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Technology Readiness and Energy Productive Capacity: Aggregate and Component Threshold Evidence

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Abstract

Economies with comparable energy infrastructure can differ in their capacity to turn energy services into productive activity, making technological capabilities an important economic policy concern. This study compares aggregate frontier technology readiness and its five components in relation to UNCTAD's Energy Productive Capacities Index across 175 economies. The principal sample has 2127 country–year observations without study-level imputations (2088 through 2021, 39 in 2022, none in 2023). Country and year fixed effects benchmarks include log-quadratic real income controls. A continuous slope change search identifies ICT readiness at 0.500 as the best-fitting component–cutoff candidate: residual sum of squares falls from 4854.977 to 4727.542, with conditional slopes of +4.074 and −2.464. The upper slope is negative under conditional inference, but global post-selection significance with heterogeneous common factors has not been established; alternative designs select other components. The economic contribution is to show why aggregate readiness scores may obscure distinct capability constraints relevant to productive energy use. For policy, the findings favor assessing digital infrastructure alongside skills, financing, implementation capacity and measurable service benefits, rather than treating 0.500 as a universal investment threshold.

Keywords: frontier technology readiness; energy productive capacity; ICT readiness; research and development; panel threshold models; common factors; economic interpretation; Productive Capacities Index

1. Introduction

Energy infrastructure and resource endowments do not, by themselves, determine how effectively energy supports production, investment and economic diversification. Economies with similar physical assets may differ substantially in the technological and organizational capabilities required to operate, adapt and upgrade energy services. Explaining that difference matters economically: public and private investment decisions involve scarce capital, competing uses of funds and the risk that infrastructure will underperform without complementary capabilities. This study therefore examines whether aggregate technological preparedness or its individual dimensions provide more informative associations with national energy productive capacity, rather than assuming that infrastructure provision alone delivers productive gains.

The modernization of energy-related production makes this question increasingly relevant. Digital technologies can facilitate information exchange, system monitoring and operational coordination [1,2], but their application depends on skills, research capabilities, industrial implementation and access to finance. These complementary inputs affect how

Check for updates

Academic Editor: George E. Halkos

Received: 10 October 2026
Revised: 15 November 2026
Accepted: 24 November 2026
Published: 27 November 2026

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technological opportunities are translated into productive use rather than simply whether new equipment can be acquired. Accordingly, the economic issue examined here is the association between frontier technology readiness and the energy dimension of national productive capacity, not the direct effectiveness of individual digital projects.

The distinction is particularly pertinent for resource-dependent economies. Revenues from energy extraction can finance technological upgrading, yet their availability does not ensure broader productive diversification. Dependence on extractive revenues can also shape investment choices and exposure to changes in external demand [3,4]. Such considerations motivate examining the capabilities that accompany energy resources and infrastructure, without presuming that countries follow a common transition path or that the present regressions identify the effects of resource dependence.

Two UNCTAD measures enable a comparison of these dimensions. The Frontier Technology Readiness Index (FTRI) summarizes preparedness across ICT, skills, R&D, industrial activity and finance [5,6]. The Energy category of the Productive Capacities Index (PCI) characterizes energy-related productive capacity [7,8]. Comparing the aggregate FTRI with its separate components permits the analysis to distinguish average national preparedness from specific capability indicators. The relationship is evaluated as an empirical association with a published composite outcome, rather than as a direct measure of sector-level production or investment returns.

The association may also differ across levels of readiness. At lower levels, limited connectivity or technical capacity may constrain the productive application of existing infrastructure. At higher levels, complementary skills, organizational adaptation and financing may become more relevant. Economic complementarity provides a rationale for allowing the fitted readiness slope to change [9]; it does not predict that the higher readiness slope must be larger or that any selected cutoff is a universal economic boundary. The continuous slope change specification examines this possibility as a conditional empirical pattern.

This study addresses two connected economic questions: whether aggregate frontier technology readiness and its five components convey different information about energy productive capacity, and whether their fitted associations change across readiness levels. Its contribution is to bring a productive capacity outcome into a matched comparison of aggregate and component readiness, distinguish conventional linear evidence from exploratory nonlinear fit, and examine the sensitivity of the selected component to sample coverage, income specification and common influences. This matters for economic interpretation because an aggregate score can conceal different constraints on productive investment; it does not imply that a readiness coefficient estimates the causal return to an intervention. The analysis complements evidence on digital energy applications and technology diffusion [1,2,10,11], without equating readiness scores with adoption, resilience to shocks or observed investment returns.

The principal analysis draws on 2127 economy–year observations without imputations undertaken for this study, using log real GDP per capita and its square, country and year fixed effects, and matched aggregate and component readiness specifications. A 2448-observation extended panel supports historical functional form and threshold sensitivity checks; a balanced 170-economy panel over 2010–2021 supports exploratory common factor assessments. By keeping these estimation designs distinct, the analysis evaluates which features of the readiness–productive capacity association remain visible under alternative empirical assumptions.

Section 2 defines the concepts and their empirical relationships. Section 3 reviews the literature and develops the hypotheses. Section 4 presents the data and methods; Sections 5 and 6 report and discuss the findings. Sections 7–9 present the conclusions, policy implications, and directions for further research.

2. Conceptual Framework

Energy services facilitate production across sectors, but their contribution depends on the infrastructure and capabilities through which they are supplied and used. UNCTAD's Energy category within the Productive Capacities Index measures an energy-related dimension of national productive capacity [7,8]. This published category, termed EnergyPCI in the study, is the outcome whose association with frontier technology readiness is estimated. It does not directly measure electricity reliability, recovery from disruptions or the causal output of individual energy investments.

The proposed economic link operates through the ability to acquire knowledge, adapt technologies, coordinate production and sustain complementary investment. These mechanisms can influence how energy infrastructure serves economic activity, but they are not separately identified by the national panel regressions. This distinction motivates comparing an aggregate readiness measure with its component indicators while allowing for their fitted associations to vary across readiness levels.

Frontier technology readiness is preparedness to use, adopt, and adapt frontier technologies. The FTRI represents this through ICT deployment, skills, research and development (R&D) activity, industry activity, and access to finance [5,6]. The aggregate index summarizes national preparedness; the components distinguish the capabilities that may support energy applications. ICT can enable communication and monitoring, skills support operation and adaptation, R&D facilitates learning, industry supports implementation, and finance enables investment. These are conceptual channels informed by the literature [1,2,10,11], rather than separate mechanisms identified by the additive component model.

For economies with substantial energy resource endowments, access to extractive rents and the development of productive capabilities are related but distinct. Resource revenues may support investment, while longer-term productive activity depends on how infrastructure, technical capacity and complementary inputs are combined [3,4]. The estimated readiness regimes do not classify economies into 'rentier' and 'productive' groups or demonstrate a causal transition between them; the economic distinction is a motivation for studying productive capacity rather than an outcome identified by the model.

The empirical framework permits the association between readiness and the EnergyPCI to differ across estimated capability regimes. Complementary investments can make this relationship nonlinear: connectivity requires the skills to use it, renewable integration requires coordination, and infrastructure upgrading requires industrial and financial support [9]. These mechanisms motivate testing regime differences without prescribing their direction or a universal cutoff. Regime membership belongs to country–year observations and can change over time. The sample is not divided beforehand by geographical region, income group, or oil exporting status. Figure 1 summarizes the relationship; Section 3 develops its theoretical basis. Although such complementary requirements motivate the theoretical discussion, the component model contains no cross-component interaction terms and therefore cannot estimate complementarities or synergies among readiness dimensions.

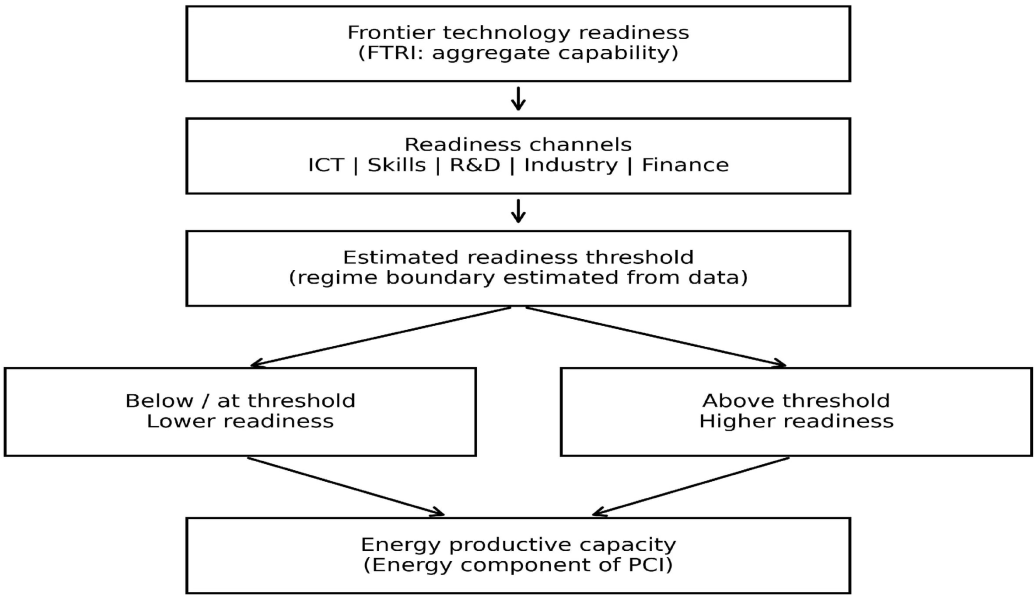


Figure 1. Conceptual channels linking frontier technology readiness to energy productive capacity. FTRI: Frontier Technology Readiness Index; ICT: information and communication technology; R&D: research and development; PCI: Productive Capacities Index. Arrows express proposed economic relationships rather than established causal effects; regime distinctions represent conditional readiness comparisons, not separately verified mechanisms.

3. Literature Review, Hypotheses, and Theoretical Proposition

3.1. Theoretical Foundations

The relationship between frontier technology readiness and energy productive capacity can be examined through theories that explain how knowledge, technological adoption, and investment contribute to production. These theories address different stages of capability development, from creating knowledge to applying it alongside other productive resources. Their relevance depends on distinguishing technological preparedness from actual technology use and energy productive capacity from economic growth or resilience to shocks.

At the stage of knowledge creation, Romer [12] explains sustained growth through purposeful investment in knowledge and the contribution of human capital to research. This perspective provides a basis for expecting skills and R&D readiness to support the development and application of technologies that improve the productive use of energy. The connection to the indicators used here is nevertheless partial. The FTRI measures preparedness rather than innovation output, while the EnergyPCI captures the energy dimension of productive capacity rather than aggregate growth. Endogenous technological change therefore supports attention to knowledge-related capabilities without prescribing a particular readiness cutoff or a uniform relationship across components.

The creation of knowledge is closely connected to the ability to use knowledge developed elsewhere. Cohen and Levinthal [13] explain this process through absorptive capacity: prior related knowledge enables firms to recognize, assimilate, and apply external knowledge, with R&D contributing to that ability. In national energy systems, this argument suggests that imported equipment and digital infrastructure may require domestic expertise to become effective productive capabilities. Its application at the country level remains an extension of a theory developed primarily to explain learning within firms. National readiness indicators may reflect conditions that facilitate technology absorption, but they do not directly measure organizational learning or the effective use of acquired technologies.

Once technologies can be adopted and applied, their productive contribution also depends on the range of activities they support. Bresnahan and Trajtenberg [14] characterize general purpose technologies by their broad applicability, continuing improvement, and potential to generate complementary innovation. They also explain how coordination difficulties can delay productive gains. This perspective provides a rationale for considering ICT as an enabling capability for energy monitoring, communication, and operational coordination. General ICT readiness, however, is not a direct measure of smart grid adoption or energy sector digitalization. The theory suggests that digital capabilities can support multiple applications, but it does not establish a universal readiness threshold or require their contribution to increase uniformly at higher readiness levels.

The importance of complementary innovation leads to a further question: whether technological capabilities are accompanied by the investments and organizational adjustments needed to use them effectively. Milgrom and Roberts [9] show how technological, strategic, and organizational choices can reinforce one another in production. Their analysis provides a basis for considering ICT, skills, R&D, industry, and finance together, since progress in one area may depend on developments in others. An aggregate readiness index summarizes these capabilities but may conceal differences in their development. Neither an aggregate score nor separate component measures directly demonstrate complementarity; that requires evidence about interactions between capabilities or the coordination of investment. In particular, including several readiness components as separate regressors does not provide a statistical test of their joint productive effect.

These capability-based explanations also help clarify why the possession of energy resources need not translate into broader productive development. Sachs and Warner [15] document an association between natural resource abundance and slower economic growth, raising questions about how resource advantages are converted into sustained productive activity. Applied to energy, this perspective supports distinguishing resource availability and rent generation from the capabilities needed to supply energy services that support production. It does not imply that resource wealth is necessarily detrimental or that technological readiness alone can overcome dependence. Nor does energy productive capacity, by itself, establish whether an economy has diversified away from resource-based activities.

Taken together, endogenous innovation, absorptive capacity, general purpose technologies and complementary investment explain why technological preparedness may matter for the productive use of energy. These arguments motivate the component comparison and the possibility of varying fitted slopes; they neither guarantee successful adoption nor imply a particular cutoff. The empirical contribution is therefore assessed through the observed relationship between FTRI measures and the EnergyPCI, with resilience and shock response remaining outside the directly measured outcome.

3.2. Frontier Technology Readiness and Energy Productive Capacity

The frontier technology literature provides the broad rationale for linking readiness to energy productive capacity, but it remains incomplete for the question examined here. UNCTAD's FTRI captures national preparedness to use, adopt, and adapt frontier technologies through ICT deployment, skills, R&D activity, industry activity, and access to finance [5,6]. These dimensions are relevant because energy modernization requires more than physical investment; it requires the capacity to deploy, adapt, finance, and scale technology.

Han and Sun [16] use the FTRI to examine load capacity factor, providing a precedent for its application to sustainability research. Their outcome concerns ecological sustainability, whereas the energy component of the PCI concerns productive capacity. The present study examines whether the relationship with this different outcome varies across readiness regimes.

H1. *Frontier technology readiness is positively associated with energy productive capacity.*

3.3. Threshold Nonlinearity and the Limits of Average Effects

A linear specification assumes that technology readiness has the same marginal effect at all readiness levels. This assumption is restrictive because frontier technologies often require complementary conditions before they generate systemic effects. Hansen's [17] threshold framework is useful precisely because it allows for the data to identify whether the relationship changes across regimes rather than imposing a predetermined cutoff. The econometric threshold framework is an estimation approach rather than an economic theory of technology adoption; Section 3.1 supplies the substantive mechanisms motivating its use.

The productive capacity implications of energy endowments also depend on the technical and industrial capabilities needed to use them [3,4]. This reinforces the case for allowing variation in readiness associations, but neither economic theory nor the cited literature determines the location or direction of a statistical kink in advance.

H2. *The association between aggregate frontier technology readiness and energy productive capacity is nonlinear and threshold-dependent.*

3.4. Digitalization, ICT Readiness, and Smart Energy Systems

The digitalization literature motivates examining ICT as a potential threshold variable. The IEA [1] discusses how digital data and analytics can reduce power system costs through improved maintenance, efficiency, outage management, and asset use. Its smart grid analysis [2] identifies applications in fault detection, asset management, demand response, and renewable energy integration in emerging and developing economies.

Recent work in *Energies* reinforces the relevance of this channel. Dzwigol et al. [18] examine digitalization and energy in the context of sustainable development, showing that digitalization is closely connected to energy consumption, energy structure, and energy intensity. Zahid et al. [19] show that ICT-related strategies are associated with energy efficiency in G20 economies and that governance conditions shape the effectiveness of ICT in energy outcomes. Campana et al. [20] review smart grids and digital technologies and emphasize energy flow optimization, renewable integration, AI, IoT, resilience, and cybersecurity. Rojek et al. [21] further argue that AI-based methods are increasingly relevant to energy productivity, industrial transformation, digitalization, and efficiency. These studies support the interpretation that ICT readiness is not a peripheral technology variable; it is a foundational energy system capability.

These mechanisms motivate testing whether the ICT association varies across readiness levels. Because a composite index combines several dimensions, its threshold pattern may differ from that of an individual component. The component search evaluates this possibility across all five dimensions, rather than treating ICT as a predetermined empirical result. The selected component represents the strongest fitted departure within the stated search design, not a causal ranking of policy interventions or a demonstrated interaction between readiness dimensions.

H3. *Nonlinear threshold effects may operate through a specific readiness channel; ICT readiness is expected to be the most likely channel.*

3.5. Skills, R&D, Industry Activity, and Finance as Complementary Channels

The remaining FTRI dimensions provide complementary mechanisms. Skills matter because modern energy systems require engineering, data science, grid management, cybersecurity, and adaptive operational capacity. The IEA [22] identifies data access, digital

infrastructure, skills, and security concerns as barriers to wider AI adoption in energy, indicating that technology deployment depends on absorptive capability rather than equipment alone. This argument is consistent with absorptive capacity theory, while the national skills indicator remains a proxy for preparedness rather than a direct measure of organizational learning [13].

The innovation channel is supported by Popp et al. [11], who show that technological knowledge contributes to the diffusion of renewable energy technologies. Munir et al. [23] also link countries' ability to adopt and adapt frontier technologies with renewable energy innovation, with global value chains acting as a moderating factor. These studies justify the R&D dimension, but they examine innovation and diffusion rather than the broader productive capacity role of energy.

Industry activity matters because energy transition technologies must be manufactured, installed, maintained, and scaled. The IEA [24] emphasizes the importance of clean energy supply chains, while Fikru and Kilinc [25] highlight the relevance of mineral raw material imports and the industrial capabilities needed to process these materials for renewable energy applications. Their findings suggest that technological preparedness operates within broader material and production constraints, qualifying the assumption that readiness alone is sufficient for effective technology deployment. Finance is also relevant, as Kim and Park [10] and Le et al. [26] associate financial development with renewable energy deployment. Taken together, these studies provide a broader rationale for considering industrial and financial readiness alongside other technological capabilities. However, their evidence concerns specific energy transition activities rather than the EnergyPCI directly, and the additive specification used here does not identify the effects of material constraints or establish statistical complementarity among readiness components.

H4 (theoretical proposition)**.** *The subcomponents of frontier technology readiness represent potentially distinct channels linking readiness to energy productive capacity. The additive specification does not directly test these mechanisms or their complementarity.*

3.6. Energy Productive Capacity and the Rentier-to-Productive Interpretation

Omar et al. [27] use an energy-related PCI measure to examine energy sustainability in energy-deficient Asian Belt and Road economies. Their study provides a related application of productive capacity indicators but addresses a different explanatory relationship. Here, the focus is on aggregate technological readiness, its components, and possible threshold nonlinearity.

The framework allows for the fitted association between readiness and EnergyPCI to vary with the level and composition of technological preparedness. Knowledge absorption, connectivity, investment coordination and complementary infrastructure may shape how technological capabilities are applied in energy-related production. The empirical threshold specifications describe whether these associations differ across observed readiness ranges, while the additive component model estimates separate conditional relationships. Direct investigation of interactions, resource rent transformation and sector-level transmission mechanisms provides a distinct avenue for future research.

H5. *As a directional hypothesis to be evaluated rather than assumed, the positive association between technological readiness and the EnergyPCI is stronger above a readiness threshold than below it.*

4. Materials and Methods

Estimation proceeds from matched linear country and year fixed effects benchmarks for aggregate and disaggregated frontier technology readiness to continuous kink and

discontinuous component–cutoff searches. Log real GDP per capita and its square are retained as parsimonious controls following common sample functional form comparisons; trade openness and renewable energy consumption share are included in the reported specifications. Independent numerical cross-checks were conducted in Python 3.13.5 (Python Software Foundation, Beaverton, OR, USA), with supplementary estimation and diagnostic analyses performed using MATLAB R2026b (The MathWorks, Inc., Natick, MA, USA) and StataNow/MP 19.5 (StataCorp LLC, College Station, TX, USA).Standard error calculations, threshold search procedures and simulations are interpreted under the dependence assumptions appropriate to each design; supplementary temporal controls and cross-sectional average projections assess their sensitivity to shared disturbances.

The estimation strategy and diagnostic procedures are specified below; complete model definitions and numerical verification are presented with the corresponding results and supplementary comparisons.

4.1. Data and Variable Definition

The assembled panel combines UNCTADstat and World Bank World Development Indicators (WDI) for 175 economies [6,8,28]. The dependent variable is the Energy category of the UNCTADstat US.PCI series, rather than the overall Productive Capacities Index. A direct economy–year reconciliation with the UNCTAD CSV extract downloaded on 27 September 2026 (source table last updated 31 October 2025) matched 2444 of the 2448 extended panel Energy scores exactly. Four source-absent records, covering Sudan and South Sudan in 2010–2011, had been filled within the study and are explicitly marked as study-level imputations; all four are removed from the principal N = 2127 sample, whose Energy scores match the published extract without discrepancy. GDP per capita is expressed in constant 2020 US dollars. The compiled 2010–2023 panel defines the extended estimation window; 2010 contains 172 of 175 economy–year records unaffected by study-level imputations (98.29%), and similarly broad coverage persists through 2021. This start reflects the assembled multivariable analysis window, not a claim that all underlying source indicators began in 2010. Economy fixed effects account for persistent level differences, and calendar year effects absorb additive shared annual shifts. Table 1 records variable definitions and sources.

The EnergyPCI is the official published Energy category score of UNCTAD's Productive Capacities Index (US.PCI), not the overall PCI or a researcher-constructed, equally weighted index. The source data used for estimation bear a last update date of 31 October 2025, identifying the PCI 25 release; the third-generation methodological report was published subsequently in September 2026 [29]. Six inputs define the category: access to electricity, transmission and distribution losses (direction reversed to measure efficiency), renewable energy consumption share, GDP per total energy supply, total primary energy supply per capita, and total energy consumption per capita. UNCTAD (2026, Appendix 7.2, Table 7.2.1 [29]) reports the following Varimax-rotated loadings, ordered as above: RC1 = (0.81, 0.73, −0.78, −0.07, 0.96, 0.96) and RC2 = (0.34, 0.13, −0.23, 0.97, −0.09, −0.09). These are medians across 200 runs (within ±0.02 of the run-specific loadings), not raw indicator scoring coefficients. The first run explains 61% and 19% of indicator variance in RC1 and RC2; normalizing the published rounded shares gives illustrative component aggregation shares of approximately 76.25% and 23.75%, not invariant exact weights for all runs. The component scores are obtained using the regression scoring method, combined according to explained variance, scaled to 1–100, and the published category score is the mean of 200 differently seeded computations [29]. Neither the published loading table nor these approximate shares suffice for independent reconstruction without the processed input panel, exact run-specific scoring coefficients, and scaling parameters. We

therefore use the original published EnergyPCI values without recalibration. Renewable share and GDP-derived energy efficiency overlap conceptually with controls; matched fixed cutoff sensitivity checks (Table A7) address specification sensitivity without establishing independent mechanisms.

Table 1. Variable definitions, data sources, and roles in the models. FTRI: Frontier Technology Readiness Index; ICT: information and communication technology; R&D: research and development; GDP: gross domestic product; WDI: World Development Indicators.

Variable	Symbol	Measurement	Source	Model Role
Energy productive capacity	EnergyPCI_it	PCI Energy dimension; US.PCI, CATEGORY = Energy	UNCTADstat	Dependent variable
Aggregate frontier technology readiness	FTRI_it	Aggregate Frontier Technology Readiness Index	UNCTADstat	Main explanatory and threshold variable in Model I
ICT readiness	ICT_it	FTRI ICT deployment component	UNCTADstat	Threshold channel in Model II
Skills readiness	Skills_it	FTRI skills component	UNCTADstat	Subcomponent control/channel in Model II
R&D readiness	RD_it	FTRI R&D component	UNCTADstat	Subcomponent control/channel in Model II
Industry readiness	Industry_it	FTRI industry activity component	UNCTADstat	Subcomponent control/channel in Model II
Finance readiness	Finance_it	FTRI access-to-finance component	UNCTADstat	Subcomponent control/channel in Model II
GDP per capita	GDPpc_it	GDP per capita in constant 2020 US dollars	World Bank WDI	Control variable
Trade openness	Trade_it	Trade as percentage of GDP	World Bank WDI/UNCTAD	Control variable
Renewable energy share	REShare_it	Renewable consumption/total final energy consumption (%); EG.FEC.RNEW.ZS	World Bank WDI; IEA	Control variable

Missing values were treated within countries before estimation. Internal gaps were filled by linear interpolation and short endpoint gaps by extrapolation from nearby observations, with nearest observation substitution when a trend was unavailable and bounded indicators constrained to their feasible ranges. The imputation log records 359 cells across 321 country–year rows (13.11% of the panel): 358 endpoint extrapolations and one internal interpolation. Renewable energy consumption share accounts for 311 cells (86.63%). This is WDI indicator EG.FEC.RNEW.ZS, sourced from the International Energy Agency (IEA). Its downloaded metadata cover 1990–2022; the 2023 panel values are imputed. All country–year identifiers are unique, and the model variables are complete after treatment.

After removing every economy–year row with an imputation recorded in this study's log, the primary analytic sample contains 2127 observations from 175 economies. Among these, 2088 are dated 2010–2021, 39 are dated 2022, and none are dated 2023. The term 'non-study-imputed' does not mean that upstream statistical agencies never estimated or revised

the source indices. The balanced subsample of 170 economies × 12 years (2010–2021; N = 2040) is reserved for common factor sensitivity. The 2448-record extended panel (2010–2023) contains 321 economy–year rows touched by 359 logged imputations and is retained only for explicitly labeled comparison specifications. All coefficients and fit criteria are assigned to the sample and income control specification that generated them; no slopes are transferred between samples.

The two models address different levels of readiness within the same analytical framework. Model I relates EnergyPCI to aggregate FTRI and allows for its coefficient to differ across an estimated cutoff. Model II replaces FTRI with ICT, skills, R&D, industry, and finance, searching across these components for the best-fitting threshold specification. Each component is considered as a possible threshold variable while the others enter additively. Model II is estimated separately from Model I; it is not a second-stage regression. Both models examine associations with productive capacity and neither estimate resilience or exposure to geopolitical shocks directly.

Log GDP per capita and its square flexibly account for variation in economic resources, income-related structural change, and investment capacity, while trade openness provides a broad measure of integration into international markets [28]. Renewable energy consumption share describes part of the national energy mix, but its presence among the inputs of the dependent EnergyPCI category limits the interpretation of its regression coefficient. Similarly, the index's underlying GDP-to-energy-supply information complicates reading the separate GDP control as an economically independent determinant. The signs of these coefficients are therefore conditional statistical associations, not the returns to income growth or renewable investment. The five readiness components enter additively, without tested interactions or separate measures of sectoral adoption and complementarity.

The income functional form was compared on identical non-study-imputed economy–year observations using GDP per capita in levels, its logarithm, and quadratic extensions of both. The logarithmic quadratic form minimizes AIC among these four planned representations and is retained for its interpretable, parsimonious curvature. A separate exploratory cubic log extension gives lower AIC and BIC on the fixed ICT = 0.500 comparison; this does not establish stability under the complete component–cutoff search. Consequently, the retained quadratic is an explicit modeling choice, not an assertion of unconditional information criterion optimality (Section 5.6).

4.2. Model Specification

Model I specifies a continuous slope change in the association between aggregate FTRI and EnergyPCI, with the unknown cutoff selected from the admissible readiness grid:

$$EnergyPCI_{it} = \mu_i + \lambda_t + \beta_F\, FTRI_{it} + \delta_F\, max(FTRI_{it} - c_F,\, 0) + X_{it}{}'\kappa + \varepsilon_{it} \quad (1)$$

Here, cF denotes the searched aggregate FTRI cutoff; $(z)_+ = \max(z, 0)$ is the continuous hinge, βF the slope below the cutoff, and βF + δF the slope above it. Country fixed effects μ_i and year effects λ_t absorb time-invariant economy heterogeneity and additive common annual shocks. X_{it} contains ln(real GDP per capita), its square, trade openness, and renewable energy consumption share; κ is their coefficient vector.

Model II replaces aggregate readiness with five component regressors and searches each component in turn as a potential continuous slope change variable while retaining the other four additively. Its principal specification is

$$EnergyPCI_{it} = \mu_i + \lambda_t + \sum \beta_j\, Q_{jit} + \delta_k\, max(Q_{kit} - c_k,\, 0) + X_{it}{}'\kappa + \varepsilon_{it} \quad (2)$$

Q_{jit} denotes ICT, skills, R&D, industry, and finance readiness (j = 1, ..., 5). In the full component–cutoff search, k identifies the selected readiness component and c_k its

fitted cutoff. The component's slope is β_k below the cutoff and $\beta_k + \delta_k$ above it. The other four components enter additively. A separate historical discontinuous comparator permits a level jump by replacing the hinge with regime-partitioned regressors; its fitted coefficients and uncertainty assessments are clearly distinguished in Section 5.4 and Appendix C.

The no-kink null is $\delta = 0$; the cutoff is unidentified under that null. Thus, conventional selected model coefficient tests and cutoff search tests answer different questions. Country-level wild bootstrap resampling repeats selection under its own cross-economy dependence assumptions. Country and year fixed effects remove time-invariant economy differences and additive calendar year disturbances but do not eliminate heterogeneous exposure to latent common factors. Sections 4.3 and 5.7 report the scope of the additional diagnostics without treating them as a globally validated dependence-robust continuous kink test.

4.3. Estimation Procedure and Diagnostic Checks

The data workflow verifies uniqueness of economy–year keys, study imputation records, and complete case coverage. Matched principal sample linear models distinguish the aggregate index from its five components under two-way fixed effects and log-quadratic income. For each threshold candidate, we compare continuous and discontinuous conditional SSR under identical sample and control definitions. Additional exercises include functional form diagnostics, influential economy deletions, shorter windows, alternative temporal controls, and exploratory factor projections; each sensitivity is reported with its own estimation sample and conditioning assumptions. Extended imputed panel results are reported for continuity with the broader coverage, but the primary substantive interpretation draws on the non-study-imputed regressions.

The baseline candidate grid consists of distinct observed readiness values that leave at least 15% of observations in each regime; 5%, 10%, and 20% trimming are examined for threshold location sensitivity. Model I searches for the aggregate FTRI grid; Model II searches the admissible grid of each of the five components and selects the specification with the lowest residual sum of squares (SSR). The search statistic is $F = (SSR_linear - SSR_threshold) / (SSR_threshold/df_threshold)$, where df_threshold is the residual degrees of freedom of the threshold specification. We use 4999 country cluster wild bootstrap replications under the fitted linear null, Rademacher weights, and random seed 20261009. Each replication repeats the entire search, including selection among components in Model II. The finite simulation p-value is $(1 + exceedances) / 5000$. The observed-only analysis follows the same protocol. Monte Carlo standard errors are approximately 0.0063 and 0.0007 for the full-sample p-values in Models I and II, respectively, and 0.0044 and 0.0021 for the observed-only p-values. They measure simulation error rather than uncertainty about the specification.

For the reported historical country wild comparisons, a country-specific Rademacher sign multiplies all residuals of that country, and the complete component–cutoff search is repeated in each draw [30]. This resampling preserves within-country dependence but does not, without stronger assumptions, preserve heterogeneous shocks shared across countries. Hansen's [17] panel threshold approach motivates estimation, although neither its original sampling assumptions nor the conditional country wild implementation establish a global searched kink test in the presence of unrestricted interactive common factors. Conventional heteroskedasticity and collinearity diagnostics are descriptive, not substitutes for such inference. The discrete grid bootstrap acceptance sets below apply only to the explicitly identified supplementary specifications and their maintained assumptions.

Joint component–threshold confidence sets for the historical discontinuous model were constructed by inverting candidate-specific bootstrap tests on the expanded 5%-trimmed grid of 33 estimable component–cutoff pairs. For each imposed pair, the fitted candi-

date produces a profile statistic N log(SSR_candidate / SSR_min), and 4999 country-level Rademacher wild bootstrap draws under that candidate repeat the complete search. Candidate pairs not rejected at the nominal 5% level form a discrete grid 95% acceptance set. Coverage was checked in five fitted wild residual simulation configurations, using 1000 Monte Carlo experiments and 499 nested bootstrap replications in each. Empirical coverage ranged from 95.1% to 99.5%, reaching 99.5% in the ICT = 0.700 configuration. These are completed finite design coverage evaluations, not guarantees for an unrestricted interactive factor error structure. The confidence construction and simulations are specific to the original discontinuous functional form, its sample, grid and resampling assumptions [17,30].

For the original extended panel continuous specification, candidate-specific discrete grid bootstrap inversion likewise yielded a nominal cutoff acceptance set involving ICT = 0.500 and 0.600. This is distinct from the principal N = 2127 log-quadratic five-component continuous search; the archived acceptance set and empirical coverage calculations are not transferred to that principal model. All confidence coverage statements identify the resampling design and functional form to which they apply.

Additional residual diagnostics are evaluated conditional on each selected partition. The Wooldridge–Drukker procedure estimates a first-differenced regression of the outcome on the partitioned regressors, controls, and differenced year indicators, then regresses those residuals on their one-year lags without an intercept. A country-clustered F test evaluates the null coefficient of −0.5 [31]. Only consecutive calendar year observations are differenced or paired. The Pesaran CD statistic uses pairwise residual correlations on common years [32]. Because estimated year effects can distort its conventional normal reference distribution [33], its *p*-value and the mean absolute pairwise correlation are reported as exploratory diagnostics, not as certification of cross-country independence.

Residual serial dependence, pairwise cross-economy correlations, weighted cross-sectional dependence tests, and alternative covariance estimators inform the uncertainty assessment. Driscoll–Kraay standard errors [34] are not treated as decisive with just 14 annual periods, or 12 in the balanced common factor subsample. Conventional country clusters and their wild bootstrap draws accommodate within-economy serial dependence but not unrestricted heterogeneous common shocks. The supplementary common correlated effects projection uses annual cross-sectional averages as factor proxies and heterogeneous economy loadings; its computed rank is a numerical check, not proof that the proxies span all latent common factors. The estimated component and cutoff vary with that factor representation, and no validated short-T, five-component, post-selection continuous kink reference distribution has been demonstrated for this design. Therefore, uncertainty in a selected nonlinear specification is not equated with evidence of a robust structural break. A fixed-T panel threshold approach with interactive fixed effects provides a related methodological benchmark [35], but its published inferential guarantees are not automatically transferred to a searched continuous hinge across five different threshold variables.

Four additional specifications retain GDP per capita in levels, the partitioned readiness terms, and 15% trimming: country-specific linear trends; the 2012–2021 period after removing rows with logged imputations; balanced 14-year coverage; and readiness lagged by one calendar year, with the outcome and controls contemporaneous. All five readiness components are lagged together in Model II. Each specification is estimated for both models using 4999 country-level null wild bootstrap replications, seed 20261009, and the complete cutoff and component search.

Model II selection stability is examined in 4999 fitted-alternative country wild bootstrap draws, using seed 20261010. The fitted threshold model supplies the conditional mean and residuals, and every draw repeats the full component and cutoff search. Reselection

frequencies describe stability within this fitted model experiment; they are distinct from confidence coverage for the cutoff. Figure 2 summarizes the principal estimation workflow and its associated sensitivity analyses.

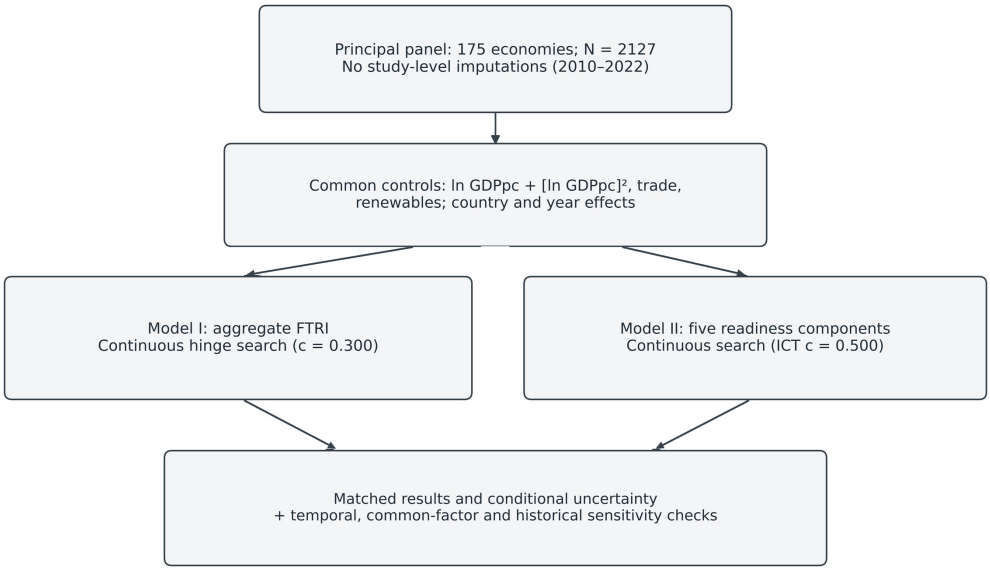


Figure 2. Principal estimation and evidence workflow: the non-study-imputed sample, common log-quadratic income controls, separate aggregate and five-component continuous searches, matched fit comparisons, and explicitly separated sensitivity analyses. The discontinuous extended panel calculations are supplementary historical comparisons.

5. Results

5.1. Descriptive Statistics and Diagnostics

Table 2 summarizes the principal 2127-observation sample; supplementary Table A9 records the descriptive distribution of the separate 2448-record extended panel. The EnergyPCI is reported on the index scale used by UNCTAD, while readiness indicators take values between zero and one. Substantial cross-economy differences in mean outcomes motivate country fixed effects analysis of within-economy associations.

Table 2. Descriptive statistics for the principal analysis sample excluding study-level imputations (N = 2127; 175 economies).

Variable	Mean	SD	Min	Max
EnergyPCI (index points)	50.774	19.826	5.700	92.300
Aggregate FTRI (0–1)	0.506	0.242	0.000	1.000
ICT readiness (0–1)	0.551	0.228	0.000	1.000
Skills (0–1)	0.450	0.224	0.000	1.000
R&D readiness (0–1)	0.282	0.239	0.000	1.000
Industry readiness (0–1)	0.499	0.226	0.000	1.000
Finance readiness (0–1)	0.824	0.111	0.000	1.000
Real GDP per capita (USD)	14,827.62	21,484.57	247	127,922
Trade openness (% of GDP)	86.100	55.058	12.860	442.620
Renewable energy share (%)	33.008	28.339	0.000	97.000

All values were calculated from the verified original panel after exclusion of 321 economy–year rows with logged study-level imputations. Source provider imputation may remain in published indices.

Conventional Breusch–Pagan screens reject homoskedasticity for the original aggregate and component threshold specifications (Table A10), and partitioned ICT terms in the latter have elevated collinearity (maximum structural regressor VIF = 9.469). These diagnos-

tics motivate covariance and resampling checks rather than an independent observation model. Serial, cross-economy and alternative covariance diagnostics are considered in Section 5.5 and Appendix B, while the residual plots in Figure A7 describe the historical discontinuous comparator.

5.2. Aggregate Readiness and Linear Benchmarks

The matched principal sample linear benchmarks (Table 3) show an aggregate FTRI coefficient of 0.572 (country-clustered $p = 0.719$) and an ICT coefficient of 0.244 ($p = 0.801$) within the five-component linear specification. The aggregate index therefore offers limited evidence of an independent linear association, whereas a more flexible component model reveals a stronger fitted change in the ICT relationship across readiness ranges. The latter model and its uncertainty are examined below. Table A11 documents a separate historical extended panel, level income specification.

Table 3. Linear two-way fixed effects benchmarks for aggregate FTRI and its five components (principal sample: N = 2127; log-quadratic GDP per capita).

Regressor	Aggregate β (SE)	*p*	Components β (SE)	*p*
Aggregate FTRI	0.5722 (1.5871)	0.7189	—	—
ICT readiness	—	—	0.2440 (0.9644)	0.8006
Skills	—	—	−0.4352 (1.6520)	0.7925
R&D readiness	—	—	1.1511 (1.4865)	0.4398
Industry	—	—	0.4896 (0.8778)	0.5777
Finance	—	—	1.2753 (2.1935)	0.5617
ln(real GDP per capita)	−8.2978 (7.4200)	0.2650	−8.2857 (7.3866)	0.2635
$[\ln(\text{GDP per capita})]^2$	1.0129 (0.4148)	0.0156	1.0144 (0.4131)	0.0151
Trade openness	−0.0097 (0.0050)	0.0532	−0.0097 (0.0051)	0.0568
Renewable energy share	−0.3011 (0.0351)	0.0000	−0.2988 (0.0353)	0.0000
SSR	4864.398	—	4854.977	—

Both models include country and calendar year effects and the selected log-quadratic GDP controls. Standard errors are country clustered, with $G - 1 = 174$ degrees of freedom. These *p*-values are conventional selected linear model statistics, not causal effects or searched threshold tests.

For the same non-study-imputed log-quadratic panel, the aggregate FTRI continuous threshold search selects a fitted cutoff of 0.300 and reduces the residual sum of squares by 12.159 relative to its own matched linear aggregate benchmark. This is a descriptive improvement in model fit, not a dependence-robust confirmation of an aggregate threshold. The component-level continuous search, discussed in Section 5.3, selects ICT = 0.500 with a larger within-model SSR improvement of 127.435; the improvements refer to distinct linear benchmarks and do not, by themselves, establish causal or structural thresholds.

The historical aggregate FTRI search using the extended panel and GDP per capita in levels selects 0.200, but the original full-search country wild bootstrap result does not support a threshold in that design (Table A11; Figure A1). The principal log-quadratic linear aggregate result remains statistically imprecise (0.572; $p = 0.719$). Taken together, the benchmarks motivate attention to individual technological capabilities rather than interpretation of a single aggregate readiness regime boundary. The historical *p*-value summaries and regime counts appear in Figures A3 and A5, respectively, under the original discontinuous specifications.

In the extended panel, level income aggregate search, the minimum occurs at FTRI = 0.200 (SSR = 7642.2003) and the model's original full-search country wild bootstrap returned $p = 0.2782$ under its maintained assumptions. Its fitted regime slopes are 6.6719 and 3.5577, but conditional coefficients at an unsupported cutoff do not themselves establish a threshold. The non-study-imputed income-controlled linear benchmark gives an aggre-

gate FTRI coefficient of 0.572 ($p = 0.719$). This contrast underscores that the regression form, sample, and conditional interpretation must remain explicit, rather than suggesting a common readiness threshold with policy relevance.

5.3. Model II: Subcomponent Threshold Model

The five-component search jointly compares ICT, skills, R&D, industry and finance readiness as possible continuous slope change variables, retaining the other four components additively. In the principal non-study-imputed log-quadratic sample (N = 2127), the minimum SSR candidate is ICT = 0.500. Table 4 presents its conditional coefficients; Appendix C (Tables A15–A17) documents historical discontinuous and extended sample comparisons. Neither those historical tables nor their bootstrap acceptance sets are treated as the principal model's cutoff confidence interval.

Table 4. Conditional coefficient estimates for the continuous ICT slope change specification selected in the principal five-component search (N = 2127; log-quadratic GDP per capita; country and year fixed effects; selected ICT cutoff = 0.500). Standard errors and *p*-values are conditional on the selected component and cutoff, not adjusted for heterogeneous interactive common factors. Upper-range slope uncertainty is computed using the full coefficient covariance matrix; all reported tests remain conditional on selection.

Regressor	β	Cluster SE	Conditional *p*
ICT readiness below cutoff	4.0739	1.8135	0.0259
ICT hinge at 0.500	−6.5376	1.9952	0.0013
Skills	−0.4029	1.6146	0.8033
R&D readiness	1.2247	1.5044	0.4167
Industry	0.8184	0.8683	0.3472
Finance	0.6803	2.1351	0.7504
ln(real GDP per capita)	−11.0465	7.1262	0.1229
[ln(GDP per capita)]^2	1.1744	0.3985	0.0036
Trade openness	−0.0088	0.0049	0.0756
Renewable energy share	−0.2768	0.0367	$p < 0.0001$
ICT slope above 0.500 (algebraic sum)	−2.4636	0.9782	0.0127
Linear model SSR/selected kink SSR	4854.977/4727.542	—	—

In the principal non-study-imputed, log-quadratic continuous model (Figure 3), the fitted ICT slope is 4.0739 below the selected 0.500 cutoff and −2.4636 above it, with a hinge change of −6.5376 (Table 4). The upper-slope country-clustered standard error, calculated from the variance of the sum of the ICT and hinge coefficients, is 0.9782 (conditional 95% CI: −4.3943 to −0.5329; conditional $p = 0.0127$). These intervals and tests condition on the selected component and cutoff and do not account for selection or heterogeneous interactive common factors. Within the fitted readiness ranges, a 0.10-unit difference in ICT corresponds to approximately +0.407 or −0.246 EnergyPCI points, respectively, holding the other regressors fixed. The opposite-signed conditional slopes motivate investigation of diminishing or changing associations between digital preparedness and energy productive capacity; they do not identify diminishing causal returns to ICT investment or a policy threshold. The original extended panel, level income model estimates slopes of 5.6575 and −2.5478, and its bootstrap $p = 0.0002$ applies only to that separate dependence and sampling design.

The ICT cutoff is selected by searching over readiness components and admissible values. All coefficient standard errors, confidence intervals and *p*-values in Table 4 condition on this selection and on country cluster covariance assumptions; they are not selection-corrected or common factor-robust global kink probabilities. The upper-range slope and its standard error are calculated using the sum of the lower-range ICT coefficient and the hinge

coefficient, including their covariance. Figure 3 plots only the partial fitted ICT contribution normalized to zero at the selected cutoff; it is neither a predicted EnergyPCI level nor a confidence band or demonstration of global threshold significance.

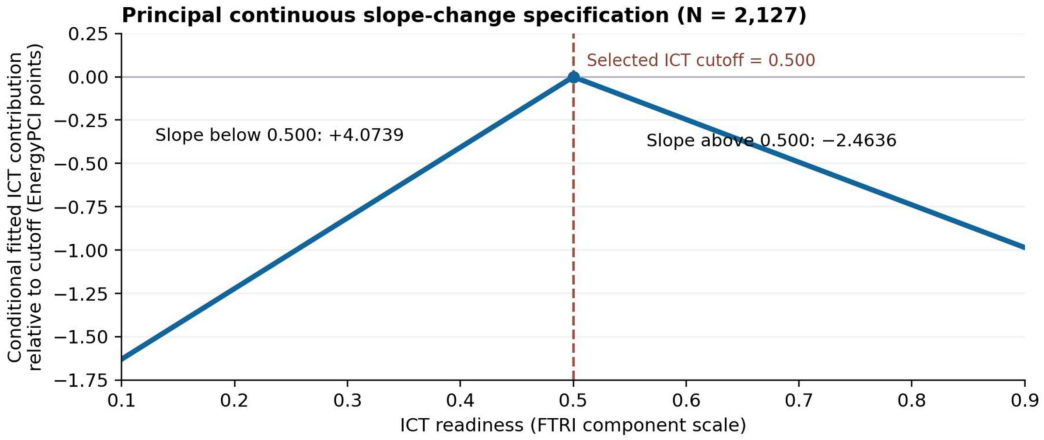


Figure 3. Conditional fitted ICT contribution in the principal continuous slope change specification (N = 2127; log-quadratic GDP per capita, economy and year fixed effects; selected ICT cutoff = 0.500). The curve is normalized to zero at the cutoff and depicts only the fitted partial effect of ICT with other regressors held fixed; it is not an unconditional prediction, a confidence interval, or factor-robust post-selection evidence.

5.4. Threshold Location Uncertainty and Functional Form Sensitivity

The historical extended panel discontinuous ICT comparison was deliberately searched beyond its original 15%-trimmed upper cutoff. Its SSR falls from 7572.758 at ICT = 0.600 to 7480.689 at 0.700, then rises to 7560.887 at 0.800; the objective therefore does not continue declining beyond 0.700 on the evaluated grid (Table A15). The 0.800 candidate leaves 11.32% of observations above the cutoff and fails 15% trimming but is informative under the broader search. The minimum at 0.700 recurs under the examined 5%, 10%, 15% and 20% trims. Historical confidence set inversion over the 33-pair expanded grid and the five fitted simulation designs yielded an ICT = 0.700 nominal 95% discrete grid acceptance set and coverage of 95.1–99.5% in the evaluated designs. These results diagnose boundary behavior and conditional uncertainty in the historical discontinuous model; they are not estimates of the principal log-quadratic continuous model. The separate discontinuous fitted-level change is not interpreted as an identified instantaneous economic event.

The continuous model adds a hinge $\max(q - c, 0)$ to the linear selected component, changing the fitted marginal slope without requiring a level discontinuity. Under the extended income-level comparison, its ICT minimizer is 0.500 (SSR = 7411.130), below the discontinuous comparator SSR of 7480.689. The principal non-study-imputed log-quadratic comparison also favors a continuous candidate (ICT = 0.500, SSR = 4727.542) over the best-fitting unrestricted discontinuous candidate (Skills = 0.200, SSR = 4778.631). When the discontinuous search is restricted to ICT alone, it selects ICT = 0.700 (SSR = 4783.092). Discontinuous cutoffs and components therefore depend on the specification. These fit differences are relevant to economic plausibility but do not substitute for a formally valid test of the searched kink under heterogeneous cross-economy dependence.

5.5. Additional Specification and Dependence Checks

Additional country trend, restricted period, lagged readiness, and balanced extended panel estimates are presented for their stated samples and controls in Table A17. Because those archived comparisons use income in levels and, in several cases, study-level imputations, they are sensitivity evidence rather than direct replications of the primary non-

study-imputed log-quadratic model. Variations in fit and selected readiness dimensions across documented temporal specifications caution against treating any cutoff as invariant. Archived region- and income group-specific results have unverified historical group assignments and are retained only as provenance-qualified comparisons in Appendix B, Table A8; they are not part of the independently verified robustness case.

Two original temporal checks also examine the continuous ICT hinge by adding country-specific linear trends or restricting the period to 2012–2021 without study-level logged imputations. In both, the full component search selects ICT = 0.500. The historical country wild conditional p-values are 0.0260 with country trends (N = 2448; 175 countries) and 0.0034 in the shorter observed sample (N = 1744; 175 countries). These values describe the maintained country wild designs, not validity under unrestricted cross-country common factor dependence. By contrast, discontinuous model searches with country trends select Skills = 0.300 ($p = 0.1426$), and the shorter sample selects ICT = 0.700 ($p = 0.1198$). Taken together, functional form, observation coverage, and temporal controls influence the fitted evidence. They do not warrant a generalized ICT tipping point conclusion.

The first-difference serial correlation tests reject the no serial correlation null in the reported aggregate and discontinuous models and both samples (all $p < 0.0001$; Table A4). In the full sample, $F(1174)$ is 83.3195 for Model I and 82.9636 for Model II. This supports allowing for dependence within countries rather than using independent observation standard errors. The CD normal reference p-values exceed 0.05 in all four cases, but this does not establish independence: the mean absolute pairwise correlations range from 0.4463 to 0.4624, and year–effect estimation can affect the statistic. These diagnostics do not validate the country-only dependence assumption for every form of cross-country correlation.

Driscoll–Kraay covariance changes conditional coefficient inference without changing any estimated slope (Table A5). In the discontinuous Model II comparator, the upper-regime ICT coefficient has conditional p-values between 0.0050 and 0.0150 in the full sample and between 0.0075 and 0.0285 in the observed-only sample; these contrast with its insignificant country-clustered p-values. The lower-regime coefficient is significant under each of these covariance choices. This is evidence that individual slope significance depends on the covariance procedure. It is not a new searched threshold test, and the short time dimension limits the reliability of the Driscoll–Kraay reference approximation. Significant conditional aggregate slopes likewise do not overturn the unsupported aggregate search.

The fitted alternative selection experiment in Table A6 reports reselection frequencies under the discontinuous model's stipulated data-generating process: ICT in 97.56% of full-sample draws and 91.00% of observed-only draws, and the exact ICT = 0.700 pair in 96.74% and 87.92%. These frequencies describe algorithmic stability under the assumed model and error process; they are not confidence probabilities that a true population threshold is 0.700. They also cannot establish stability across factor-adjusted or alternative regional and income group specifications.

5.6. GDP per Capita Functional Form and Influential Observation Diagnostics

To evaluate income functional form in the principal model, GDP per capita in levels, its logarithm, and the quadratic extension of each were compared on the same N = 2127 sample under identical fixed effects and controls. The log-quadratic form yields the lowest AIC among these four planned specifications. The separately examined log-cubic extension yields lower AIC and BIC in a fixed ICT = 0.500 regression, whereas its entire component–cutoff search has not been established by this diagnostic. The quadratic is retained as an interpretable, parsimonious main control following the previously specified comparison, with the additional cubic result acknowledged as a relevant specification sensitivity.

For the four planned income models (N = 2127; 175 economies), the conditional ICT = 0.500 comparisons give AIC values of 2441.41 for levels, 2191.71 for the log, 2320.83 for levels with a squared term, and 2092.82 for the log and its square (Table 5). In an additional fixed ICT diagnostic, the cubic log extension yields AIC = 2075.06, a reduction of 17.76, and an approximately 12.09-point lower BIC relative to log-quadratic income. These comparisons do not implement an unrestricted reselection of the readiness component and cutoff under the cubic form. Thus, neither information criterion establishes universal optimality of the retained income polynomial.

Table 5. Comparison of four principal GDP per capita functional forms within the continuous five-component threshold search (same N = 2127 sample and country/year fixed effects). AIC comparisons apply to these four candidates; the separately examined log-cubic alternative is not included in this table. Search statistics are conditional on the maintained resampling assumptions.

Income Form	AIC	Selected Component	Cutoff	Conditional Search p *
Levels	2441.41	ICT	0.500	0.0034
Logarithm	2191.71	ICT	0.500	0.0954
Levels and squared levels	2320.83	ICT	0.500	0.0002
Logarithm and squared logarithm	2092.82	ICT	0.500	0.0030

* Conditional search p-values are based on country-level wild-bootstrap resampling under the maintained dependence assumptions; they do not establish significance under unrestricted cross-country common factors.

In the non-study-imputed log-quadratic continuous ICT candidate, the conditional fitted income term is $-11.04645\ \ln(\text{GDPpc}) + 1.17437[\ln(\text{GDPpc})]^2$. Its stationary point is approximately USD 110 per capita, below the observed GDP range of USD 247–127,922, so the fitted slope with respect to log income remains positive within the observed range. This is not evidence of an observed U-shaped income relationship. Because the EnergyPCI input indicators include a GDP-related energy efficiency measure in published methodological descriptions, some income association may also reflect construct-level overlap rather than solely an independent economic mechanism.

Influence was evaluated with upper-tail exclusions and 175 leave-one-economy-out re-estimations of the fixed ICT = 0.500 log-quadratic model. Excluding the highest 1% and 5% GDP per capita observations retains a positive squared log coefficient, but omitting Yemen reduces it from 1.1744 to 0.6399 and changes its conventional country-clustered p-value from 0.00365 to approximately 0.078. The log-quadratic form nevertheless retains lower AIC than the simple log model in this country exclusion comparison. Thus, the flexible income form remains preferable for fit, whereas statistical certainty about the curvature is sensitive to influential economy histories. These are conditional diagnostics and should not be mistaken for a fully recomputed global threshold search after each deletion.

The income comparisons indicate that the measured readiness relationship is sensitive to how national income is represented. The log-quadratic control balances goodness of fit and interpretability within the four conventional alternatives, while the additional cubic log exercise and influential economy diagnostics delineate the strength of this choice. The main component estimates are consequently interpreted as conditional associations under the retained income specification, with the sensitivity comparisons reported alongside them.

5.7. Cross-Economy Dependence, Group-Specific Time Patterns, and Economic Interpretation

Country and calendar year fixed effects define the principal temporal control structure. Archived analyses additionally considered region-specific and income group-specific trends

and group-by-year effects on the N = 2127 non-study-imputed log-quadratic sample. Those exercises indicated specification-dependent cutoff selection, but their original country-by-group assignment matrices and classification vintage were not preserved in the recoverable numerical records. They are consequently retained only as historical, provenance-qualified exploratory comparisons in Appendix B, Table A8, and do not determine the preferred component, provide officially certified regional comparisons, or support threshold significance claims. The principal and common factor projection results are established independently of these historical group labels.

Residual cross-economy diagnostics show sensitivity to the treatment of common influences. The conventional Pesaran CD screen gives $p = 0.047$, whereas the weighted CD test with 999 repetitions gives $p = 0.376$; bias-adjusted findings also vary with factor assumptions. On the balanced 170-economy, 2010–2021 subsample, a fixed common projection search over 22 eligible component–cutoff candidates selects R&D = 0.500 by minimum SSR (matched linear-to-kink SSR improvement = 5.042247). A separate candidate-specific augmented projection gives conditional R&D slopes of 1.234 and 8.879, with a fitted change of 7.646; its SSR must not be compared with SSRs calculated under a different projection. An archived 999-draw bootstrap screen yields 521 statistics at least as large as the observed one, corresponding to $(521 + 1) / (999 + 1) = 0.522$. This arithmetic has been independently verified but the screen has not been validated as global, selection-adjusted inference for a continuous kink with interactive common factors. These exercises demonstrate sensitivity rather than confirming an alternative population threshold.

The principal two-way fixed effects search selects ICT = 0.500, whereas a supplementary common projection search selects R&D = 0.500. These exercises differ both in sample composition and in treatment of common influences; the difference in selected components therefore cannot be attributed to factor adjustment alone. Year effects absorb additive annual shifts but not heterogeneous factor exposure. The continuous kink estimates remain conditional, exploratory associations after data-driven selection: a valid global post-selection test under heterogeneous interactive common factors and corresponding cutoff confidence coverage have not been established. The matched linear fixed effects models, with country-clustered errors under their maintained assumptions, supply the primary inferential benchmarks; the searched nonlinear fits offer specification-dependent hypotheses for later testing.

A targeted overlap sensitivity check re-estimated the fixed ICT = 0.500 continuous specification on the same 2127 observations with the same country and year effects, alternately omitting renewable energy share, log GDP per capita and its square, or both. The fitted ICT slope remained positive below 0.500 and negative above 0.500 in all four specifications; the magnitudes varied appreciably. These are conditional fixed cutoff checks rather than renewed component–cutoff searches or independently valid tests of a threshold. Detailed matched model SSRs and slopes are provided in Appendix B, Table A7.

6. Discussion

The principal economic finding is that aggregate and component-level technological readiness do not convey identical information about national energy productive capacity. Aggregate FTRI shows little independent linear evidence in the matched log-quadratic panel, whereas the continuous component search finds better conditional fit for ICT readiness with a changing slope around 0.500. This difference is relevant to investment appraisal: similar composite readiness scores can mask distinct needs for connectivity, skills, technical absorption and financing. The negative fitted slope above the selected ICT range is not an adverse causal return on digital spending; the index measures national capabilities, not controlled investments. Other temporal and factor specifications change the selected

component, including favoring R&D in one alternative design. The result therefore supports more discriminating diagnosis of capability constraints, not a universal cutoff rule.

A changing ICT association is economically plausible because the constraints facing low-readiness and higher-readiness economies need not be identical. Initial improvements in communications infrastructure may support monitoring, information exchange and coordination, whereas further gains in productive capacity can require skills, technological absorption, industrial adaptation, financing and physical investment. These are mechanisms suggested by theory rather than causal channels identified by the estimated kink. The conditional pattern is thus most informative as a hypothesis about capability composition and productive complementarities, not as a country-specific target score.

Evidence on smart grids, demand response, renewable integration and energy management illustrates how digital capability can support the productive use of infrastructure [1,2,20]. Studies of digitalization, ICT and AI similarly associate technological applications with selected energy outcomes [18,19,21]. These external studies supply plausible mechanisms for interpreting readiness patterns; the national FTRI measure does not identify individual applications, and the EnergyPCI regression does not isolate their sector-specific effects. The empirical finding is a change in a conditional association with the productive capacity index, not a measured improvement in reliability or recovery from disturbances.

The estimated principal ICT slopes are +4.0739 and −2.4636, expressed as EnergyPCI points per unit of ICT readiness on the two sides of the fitted cutoff. Their algebraic difference identifies the estimated change in the fitted conditional slope, not an observed change in energy output or national welfare. The result motivates examining when digital infrastructure complements versus proxies for other productive constraints; evaluating those mechanisms would require sector-level investment, productivity and implementation data.

Uncertainty is addressed through selected model coefficient intervals, historical component–cutoff bootstrap test inversion, and dependence sensitivity assessments. The original discontinuous full-sample procedure produced a nominal 95% discrete grid acceptance set containing $(\mathrm{ICT}, 0.700)$, and five fitted simulation designs yielded empirical coverages of 95.1–99.5% under those designs. These are documented positive checks of the historical procedure. The principal log-quadratic continuous five-component model does not have a separately verified cross-factor-robust cutoff confidence set. The fitted ICT slopes are therefore presented as conditional economic associations, alongside sensitivity to the specification of common temporal influences.

ICT readiness may contribute to energy-related productive activity by facilitating operational information, coordination and technological adaptation. Its economic value is likely mediated by complementary factors—physical infrastructure, technical skills, organizational capabilities and financing—which differ markedly across economies [9,13,14]. The component results support examining those capabilities separately from an aggregate technology score; direct complementarities would require interaction specifications and relevant sectoral observations.

The conditional coefficient of renewable energy consumption share is negative in the reported models, but it should not be interpreted as evidence that greater renewable deployment reduces economic productive capacity. The share measures a broad composition of final energy use, including technologies with distinct economic functions [28]. More importantly, the energy category score itself incorporates an energy mix indicator under UNCTAD's published construction [7,8,29]; this creates possible arithmetic as well as conceptual overlap between the dependent index and the control. Interpreting its coefficient as a net return on renewable investment would consequently be inappropriate. Independent evidence on costs, reliability and sector-specific productive outcomes would be necessary for such a policy claim.

The interpretation also depends on the construction of the EnergyPCI outcome. The published UNCTAD Energy component combines information on access, use and related productive conditions; some of its underlying indicators overlap with GDP and the renewable energy share control. This feature makes the estimated relationship economically meaningful as an association among observed capacity indicators but also calls for care when attributing particular coefficient estimates to autonomous technology effects. A component-level decomposition would help distinguish measurement overlap from substantive production mechanisms.

The present study differs from Han and Sun [16], who relate frontier technology readiness to load capacity factors, by examining the Energy category of national productive capacity and comparing the aggregate FTRI with each of its five components. It further examines whether the fitted association is nonlinear and how its selected form varies with the specification of income, available observations and common temporal influences. The contribution is thus a transparent comparison of national capability measures for a productive capacity outcome, not identification of the causal returns to technology adoption.

Theoretical perspectives on absorptive capacity [13], complementarities [9] and resource-based development [15] help interpret why measured readiness and productive energy capacity need not move proportionally. The results are consistent with the relevance of capability composition: research, skills and investment conditions can matter for how digital infrastructures are employed, even where their individual additive coefficients are statistically imprecise. A broader research agenda can test these mechanisms through component interactions, measures of resource dependence and sector-specific evidence on productive energy use.

7. Conclusions

This study shows why aggregate frontier technology readiness and its five measured capabilities should not be treated as interchangeable indicators of energy productive capacity. The matched linear fixed effects estimates on 2127 economy–year observations provide the main conventional inferential benchmark, conditional on the maintained panel dependence assumptions. In the exploratory continuous slope change search, ICT = 0.500 is the best-fitting component–cutoff candidate in the principal log-quadratic specification: SSR declines from 4854.977 to 4727.542, with conditional fitted slopes of +4.074 and −2.464. The latter slope is negative under conditional country-clustered inference (SE = 0.978; 95% CI −4.394 to −0.533), but post-selection and common factor uncertainty prevent this finding from establishing a universally valid threshold.

The favored readiness dimension is sensitive to design choices: a separate balanced panel projection that represents common influences selects R&D rather than ICT at 0.500, but its sample and projection also differ from those of the principal model. The difference cannot be assigned to common factors alone without a matched sample comparison. Historical region and income comparisons are not independently replicated because the original group assignments were not recovered. Historical cutoff acceptance sets for discontinuous models are not confidence sets for the principal continuous specification. These qualifications place a clear boundary between estimated within-model fit and confirmatory evidence about a population threshold.

The main contribution is economic as well as methodological: aggregate technology readiness rankings alone may be insufficient for interpreting cross-country differences in energy productive capacity, because their components can indicate distinct and potentially complementary constraints. The exploratory ICT pattern focuses attention on the conditions under which connectivity is converted into productive energy services, while its sensitivity to specification prevents it from establishing a transferable investment threshold. For

governments and investors, the practical implication is to evaluate digital infrastructure jointly with skills, industrial implementation, financing and operating requirements, and to compare expected service and productivity benefits against costs and alternative uses of resources. These are appraisal priorities motivated by the findings, not estimated causal returns. Demonstrating which investments deliver the greatest economic gains requires project- or sector-level outcomes, observed costs and credible identification strategies.

8. Policy Implications

The policy implication is diagnostic rather than a numerical cutoff rule. Governments and investors should assess ICT, skills, research capability, industrial implementation and financing jointly with the condition of energy infrastructure, because aggregate readiness rankings may conceal different capability constraints. The fitted ICT = 0.500 cutoff must not be used as a threshold for allocating public funds or approving projects. Economic appraisal should instead compare expected output and service gains against capital and operating costs, opportunity costs, financing limits and credible counterfactual alternatives [1,2,9,20].

Readiness scores are most useful as screening indicators to be interpreted alongside information on technical requirements, institutional capacity and the existing capital stock. They can help structure questions about why countries with similar digital connectivity exhibit different productive energy outcomes. For public investment decisions, these questions should be tested against project-level costs and benefits, infrastructure conditions and measurable service outcomes rather than resolved by the cross-country cutoff alone.

Economic complementarity offers a rationale for assessing ICT expenditure jointly with human capital, technical skills, maintenance, organizational capability, and financing. Where complementary inputs are scarce, the returns to isolated digital spending may differ substantially from returns to coordinated programs; however, no such interaction or causal return has been estimated here. Project-level evaluation should therefore compare alternatives in terms of expected economic benefits, resource constraints, and lifecycle costs rather than assuming the fitted readiness coefficient measures investment productivity [9].

External supply chain conditions, technology costs and institutional constraints can influence the feasibility of energy-related upgrading [3,4,24]. Their relevance is economic context for assessing productive investments, not a directly tested geopolitical mechanism in this study. Decisions about procurement, diversification or technological sourcing therefore require separate evidence on costs, exposure and operational performance.

For resource-dependent economies, resource revenues can finance technical upgrading but are subject to opportunity costs, fiscal volatility, and competing development needs [3,4,15]. The empirical models do not estimate the effect of spending resource rents on energy capacity or the productivity of renewable investment. In particular, the negative conditional association of renewable energy consumption share in certain specifications must not be interpreted as evidence that renewable deployment reduces productive capacity; composition effects, transition costs, and simultaneity remain plausible. Policy appraisal should rely on separate evidence on integration costs, reliability, productivity, and long-run economic returns.

Policy evaluation should prioritize independently observable outcomes—energy service reliability, productive use, operating costs and firm-level or sector-level value added—so that the economic value of complementary technology and skills investments can be assessed. Such evidence is needed to determine which capability constraints are binding and whether coordinated investment packages deliver benefits sufficient to justify their costs. The cross-country fitted readiness cutoffs alone cannot answer those questions.

9. Limitations and Future Research

The outcome is UNCTAD's Energy category, which summarizes aspects of national productive capacity rather than individual energy sector performance. Future work can link this measure to observed output, service quality, infrastructure investment and technological adoption to test the economic channels proposed here. The present panel is best suited to comparative associations at the national level.

Three limitations shape the interpretation. First, observational data and the overlap between some EnergyPCI inputs and controls preclude a causal reading of coefficients. Second, the additive component specification does not directly test complementarities or the relative returns to investment. Third, the short annual panel, the selection of a component and cutoff from the same data, and heterogeneous responses to common shocks complicate confirmatory inference for a continuous kink. The common factor projections are specification sensitivities rather than a globally validated post-selection test.

Historical bootstrap acceptance sets and five fitted empirical coverage exercises (95.1–99.5%) document uncertainty within the earlier discontinuous specification; they are not confidence sets for the current log-quadratic continuous component search. More informative inference would require validated methods for joint component and cutoff selection under cross-sectional dependence, along with longer panels and independent information on sectoral productive outcomes. These extensions would help distinguish functional form sensitivity from persistent economic heterogeneity.

Funding: This research was funded by Ongoing Research Funding Program, (ORF-2026-1890), King Saud University, Riyadh, Saudi Arabia.

Data Availability Statement: Source indicators are publicly accessible through UNCTADstat and World Bank WDI [6,8,28]. The Energy dimension is CATEGORY = Energy in dataset US.PCI; renewable energy consumption share is EG.FEC.RNEW.ZS. Data treatment and sample definitions are specified in Section 4.1.

Acknowledgments: The author extends appreciation to Ongoing Research Funding Program, (ORF-2026-1890), King Saud University.

Conflicts of Interest: The author declares no conflicts of interest.

Appendix A. Benchmark and Observed-Only Estimates

Tables A1 and A2 report complementary linear and discontinuous specifications for the extended and non-study-imputed panels. Their archived estimates use GDP per capita in levels and should be interpreted within that separate specification, not as coefficients of the log-quadratic main model. The principal matched log-quadratic benchmarks appear in Table 3, the conditional continuous ICT candidate in Table 4, and income form diagnostics in Table 5. The appendices preserve useful robustness comparisons without determining the main interpretation.

Table A1. Historical extended sample linear fixed effects benchmarks (N = 2448; 2010–2023; GDP per capita in levels; includes study-level imputed records). No readiness threshold is imposed.

Model/Variable	Coefficient	Standard Error	*p*-Value
I: Aggregate FTRI	2.5126	1.8270	0.1708
I: GDP per capita	0.000332	0.000052	<0.0001
I: Trade openness	−0.0041	0.0051	0.4317
I: Renewable share	−0.3373	0.0346	<0.0001

Table A1. *Cont.*

Model/Variable	Coefficient	Standard Error	*p*-Value
II: ICT readiness	0.8740	1.0282	0.3965
II: Skills readiness	0.3542	1.8604	0.8492
II: R&D readiness	2.5005	1.7276	0.1496
II: Industry readiness	0.4305	1.0680	0.6874
II: Finance readiness	1.6991	2.4779	0.4938
II: GDP per capita	0.000337	0.000055	<0.0001
II: Trade openness	−0.0038	0.0051	0.4616
II: Renewable share	−0.3330	0.0352	<0.0001

Table A2. Historical discontinuous threshold model estimates on the sample excluding study-level imputations (N = 2127; GDP per capita in levels, distinct from the principal log-quadratic specification). Model I selects FTRI = 0.300 (country wild full-search $p = 0.1066$), and Model II selects ICT = 0.700 ($p = 0.0224$), conditional on the original specification and resampling design.

Model/Variable	Coefficient	Standard Error	*p*-Value
I: FTRI ≤ 0.300	−0.7514	2.0321	0.7120
I: FTRI > 0.300	0.9916	1.6588	0.5508
I: GDP per capita	0.000321	0.000053	<0.0001
I: Trade openness	−0.0049	0.0058	0.3951
I: Renewable share	−0.3574	0.0378	<0.0001
II: ICT ≤ 0.700	2.2997	1.2214	0.0614
II: ICT > 0.700	1.0227	1.0106	0.3130
II: Skills readiness	0.7496	1.7406	0.6673
II: R&D readiness	1.4747	1.6399	0.3697
II: Industry readiness	0.4409	0.9351	0.6378
II: Finance readiness	1.2905	2.1986	0.5580
II: GDP per capita	0.000337	0.000060	<0.0001
II: Trade openness	−0.0044	0.0059	0.4555
II: Renewable share	−0.3396	0.0398	<0.0001

Appendix B. Additional Specification and Dependence Results

Table A3 preserves supplementary discontinuous searches that use income in levels, including country trends, shorter observed windows, balanced extended observations, and one-year lagged readiness. Tables A4–A6 report serial and cross-economy dependence diagnostics, alternative covariance calculations and fitted alternative reselection frequencies. These results describe their explicitly stated model and sample designs; none supplies a valid common factor-robust, post-selection *p*-value for the principal continuous ICT kink.

Table A3. Historical supplementary discontinuous threshold specifications with GDP per capita in levels. Conditional regime coefficients (β) and country cluster standard errors (SE); original full-search test results are summarized in Table A17. Samples and temporal controls differ across rows.

Check	Model	Variable/Regime	β	SE	*p*
Trends	I	FTRI ≤ 0.200	1.6225	1.6788	0.3352
Trends	I	FTRI > 0.200	1.1857	0.8628	0.1711
Trends	I	GDP per capita	2.944×10^{-4}	9.747×10^{-5}	0.0029
Trends	I	Trade openness	0.0016	0.0034	0.6456
Trends	I	Renewable share	−0.1587	0.0280	<0.0001
Trends	II	Skills ≤ 0.300	0.9820	1.7104	0.5666
Trends	II	Skills > 0.300	−1.5321	1.1460	0.1830

Table A3. *Cont.*

Check	Model	Variable/Regime	β	SE	*p*
Trends	II	ICT	0.8410	0.6340	0.1864
Trends	II	R&D	−0.8970	1.0354	0.3875
Trends	II	Industry	−0.4439	0.6794	0.5143
Trends	II	Finance	−1.9905	1.4375	0.1679
Trends	II	GDP per capita	2.894×10^{-4}	9.672×10^{-5}	0.0032
Trends	II	Trade openness	0.0020	0.0036	0.5759
Trends	II	Renewable share	−0.1569	0.0278	<0.0001
Period	I	FTRI ≤ 0.300	1.3174	1.8826	0.4850
Period	I	FTRI > 0.300	2.4227	1.4560	0.0979
Period	I	GDP per capita	3.152×10^{-4}	4.985×10^{-5}	<0.0001
Period	I	Trade openness	−0.0029	0.0058	0.6178
Period	I	Renewable share	−0.3464	0.0357	<0.0001
Period	II	ICT ≤ 0.700	1.3874	1.0845	0.2025
Period	II	ICT > 0.700	0.4356	0.9340	0.6415
Period	II	Skills	0.8618	1.5726	0.5844
Period	II	R&D	2.0841	1.4213	0.1443
Period	II	Industry	0.8040	0.8581	0.3500
Period	II	Finance	−0.0083	1.9123	0.9965
Period	II	GDP per capita	3.169×10^{-4}	5.617×10^{-5}	<0.0001
Period	II	Trade openness	−0.0027	0.0059	0.6475
Period	II	Renewable share	−0.3390	0.0368	<0.0001
Balanced	I	FTRI ≤ 0.300	0.0969	2.2928	0.9663
Balanced	I	FTRI > 0.300	2.0828	1.8313	0.2570
Balanced	I	GDP per capita	3.312×10^{-4}	5.174×10^{-5}	<0.0001
Balanced	I	Trade openness	−0.0044	0.0051	0.3898
Balanced	I	Renewable share	−0.3345	0.0341	<0.0001
Balanced	II	ICT ≤ 0.700	2.7494	1.2255	0.0261
Balanced	II	ICT > 0.700	1.1680	1.0346	0.2605
Balanced	II	Skills	0.5278	1.8252	0.7728
Balanced	II	R&D	2.3132	1.7192	0.1802
Balanced	II	Industry	0.8718	1.0617	0.4127
Balanced	II	Finance	1.1969	2.3651	0.6135
Balanced	II	GDP per capita	3.484×10^{-4}	6.040×10^{-5}	<0.0001
Balanced	II	Trade openness	−0.0042	0.0051	0.4150
Balanced	II	Renewable share	−0.3169	0.0348	<0.0001
Lag	I	Lagged FTRI ≤ 0.300	−0.3961	1.9685	0.8408
Lag	I	Lagged FTRI > 0.300	1.2992	1.6340	0.4276
Lag	I	GDP per capita	3.277×10^{-4}	5.173×10^{-5}	<0.0001
Lag	I	Trade openness	−0.0045	0.0050	0.3758
Lag	I	Renewable share	−0.3242	0.0334	<0.0001
Lag	II	Lagged ICT ≤ 0.700	2.9233	1.1969	0.0156
Lag	II	Lagged ICT > 0.700	1.3669	1.0188	0.1814
Lag	II	Lagged Skills	1.4168	1.9345	0.4649
Lag	II	Lagged R&D	2.1699	1.6741	0.1967
Lag	II	Lagged Industry	0.5282	0.9563	0.5814
Lag	II	Lagged Finance	0.0292	2.2319	0.9896
Lag	II	GDP per capita	3.458×10^{-4}	6.132×10^{-5}	<0.0001
Lag	II	Trade openness	−0.0044	0.0050	0.3819
Lag	II	Renewable share	−0.3078	0.0330	<0.0001

Table A4. Historical residual serial correlation and cross-sectional dependence diagnostics for the extended sample threshold specifications. Serial F evaluates the first-difference residual lag hypothesis; CD diagnostics have model-dependent reference distributions and are not proofs of cross-sectional independence.

Sample/Model	Serial Pairs	Serial F	Serial p	CD (p)	Mean $\|\rho\|$
Full/I	2098	83.3195	<0.0001	1.0987 (0.2719)	0.4612
Full/II	2098	82.9636	<0.0001	0.5485 (0.5834)	0.4463
Observed/I	1775	75.0236	<0.0001	1.8062 (0.0709)	0.4624
Observed/II	1775	75.2732	<0.0001	1.5201 (0.1285)	0.4475

Table A5. Historical Driscoll–Kraay coefficient standard error sensitivity in the extended sample, level income discontinuous threshold specifications (T = 14). Values are conditional on selected regimes; they are not post-selection inference for a searched kink.

Sample/Model	L	SE_1	p_1	SE_2	p_2
Full/I	1	2.0911	0.0071	0.5114	<0.0001
Full/I	2	2.2998	0.0124	0.5128	<0.0001
Full/I	3	2.3823	0.0150	0.5113	<0.0001
Full/II	1	0.6045	0.0006	0.4181	0.0150
Full/II	2	0.5805	0.0004	0.3777	0.0085
Full/II	3	0.5663	0.0003	0.3473	0.0050
Observed/I	1	1.6384	0.6547	1.0412	0.3597
Observed/I	2	1.8254	0.6879	1.1313	0.3979
Observed/I	3	1.8651	0.6941	1.1382	0.4007
Observed/II	1	0.5534	0.0013	0.4109	0.0285
Observed/II	2	0.4975	0.0006	0.3587	0.0146
Observed/II	3	0.4651	0.0003	0.3187	0.0075

Table A6. Historical discontinuous five-component search: component and cutoff reselection frequencies in 4999 fitted alternative country wild bootstrap draws (original extended sample, level income model; seed 20261010). These frequencies are not cutoff confidence coverage.

Sample	ICT Reselected	ICT = 0.700 Reselected	Exact Pair Count/4999
Full	97.56%	96.74%	4836/4999
Observed	91.00%	87.92%	4395/4999

Table A7. Targeted control overlap sensitivity for the principal non-study-imputed panel (N = 2127; country and year fixed effects; continuous ICT hinge fixed at 0.500). Results are conditional fitted comparisons, not renewed component selection or dependence-robust threshold tests.

Control Specification	Linear SSR	Hinge SSR	ICT Slope $\leq$ 0.500	ICT Slope > 0.500
Full controls	4854.977	4727.542	4.0739	−2.4636
Without renewable share	6360.247	5940.818	7.4211	−4.0753
Without log GDP terms	6352.138	6230.844	4.3536	−1.9036
Without both controls	8478.331	7849.433	9.5043	−4.0071

The archived group-specific exercises are listed separately to preserve numerical provenance without incorporating unverifiable historical group assignments into the principal evidence. Their results neither replace the observed-only baseline nor establish a factor-robust search test.

Table A8. Archived sensitivity of component and cutoff to historical region/income group temporal controls (N = 2127; log-quadratic GDP per capita). Country group assignment matrices and vintage were not recovered; shown for historical transparency, not as independently certified UN M49 or World Bank group comparisons or formal threshold tests.

Time Structure	Selected Component	Cutoff	Null SSR	Kink SSR	Gain
Country and year effects	ICT	0.500	4854.977	4727.542	127.435
Income group-specific trends *	ICT	0.600	4461.697	4437.242	24.455
Income group × year *	ICT	0.700	4397.387	4373.867	23.521
Region-specific trends *	ICT	0.500	4659.923	4585.480	74.443

Notes: Each SSR improvement compares a searched candidate against its own linear baseline under the same temporal controls. Labels and coefficients reproduce the archived output; the country-level group definitions cannot be independently reproduced from the preserved files. No inference about formally robust group-adjusted threshold significance is drawn. * Indicates specifications using historical income-group or regional classifications.

Appendix C. Historical Analyses and Robustness Checks

This appendix preserves historical extended-panel and level income analyses, which are separate from the principal non-study-imputed, log-quadratic continuous specifications. Figures A1–A7 must be interpreted only within their labeled models and samples. Figure A3 reports scalar full-search *p*-values, while Figure A5 distinguishes the historical cutoffs used in the two samples. None of these figures provides factor-robust global inference or threshold confidence coverage for the principal continuous kink search.

Table A9. Descriptive statistics for the extended 2010–2023 panel (N = 2448; includes country–year rows with study-level imputations). N denotes observations; SD denotes standard deviation.

Variable	N	Mean	SD	Minimum	Maximum
Energy productive capacity	2448	51.177	19.703	5.700	100.000
Aggregate FTRI	2448	0.507	0.243	0.000	1.000
ICT readiness	2448	0.561	0.231	0.000	1.000
Skills readiness	2448	0.454	0.226	0.000	1.000
R&D readiness	2448	0.290	0.238	0.000	1.000
Industry readiness	2448	0.496	0.227	0.000	1.000
Finance readiness	2448	0.823	0.110	0.000	1.000
GDP per capita	2448	15,063.930	21,678.628	86.833	127,922.000
Trade openness	2448	87.058	55.971	0.000	442.620
Renewable energy share	2448	32.933	28.063	0.000	97.000

Table A10. Historical heteroskedasticity and collinearity diagnostics for the original extended sample, level income aggregate and discontinuous component threshold models (N = 2448). Breusch–Pagan *p*-values use exploratory conventional chi-square inference.

Diagnostic	Model I	Model II	Interpretation
BP statistic	60.2172	80.9802	Exploratory residual heteroskedasticity test.
BP *p*-value	<0.0001	<0.0001	Reject homoskedasticity under the conventional test.
Maximum structural VIF	3.478	9.469	Partitioned ICT regressors show appreciable collinearity.
Bootstrap 95% critical F	21.0461	30.5732	Country wild bootstrap repeats the complete search.

Table A11. Historical aggregate FTRI discontinuous threshold estimates for the extended sample (N = 2448; GDP per capita in levels; cutoff = 0.200; country wild full-search $p = 0.2782$). Conditional country-clustered coefficients are not evidence of a significant threshold.

Variable/Regime	Coefficient	Standard Error	*p*-Value
Aggregate FTRI ≤ 0.200	6.6719	2.4993	0.0083
Aggregate FTRI > 0.200	3.5577	1.5505	0.0230
GDP per capita	0.000334	0.000052	<0.0001
Trade openness	−0.0041	0.0051	0.4203
Renewable share	−0.3347	0.0347	<0.0001

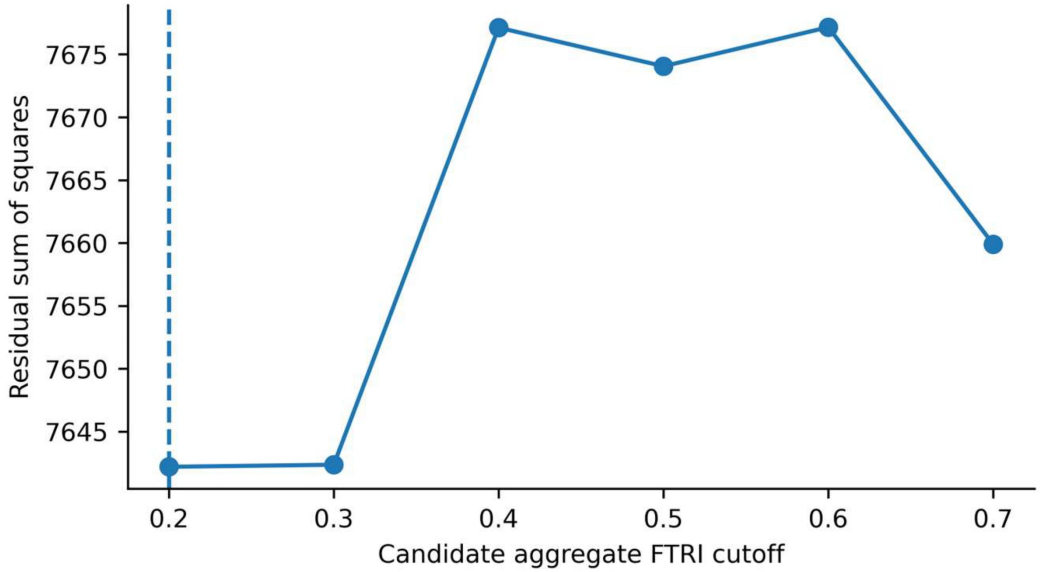


Figure A1. Historical extended panel, level income SSR profile for the aggregate FTRI threshold model (N = 2448). Candidate split 0.200 is indicated by the vertical dashed line; country wild full-search $p = 0.2782$ under its maintained assumptions.

Table A12. Historical extended panel conditional estimates of the continuous ICT slope change model (cutoff = 0.500; N = 2448, including study-level imputations; level income controls). The reported full-search country wild bootstrap $p = 0.0002$ is conditional on its cross-economy dependence assumptions, not validated under unrestricted heterogeneous common factors. Country-clustered coefficient *p*-values also condition on selected model terms. This table does not establish a universal or causal ICT threshold.

Variable/Regime	Coefficient	Standard Error	*p*-Value
ICT ≤ 0.500	5.6575	1.8208	0.0022
ICT > 0.500	−2.5478	1.1774	0.0318
Skills readiness	0.2367	1.8126	0.8963
R&D readiness	2.6281	1.7545	0.1360
Industry readiness	0.8512	1.0608	0.4234
Finance readiness	0.9636	2.3428	0.6814
GDP per capita	0.000347	0.000061	<0.0001
Trade openness	−0.0030	0.0050	0.5499
Renewable share	−0.3079	0.0357	<0.0001
ICT slope change	−8.2053	2.1125	0.0001

Table A13. Historical extended panel conditional estimates of the discontinuous ICT comparator (cutoff = 0.700; N = 2448, including study-level imputations; level income controls). The originally reported full-search bootstrap $p = 0.0024$ is conditional on the maintained resampling assumptions, not evidence of a structural discontinuity or dependence-robust cutoff.

Variable/Regime	Coefficient	Standard Error	*p*-Value
ICT readiness ≤ 0.700	2.7464	1.2201	0.0256
ICT readiness > 0.700	1.1706	1.0305	0.2576
Skills readiness	0.6303	1.8113	0.7283
R&D readiness	2.3337	1.7111	0.1744
Industry readiness	0.8161	1.0546	0.4400
Finance readiness	1.2454	2.3531	0.5973
GDP per capita	0.000349	0.000060	<0.0001
Trade openness	−0.0040	0.0051	0.4326
Renewable share	−0.3165	0.0347	<0.0001

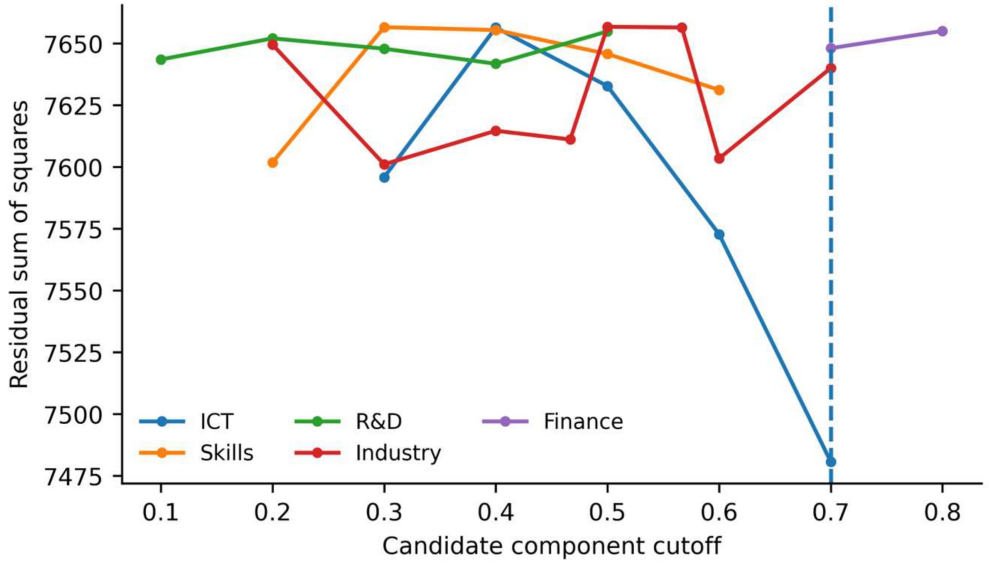


Figure A2. Historical extended panel, level income SSR profiles for five readiness components in the discontinuous functional form comparison (N = 2448; original 15% trimming design).The vertical dashed line indicates the selected ICT cutoff of 0.700.

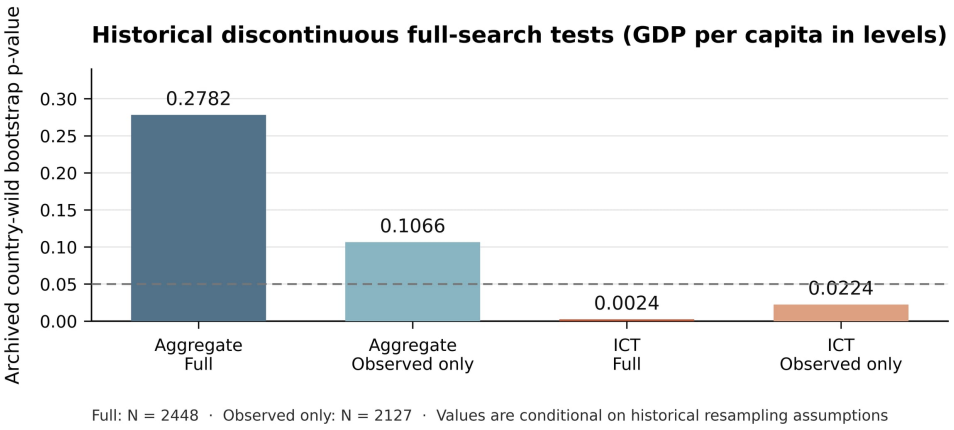


Figure A3. Historical country wild bootstrap full-search *p*-values for discontinuous aggregate and ICT threshold models with GDP per capita in levels: extended panel (N = 2448) and sample excluding study-level imputations (N = 2127). Bars display archived scalar *p*-values, not bootstrap distributions; the dashed line denotes 0.05. Inference is conditional on the historical country-level resampling and cross-economy dependence assumptions, not a factor-robust global continuous kink test.

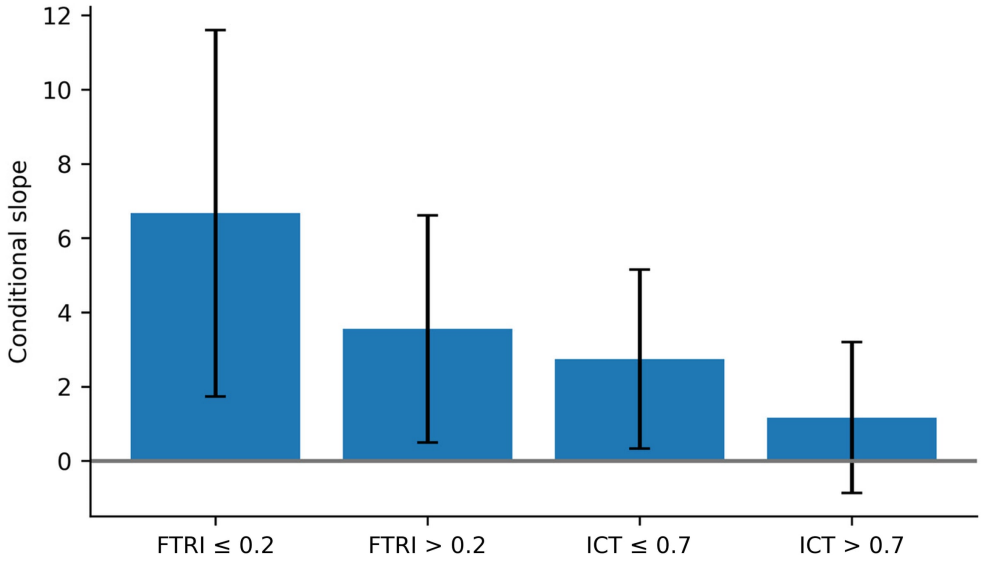


Figure A4. Historical extended sample conditional readiness coefficients and 95% slope intervals for the discontinuous threshold model (GDP per capita in levels). The intervals treat the selected model, component and cutoff as fixed; they do not incorporate selection uncertainty or provide confidence coverage for the cutoff.

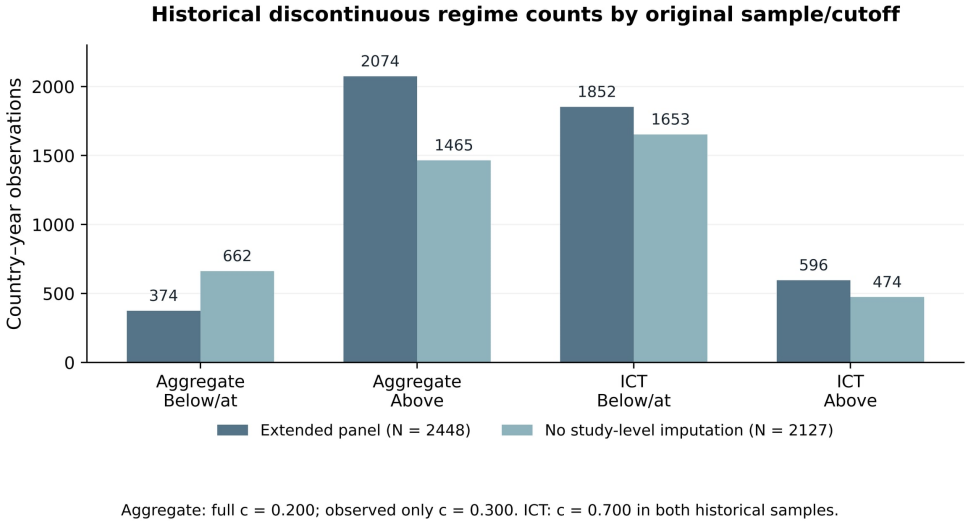


Figure A5. Historical discontinuous readiness regime observation counts from the verified source workbook: aggregate FTRI cutoff 0.200 in the extended panel (N = 2448), aggregate cutoff 0.300 without study-level imputations (N = 2127), and ICT cutoff 0.700 in both historical samples. Regime counts are not those of the principal continuous ICT = 0.500 model.

The expanded grid exercise answers the boundary concern for the historical discontinuous specification: the observed SSR minimum lies at 0.700 rather than continuing to fall as the cutoff increases. At 0.800, 277 of 2448 observations (11.32%) lie above the cutoff, compared with 596 (24.35%) above 0.700. The original 95% discrete grid bootstrap acceptance set contains only (ICT, 0.700), and five fitted simulation exercises found coverage of 95.1–99.5% (99.5% for the ICT = 0.700 configuration). The simulation results assess the procedure under the designs actually studied; they cannot establish factor-robust confidence coverage for the later five-component continuous kink analysis. A narrow set on the evaluated discrete grid should not be conflated with precise identification of an invariant continuous valued economic cutoff.

Table A14. Original hypotheses and theoretical proposition compared with historical model results. Interpretations are descriptive; the principal log-quadratic continuous specifications and common factor sensitivities are discussed in Section 5.

Hypothesis	Evidence Used	Decision	Interpretation
H1	Primary observed-only log-quadratic aggregate linear benchmark; extended panel aggregate search	Not supported by primary linear evidence	FTRI = 0.572 ($p = 0.719$) in the main observed-only benchmark; conditional extended panel regime slopes do not identify an aggregate threshold.
H2	Aggregate readiness threshold searches under distinct maintained dependence conditions	No confirmed population threshold	Fitted aggregate candidates are descriptive; a robust structural breakpoint is not identified.
H3	Primary observed-only continuous search (ICT = 0.500); alternative time structures and factor projections	Fitted nonlinearity; confirmatory evidence unavailable	Observed sample SSR falls 4854.98 to 4727.54; alternative factor controls can select R&D. No validated post-selection, common factor-robust p-value.
H4 (proposition)	Subcomponent estimates and literature channels	Not directly tested	The additive component estimates do not identify distinct mechanisms or test complementarity. H4 is retained as a theoretical proposition rather than an empirically tested hypothesis.
H5	Selected conditional slopes; test of a stronger upper-readiness association	Not supported by point estimates	The fitted upper ICT slope (−2.464) is below the lower slope (+4.074); the pattern is not causal or a stable population law.

Table A15. Historical extended sample discontinuous five-component search under alternative trimming rules (Panel A) and ICT objective function profile beyond cutoff 0.700 (Panel B; original GDP per capita level specification).

Analysis	Trim/Cutoff	Selected Component	Threshold/Candidate	SSR
Panel A—Search	5%	ICT	0.700	7480.6886
Panel A—Search	10%	ICT	0.700	7480.6886
Panel A—Search	15%	ICT	0.700	7480.6886
Panel A—Search	20%	ICT	0.700	7480.6886
Panel B—ICT profile	—	ICT	0.600	7572.7579
Panel B—ICT profile	—	ICT	0.700	7480.6886
Panel B—ICT profile	—	ICT	0.800	7560.8865

Note: All SSR values in Panels A and B are obtained from the full estimation sample (N = 2448) with the same controls and country and year fixed effects. Panel A reports the minimum SSR from the complete search across five readiness components; Panel B evaluates the discontinuous ICT specification at alternative cutoffs. Under 5% trimming, 33 component–cutoff pairs are estimable. ICT = 0.800 is admissible under 5% and 10% trimming, while ICT = 0.900 is not admissible at 5%. The nominal 95% joint bootstrap acceptance set on the discrete grid is {(ICT, 0.700)}. The balanced panel, observed-only, and continuous model SSR values refer to separate specifications or samples and are not included in this table.

The unrestricted level-and-slope checks at fixed ICT cutoffs do not reject a zero level jump at 5% under the country-level wild bootstrap (19,999 draws), although covariance-based inference varies by estimator. These conditional tests do not resolve all selection and cross-country dependence uncertainty. Together with the lower SSR and information criteria, the diagnostics favor the continuous functional form without establishing that an abrupt level change is impossible.

Table A16. Historical extended panel, level income functional form comparison for Model II (N = 2448). Relative AIC and BIC use the same estimation convention. The nominal 95% discrete grid bootstrap acceptance sets relate to these historical candidates and maintained resampling assumptions; neither is the confidence set for the principal non-study-imputed log-quadratic specification.

Criterion	Continuous (Extended)	Discontinuous (Sensitivity)
Selected component	ICT	ICT
Estimated cutoff	0.500	0.700
SSR	7411.1295	7480.6886
Relative AIC	3107.6777	3130.5469
Relative BIC	4256.6770	4279.5462
Nominal 95% discrete grid cutoff acceptance set	{0.500, 0.600}	{0.700}
Fitted-level jump (unrestricted model at respective cutoff)	+0.4344; wild bootstrap $p = 0.0788$	−0.4288; wild bootstrap $p = 0.1569$

Table A17. Historical supplementary full-search bootstrap tests: aggregate and discontinuous component threshold models using GDP per capita in levels, plus separately identified continuous-model checks. Samples, time controls, and functional forms differ by row; statistics are not pooled across designs.

Check	Model	N	G	Selected Cutoff	F	Bootstrap p
Country linear trends	I	2448	175	FTRI = 0.200	0.4205	0.9912
Country linear trends	II	2448	175	Skills = 0.300	14.3312	0.1426
Country linear trends (continuous)	II-C	2448	175	ICT = 0.500	21.3223	0.0260
2012–2021 observed rows	I	1744	175	FTRI = 0.300	3.6130	0.5372
2012–2021 observed rows	II	1744	175	ICT = 0.700	16.8152	0.1198
2012–2021 observed rows (continuous)	II-C	1744	175	ICT = 0.500	33.8682	0.0034
Balanced coverage	I	2436	174	FTRI = 0.300	10.8487	0.2692
Balanced coverage	II	2436	174	ICT = 0.700	53.1136	0.0020
One-year-lagged readiness	I	2273	175	FTRI = 0.300	8.1746	0.1898
One-year-lagged readiness	II	2273	175	ICT = 0.700	49.7940	0.0016

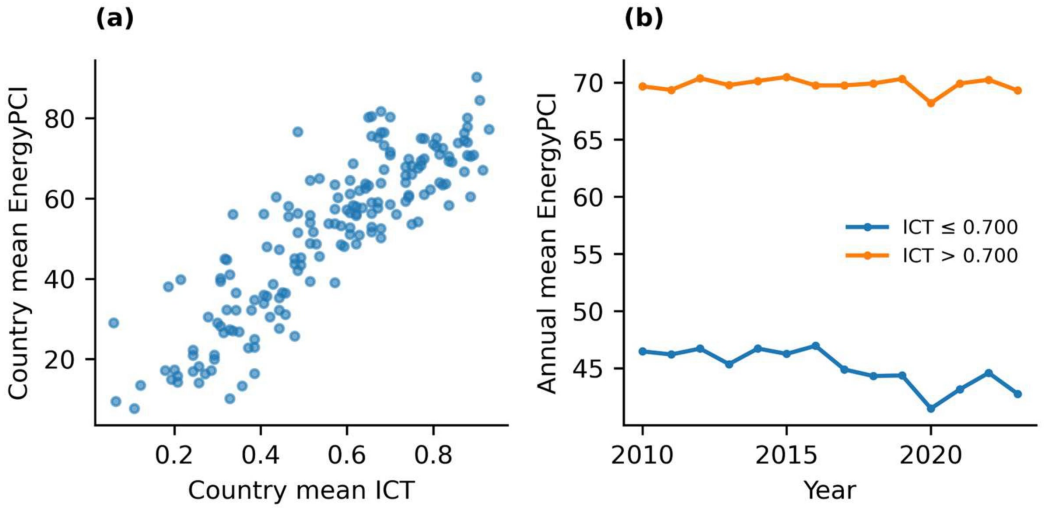


Figure A6. Historical descriptive plots of ICT readiness and EnergyPCI in the extended panel: (**a**) economy means, (**b**) annual mean EnergyPCI by ICT group. These descriptive relationships are distinct from the principal fixed effects fitted slopes.

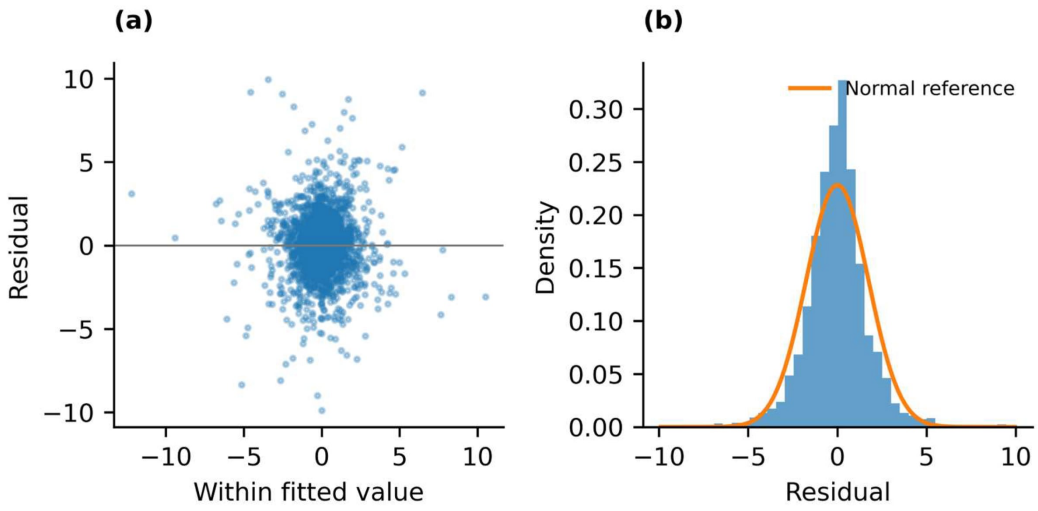


Figure A7. Historical extended panel residual diagnostics for the discontinuous ICT comparison: (**a**) within residuals against within fitted values, (**b**) residual density with normal reference. Negative within fitted values result from centering. The gray horizontal line indicates zero residuals.

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