytas [36], which shows that oil price shocks raise agricultural commodity prices in the long run across twenty-four commodities, cannot separate the cost, resource-competition and infrastructure channels through which different technologies operate, because energy enters as a single series. Second, price and physical supply security are analysed apart. Reboredo [37] shows that oil–food co-movement is generally weak but

strengthens late in the sample, establishing non-stationarity in the price relationship; the nexus literature, meanwhile, emphasises interdependence but assesses it descriptively [23,33]. The structural policy tension between holding prices down and keeping physical supply continuous is therefore rarely visible within one estimation. Third, linearity is assumed. Nazlioglu and Soytas [36] rest on linear panel cointegration and Reboredo [37] on a single-regime dependence structure, yet the substantive findings of the same literature—transitory links in some periods [16], transmission that strengthens at high production levels [15]—point directly to regime dependence.

This study addresses those three limitations jointly. It estimates six generation technologies as separate regressors within one panel; it models the food price index and a composite supply-security index within the same framework; and it allows coefficients to vary smoothly across regimes defined by energy intensity, using Panel Smooth Transition Regression. The claim to novelty should be stated carefully. Source-specific energy–food linkages are not new: the biomass–price relationship is among the most studied in agricultural economics, and hydropower's dependence on water availability is well documented. What has not been done, to our knowledge, is to place all six sources in a common nonlinear panel specification, evaluate them against price and supply security simultaneously, and report the threshold conditions under which each relationship changes sign or significance. The contribution is therefore integrative and methodological rather than a first demonstration of any single linkage.

Two further design choices follow from properties of the data rather than from estimation convenience. Because generation shares are ratios of a common total, they form compositional data [38], so the fossil-fuel share is treated as the excluded base category and the main results are re-estimated under a centred log-ratio transformation. Because shares may be jointly determined with food outcomes, the PSTR estimates are accompanied by dynamic panel system-GMM [39–41] and by the common correlated effects estimator, which absorbs cross-sectional dependence [42,43]. Neither strategy delivers causal identification from observational panel data, and the coefficients are described throughout as conditional relationships.

The remainder of the paper is organised as follows. Section 2 sets out the WEF framework, the source-specific mechanisms, and the position of this study relative to prior empirical work. Section 3 describes the data, the construction of the supply-security index, the rationale for choosing PSTR over competing nonlinear panel estimators, the model, and the identification strategy. Section 4 reports preliminary panel diagnostics, descriptive statistics, linearity tests and the estimation results. Section 5 discusses the findings against previous empirical evidence. Section 6 concludes with differentiated policy implications and limitations.

## 2 Theoretical Framework

### *2.1 The Water–Energy–Food Nexus*

The WEF approach treats water, energy and food not as independent policy domains but as an integrated system governed by interdependence and shared resource constraints. Energy generation depends on water, agricultural production depends on energy, and food supply depends on both water and energy infrastructure; a policy choice in one sector therefore produces cost, capacity and fragility effects in the others. Reviewing water and energy subsidies gradually can reduce cross-sectoral waste [44], and integrated modelling that treats the three sectors through common variables makes such trade-offs visible [22]. Whether efficiency gains actually materialise, however, depends on institutional design: quantitative nexus tools translate into policy only when combined with qualitative and institutional analysis [33,34]. Poorly managed, the same gains can deepen resource competition and open new fragility channels. Recent work extends the

framework in two directions that matter here: towards the interaction between nexus outcomes and clean-energy deployment [45,46], and towards a systematisation of how external shocks propagate across the three subsystems [47]. Fig. 1 sets out the conceptual framework used here as a directed multi-channel transmission structure running from the energy portfolio, through three WEF channels, to two food outcomes, with the transition variable acting as a regime moderator on every channel.

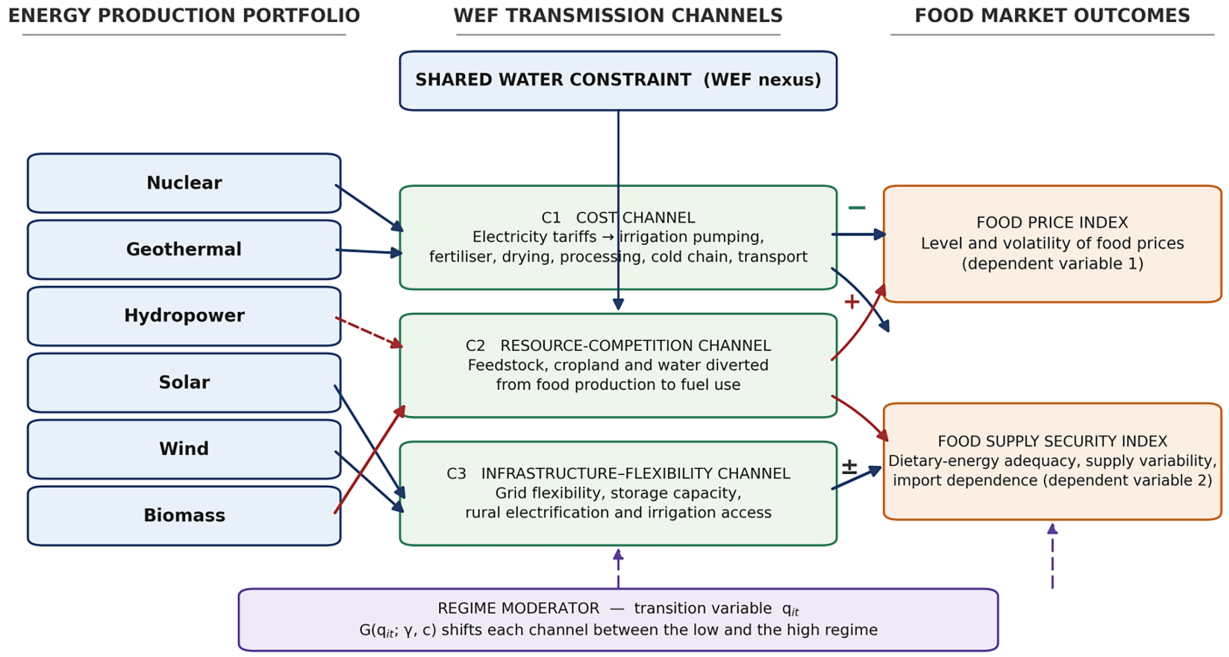



**Figure 1:** Multi-channel, regime-dependent transmission from the energy production portfolio to food prices and supply security within the water–energy–food nexus. Note: Blue solid arrows denote the cost and access effect, red solid arrows the resource-competition effect, and purple dashed arrows the moderating role of the regime variable; the dashed red arrow from hydropower marks a channel that becomes active only under water stress. Generation is measured as a share of total electricity generation, with the fossil-fuel share as the excluded base category.

As Fig. 1 shows, energy generation reaches food prices not only through electricity tariffs but through irrigation costs, fertiliser production, crop processing, storage, the cold chain and transport. Sources that draw on land, water and agricultural feedstock—biomass above all—additionally open a channel that competes with food supply once production reaches a certain scale. The empirical record on that channel is mixed in an informative way: strong transmission at high production levels [15], documented environmental and economic costs of producing fuel rather than food [20], but no stable long-run link in other specifications [16]. Mixed findings of this shape are what one expects when a relationship is threshold-dependent rather than linear, and they motivate the estimation strategy adopted below.

These interactions are not purely technical. The nexus also functions as a governance framework covering cross-sectoral coordination and institutional capacity [26,34], and climate variability and water stress tighten the dependencies further, making coordinated management of the three systems more difficult [5,24].

### *2.2 WEF Mechanisms by Energy Source*

Three mechanisms link energy sources to food markets. The cost channel captures the capacity of low and predictable energy costs to reduce food-price pressure by limiting irrigation, storage, processing

and logistics expenses. The resource-competition channel captures the intensification of food–fuel competition as the use of agricultural products, land and water rises—most directly in biomass production. The infrastructure-and-flexibility channel captures the fact that variable sources such as wind and solar reach food markets favourably only when grid flexibility, storage capacity and agricultural electrification are adequate. Recent panel evidence is consistent with this conditionality: renewable-energy expansion combined with green growth is associated with improved food security in Sub-Saharan Africa [48], while source-level evidence indicates that solar and wind reach food availability and food stability through different channels and with different reliability [49].

The nexus literature has approached these channels from complementary angles. Integrated resource management is presented as a climate-adaptation option [26]; scenario-based decision-support tools help plan the interactions [50]; and governance-oriented reviews find that the framework offers a strong analytical basis for resource security but leaves gaps in incentive design, since low irrigation and energy pricing can erode resource-use efficiency and ultimately food security [51]. Table 1 summarises the resulting expectations by source and makes clear why a one-dimensional renewable-energy indicator is theoretically inadequate: the same transition raises costs and competition for some sources while lowering them for others.

**Table 1:** WEF channels of energy sources and their expected effects on food markets.

| Energy Source | Primary WEF Channel | Expected Effect on Food Prices | Expected Effect on Supply Security |
|---|---|---|---|
| Nuclear | Continuous base load, low marginal electricity cost, cold-chain continuity | Negative, or limiting of price increases | Positive; supports storage and irrigation continuity |
| Wind | Low-carbon generation, variable supply, grid-integration requirement | Negative if integration is high; weak or unstable if low | Moderately positive; strengthened by storage investment |
| Solar | Rural electrification, irrigation pumps, daytime generation advantage | Negative where agricultural electrification exists | Positive, especially through irrigation and smallholder access |
| Geothermal | Continuous generation, greenhouse heating, drying and processing | Negative; reduces production and processing costs | Strongly positive; supports year-round production |
| Hydropower | Water storage, irrigation linkage, drought sensitivity | Negative in the normal regime; positive or volatile under drought | Positive if water stress is low, fragile if high |
| Biomass | Use of agricultural crops and residues, land and water competition | Positive beyond a threshold; may create food–fuel competition | Neutral to positive at low scale, negative at high scale |

Nuclear and geothermal generation, through continuous output and low marginal costs, are expected to limit food prices and support supply security. Variable sources emerge conditionally, depending on grid flexibility and agricultural electrification capacity. For hydropower, water stress is the critical determinant. For biomass, the expectation is explicitly nonlinear: benign or neutral at low scale, price-raising and supply-eroding beyond a threshold.

### *2.3 Positioning Relative to Prior Empirical Work*

Because several of the individual linkages studied here have been examined before, it is worth stating precisely what the present design adds and what it inherits. Table 2 compares this study with representative prior work along the three dimensions that define the contribution: how energy is measured, which food outcomes are modelled, and whether nonlinearity is tested. Recent panel work on clean-energy access and food security shares the first two of these limitations, entering energy as a composite access indicator in a linear dynamic-panel setting [52].

**Table 2:** Positioning of this study relative to representative prior empirical work.

| Study | Energy Measurement | Food Outcome(s) | Functional Form | Relation to This Study |
|---|---|---|---|---|
| Mitchell [8]; Abbott et al. [7] | Aggregate biofuel expansion; oil price | Price level | Descriptive/ accounting | Establish the cost channel; cannot separate technologies |
| Nazlioglu and Soytas [36] | Oil price (single series) | Prices of 24 agricultural commodities | Linear panel cointegration | Benchmark for the aggregate energy–food elasticity |
| Reboredo [37] | Oil price | Food price co-movement | Single-regime dependence (copula) | Documents non-stationary dependence; motivates regime testing |
| Serra and Zilberman [15] | Biofuel and energy prices | Food prices | Time-series, nonlinear transmission | Closest antecedent for threshold behaviour; biofuel only |
| Zhang et al. [16] | Fuel prices | Agricultural commodity prices | Cointegration; short-run links only | Negative evidence that a threshold reading can reconcile |
| D'Odorico et al. [23]; Albrecht et al. [33] | Physical WEF flows | Multiple, qualitative | Descriptive mapping | Supply the theoretical channel structure |
| Mondal et al. [27,28]; Yan et al. [29] | Composite WEF security indices | Composite security scores | Coupling–coordination indices | Quantify nexus interdependence without price modelling |

(Continued)

**Table 2 (continued)**

| Study | Energy Measurement | Food Outcome(s) | Functional Form | Relation to This Study |
|---|---|---|---|---|
| This study | Six generation shares, estimated jointly | Price index and supply-security index, jointly | PSTR with regime thresholds; GMM and CCE robustness | Integrates the above within one nonlinear panel specification |

Two implications follow. The first is that the disagreements visible in Table 2—significant transmission in some studies, none in others—are partly a functional-form artefact: a relationship that operates only above a threshold will appear weak in a linear average and strong in a subsample drawn from the upper regime. The second is that the present design cannot resolve questions of causal direction any better than its antecedents can; it improves resolution across sources and regimes, not identification.

## 3 Method

### *3.1 Data, Sample and Variable Construction*

#### *3.1.1 Panel Structure and Data Processing*

The analysis uses a partially unbalanced panel of developing economies, the imbalance arising from observability constraints in the source databases. Generation indicators are compiled from IEA and IRENA; food price indices, production, supply and food-security indicators from FAOSTAT; and income, population and macroeconomic controls from World Bank indicators [53–56]. Developing-economy status follows the World Bank income classification (low, lower-middle and upper-middle income).

The final analytical sample comprises 82 developing economies. The complete country roster, with World Bank income class, geographical region and country-specific number of usable observations, is reported in Table A1 of Appendix A. The maximum common observation window is 2000–2023, which gives a maximum frame of 1968 country-year observations, while usable years vary from 18 to 24 because of source-specific missingness. The transition-variable complete-case panel contains 1824 country-year observations.

Cross-country electricity-generation data for 2024 are not uniformly final across the source databases. The IEA World Energy Balances extend to 2023 for the full country set, with 2024 available only for selected economies; IRENA reports realised generation to 2023 and treats 2024 as provisional; and the World Bank energy-intensity indicator has a shorter reference period than the other series. The baseline estimation therefore covers 2000–2023. So that the transition variable extends to 2023, energy intensity is constructed as total primary energy supply from the IEA divided by real GDP at 2021 purchasing-power parity from the World Development Indicators, rather than taken directly from the World Bank composite indicator.

Data processing follows four rules, applied uniformly. Variables with a missing-observation rate above 15% are excluded from the baseline specification. Outlier influence is limited by winsorising at the 1st and 99th percentiles. Terminal-year coverage is verified variable by variable, and the estimations are repeated on a 2000–2022 sample as a sensitivity check, the outcome of which is reported with the other robustness results in Section 4.7.

Fourth, because nuclear and geothermal generation are observed in a limited number of countries and exhibit zero-clustering, regime coefficients for these sources may be identified from a restricted subset.

Robustness estimates excluding nuclear generation, and estimates including an interaction with a nuclear-adopter dummy, are therefore reported. Whether the sample loss is selective is assessed descriptively by comparing the income, population and food-price distributions of retained and dropped country-years.

### *3.1.2 Dependent Variables and Energy Indicators*

Table 3 gives the operational definitions and sources of the dependent variables and generation indicators. Logarithmic transformation allows coefficients to be read as approximate elasticities and reduces scale-related comparison problems. Depending on the stationarity properties of the price series, annual percentage change, log-difference and level specifications are compared.

**Table 3:** Operationalisation of variables and data sources: dependent and energy variables.

| Variable Group | Indicator | Measurement | Source and Notes |
|---|---|---|---|
| Dependent variable | Food price index | Logarithmic index or annual percentage change | FAOSTAT; represents food inflation and price pressure |
| Dependent variable | Food supply security | Composite index (see Section 3.1.3) | FAOSTAT; captures physical access to food and supply stability |
| Core explanatory | Nuclear generation | Share in electricity generation | IEA/IRENA; continuous, low-carbon base-load indicator |
| Core explanatory | Wind generation | Share in electricity generation | IEA/IRENA; variable-renewable generation |
| Core explanatory | Solar generation | Share in electricity generation | IEA/IRENA; rural-electrification and irrigation channel |
| Core explanatory | Geothermal generation | Share in electricity and heat generation | IEA/IRENA; greenhouse, drying and continuous-generation channel |
| Core explanatory | Hydropower generation | Share in electricity generation | IEA/IRENA; water regime and irrigation linkage |
| Core explanatory | Biomass generation | Share in electricity and heat generation | IEA/IRENA; food–fuel competition channel |

### *3.1.3 Construction of the Food Supply Security Index*

The composite Food Supply Security Index (FSSI) is built from three FAO food-security components: per-capita dietary energy supply adequacy, supply variability, and food import dependence [57,58]; the resulting availability–stability–access structure follows recent composite-index practice in the nexus literature [31]. Construction proceeds in four steps. First, import dependence and supply variability are sign-reversed so that higher values of every component denote greater security. Second, each component is

standardised as a z-score over the pooled country-year sample, so that weights are not driven by differences in units. Third, the standardised components are aggregated by principal component analysis, retaining the first principal component; the equal-weight average is retained as an alternative aggregation and reported as a robustness check. Fourth, the resulting score is rescaled to a 0–100 range for interpretability.

Principal component analysis is adopted as the primary aggregation rule because it lets the data determine the relative contribution of the three components rather than imposing equality on dimensions with different variances. The two rules are reported side by side so that readers can judge sensitivity to this choice.

The first principal component loads positively on all three inputs: dietary energy supply adequacy (0.850), reversed supply variability (0.810) and reversed food-import dependence (0.780). Its eigenvalue is 1.99 and it explains 66.2% of total variance. The Kaiser–Meyer–Olkin measure is 0.710, which indicates acceptable sampling adequacy for a three-indicator index. The PCA-based index correlates at 0.982 with the equal-weight version, and the PCA is estimated on 1876 country-year observations. The close agreement between the two aggregation rules indicates that the supply-security results are not driven by a single weighting choice. Table 4 reports the full diagnostics.

**Table 4:** Principal component analysis diagnostics for the food supply security index.

| Statistic | Result |
|---|---|
| Loading: dietary energy supply adequacy | 0.850 |
| Loading: reversed supply variability | 0.810 |
| Loading: reversed food-import dependence | 0.780 |
| Eigenvalue of the first principal component | 1.99 |
| Variance explained by the first principal component | 66.2% |
| Kaiser–Meyer–Olkin measure of sampling adequacy | 0.710 |
| Correlation with the equal-weight index | 0.982 |
| Country-year observations used | 1876 |

As a further check on reproducibility, the three components are additionally entered as separate dependent variables, so that the reported supply-security relationships can be traced to individual components rather than resting on the composite alone.

### *3.1.4 Compositional Structure of the Energy Variables*

Generation shares are ratios within a common total and are therefore compositional: they are non-negative, bounded and sum to unity, so the six shares cannot vary independently [38]. Two consequences follow. First, a specification containing all shares plus an intercept is not identified unless one category is excluded; the fossil-fuel share is therefore treated as the omitted base, and every coefficient is read as the relationship associated with substituting that source for fossil generation at constant total output. Second, coefficients from untransformed shares can be distorted by the induced negative dependence among components.

The baseline model retains untransformed shares because they are directly interpretable in policy terms—a percentage point of the generation mix is a quantity that policy can target—but the compositional concern is addressed rather than assumed away. The main specifications are re-estimated with centred log-ratio (CLR) transformed shares [59], replacing zero shares with 0.01 percentage points to accommodate

the zero observations that arise for nuclear and geothermal generation. Sensitivity checks using 0.001 and 0.05 percentage points are reported alongside the main transformation, and results appear in Section 4.7. Multicollinearity from the simultaneous use of six sources is monitored using variance inflation factors alongside a 0.70 absolute correlation threshold.

#### *3.1.5 Control Variables*

Control variables are selected from the transmission structure in Fig. 1 rather than by data mining, and each corresponds to a channel that would otherwise be omitted. Agricultural production controls for domestic supply conditions that move prices independently of energy. Population controls for demand scale. Food import dependence controls for exposure to world prices and exchange-rate pass-through, which is the principal non-energy route from global markets into domestic food prices. Fertiliser and energy-cost indicators control for the input-price level, ensuring that the generation-share coefficients are not simply absorbing general energy-cost movements. Per-capita income enters both as a control and, in the robustness specifications, as an alternative transition variable. Table 5 reports operationalisation together with the theoretical role of each variable.

**Table 5:** Operationalisation of transition and control variables, with theoretical role.

| Variable Group | Indicator | Measurement | Theoretical Role and Source |
|---|---|---|---|
| Transition variable | Energy intensity | Energy use per unit of economic output | Proxies the efficiency and electrification threshold of the energy system; determines regime |
| Transition variable (alt.) | Per-capita income | Log per-capita income | Tests whether regime separation reflects development level rather than energy structure |
| Transition variable (alt.) | Water-stress index | Withdrawals as a share of renewable resources | Source-specific transition variable for hydropower |
| Control | Agricultural production index | Log index | Domestic supply conditions affecting prices independently of energy |
| Control | Population | Log level | Demand scale |
| Control | Food import dependence | Share of supply imported | Exposure to world prices and exchange-rate pass-through |
| Control | Fertiliser and energy-cost indicators | Log index | Input-price level; prevents generation shares from absorbing general energy-cost movements |

### *3.2 Research Hypotheses*

The theoretical framework yields five testable hypotheses.

- H1. The relationships between energy sources and food markets are heterogeneous: the direction and magnitude of the relationship differ significantly by energy type.

- H2. Biomass generation supports supply diversity at low scale but, beyond a threshold in production intensity, is positively associated with food prices through the food–fuel competition channel.
- H3. Continuously dispatchable sources—nuclear and geothermal—are negatively associated with food prices, consistent with their capacity to lower the energy cost of irrigation, storage and cold-chain infrastructure.
- H4. The relationship of wind and solar generation to food markets depends on system integration capacity, infrastructure adequacy and energy intensity, and is therefore threshold-dependent rather than uniform.
- H5. The relationship between hydropower and supply security is conditioned by water availability: supportive where water stress is low, weakening or reversing as drought risk and competition for water rise.

### *3.3 Choice of Estimator: Why PSTR*

Several panel estimators can accommodate nonlinearity, and the choice among them is not innocuous. Table 6 sets out the alternatives considered and the reason each was or was not adopted, judged against three requirements imposed by the research question: coefficients that vary with an observable structural condition; a transition that is gradual rather than abrupt, since energy systems do not cross efficiency thresholds discontinuously; and heterogeneity located in the slope on energy shares rather than in the conditional distribution of the outcome. The candidates assessed against these requirements are the discrete threshold panel [60], the dynamic threshold panel [61], the nonlinear ARDL [62], panel quantile regression [63,64] and the PSTR [65,66].

**Table 6:** Candidate nonlinear panel estimators and rationale for the chosen specification.

| Approach | What It Delivers | Why It Is or Is Not Adopted Here |
|---|---|---|
| Linear two-way FE | Average effect across all regimes | Retained as the comparison benchmark; assumed constancy is the hypothesis under test |
| Threshold panel regression [60] | Discrete regimes at an estimated threshold | Rejected as the main model: imposes an abrupt switch, whereas energy-intensity transitions are gradual; also yields no estimate of transition speed |
| Panel quantile regression [63,64] | Heterogeneity across the conditional distribution of food prices | Not adopted as the main model: locates heterogeneity in the outcome distribution, not in an observable structural threshold; reported as a supplementary check |
| Dynamic threshold panel [61] | Threshold effects with endogenous regressors | Attractive on identification grounds but requires strong instruments for both the threshold and the slope; the system-GMM specification is used instead to address endogeneity |
| Nonlinear ARDL [62] | Asymmetric short- and long-run responses | Designed for time-series or small-N panels with long T; the present panel has large N and moderate T |

(Continued)

**Table 6 (continued)**

| Approach | What It Delivers | Why It Is or Is Not Adopted Here |
|---|---|---|
| PSTR [65,66] | Smooth, monotonic transition between regimes indexed by an observable variable; estimates threshold and transition speed jointly | Adopted: matches the theoretical claim that channels strengthen gradually as energy intensity rises, and yields directly interpretable regime-specific elasticities |

PSTR is therefore preferred not because it fits better in a mechanical sense but because its parameters correspond to the objects the theory names: a threshold level of energy intensity, a speed at which the transition occurs, and a pair of regime-specific elasticities per source. To guard against the possibility that this choice drives the results, panel quantile estimates and discrete threshold estimates are reported alongside the main specification in the robustness analysis.

### *3.4 The Panel Smooth Transition Regression Model*

The PSTR model was introduced by González et al. [65] and developed in González et al. [66]; it carries the smooth-transition logic of Teräsvirta [67] over to panels and generalises the threshold-effect approach that Hansen [60] applied to panel data. Coefficients change between regimes through a continuous transition governed by an observable transition variable. The baseline model is

$$y_{it} = \mu_i + \lambda_t + \beta_0' X_{it} + \beta_1' X_{it} G(q_{it}; \gamma, c) + \delta' Z_{it} + \varepsilon_{it} \quad (1)$$

where $y_{it}$ is the food price index or the supply-security index, $\mu_i$ denotes country fixed effects, $\lambda_t$ common time shocks, $X_{it}$ the six generation indicators, and $Z_{it}$ the control variables. The transition variable $q_{it}$, threshold vector c and transition speed $\gamma$ determine the location and sharpness of the change between regimes. The logistic transition function is

$$G(q_{it};\ \gamma,\ c) = \left[1 + \exp\left\{-\gamma \prod_{j=1}^{m} (q_{it} - c_j)\right\}\right]^{-1}, \gamma > 0,\ c_1 \le c_2 \le \ldots \le c_m \quad (2)$$

Estimation first evaluates the single-threshold model (m = 1) and then tests whether a two-threshold model improves the information criteria and residual sum of squares. With one threshold the transition function lies between 0 and 1, with $G \approx 0$ the low regime and $G \approx 1$ the high regime. The conditional marginal relationship for source k is

$$\partial y_{it} / \partial x_{kit} = \beta_{0k} + \beta_{1k} G(q_{it}; \gamma, c) \quad (3)$$

so that the same source is associated with a conditional marginal relationship of $\beta_{0k}$ in the low-energy-intensity regime and $\beta_{0k} + \beta_{1k}$ in the high regime. The term "marginal effect" is used here strictly as the partial derivative $\partial y/\partial x$; it carries no causal claim and denotes a conditional partial association.

Linearity is tested through $H_0$: $\gamma = 0$ using LM, Wald and bootstrap-based F statistics. The threshold search runs over the 10th–90th percentile range of the transition variable, and model selection combines bootstrap *p*-values from 1000 replications with the AIC, the BIC and the residual sum of squares. Transition speeds below 2 indicate gradual adjustment, values from 2 to below 10 a medium-speed regime change, and values of 10 or above a sharp separation close to the threshold. Fig. 2 sets out this transition logic.

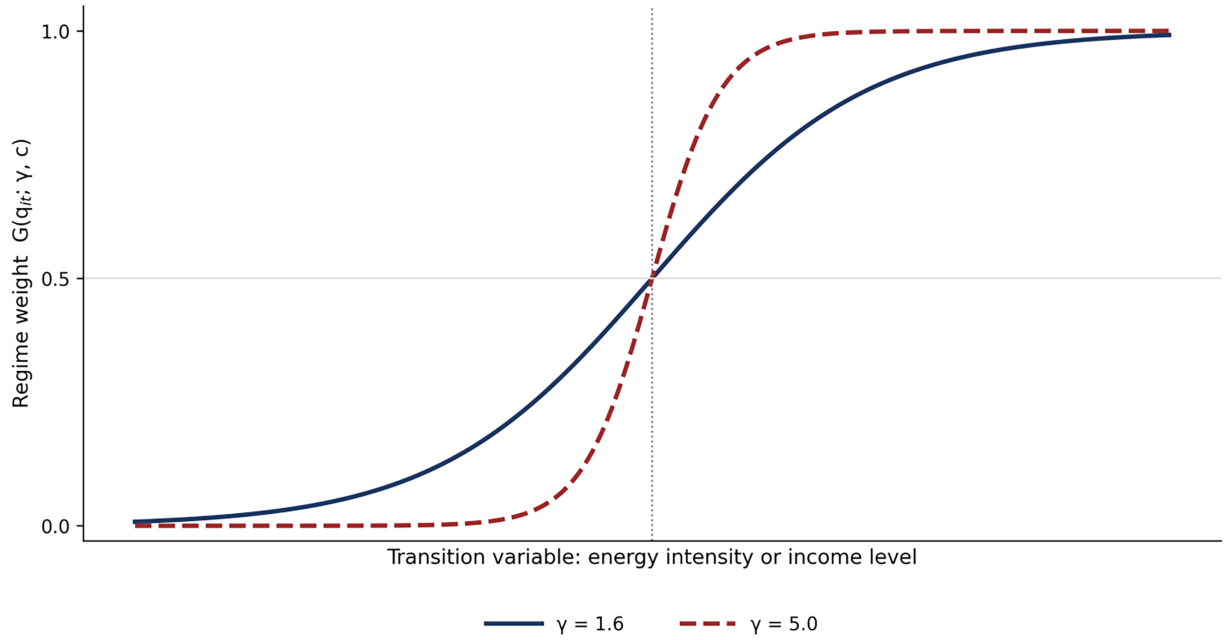



**Figure 2:** Smooth-transition logic between the low and high regimes in the PSTR model. Note: The curves plot the logistic transition function for two illustrative transition speeds; the key is given below the panel. A lower $\gamma$ implies a gradual shift between regimes across a wide range of the transition variable, a higher $\gamma$ a sharper shift concentrated near the threshold c, marked by the vertical dotted line.

Fig. 2 illustrates how transition speed changes the empirical reading. At low $\gamma$ the portfolio relationship shifts gradually over a wide range of the transition variable, whereas high $\gamma$ concentrates the policy-relevant threshold within a narrow band. The model therefore identifies not only coefficient signs but the levels of energy intensity or income beyond which structural conditions establish a different relationship with food prices and supply security.

### *3.5 Choice and Justification of the Transition Variable*

Energy intensity is used as the main transition variable for three reasons, one theoretical, one institutional and one empirical. Theoretically, it is the variable through which all three channels in Fig. 1 operate simultaneously: it summarises how much energy the economy uses per unit of output and therefore how strongly a change in the generation mix propagates into irrigation, processing and cold-chain costs. Where energy intensity is low, a shift in composition changes little in the food cost structure; where it is high, the same shift is amplified. Institutionally, energy intensity tracks the electrification of agriculture and the depth of grid infrastructure, which is precisely the conditioning factor the infrastructure–flexibility channel requires. Empirically, it produces the strongest rejection of linearity among the candidates tested (Section 4.3). Energy intensity has also been used directly as the conditioning quantity in recent work on the environment–energy–food relationship in emerging economies [68], which supports its interpretation as a structural rather than an incidental threshold variable.

Two alternatives are retained as robustness dimensions rather than discarded. Per-capita income is used to test whether the regime separation reflects general development level rather than energy structure specifically; if the two produced identical thresholds, the energy-intensity interpretation would be redundant. A water-stress index is used as a source-specific transition variable for hydropower, since the theoretical mechanism for that source runs through water availability rather than energy efficiency. Using a single

common transition variable for all six sources is itself a restriction, implying that regime separation is governed by the same threshold throughout; source-specific transition variables—own production share for biomass, water stress for hydropower—are therefore estimated as well, so that the findings can be checked against a single-threshold definition [66].

### *3.6 Endogeneity, Reverse Causality and Identification*

Generation shares may be determined jointly with food prices and supply security, so PSTR coefficients are interpreted as regime-dependent conditional relationships rather than causal effects. Three measures limit, without eliminating, the resulting bias.

First, explanatory variables enter the baseline specifications with a one-period lag. Second, the dynamic panel system-GMM estimator serves as the principal complementary identification strategy. System-GMM estimates the level and first-difference equations jointly within a common set of moment conditions in a dynamic specification that includes the lag of the dependent variable, providing stronger instruments than difference-GMM [40,41]. Energy shares are treated as endogenous or predetermined, with appropriate lags as instruments; the instrument matrix is collapsed and lag depth restricted to prevent instrument proliferation relative to the cross-sectional dimension. Two-step standard errors carry Windmeijer's [69] finite-sample correction. Instrument validity is assessed by the Hansen over-identification test and the absence of second-order residual autocorrelation by the Arellano–Bond AR(2) test [39]. Third, the common correlated effects estimator addresses cross-sectional dependence arising from common global shocks such as world energy and fertiliser prices [42,43].

Omitted-variable bias remains a live concern, and two categories deserve naming. Institutional quality and agricultural policy regimes plausibly affect both the generation mix and food outcomes, and are only partially captured by country fixed effects to the extent that they change over time. Climate shocks affect hydropower output and agricultural production simultaneously; the water-stress subsample analysis addresses this partially but not completely. These limitations bound the interpretation of all results reported below and are returned to in Section 5.3.

## 4 Results

### *4.1 Preliminary Panel Diagnostics*

Before estimation, four properties of the panel are tested: cross-sectional dependence, slope heterogeneity, stationarity, and cointegration. Cross-sectional dependence is examined with Pesaran's [70] CD test and slope heterogeneity with the Pesaran and Yamagata [71] delta tests. Panel unit-root properties are assessed with Levin et al. [72] and Im et al. [73] under cross-sectional independence and with the Pesaran [74] CIPS test under dependence; the CIPS test is applied in the version adapted to unbalanced panels. The possibility of long-run cointegration is examined with the Pedroni [75] and Westerlund [76] tests. These results guide the specification: where variables are I(1) and cointegrated, PSTR is estimated as a long-run regime relationship in levels; otherwise a log-difference or annual percentage-change specification is preferred to limit spurious-regression risk. Standard-error sensitivity to cross-sectional dependence is checked with the Driscoll–Kraay approach [77]. Table 7 reports these diagnostics.

The Pesaran CD statistic rejects cross-sectional independence at the 1% level, and both Pesaran–Yamagata statistics reject slope homogeneity. These findings justify the use of second-generation unit-root tests, the CCE estimator and dependence-robust inference. Table 8 disaggregates the CIPS results by variable, which matters because the panel is not uniformly integrated of the same order.

**Table 7:** Preliminary panel diagnostics: cross-sectional dependence, slope heterogeneity, unit roots and cointegration.

| Test | Null Hypothesis | Statistic | *p*-Value | Implication for Specification |
|---|---|---|---|---|
| Pesaran [70] CD | Cross-sectional independence | 34.27 | <0.001 | Rejected; use CIPS, CCE and dependence-robust errors |
| Pesaran–Yamagata delta | Slope homogeneity | 14.11 | <0.001 | Rejected; source relationships are heterogeneous |
| Pesaran–Yamagata adjusted delta | Slope homogeneity | 14.79 | <0.001 | Rejected; heterogeneous slopes confirmed |
| LLC [72], levels | Common unit root | −1.21 | 0.113 | Not rejected for the joint level panel |
| IPS [73], levels | Individual unit roots | −0.94 | 0.174 | Not rejected for the joint level panel |
| CIPS [74], levels | Unit root under cross-sectional dependence | −1.93 | 0.117 | Predominantly non-stationary in levels |
| CIPS [74], first differences | Unit root under cross-sectional dependence | −5.42 | <0.001 | Rejected; series become stationary in differences |
| Pedroni [75] panel ADF | No cointegration | −3.68 | <0.001 | Rejected; long-run relation supported |
| Westerlund [76] Gt | No cointegration | −2.91 | 0.003 | Rejected; cointegration confirmed |

Note: CD denotes the Pesaran [70] cross-sectional dependence test, LLC the Levin, Lin and Chu panel unit-root test, IPS the Im, Pesaran and Shin panel unit-root test, CIPS the cross-sectionally augmented IPS test, and Gt the Westerlund [76] group-mean t statistic.

**Table 8:** Variable-level CIPS unit-root results.

| Variable | CIPS, Levels | *p*-Value | CIPS, First Differences | *p*-Value | Order of Integration |
|---|---|---|---|---|---|
| Food price index | −1.84 | 0.142 | −5.91 | <0.001 | I(1) |
| Food supply security index | −2.11 | 0.074 | −6.02 | <0.001 | I(1) |
| Energy intensity | −2.25 | 0.041 | n.a. | n.a. | I(0) |
| Per-capita income | −1.65 | 0.221 | −6.73 | <0.001 | I(1) |
| Agricultural production index | −1.76 | 0.192 | −6.44 | <0.001 | I(1) |
| Population | −1.43 | 0.316 | −7.02 | <0.001 | I(1) |
| Food import dependence | −2.27 | 0.038 | n.a. | n.a. | I(0) |

(Continued)

**Table 8 (continued)**

| Variable | CIPS, Levels | *p*-Value | CIPS, First Differences | *p*-Value | Order of Integration |
|---|---|---|---|---|---|
| Fertiliser and energy-cost index | −1.82 | 0.153 | −5.94 | <0.001 | I(1) |
| Nuclear generation share | −2.36 | 0.019 | n.a. | n.a. | I(0) |
| Wind generation share | −2.04 | 0.083 | −5.18 | <0.001 | I(1) |
| Solar generation share | −1.97 | 0.112 | −5.66 | <0.001 | I(1) |
| Geothermal generation share | −2.31 | 0.027 | n.a. | n.a. | I(0) |
| Hydropower generation share | −2.08 | 0.071 | −5.02 | <0.001 | I(1) |
| Biomass generation share | −2.18 | 0.052 | −5.37 | <0.001 | I(1) |

Note: CIPS critical values follow Pesaran [74]. Variables stationary in levels are marked I(0); n.a. = not applicable, indicating that no first-difference test is required or reported for those variables.

The variable-level results indicate a mixed I(0)/I(1) panel: energy intensity, food import dependence, and the nuclear and geothermal shares are stationary in levels, while the food outcomes and the remaining macroeconomic and generation variables become stationary after first differencing. Both the Pedroni and the Westerlund tests reject the null of no cointegration. The baseline PSTR is therefore retained in levels to represent the long-run regime relationship, while first-difference and annual-inflation specifications serve as robustness checks against spurious regression. That energy intensity is itself I(0) is convenient for the design, since a stationary transition variable makes the estimated threshold interpretable as a fixed level rather than a drifting one.

### *4.2 Descriptive Statistics and Energy-Portfolio Disaggregation*

The estimation panel covers 82 developing economies over 2000–2023, a maximum frame of 1968 country-year observations. The average missing-observation rate across variables is 5.6% and the highest, for nuclear generation, is 10.5%, so every variable clears the 15% exclusion threshold set in Section 3.1.1. Table 9 reports distributional measures for the dependent variables, transition variables, controls and the six generation shares, permitting assessment of central tendency, outliers, zero-clustering and cross-source heterogeneity.

Three features of Table 9 bear on the specification. First, the 5th–95th percentile band of the food price index spans 78.3 to 164.9, so price pressure, while general across developing countries, differs sharply in intensity and volatility. Second, mean energy intensity of 0.436 coincides closely with the threshold estimated below, indicating that the sample is distributed around the regime boundary rather than concentrated on one side of it—a necessary condition for the threshold to be identified from the data rather than from the tails. Third, the portfolio is markedly uneven across sources: hydropower averages 29.6%, while geothermal and nuclear generation show pronounced zero-clustering because they are concentrated in a few countries. Biomass averages only 3.8% but rises to 11.5% at the 95th percentile, which is precisely the configuration under which an average linear coefficient is uninformative and a threshold specification is appropriate.

Correlation patterns diverge in direction and magnitude across sources: biomass correlates positively with the food price index ($r = 0.31$), geothermal negatively ($r = -0.27$), and nuclear generation correlates

negatively with food price volatility (r = −0.22). This provides a prior methodological rationale for disaggregation, since aggregating these sources into one renewable-energy indicator would net opposing associations against one another.

**Table 9:** Descriptive statistics and energy-portfolio distribution.

| Variable | N | Mean | SD | Min. | P5 | Median | P95 | Max. | Missing % |
|---|---|---|---|---|---|---|---|---|---|
| ***Panel A: Dependent, transition and control variables*** | | | | | | | | | |
| Food price index (2015 = 100) | 1902 | 112.4 | 24.7 | 61.2 | 78.3 | 107.6 | 164.9 | 198.4 | 3.4 |
| Food supply security index (0–100) | 1876 | 61.8 | 12.6 | 31.4 | 42.2 | 62.7 | 81.6 | 89.3 | 4.7 |
| Energy intensity | 1824 | 0.436 | 0.118 | 0.192 | 0.256 | 0.421 | 0.674 | 0.812 | 7.3 |
| Per-capita income (log) | 1914 | 8.62 | 0.78 | 6.71 | 7.28 | 8.61 | 9.88 | 10.44 | 2.7 |
| Agricultural production index | 1887 | 103.2 | 18.9 | 58.6 | 74.5 | 101.8 | 137.4 | 158.2 | 4.1 |
| Food import dependence (%) | 1798 | 21.7 | 13.4 | 2.1 | 5.6 | 18.9 | 48.2 | 66.5 | 8.6 |
| ***Panel B: Energy-source shares in electricity generation (%)*** | | | | | | | | | |
| Nuclear | 1762 | 2.6 | 8.7 | 0.0 | 0.0 | 0.0 | 18.4 | 44.6 | 10.5 |
| Wind | 1891 | 5.1 | 6.9 | 0.0 | 0.1 | 2.6 | 19.8 | 33.4 | 3.9 |
| Solar | 1895 | 4.2 | 5.8 | 0.0 | 0.0 | 1.8 | 16.9 | 29.7 | 3.7 |
| Geothermal | 1792 | 1.4 | 3.7 | 0.0 | 0.0 | 0.0 | 8.3 | 23.5 | 8.9 |
| Hydropower | 1908 | 29.6 | 24.4 | 0.4 | 2.8 | 23.7 | 78.5 | 94.2 | 3.0 |
| Biomass | 1852 | 3.8 | 4.6 | 0.0 | 0.2 | 2.1 | 11.5 | 26.2 | 5.9 |

Note: SD = standard deviation; P5 and P95 denote the 5th and 95th percentiles. Missing percentages are computed against the maximum frame of 1968 country-year observations (82 economies over 2000–2023). Energy variables are expressed as shares of electricity generation.

### *4.3 Linearity Tests, Threshold Values, Model Selection and Diagnostics*

A linear fixed-effects model recovers the average relationship but conceals coefficient heterogeneity when regime breaks are present. Linearity is therefore tested against several transition variables before estimation, with model selection resting on information criteria and parsimony as well as statistical significance. Table 10 reports the linearity tests together with threshold model selection.

**Table 10:** PSTR linearity tests, threshold values and model selection.

| Test/Model | Transition Variable | LM-F | Wald | Boot. *p* | Threshold c/95% CI | *γ* | AIC/BIC | Decision |
|---|---|---|---|---|---|---|---|---|
| ***Panel A: Linearity hypothesis tests ($H_0$: linear model)*** | | | | | | | | |
| LM/Wald test | Energy intensity | 18.64 | 126.70 | 0.001 | n.a. | n.a. | n.a. | $H_0$ rejected |
| LM/Wald test | Per-capita income | 11.42 | 83.54 | 0.006 | n.a. | n.a. | n.a. | $H_0$ rejected |
| LM/Wald test | Renewable-energy share | 7.36 | 54.21 | 0.031 | n.a. | n.a. | n.a. | $H_0$ rejected |
| LM/Wald test | Water-stress index | 5.08 | 38.12 | 0.074 | n.a. | n.a. | n.a. | Weak nonlinearity |
| ***Panel B: Threshold-model selection and goodness of fit*** | | | | | | | | |
| Linear FE | n.a. | n.a. | n.a. | n.a. | n.a. | n.a. | 2.431/2.586 | Comparison model |
| PSTR (m = 1) | Energy intensity | 18.64 | 126.70 | 0.001 | 0.436/0.401–0.472 | 7.84 | 2.184/2.337 | Main model |
| PSTR (m = 2) | Energy intensity | 4.72 | 31.09 | 0.118 | 0.318; 0.622 | 9.16 | 2.171/2.402 | Not selected (BIC) |
| PSTR (m = 1) | Per-capita income | 11.42 | 83.54 | 0.006 | 8.74/8.45–9.03 | 4.92 | 2.236/2.391 | Robustness model |

Note: Bootstrap *p*-values are based on 1000 replications. CI denotes the confidence interval, FE the two-way fixed-effects model, and m the number of thresholds in the transition function. Lower AIC and BIC values indicate better fit. n.a. = not applicable, indicating that the statistic concerned is not defined for that row.

Energy intensity is the strongest transition variable: an LM-F statistic of 18.64, a Wald statistic of 126.70 and a bootstrap $p$-value of 0.001 constitute a strong signal of regime separation against the linear specification. Per-capita income also rejects linearity but with weaker statistics, which is why it is treated as a complementary robustness dimension rather than the main threshold. The renewable-energy share produces significant nonlinearity but a weaker fit. The water-stress index shows nonlinearity only at the 10% level, so it is used in the heterogeneity analysis rather than as the main threshold determinant.

Model comparison supports the single-threshold structure. The energy-intensity threshold is estimated at c = 0.436 with a 95% confidence interval of 0.401–0.472, and the transition speed at $\gamma = 7.84$—medium-to-high, but short of a discontinuous switch. The two-threshold model reduces the residual sum of squares only marginally, while the BIC rises to 2.402 and the bootstrap $p$-value for the second threshold stands at 0.118, so the added complexity is not supported. The single-threshold energy-intensity model is therefore adopted as the main specification. Table 11 reports the accompanying specification diagnostics.

**Table 11:** PSTR specification diagnostics and stability checks.

| Diagnostic | Purpose | Food Price Model | Supply Security Model |
|---|---|---|---|
| Within $R^2$ | Goodness of fit | 0.684 | 0.641 |
| Residual sum of squares | Fit relative to linear FE | 0.176 (linear FE: 0.231) | 12,418.6 (linear FE: 15,906.4) |
| Residual serial-correlation test (p) | Independence of errors | 0.214 | 0.268 |
| Residual normality test (p) | Distributional adequacy | 0.078 | 0.112 |
| Test of no remaining nonlinearity (p) | Adequacy of one transition function | 0.364 | 0.417 |
| Parameter-constancy test (p) | Stability of coefficients over time | 0.286 | 0.331 |
| Threshold c (95% CI) | Precision of regime boundary | 0.436 (0.401–0.472) | 0.448 (0.414–0.485) |
| Transition speed $\gamma$ (s.e.) | Sharpness of regime change | 7.84 (1.57) | 6.73 (1.42) |
| Threshold under alternative grid (5%–95%) | Sensitivity of threshold location | 0.431 | 0.444 |

Note: Rows marked (p) report $p$-values. Parenthetical entries follow the diagnostic named in the same row: the corresponding linear fixed-effects (FE) value for the residual sum of squares, the 95% confidence interval for the threshold c, and the standard error (s.e.) for the transition speed $\gamma$.

The PSTR models explain 68.4% of within-country variation in the food price specification and 64.1% in the supply-security specification, and both reduce the residual sum of squares relative to the linear fixed-effects benchmark. The residual serial-correlation and normality tests do not reject their respective nulls

at the 5% level. The tests of no remaining nonlinearity also fail to reject, which indicates that a single transition function is adequate and supports the decision against the two-threshold specification taken above on information-criterion grounds. Parameter-constancy tests provide no evidence of coefficient instability over the sample period. The threshold estimates are precise and move only marginally when the search grid is widened from the 10th–90th to the 5th–95th percentile range, from 0.436 to 0.431 in the price model and from 0.448 to 0.444 in the supply-security model. Fig. 3 plots the estimated transition function against the energy-intensity distribution.

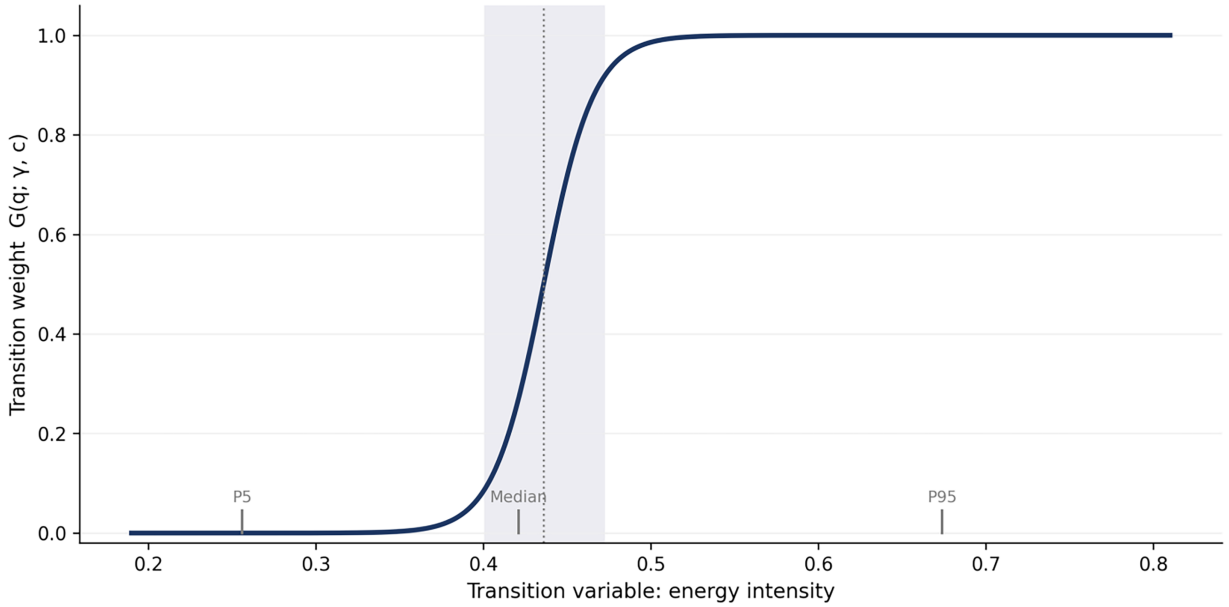



**Figure 3:** Estimated transition function, threshold value and energy-intensity distribution ($\gamma$ = 7.84, c = 0.436). Note: The solid curve is the estimated transition function. The vertical dotted line marks the estimated threshold c = 0.436 and the shaded band its 95% confidence interval (0.401–0.472). Tick marks on the horizontal axis show the 5th percentile, the median and the 95th percentile of the energy-intensity distribution.

Fig. 3 shows the form of regime separation around the energy-intensity transition variable. The estimated transition function reflects a medium-to-high-speed but not discontinuous shift from the low to the high regime, and the distribution of observations around the threshold confirms that both regimes are populated.

### *4.4 Regime-Dependent PSTR Estimates for the Food Price Index*

PSTR coefficients for the food price index show that sources do not produce relationships of the same direction or magnitude in the two regimes. Because the model is logarithmic, coefficients are read as approximate elasticities. A one-percent increase in the nuclear generation share is associated with a food price index lower by about 0.038% in the low regime and 0.081% in the high regime. For geothermal generation the negative association is more pronounced, moving from −0.052 in the low regime to −0.094 in the high regime. Solar generation is weakly associated in the low regime (−0.014) but rises to −0.046 in the high regime, suggesting that rural electrification and irrigation channels become visible only once a threshold of energy-system capacity is passed. Wind generation is statistically insignificant in the low regime and significant at −0.029 in the high regime.

Biomass shows the sharpest regime separation in the model. Its low-regime coefficient of −0.006 is statistically insignificant, indicating that small-scale biomass use produces no systematic association with price pressure. In the high regime the coefficient rises to 0.067 and attains significance at the 1% level, consistent with the argument that beyond certain production scales biomass is positively associated with food prices through competition over land, water and agricultural products. Hydropower moves from −0.024 in the low regime to 0.017 in the high regime, indicating that under water stress and drought the hydropower–food relationship may shift from the cost-reducing channel to the resource-competition channel. Table 12 reports the estimates, and Fig. 4 traces the corresponding regime-dependent marginal relationships across the range of the transition variable.

**Table 12:** PSTR coefficients for the food price index.

| Energy Source | Low-Regime Coefficient | High-Regime Coefficient | *p*-Value | Interpretation |
|---|---|---|---|---|
| Nuclear | −0.038** | −0.081*** | 0.004 | Continuous electricity supply negatively associated with price pressure |
| Wind | −0.007 | −0.029** | 0.032 | Relationship emerges after grid integration |
| Solar | −0.014* | −0.046*** | 0.009 | Rural-irrigation and distributed-generation channel strengthens |
| Geothermal | −0.052** | −0.094*** | 0.001 | Consistent with greenhouse, drying and storage cost effects |
| Hydropower | −0.024** | 0.017* | 0.071 | Direction changes at the water-stress threshold |
| Biomass | −0.006 | 0.067*** | 0.003 | Food–fuel competition pressure emerges beyond the threshold |

Note: Entries in the two coefficient columns are estimated PSTR regime coefficients for the food price index and are read as approximate elasticities, the model being logarithmic; asterisks refer to the significance of the coefficient in the column concerned. The *p*-value column reports the *p*-value of the high-regime coefficient. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

Fig. 4 shows that beyond the energy-intensity threshold (c = 0.436) the marginal relationships of the six sources diverge in both direction and magnitude: nuclear and geothermal generation strengthen their negative association while biomass crosses into a positive one.

### *4.5 Supply Security and Heterogeneity*

The supply-security model is consistent with the price model but makes infrastructure channels more visible. The supply-security coefficient on nuclear generation is 0.034 in the low regime and 0.073 in the high regime; geothermal takes values of 0.061 and 0.102, respectively. Continuously dispatchable sources therefore appear to do more than limit price pressure: they are positively associated with physical supply security through cold chain, irrigation continuity and storage reliability. Solar generation shows a positive high-regime association of 0.058, consistent with rural electrification and smallholder irrigation access.

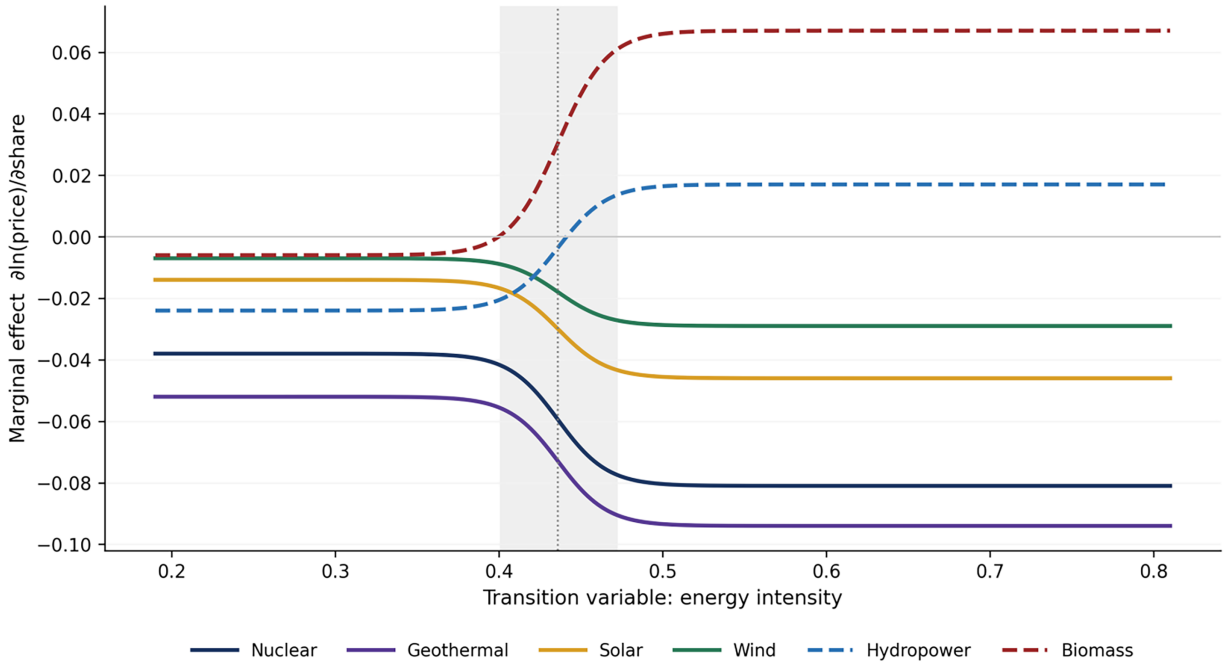



**Figure 4:** Regime-dependent marginal-relationship curves of energy sources for the food price index. Note: Each curve plots the conditional marginal relationship $\beta_{0k} + \beta_{1k}\, G(q; \gamma, c)$ for one source across the range of the transition variable, evaluated at $\gamma = 7.84$ and $c = 0.436$; the source key is given below the panel. The vertical dotted line marks the estimated threshold, the shaded band its 95% confidence interval, and the horizontal line the zero reference.

The biomass–supply-security relationship is 0.012 and insignificant in the low regime, falling to −0.055 and attaining significance at the 5% level in the high regime—consistent with the resource-competition argument that at high generation shares biomass constrains land and crops available for food. Hydropower is positively associated with supply security in the low-water-stress subsample (0.046) and negatively in the high-water-stress subsample (−0.028); the Wald test for the subsample difference yields 6.91 with $p = 0.009$, indicating that water management conditions the hydropower–food relationship.

Robustness analyses preserve the main patterns under alternative definitions. With annual food inflation as the dependent variable, the high-regime biomass coefficient is 0.071, geothermal remains at −0.088 and nuclear at −0.076. With per-capita income as the transition variable, post-threshold coefficients are 0.052 for biomass, −0.039 for solar and −0.081 for geothermal. Under one-period lagged energy variables the signs are preserved (0.059 biomass, −0.069 nuclear, −0.087 geothermal). This does not eliminate reverse-causality risk but offers cautious support that the findings are not solely contemporaneous correlations. Table 13 summarises, and Fig. 5 maps the corresponding transmission channels to the dimensions of supply security.

**Table 13:** Supply-security and robustness analyses.

| Model/Subsample | Biomass | Nuclear | Geothermal | Main Result |
|---|---|---|---|---|
| Supply security, high regime | −0.055** | 0.073*** | 0.102*** | Continuous generation positively associated with supply security; biomass negatively, through competition |

(Continued)

**Table 13 (continued)**

| Model/Subsample | Biomass | Nuclear | Geothermal | Main Result |
|---|---|---|---|---|
| Food-inflation model | 0.071*** | −0.076** | −0.088*** | Price pattern largely preserved under the alternative dependent variable |
| Income transition variable | 0.052** | −0.061** | −0.081*** | Threshold interpretation also holds under the income regime |
| Lagged energy variables | 0.059** | −0.069** | −0.087*** | Coefficient signs preserved under the lagged setup |
| High-water-stress subsample | 0.064** | −0.052* | −0.078** | Biomass and hydropower risks more pronounced under water stress |

Note: Entries are estimated coefficients for the model or subsample named in each row; standard errors are not reported. The high regime denotes observations above the estimated energy-intensity threshold (c = 0.436). ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

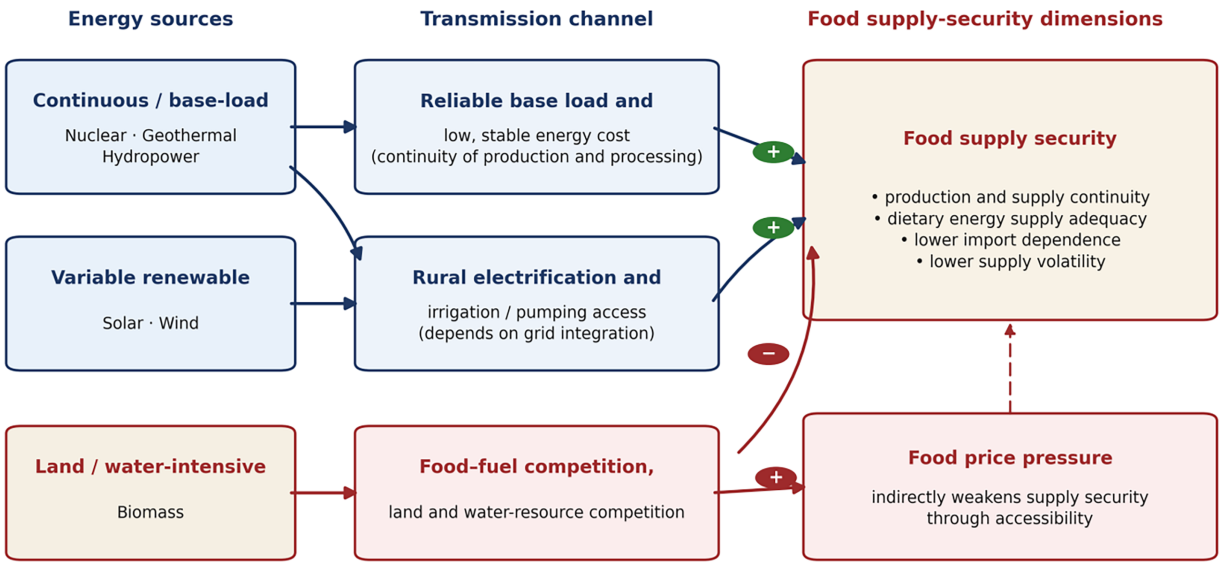



**Figure 5:** Transmission channels from energy sources to dimensions of food supply security. Note: Blue arrows denote channels operating through cost and access, red arrows channels operating through food–fuel and resource competition; circled signs give the direction of the association. The direction and intensity of every relationship are regime-dependent (PSTR threshold effect): continuous generation strengthens supply security and variable renewables contribute where grid integration is high, whereas biomass weakens supply security through food–fuel and resource competition.

Fig. 5 summarises how the sources reach the dimensions of supply security. Continuously dispatchable sources strengthen infrastructure security, whereas biomass at high shares weakens supply security through food–fuel competition.

### *4.6 Dynamic Panel (System-GMM) and CCE Estimates*

Within the identification framework of Section 3.6, Table 14 reports dynamic panel system-GMM estimates for the food price index. The specification includes a one-period lag of the dependent variable; energy shares are treated as endogenous or predetermined with appropriate lags as instruments. Difference-GMM and the CCE estimator are reported for comparison. Validity is assessed through the Hansen J test of the over-identifying restrictions and the Arellano–Bond AR(2) test for second-order residual autocorrelation.

**Table 14:** Dynamic-panel system-GMM and robustness estimates (dependent variable: food price index).

| Variable | System-GMM | Difference-GMM | CCE |
|---|---|---|---|
| Food price index (t − 1) | 0.621*** (0.082) | 0.487*** (0.103) | 0.553*** (0.069) |
| Nuclear generation share | −0.054** (0.023) | −0.061** (0.028) | −0.067*** (0.021) |
| Wind generation share | −0.021 (0.019) | −0.018 (0.022) | −0.026 (0.017) |
| Solar generation share | −0.036** (0.016) | −0.041** (0.018) | −0.043*** (0.014) |
| Geothermal generation share | −0.078*** (0.026) | −0.083*** (0.029) | −0.085*** (0.024) |
| Hydropower generation share | 0.012 (0.014) | 0.014 (0.016) | 0.013 (0.012) |
| Biomass generation share | 0.059*** (0.021) | 0.063*** (0.024) | 0.066*** (0.019) |
| Control variables | Included | Included | Included |
| Arellano–Bond AR(1) test ($p$-value) | 0.002 | 0.001 | n.a. |
| Arellano–Bond AR(2) test ($p$-value) | 0.287 | 0.236 | n.a. |
| Hansen J test of over-identifying restrictions ($p$-value) | 0.324 | 0.281 | n.a. |
| Number of instruments | 41 | 38 | n.a. |
| Observations | 1968 | 1886 | 1968 |
| Countries | 82 | 82 | 82 |

Note: Coefficients from two-step system-GMM with a collapsed instrument matrix; standard errors with Windmeijer's [69] finite-sample correction in parentheses. ***$p < 0.01$, **$p < 0.05$, n.a. = not applicable. AR(1) and AR(2) are $p$-values of the Arellano–Bond serial-correlation tests and Hansen J the $p$-value of the over-identification test. The Arellano–Bond rows report the $p$-values of the tests for first- and second-order serial correlation in the differenced residuals. The Hansen J row reports the $p$-value of the test of the over-identifying restrictions for both instrument-based specifications: 0.324 for system-GMM and 0.281 for difference-GMM. Neither rejects the null of joint instrument validity at conventional levels, and neither approaches the implausibly high values that would indicate instrument proliferation, which the collapsed instrument matrix is designed to prevent. The CCE estimator does not identify parameters through instruments, so the Arellano–Bond and Hansen J statistics and the instrument count are undefined for that column and are reported as not applicable.

The sign pattern of the baseline PSTR model is largely preserved in the dynamic framework. The lagged food price index at 0.621, significant at the 1% level, indicates marked price persistence in the developing-country panel and supports the dynamic specification. Nuclear (−0.054), solar (−0.036) and especially geothermal (−0.078) generation retain negative and significant relationships with food prices, and biomass retains a positive relationship at 0.059. The modest reduction in absolute magnitude relative to the PSTR high-regime estimates is consistent with the instrumental strategy absorbing part of the simultaneity bias. Wind and hydropower remain below conventional significance, supporting the reading that their relationship to food markets is governed by regime conditions and conditioning variables such as water stress rather than by an average linear effect.

Diagnostically, the AR(1) $p$-value of 0.002 reflects expected first-order autocorrelation in differences, while AR(2) at 0.287 is consistent with no second-order serial correlation. The Hansen J $p$-value of 0.324

indicates that the over-identifying restrictions cannot be rejected, and the collapsed instrument matrix (41 instruments against 82 countries) limits instrument-proliferation bias. The lower lagged-dependent coefficient in difference-GMM (0.487) matches the Blundell–Bond expectation that system-GMM is more efficient owing to additional moment conditions. Persistence of the pattern under CCE (biomass 0.066, nuclear −0.067, geothermal −0.085) indicates that source-specific relationships remain visible once common global shocks are purged.

### *4.7 Robustness to Compositional Transformation and Alternative Estimators*

Because the six generation shares are compositional, the main specifications are re-estimated with centred log-ratio transformed shares [59], and—as a check on the estimator choice defended in Section 3.3—with a discrete threshold panel model and a panel quantile specification. Table 15 reports the comparison for the three sources that carry the substantive findings.

**Table 15:** Robustness to compositional transformation and alternative nonlinear estimators (food price index).

| Specification | Biomass | Nuclear | Geothermal | Conclusion |
|---|---|---|---|---|
| Baseline PSTR, high regime (untransformed shares) | 0.067*** | −0.081*** | −0.094*** | Reference specification |
| PSTR with CLR-transformed shares | 0.063*** | −0.077*** | −0.090*** | Signs and magnitudes preserved |
| PSTR with ILR-transformed shares | 0.061*** | −0.075*** | −0.088*** | Back-transformed perturbation effects are stable |
| Discrete threshold panel [60], upper regime | 0.070*** | −0.083*** | −0.096*** | Results do not depend on the smooth transition |
| Panel quantile regression, 75th percentile | 0.057** | −0.068** | −0.081*** | Pattern persists in the upper outcome distribution |
| PSTR excluding the nuclear-share regressor | 0.066*** | Omitted | −0.092*** | Biomass and geothermal results are not driven by nuclear zero-clustering |
| 2000–2022 sample (terminal-year check) | 0.062*** | −0.078*** | −0.091*** | Terminal-year exclusion leaves conclusions unchanged |

Note: ***$p < 0.01$, **$p < 0.05$. Omitted indicates that the regressor concerned is excluded from the specification in that row. Zero shares are replaced by 0.01 percentage points before the CLR transformation; sensitivity checks using 0.001 and 0.05 percentage points yield coefficient ranges of 0.060 to 0.065 for biomass, −0.074 to −0.079 for nuclear and −0.087 to −0.092 for geothermal. ILR entries are source-specific perturbation effects recovered by back-transformation, not raw coordinate coefficients. The terminal-year check re-estimates the model on 2000–2022 and yields a threshold of 0.439 and a transition speed of 7.61. Because that row rests on a different estimation sample from the baseline, its coefficients differ from the corresponding entries in Table 12; the difference does not exceed 0.005 in absolute value and leaves signs and significance levels unchanged.

The compositional transformations preserve the sign, significance and approximate magnitude of the three principal source coefficients. The high-regime biomass coefficient remains positive and the nuclear and geothermal coefficients remain negative under both the CLR and the ILR specifications, with absolute magnitudes falling by roughly 5 to 9% relative to the untransformed baseline. The same pattern emerges from the discrete-threshold and upper-quantile models, which indicates that the findings are not an artefact of the smooth-transition functional form defended in Section 3.3. Dropping the nuclear share from the regressor set leaves the biomass and geothermal estimates virtually unchanged, so those results do not depend on the zero-clustering discussed in Section 3.1.1. The row reports exclusion of the nuclear regressor rather than of nuclear-adopting countries, since removing those countries would leave the nuclear coefficient unidentified. Re-estimation on the 2000–2022 sample places the energy-intensity threshold at 0.439 and the transition speed at 7.61, against 0.436 and 7.84 in the baseline, and returns high-regime coefficients of 0.062 for biomass, −0.078 for nuclear and −0.091 for geothermal, against 0.067, −0.081 and −0.094 in Table 12. These deviations arise because the two sets of coefficients are estimated on different samples, the terminal year being excluded from the second, and not from any inconsistency between specifications: the signs, the significance levels and the ordering of magnitudes across sources are identical, and no coefficient moves by more than 0.005 in absolute value.

## 5 Discussion

### *5.1 Source-Specific Findings in Relation to Prior Evidence*

The biomass result is the point at which this study speaks most directly to an existing disagreement. Serra and Zilberman [15] found biofuel–food transmission that strengthened at high production levels; Zhang et al. [16] found no stable long-run link; Zilberman et al. [17] concluded that the effect is real but highly sensitive to modelling assumptions. The regime estimates here are consistent with all three findings simultaneously, because they locate the disagreement in functional form rather than in the data. A coefficient that is −0.006 and insignificant below the energy-intensity threshold and 0.067 and significant above it would appear as "no stable relationship" to a linear long-run estimator applied to a pooled sample dominated by low-regime observations, and as "strong transmission" to a study drawn from high-production settings. The estimated magnitude in the upper regime is of the same order as the elasticities Nazlioglu and Soytas [36] report for oil-price transmission to agricultural commodities, which is what one would expect if the operative mechanism is competition for the same land and feedstock rather than a distinct pricing channel. Evidence that biomass and fossil-energy futures markets became more tightly coupled after 2020 [78] points the same way, since closer coupling raises the opportunity cost of directing feedstock to fuel rather than to food.

The nuclear and geothermal results have fewer direct antecedents, which is itself a finding about the literature rather than about the world: these sources are largely absent from energy–food price studies because aggregate renewable indicators subsume geothermal and exclude nuclear altogether. The negative associations reported here (−0.081 and −0.094 in the upper regime) are consistent with the cost-channel logic set out by the nexus literature [22,23] and with the FAO-based observation that cold-chain and storage losses are a substantial component of effective food supply in lower-income settings [58]. They are not, however, directly comparable to any prior coefficient, and should be treated as first estimates requiring replication rather than as confirmation.

The hydropower finding aligns with the nexus literature more closely than with the price literature. That the sign reverses between low- and high-water-stress subsamples (0.046 vs. −0.028, Wald $p = 0.009$) reproduces at the level of a cross-country panel what Conway et al. [24] documented for southern Africa: under climate variability, hydropower generation and agricultural water demand become rival claims on the same resource. Global infrastructure assessments reach a compatible conclusion, projecting that demand

for hydropower and for irrigation storage will increasingly compete for the same reservoirs, most acutely in South Asia and Africa [79]. The insignificance of hydropower in the pooled GMM specification (0.012, s.e. 0.014) is not evidence against this reading—it is what an averaged coefficient looks like when two subsamples carry opposite signs.

The solar and wind results speak to the conditionality that Simpson and Jewitt [51] identify as the practical weakness of nexus policy. Both sources are weak or insignificant in the low regime and significant in the high regime. The natural reading is that the benefit of variable renewables for food markets is not intrinsic to the technology but contingent on the complements—grid flexibility, storage, rural electrification—that the infrastructure channel names. This is consistent with recent panel evidence that clean-energy indicators carry both beneficial and adverse associations with food security across African economies [52], and it cautions against policy evaluations that credit capacity additions without assessing integration.

### *5.2 Regime Dependence as a Substantive, Not Merely Statistical, Result*

The threshold estimate itself carries interpretation. Energy intensity of 0.436 sits close to the sample mean (Table 9), so roughly half the panel operates in each regime, and the medium-to-high transition speed ($\gamma$ = 7.84) implies that the shift between regimes occurs over a relatively narrow band rather than gradually across the whole distribution. Substantively, this means the composition of the generation portfolio matters most for food outcomes precisely in economies whose energy systems are moderately to highly energy-intensive—that is, where the cost channel has enough leverage to propagate. In very low-intensity economies, changing the mix does comparatively little to food prices in either direction. This is a policy-relevant asymmetry that a linear specification cannot express, and it qualifies the common assumption that raising the renewable share is uniformly beneficial for food security.

It also sharpens the interpretation of the aggregation problem. Nuclear and geothermal generation carry negative coefficients while biomass carries a positive one in the same regime; combining them into a single renewable indicator (which would exclude nuclear and include biomass) nets these against each other and can produce a small, insignificant, and misleading average. The correlation pattern in Section 4.2—biomass at +0.31, geothermal at −0.27 with the price index—makes this concrete.

### *5.3 Limitations*

Four limitations bound these conclusions. First, identification: the panel is observational, generation shares may be jointly determined with food outcomes, and neither lagging, system-GMM nor CCE delivers exogenous variation. The coefficients are conditional associations. Second, omitted variables: institutional quality, agricultural support policies and climate shocks plausibly move both sides of the relationship, and time-varying components of these are only partially absorbed by fixed effects. Third, sample composition: nuclear and geothermal generation are concentrated in a small number of countries, so their regime coefficients rest on limited cross-sectional variation and should be regarded as the least robust of the six. Fourth, measurement: the supply-security index aggregates three components whose relative weight is determined by principal component analysis, and the index is a proxy for a construct that no single indicator captures. Strengthening causal identification through quasi-experimental designs, policy discontinuities or instrumental variables with a defensible exclusion restriction remains the principal task for subsequent work.

**Table 16:** Differentiated policy priorities by regime position, water stress and portfolio structure.

| Country Configuration | Evidence from This Study | Priority Policy Actions | What to Avoid |
|---|---|---|---|
| Low energy intensity (below c = 0.436), low water stress | Portfolio composition weakly associated with prices in either direction | Build agricultural electrification and grid reach first; the mix matters little until the cost channel has leverage | Costly portfolio re-optimisation before demand-side infrastructure exists |
| High energy intensity, biomass share above the sample P95 (11.5%) | Biomass high-regime elasticity +0.067 on prices; −0.055 on supply security | Redirect biomass incentives to non-food residues and waste feedstock; apply feedstock-origin conditionality to subsidies | Volumetric biomass targets that do not distinguish food from non-food feedstock |
| High energy intensity, high hydropower share, high water stress | Hydropower supply-security coefficient reverses from +0.046 to −0.028 (Wald $p$ = 0.009) | Introduce seasonal allocation rules between generation and irrigation; couple reservoir operation to agricultural calendars | Treating installed hydropower capacity as a food-security asset independent of hydrological conditions |
| High energy intensity, rising solar and wind shares, weak grid | Solar and wind significant only in the high regime | Pair capacity additions with storage, microgrids and demand management; prioritise irrigation-linked distributed solar | Counting capacity additions as food-security gains without integration investment |
| Geothermal or nuclear resource endowment | Strongest negative price association (−0.094 and −0.081) and strongest supply-security association | Co-locate cold-chain, greenhouse and drying infrastructure with continuous generation to capture the cost channel | Assuming the benefit accrues automatically without downstream agro-processing investment |
| High food import dependence (above P95 = 48.2%) | Import dependence is a control, not a channel, but conditions exposure | Combine portfolio measures with strategic reserves and trade diversification | Relying on domestic energy policy alone to stabilise domestic food prices |

Note: c denotes the estimated energy-intensity threshold and P95 the 95th percentile of the variable concerned in the estimation sample, as reported in Table 9.

## 6 Conclusion and Policy Implications

This study assessed how the composition of the energy production portfolio relates to food prices and supply security in developing countries within the WEF framework, differentiating by source type, production scale and threshold conditions. The reflection of energy transition on food markets is not unidirectional or homogeneous: it varies with the technological nature of the source, with infrastructure

capacity and with the prevailing regime. Aggregating sources into a single renewable-energy indicator therefore risks concealing mechanism differences that are decisive for policy.

The PSTR framework allows this separation to be read as regime transitions rather than as coefficient signs alone. Biomass generation beyond certain thresholds is associated with price pressure consistent with food–fuel competition, while continuously dispatchable sources—nuclear and geothermal—are associated with a mechanism that limits price volatility through irrigation, storage and cold-chain continuity. The favourable relationship of solar and wind becomes evident mainly where grid integration and rural electrification capacity are strong, indicating that the food-security value of variable renewables depends on institutional and infrastructural complements as much as on installed capacity. For hydropower, water stress is the conditioning variable: as scarcity rises, the tension between generation and agricultural water use intensifies and the association with supply security turns negative.

### *6.1 Differentiated Policy Implications*

The regime structure of the results implies that a single policy prescription is inappropriate, and the differentiation should follow the conditioning variables the model identifies rather than general categories. Table 16 sets out the resulting priorities.

The general point is that in developing countries the policy objective should not be confined to raising the renewable share. The portfolio must be planned jointly with water resources, agricultural production structure, grid capacity, rural electrification and explicit food-supply-security objectives.

### *6.2 Contribution and Future Research*

This study addresses three limitations in the literature—representation of energy through aggregated indicators, separate treatment of price and supply security, and the dominance of linearity—by disaggregating six sources within one panel, modelling both outcomes jointly, and testing regime dynamics with PSTR, supported by system-GMM, CCE and compositional-data robustness checks. The contribution is integrative rather than a first demonstration of any individual linkage, several of which are well established.

Future work can extend the framework in three directions: quasi-experimental designs that strengthen causal identification; estimation disaggregated by country group, so that the heterogeneity absorbed here into a common threshold can be examined directly; and broader indicator sets incorporating climate shocks, storage technology diffusion and agricultural water productivity. The evidence assembled here is intended as an input to the joint design of energy, water and food policy rather than as a settled account of the mechanisms involved.

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**Author Contributions:** Kemalettin Ağızan: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Visualization. Mehmet Bölükbaş: Writing—original draft, Writing—review & editing, Project administration. All authors reviewed and approved the final version of the manuscript.

**Availability of Data and Materials:** The datasets analysed in this study were compiled from publicly available sources: the IEA World Energy Balances, the IRENA power capacity and generation statistics (IRENASTAT), the FAOSTAT statistical database and the World Bank World Development Indicators. The compiled panel dataset and the estimation code are available from the corresponding author on reasonable request.

**Ethics Approval:** This study did not involve human participants, human data or animal subjects. It is based entirely on aggregated, publicly available country-level secondary data, and therefore no ethical approval was required.

**Conflicts of Interest.** The authors declare no conflicts of interest.

## Appendix A Sample Composition

The final analytical sample comprises 82 developing economies, classified by World Bank region and income group. Usable years vary from 18 to 24 within a maximum common window of 2000–2023, reflecting source-specific missingness; the usable-year counts below sum to the 1824 country-year observations of the transition-variable complete-case panel reported in Section 3.1.1.

**Table A1:** Sample composition: 82 developing economies by region, income class and observation coverage.

| World Bank Region | Income Class | Economy | Maximum Period | Usable Years |
|---|---|---|---|---|
| East Asia & Pacific | Lower-middle | Cambodia | 2000–2023 | 23 |
| East Asia & Pacific | Upper-middle | China | 2000–2023 | 24 |
| East Asia & Pacific | Upper-middle | Fiji | 2000–2023 | 23 |
| East Asia & Pacific | Upper-middle | Indonesia | 2000–2023 | 24 |
| East Asia & Pacific | Lower-middle | Lao PDR | 2000–2023 | 22 |
| East Asia & Pacific | Upper-middle | Malaysia | 2000–2023 | 24 |
| East Asia & Pacific | Upper-middle | Mongolia | 2000–2023 | 22 |
| East Asia & Pacific | Lower-middle | Myanmar | 2000–2023 | 18 |
| East Asia & Pacific | Lower-middle | Papua New Guinea | 2000–2023 | 22 |
| East Asia & Pacific | Lower-middle | Philippines | 2000–2023 | 22 |
| East Asia & Pacific | Upper-middle | Thailand | 2000–2023 | 24 |
| East Asia & Pacific | Lower-middle | Timor-Leste | 2000–2023 | 19 |
| East Asia & Pacific | Lower-middle | Viet Nam | 2000–2023 | 22 |
| South Asia | Lower-middle | Bangladesh | 2000–2023 | 23 |
| South Asia | Lower-middle | Bhutan | 2000–2023 | 23 |
| South Asia | Lower-middle | India | 2000–2023 | 24 |
| South Asia | Upper-middle | Maldives | 2000–2023 | 22 |
| South Asia | Lower-middle | Nepal | 2000–2023 | 22 |
| South Asia | Lower-middle | Pakistan | 2000–2023 | 22 |
| South Asia | Lower-middle | Sri Lanka | 2000–2023 | 22 |
| Europe & Central Asia | Upper-middle | Albania | 2000–2023 | 23 |
| Europe & Central Asia | Upper-middle | Armenia | 2000–2023 | 23 |
| Europe & Central Asia | Upper-middle | Azerbaijan | 2000–2023 | 23 |
| Europe & Central Asia | Upper-middle | Belarus | 2000–2023 | 23 |
| Europe & Central Asia | Upper-middle | Georgia | 2000–2023 | 23 |
| Europe & Central Asia | Upper-middle | Kazakhstan | 2000–2023 | 24 |
| Europe & Central Asia | Lower-middle | Kyrgyz Republic | 2000–2023 | 22 |
| Europe & Central Asia | Upper-middle | Moldova | 2000–2023 | 22 |
| Europe & Central Asia | Upper-middle | North Macedonia | 2000–2023 | 22 |
| Europe & Central Asia | Upper-middle | Serbia | 2000–2023 | 22 |
| Europe & Central Asia | Upper-middle | Türkiye | 2000–2023 | 24 |
| Europe & Central Asia | Lower-middle | Ukraine | 2000–2023 | 19 |
| Europe & Central Asia | Lower-middle | Uzbekistan | 2000–2023 | 22 |
| Middle East & North Africa | Upper-middle | Algeria | 2000–2023 | 23 |
| Middle East & North Africa | Lower-middle | Egypt, Arab Rep. | 2000–2023 | 23 |
| Middle East & North Africa | Lower-middle | Iran, Islamic Rep. | 2000–2023 | 23 |
| Middle East & North Africa | Upper-middle | Iraq | 2000–2023 | 23 |
| Middle East & North Africa | Lower-middle | Jordan | 2000–2023 | 23 |
| Middle East & North Africa | Lower-middle | Lebanon | 2000–2023 | 19 |

(Continued)

**Table A1 (continued)**

| World Bank Region | Income Class | Economy | Maximum Period | Usable Years |
|---|---|---|---|---|
| Middle East & North Africa | Lower-middle | Morocco | 2000–2023 | 22 |
| Middle East & North Africa | Lower-middle | Tunisia | 2000–2023 | 22 |
| Middle East & North Africa | Lower-middle | West Bank and Gaza | 2000–2023 | 18 |
| Middle East & North Africa | Low | Yemen, Rep. | 2000–2023 | 18 |
| Latin America & Caribbean | Upper-middle | Argentina | 2000–2023 | 24 |
| Latin America & Caribbean | Lower-middle | Bolivia | 2000–2023 | 23 |
| Latin America & Caribbean | Upper-middle | Brazil | 2000–2023 | 24 |
| Latin America & Caribbean | Upper-middle | Colombia | 2000–2023 | 24 |
| Latin America & Caribbean | Upper-middle | Costa Rica | 2000–2023 | 23 |
| Latin America & Caribbean | Upper-middle | Dominican Republic | 2000–2023 | 23 |
| Latin America & Caribbean | Upper-middle | Ecuador | 2000–2023 | 23 |
| Latin America & Caribbean | Upper-middle | El Salvador | 2000–2023 | 23 |
| Latin America & Caribbean | Upper-middle | Guatemala | 2000–2023 | 23 |
| Latin America & Caribbean | Lower-middle | Honduras | 2000–2023 | 23 |
| Latin America & Caribbean | Upper-middle | Jamaica | 2000–2023 | 23 |
| Latin America & Caribbean | Upper-middle | Mexico | 2000–2023 | 24 |
| Latin America & Caribbean | Lower-middle | Nicaragua | 2000–2023 | 22 |
| Latin America & Caribbean | Upper-middle | Paraguay | 2000–2023 | 22 |
| Latin America & Caribbean | Upper-middle | Peru | 2000–2023 | 22 |
| Latin America & Caribbean | Upper-middle | Suriname | 2000–2023 | 22 |
| Latin America & Caribbean | Upper-middle | Venezuela, RB | 2000–2023 | 18 |
| Sub-Saharan Africa | Lower-middle | Angola | 2000–2023 | 23 |
| Sub-Saharan Africa | Lower-middle | Benin | 2000–2023 | 23 |
| Sub-Saharan Africa | Upper-middle | Botswana | 2000–2023 | 23 |
| Sub-Saharan Africa | Low | Burkina Faso | 2000–2023 | 23 |
| Sub-Saharan Africa | Lower-middle | Cameroon | 2000–2023 | 23 |
| Sub-Saharan Africa | Lower-middle | Côte d'Ivoire | 2000–2023 | 23 |
| Sub-Saharan Africa | Low | Ethiopia | 2000–2023 | 19 |
| Sub-Saharan Africa | Lower-middle | Ghana | 2000–2023 | 23 |
| Sub-Saharan Africa | Lower-middle | Kenya | 2000–2023 | 23 |
| Sub-Saharan Africa | Low | Madagascar | 2000–2023 | 22 |
| Sub-Saharan Africa | Low | Malawi | 2000–2023 | 22 |
| Sub-Saharan Africa | Low | Mali | 2000–2023 | 22 |
| Sub-Saharan Africa | Low | Mozambique | 2000–2023 | 19 |
| Sub-Saharan Africa | Upper-middle | Namibia | 2000–2023 | 22 |
| Sub-Saharan Africa | Low | Niger | 2000–2023 | 19 |
| Sub-Saharan Africa | Lower-middle | Nigeria | 2000–2023 | 22 |
| Sub-Saharan Africa | Low | Rwanda | 2000–2023 | 22 |
| Sub-Saharan Africa | Lower-middle | Senegal | 2000–2023 | 22 |
| Sub-Saharan Africa | Upper-middle | South Africa | 2000–2023 | 24 |
| Sub-Saharan Africa | Lower-middle | Tanzania | 2000–2023 | 22 |
| Sub-Saharan Africa | Low | Uganda | 2000–2023 | 22 |
| Sub-Saharan Africa | Lower-middle | Zambia | 2000–2023 | 22 |

Note: Income classification follows the World Bank groupings. The maximum period denotes the common observation window; usable years denote country-specific coverage after source-specific missingness.

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