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Article

Uncertainty Meets the Sun: The Role of ESG Uncertainty, US–China Trade Tensions, and Oil Shocks in Shaping Solar Energy Adoption

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ABSTRACT

Motivated by the view that sustainability uncertainty, policy uncertainty, trade frictions, and oil-price movements can jointly shape the pace of clean-energy adoption, this study investigates the drivers of solar energy consumption (SOC) in the United States by focusing on ESGUI, EPU, UCT, and OP. The study employs monthly observations spanning 01/11/2002 to 01/02/2024 and highlights a significant upward trajectory in SOC with recurring seasonal fluctuations. To capture potential nonlinearities and regime-dependent effects, the study relies on Quantile-threshold Kernel Regularized Least Squares approach. This approach evaluates marginal impacts across SOC quantiles and explicitly assesses their statistical significance over the distribution. Specifically, ESGUI is positive at the tails but negative and strongest around the median, EPU is insignificant at the lowest quantile but positive in the middle and negative at the top, UCT is consistently positive and increasing toward higher quantiles, and OP is positive and significant across most quantiles with a stronger influence in the middle-to-upper range before weakening at the extreme upper tail. Overall, the findings highlight that sustaining US solar growth requires a combination of policy credibility, resilient financing, and rapid removal of grid and interconnection bottlenecks, so that uncertainty and external shocks do not translate into delayed deployment when the system is positioned to expand.

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Research Highlights

- Drivers of solar energy consumption (SOC) in the United States by focusing on ESGUI, EPU, UCT, and OP.
- Significant upward trajectory in SOC with recurring seasonal fluctuations.
- Need for policy credibility, resilient financing, and rapid removal of grid and interconnection bottlenecks.

1. Introduction

The accelerating climate challenge and the growing urgency of decarbonization have pushed solar energy to the center of the United States' clean-energy transition. Solar energy consumption (SOC) is increasingly viewed as a strategic pathway for reducing carbon intensity, strengthening energy security, and meeting long-term climate commitments. Yet, the pace of solar deployment is rarely smooth. It reacts not only to technology costs and grid readiness, but also to uncertainty shocks that alter expectations, financing conditions, and the risk–return calculus of households, firms, and utilities. In this context, understanding how uncertainty and energy-market conditions shape SOC is essential for designing policies that sustain solar adoption even during turbulent periods.

Uncertainty is particularly relevant because solar investments are capital-intensive and typically depend on stable policy signals, predictable financing costs, and reliable supply chains. Economic policy uncertainty (EPU)—capturing uncertainty over fiscal, regulatory, and macro-policy directions—has been widely used to explain fluctuations in investment and real activity, and its measurement is formalized through the well-known newspaper-based index developed by [1]. When EPU rises, solar projects may face delayed approvals, postponed procurement, higher risk premia, and tighter credit conditions, all of which can suppress SOC growth, especially when investment horizons are long and payback periods are sensitive to discount rates [1, 2].

Beyond general policy uncertainty, ESG-related uncertainty has emerged as a newer but increasingly influential channel. The ESG-based Sustainability Uncertainty Index (ESGUI) was introduced to capture uncertainty associated with environmental, social, and governance sustainability considerations and the broader information environment surrounding them [3]. ESGUI can affect SOC through multiple mechanisms: (i) shifting investor sentiment toward (or away from) sustainability-themed assets, (ii) altering corporate disclosure pressures and transition strategies, and (iii) influencing the stability of green-finance flows. In periods of elevated ESG uncertainty, clean-energy financing can become more selective and risk-averse, potentially slowing the diffusion of solar capacity and, by extension, SOC [3].

Trade-related frictions add another layer of disruption, especially for a technology that relies on globally integrated value chains. The US–China Tension (UCT) index—constructed from newspaper coverage that captures rising bilateral tensions—provides a systematic way to quantify these shocks [4]. Elevated UCT can influence SOC by affecting solar equipment imports, supply-chain reconfiguration, input costs, and the timing of project pipelines, while also increasing uncertainty for firms exposed to cross-border trade and technology linkages [4]. These dynamics reinforce the broader argument that trade-policy-related uncertainty can hinder renewable-energy momentum by discouraging long-horizon investment and delaying clean-technology diffusion [5].

Oil prices (OP) also remain a key conditioning factor for SOC because they shape relative energy-price incentives, inflation dynamics, and macro-financial conditions. OP movements can either stimulate renewables (by improving their relative competitiveness and supporting green investment narratives) or dampen them (by lowering incentives to substitute away from fossil fuels and tightening macro conditions through inflation/monetary responses). Empirical evidence shows that oil-price shocks can transmit to green finance and renewable investment channels, indicating that OP is not merely an energy-market variable but also a financial and expectations-driven driver of energy transition outcomes [6, 7].

SOC has experienced substantial growth in recent years in the United States (see Figure 1). SOC rises by about 1604% from 3.821 in 2002M11 to 65.106 in 2024M02, while the peak level in 2023M07 represents about 2450% growth relative to the 2002M11 starting point, indicating a structural shift rather than a temporary fluctuation [8]. Annual-average SOC also increases by roughly 1540% from about 4.46 in 2003 to about 73.20 in 2023, which implies an approximate 15% compound annual growth over two decades, reinforcing that the expansion is persistent and cumulative [8]. Such large percentage gains are consistent with sustained capacity additions, technology cost declines, supportive policy and market incentives, and broader electrification-driven demand for low-carbon generation, making SOC growth a significant proxy for the speed and depth of solar scaling in the United States. These stylized facts align with the broader US trend of rapidly rising solar electricity generation and capacity expansion [8].

Despite this expansion, the literature still leaves important gaps when it comes to jointly evaluating multiple uncertainty channels such as ESGUI, EPU, and UCT alongside OP in explaining solar-energy dynamics for the United States. Much of the uncertainty-energy literature focuses on emissions or aggregate energy outcomes [9–12] rather than technology-specific consumption measures such as SOC. In addition, impacts are plausibly nonlinear and state-dependent because the effect of uncertainty may differ when SOC is low versus when SOC is already high, and OP effects may vary across regimes of policy credibility and supply-chain stress. This motivates an empirical strategy that can accommodate nonlinearities and heterogeneous responses rather than imposing a single average slope across the entire sample.

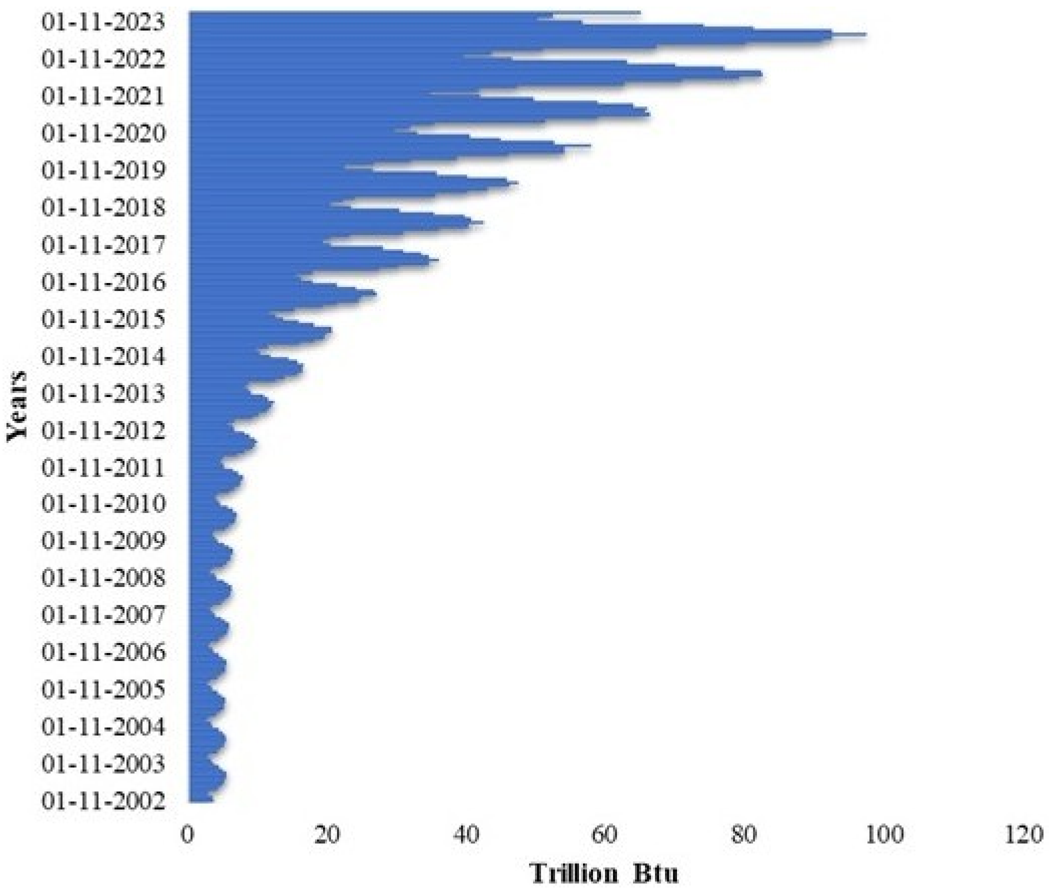

Figure 1. Trend of solar energy consumption in United States. Source: [8].

Considering the aforementioned gaps in the literature, this study investigates how ESGUI, EPU, UCT, and OP shape SOC in the United States over 2002M11–2024M02. By integrating sustainability uncertainty, macro-policy uncertainty, bilateral geopolitical-economic tension, and energy-price signals into one coherent framework, the study offers a more realistic representation of the risk environment in which solar adoption decisions are made. In addition, the study introduces a Quantile-threshold Kernel Regularized Least Squares (QT-KRLS) as a core methodological contribution. The modified framework is designed to accommodate nonlinear and distribution-dependent relationships while also delivering quantile-based marginal effects that are directly testable. This matters because uncertainty and oil-price shocks are unlikely to influence solar consumption uniformly across the SOC distribution, meaning the same driver can exert different effects in low-, middle-, and high-SOC regimes. This improves policy relevance by identifying the SOC regimes in which ESGUI, EPU, UCT, and OP exert the strongest and statistically supported marginal impacts, rather than relying only on average responses.

The remainder of the paper is structured as follows: the next section (Section 2) reviews related literature; the methodology and data are then presented (see Section 3); empirical results are discussed thereafter (see Section 4); and the final section concludes with implications for policy-makers (see Section 5).

2. Literature Review

Uncertainty has become a central conditioning factor in the renewable energy consumption and energy-transition literature because low-carbon projects are capital-intensive, long-horizon, and policy-sensitive, so risk shocks quickly translate into postponed investment, higher financing costs, and slower diffusion of clean technologies. Within this broad uncertainty-transition argument, economic policy uncertainty remains the most established measure and mechanism. The canonical economic policy uncertainty index is widely used to capture policy-related macroeconomic uncertainty and its investment-discouraging channel [1]. The study of [2] finds that higher economic policy uncertainty reduces renewable energy transition indicators, with effects that are heterogeneous across regimes and stronger where project bankability depends on credible support schemes and stable regulation. Likewise, the studies of [12–14] emphasizes nonlinearity, showing that institutional quality and complementary governance can dampen the adverse effect of uncertainty on renewables adoption, which helps explain why some economies maintain deployment momentum despite uncertainty spikes.

A newer strand extends the policy-uncertainty logic to ESG uncertainty, formalized by the ESG-Related sustainability uncertainty index. The ESGUI was introduced to capture sustainability-relevant ambiguity that is not fully reflected in standard macro uncertainty measures, including uncertainty about ESG disclosure enforcement, ratings consistency, transition policy durability, and the credibility of sustainability commitments [3]. The emerging empirical record links ESG uncertainty to weaker clean-energy financial conditions and riskier pricing of green assets, which matters for renewable deployment because adoption depends heavily on the cost of capital and the depth of sustainable finance [15, 16]. Likewise, the study of [17] supports the view that sustainability uncertainty becomes most binding when markets reprice long-duration green cash flows and when policy credibility is contested.

Oil price dynamics enter the renewable energy consumption and energy-transition literature through two competing mechanisms that explain mixed findings. The substitution-incentive channel predicts that higher oil prices raise the relative attractiveness of renewables and efficiency, encouraging clean adoption, yet the macro-stress channel predicts that oil price increases can compress demand, raise inflation and interest rates, and tighten financial conditions, thereby constraining investment in renewables. This ambiguity is reflected in several studies [7, 18] where oil prices are embedded in broader macro-energy dynamics rather than operating in isolation. More recent studies [19, 20] explicitly emphasize nonlinearities and threshold behavior, showing that the sign and strength of oil price effects can flip across regimes and income groups, which aligns with the idea that oil price spikes may hinder renewable growth when financing conditions deteriorate or when energy systems rely on oil-linked input costs.

The geopolitical-economy channel is sharpened further by US–China trade tensions, which affect energy transition outcomes through supply-chain disruptions, tariff-induced cost inflation, and strategic industrial policy responses. The renewable technology supply chain is deeply globalized, with the solar PV sector being the most visible example. The study of [21] affirmed that US–China disputes in solar trade altered industry structure, investment incentives, and policy coalitions, implying that trade conflict can reshape the pace and geography of renewable deployment. The study of [22] on the solar tariff episode indicates that tariff incidence can burden downstream installers and consumers via pass-through, which is consistent with a deployment-slowdown mechanism when module and component prices rise.

Finally, a closely related literature uses trade-uncertainty constructs to operationalize the trade-tension mechanism more directly. The trade policy uncertainty framework shows that uncertainty about tariffs and trade rules depresses investment, and renewable-energy studies [5, 23, 24] increasingly find that trade policy uncertainty harms renewable energy consumption, consistent with delayed equipment imports, disrupted technology diffusion, and weaker investor confidence in project cash flows. Likewise, recent investigation by [25–27] on the US–China tension and energy report adverse effects of bilateral tension shocks on renewable energy production and persistence over several periods, strengthening the argument that US–China trade tension is not merely background risk but a measurable driver of transition slowdowns via supply chains and strategic trade policy.

The empirical record supports a unified interpretation in which ESG uncertainty and economic policy uncertainty operate primarily through credibility and financing channels, oil price operates through regime-dependent substitution versus macro-stress channels, and US–China trade tensions operate through cost and supply-chain channels. Importantly, the dominant effect is often nonlinear and distribution-dependent, which motivates quantile- and state-aware empirical strategies in renewable energy consumption and energy-transition research.

Despite the expanding evidence on uncertainty, commodity prices, and geopolitical frictions in shaping clean-energy outcomes, important gaps remain that motivate a focused investigation of how ESG uncertainty, oil price, economic policy uncertainty, and US–China trade tension influence solar energy consumption. Much of the existing literature relies on broad renewable energy consumption aggregates, which can conceal technology-specific sensitivities and blur the channels through which uncertainty shocks operate. Solar energy consumption provides a sharper lens because solar deployment is tightly linked to manufactured components, import exposure, and project-level investment timing, so ESG-related ambiguity, policy uncertainty, trade frictions, and oil-price movements can transmit quickly through financing costs, equipment prices, delivery schedules, and risk premia. Using solar consumption therefore reduces aggregation bias and strengthens identification by connecting each driver to a technology pathway where supply-chain dependence and investment deferral are central and observable. In addition, the empirical literature still often imposes linear average effects, even though solar adoption dynamics are plausibly nonlinear and state dependent, with responses that vary across low-, middle-, and high-solar regimes. Based on this limitation, the study introduces modified kernel regularised quantile regression which is designed to accommodate nonlinear and distribution-dependent relationships while also delivering quantile-based marginal effects that are directly testable. Quantile-threshold Kernel Regularized Least Squares (QTKRLS) explicitly capture the statistical significance of marginal effects across the variables' quantiles, thereby enabling clear inference on where in the distribution each driver becomes influential and where it does not. This improves policy relevance by identifying the SOC regimes in which ESGUI, EPU, UCT, and OP exert the strongest and statistically supported marginal impacts, rather than relying only on average responses.

3. Data and Method

3.1. Data

This study explores how ESG uncertainty (ESGUI), US–China trade tensions (UCT), economic policy uncertainty (EPU), and oil prices (OP) shape the adoption of solar energy. The study focuses on the United States, using monthly data from 01/11/2002 to 01/02/2024. Furthermore, the study employed log difference ($\Delta \ln(P_t) = \ln(P_t) - \ln(P_{t-1})$ (multiplied by 100%).). This study commenced in 01/11/2002 because ESGUI data are unavailable prior to that date. Table 1 provides detailed descriptions of the variables used.

3.2. Empirical Method

Let $\{(Y_t, X_t)\}_{t=1}^{T}$ denote the sample, where Y_t is the dependent variable (e.g., solar energy consumption) and $X_t \in \mathbb{R}^p$ is a vector of regressors (e.g., uncertainty measures and controls). To accommodate delayed transmission, the analysis may employ an optimal lag length L so that the effective regressor vector becomes $X_t = Z_{t-L}$. This approach defines outcome-based regimes using quantile thresholds of Y_t and estimates a nonlinear kernel ridge model within each regime, following the kernel-regularized least squares tradition in applied social science and machine learning [28, 29].

For a quantile level $\tau \in (0,1)$, define the sample τ-quantile threshold of Y_t as

$$c_\tau = Q_\tau\left(\{Y_t\}_{t=1}^{T}\right) \tag{1}$$

and construct the corresponding quantile-threshold regime (or "low-Y" regime up to τ) as

$$\mathcal{I}_\tau = \{t \in \{1,\ldots,T\} : Y_t \le c_\tau\}, T_\tau = |\mathcal{I}_\tau|. \tag{2}$$

Let $y_\tau = (Y_t)_{t\in\mathcal{I}_\tau} \in \mathbb{R}^{T_\tau}$ and $X_\tau = (X_t^\top)_{t\in\mathcal{I}_\tau} \in \mathbb{R}^{T_\tau \times p}$ collect the regime-specific dependent variable and regressors.

Nonlinearities are captured using a positive semi-definite kernel $K(\cdot,\cdot)$. Under the radial basis function (RBF) kernel (a standard choice in kernel learning),

$$K(x_i, x_j) = \exp\left(-\frac{\|x_i - x_j\|^2}{2\sigma^2}\right), \tag{3}$$

where $\sigma > 0$ is a bandwidth parameter [29]. Define the regime-specific kernel matrix $K_\tau \in \mathbb{R}^{T_\tau \times T_\tau}$ with elements

$$[K_\tau]_{ij} = K(X_i, X_j), i, j \in \mathcal{I}_\tau. \tag{4}$$

Quantile-threshold Kernel Regularized Least Squares (QT-KRLS) estimates $\alpha_\tau \in \mathbb{R}^{T_\tau}$ by solving a ridge-regularized kernel least squares problem,

$$\widehat{\alpha}_\tau = \arg \min_{\alpha\in\mathbb{R}^{T_\tau}} \|y_\tau - K_\tau \alpha\|^2 + \lambda\|\alpha\|^2, \tag{5}$$

where $\lambda > 0$ governs smoothness and mitigates overfitting [28, 29]. The closed-form solution is

$$\widehat{\alpha}_\tau = (K_\tau + \lambda I)^{-1} y_\tau, \tag{6}$$

implying the fitted nonlinear function for any $x \in \mathbb{R}^p$ is

$$\widehat{f}_\tau(x) = \sum_{j\in\mathcal{I}_\tau} \widehat{\alpha}_{\tau,j} K(x, X_j), \tag{7}$$

and the fitted value for observation t is $\widehat{Y}_{t,\tau} = \widehat{f}_\tau(X_t)$.

Interpretation is based on derivative-informed marginal effects, which are widely used with KRLS to summarize local sensitivities in nonlinear [28]. For regressor $k \in \{1,\ldots,p\}$, the marginal effect at point x is

$$ME_{k,\tau}(x) = \frac{\partial \widehat{f}_\tau(x)}{\partial x_k} = \sum_{j\in\mathcal{I}_\tau} \widehat{\alpha}_{\tau,j} \frac{\partial K(x, X_j)}{\partial x_k}. \tag{8}$$

Under the RBF kernel, the derivative has a closed form,

$$ME_{k,\tau}(x) = -\sum_{j\in\mathcal{I}_\tau} \widehat{\alpha}_{\tau,j} \frac{(x_k - X_{j,k})}{\sigma^2} K(x, X_j). \tag{9}$$

These marginal effects are evaluated at $x = X_t$ for all $t \in \mathcal{I}_\tau$, producing a regime-specific distribution $\{ME_{k,\tau}(X_t)\}_{t\in\mathcal{I}_\tau}$. A compact summary is the mean marginal effect,

$$\overline{ME}_{k,\tau} = \frac{1}{T_\tau} \sum_{t\in\mathcal{I}_\tau} ME_{k,\tau}(X_t). \tag{10}$$

Table 1. Data measurement and sources.

Symbol	Variables	Measurement	Sources
ESGUI	ESG Uncertainty	Index	[30]
SOC	Solar energy consumption	Trillion Btu	[8]
OP	Oil price	Index	https://www.investing.com
UCT	US–China Trade Tension	Index	[30]
EPU	Economic Policy Uncertainty	Index	[30]

4. Results and Discussion

4.1. Descriptive Statistics

Figure 2 reports descriptive statistics for UCT, SOC, OP, ESGUI, and EPU and uses red to indicate larger positive values and green to indicate negative values. The maximum and minimum values show wide ranges for all variables, with particularly large swings for EPU and ESGUI, indicating strong variability over time. Means and medians remain close to zero across the series, suggesting fluctuations around a central level rather than a persistent upward or downward tendency. Standard deviations are highest for ESGUI and EPU, confirming that these two series are the most volatile in the sample. Kurtosis values exceed 3 for every variable, implying heavy tails and a higher likelihood of extreme observations than a normal distribution. Skewness values are generally small, with OP and UCT leaning negative and SOC and EPU leaning positive, showing mild asymmetry in the distribution of shocks.

Next, we explore the correlation between SOC and its determinants (see Figure 3). We observed that SOC is only weakly related to the other variables. It has a small positive association with OP ($r = 0.10$) and ESGUI ($r = 0.03$), and a slight negative association with EPU ($r = -0.08$) and UCT ($r = -0.02$). Overall, these near-zero coefficients imply that SOC moves largely independently of the uncertainty and oil-price indicators in the sample, suggesting limited linear co-movement (and low multicollinearity risk) with SOC as a regressor or dependent variable.

4.2. Diagnostic Test Results

Table 2 reports whether the series satisfy key time-series assumptions before estimation. Part A (nonlinearity/independence tests) shows that most variables exhibit nonlinear dependence and/or departures from randomness. In particular, the BDS test strongly rejects i.i.d. for SOC (0.000*), OP (0.004***), ESGUI (0.000***), and UCT (0.000***), indicating complex nonlinear dynamics; EPU is the only series where BDS does not reject at conventional levels (0.133). The Keenan and Teräsvirta/White nonlinearity tests further reinforce this pattern: ESGUI (Keenan $= 0.0239$) and UCT (Keenan $= 0.0037^{*}$)** show clear nonlinear structure, while the others are weaker by these specific tests. For serial dependence/randomness, the Runs test rejects randomness for SOC (0.000*) and UCT (0.001***)**, suggesting non-random sequencing, while Mann–Kendall p-values are mostly insignificant, implying no strong monotonic trend is detected in most series.

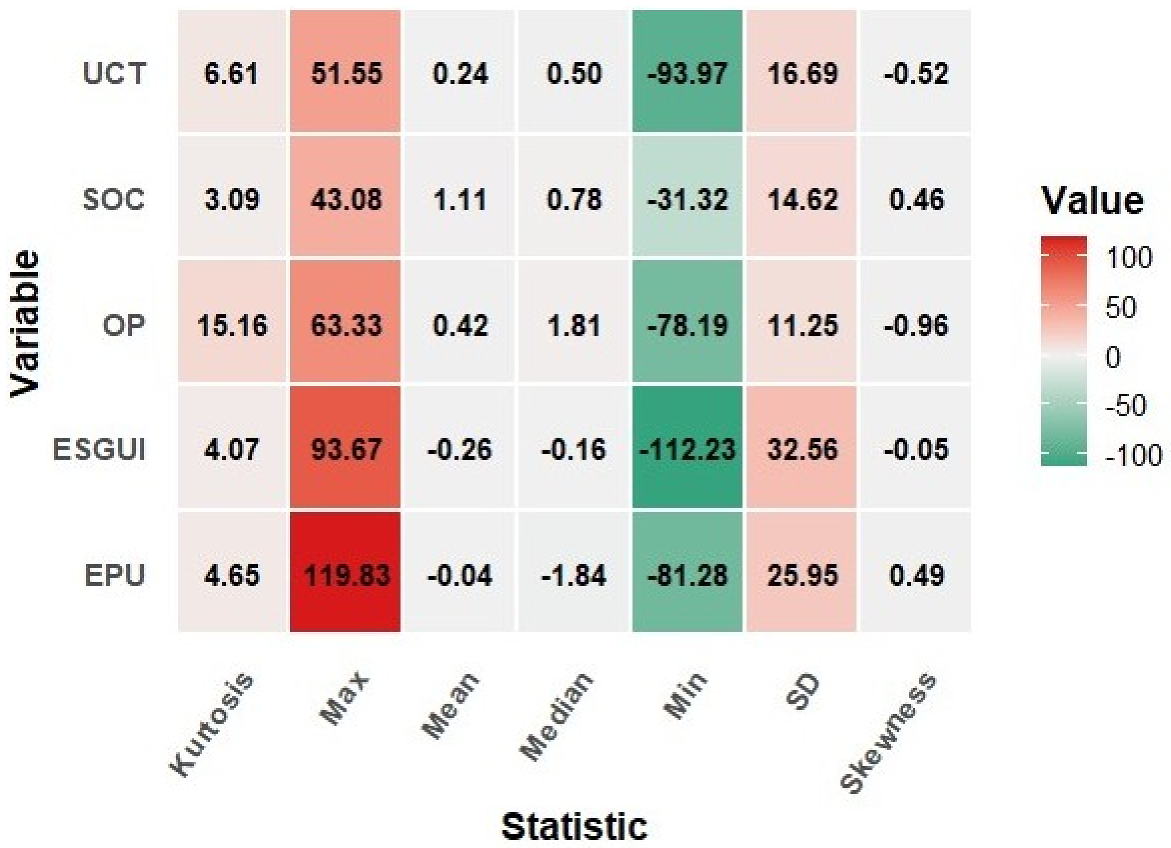

Figure 2. Descriptive statistics.

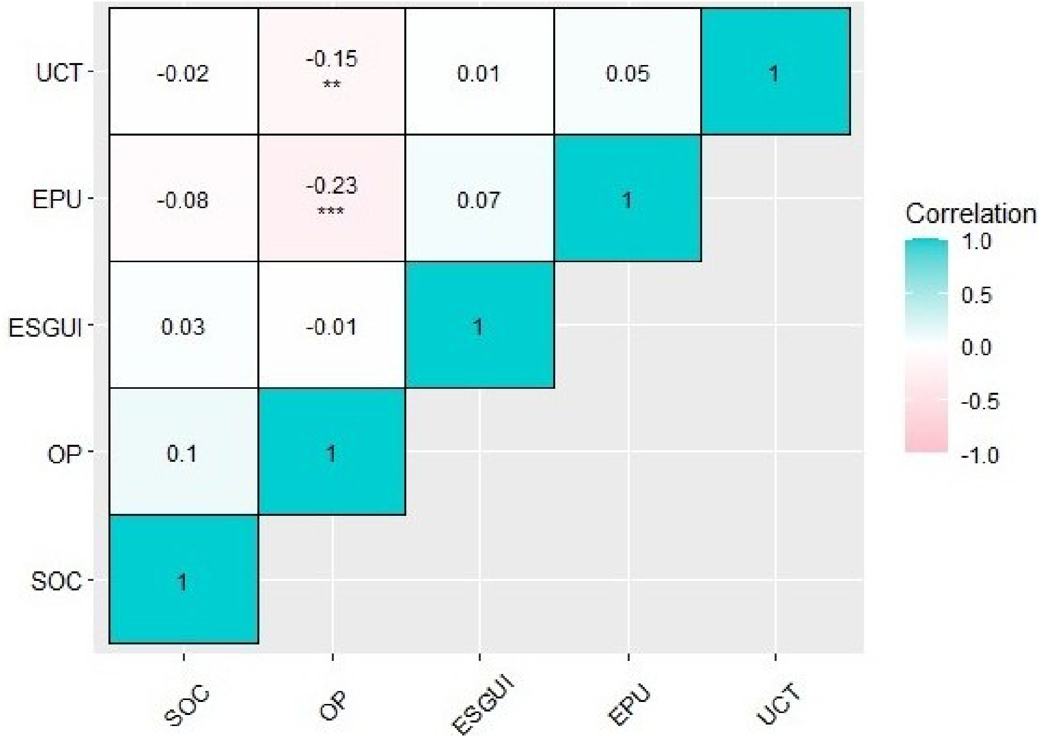

Figure 3. Correlation plot.

Table 2. Diagnostic test results.

	Part A: Nonlinearity Tests					
Variable	Terasvirta	White	Keenan	BDS	MannKendall	Runs
SOC	0.8209	0.8086	0.639	0***	0.4926	0***
OP	0.5544	0.5177	0.2243	0.004***	0.3257	0.2578
ESGUI	0.7905	0.8482	0.0239**	0.000***	0.8028	0.1666
EPU	0.9028	0.8898	0.7222	0.133	0.9918	0.2578
UCT	0.8698	0.8694	0.0037***	0.000***	0.5295	0.001***
	Part B: Normality Tests					
Variable	RobustJB	Shapiro	Skewness	Kurtosis	SJ	
SOC	0.0107**	0.004***	0.0032***	0.606	0.4445	
OP	0.000***	0.000***	0.000***	0.000***	0.000***	
ESGUI	0.000***	0.002***	0.735	0.0073***	0.000***	
EPU	0.000***	0.0024***	0.0018***	0.004***	0.0217**	
UCT	0.000***	0.000***	0.004***	0***	0.0023***	
	Part C: ARCH Tests					
Variable	White	ARCH_LM				
SOC	0.8212	0.000***				
OP	0.5314	0.000***				
ESGUI	0.8842	0.0021***				
EPU	0.9385	0.7848				
UCT	0.8665	0.0106**				
	Part D: Stationarity Tests					
Variable	ADF	PP				
SOC	−2.87***	−2.873***				
OP	−2.87***	−2.873***				
ESGUI	−2.87***	−2.873***				
EPU	−2.87***	−2.873***				
UCT	−2.87***	−2.873***				

Note: ***$p \leq 0.01$, **$p \leq 0.05$, *$p \leq 0.10$.

Part B (normality) indicates that the variables are generally non-normally distributed: OP, ESGUI, EPU, and UCT reject normality strongly across Robust JB and Shapiro–Wilk tests (mostly 0.000***), while SOC also departs from normality (RobustJB $=$ 0.0107**, Shapiro $=$ 0.004***), even though its kurtosis test alone is not significant (0.606). Part C (ARCH effects) reveals pronounced conditional heteroskedasticity for SOC, OP, ESGUI, and UCT (ARCH-LM significant), but not for EPU (ARCH-LM $=$ 0.7848), implying volatility clustering in most series and supporting volatility-robust modeling/inference. Finally, Part D (stationarity) shows that ADF and PP statistics are significant for all variables, implying the series are stationary at first difference, which is crucial for avoiding spurious relationships and for the validity of subsequent dynamic/nonlinear analyses.

4.3. Kernel Regularized Quantile Regression Results

Figure 4 shows the effect of ESGUI on solar energy consumption (SOC) in the United States. We observed that when SOC is low ($\tau = 0.1$), ESGUI has a small but statistically significant positive marginal effect, meaning that in "weak-solar" regimes an increase in ESGUI tends to coincide with a modest increase in SOC; however, as SOC moves into the lower-middle and median regimes ($\tau = 0.3$ and $\tau = 0.5$), the marginal effect turns negative and remains highly significant, with the most significant contraction around the median. This implies that heightened ESG uncertainty reduces SOC most strongly when the market is operating in its "normal" range rather than at extremes. This mid-distribution negative response is economically intuitive for the US because ESG uncertainty captures ambiguity about ESG rules, ratings consistency, disclosure enforcement, and political/legal durability of sustainability commitments, which can raise financing frictions and risk premia—especially in US solar where deployment often depends on tax-equity structures, long-dated contracting (e.g., PPAs), and regulatory clarity—thereby encouraging a classic "wait-and-see" posture that slows incremental solar adoption.

This mechanism is consistent with evidence that uncertainty shocks dampen renewables by delaying investment and adoption decisions [12, 31]. Yet, at the upper tail ($\tau = 0.7$ and $\tau = 0.9$), the effect becomes positive again and significant, and it is strongest at $\tau = 0.9$, implying that when SOC is already high (a "high-penetration/high-commitment" regime), increases in ESG uncertainty are associated with higher SOC—consistent with a risk-hedging/reputational-insurance channel in the US: utilities and large corporates facing stronger stakeholder pressure and transition commitments may respond to ESG ambiguity by over-complying (locking in more observable clean electricity use) to protect market access, investor relations, or sustainability-linked financing. This kind of heterogeneity across the distribution is also aligned with the emerging ESGUI literature emphasizing that ESG-based uncertainty is not uniform in its consequences and can vary across market states and quantiles [3, 32].

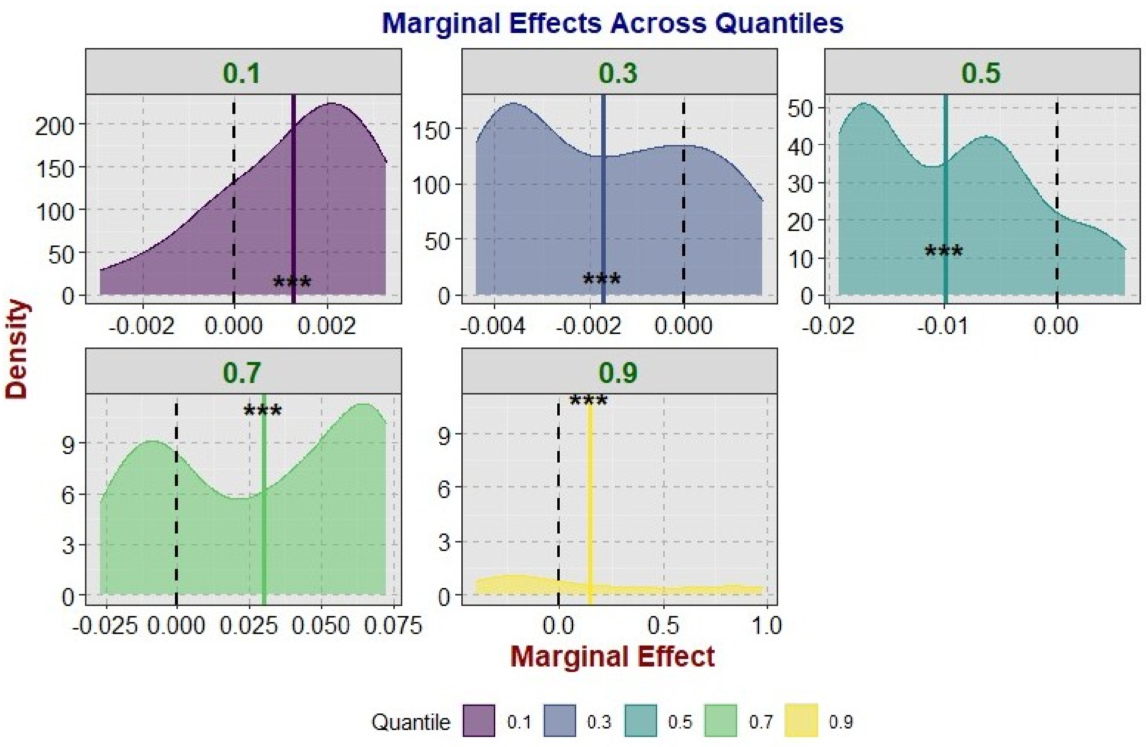

Figure 4. Impact of ESGUI on SOC. The Y-axis shows how often each marginal-effect value occurs (its frequency) at the relevant quantiles, while the X-axis reports the marginal-effect magnitudes. Each subplot corresponds to a quantile (0.1, 0.3, 0.5, 0.7, 0.9) and displays the distribution of marginal effects at that quantile. $^{***}p \leq 0.01$, $^{**}p \leq 0.05$, $^{*}p \leq 0.10$.

Figure 5 presents the marginal effect of economic policy uncertainty (EPU) on solar energy consumption. At the lower tail (0.1 quantile) of SOC, the estimated effect is statistically indistinguishable from zero, implying that when solar use is relatively weak, uncertainty shocks do not measurably shift consumption at the margin, which is consistent with a situation where adoption is constrained by fundamentals such as installation capacity, awareness, and baseline affordability rather than policy expectations. Moving into the middle of the distribution at the 0.3, 0.5, and 0.7 quantiles, the marginal effect turns positive and statistically significant, suggesting that higher policy uncertainty is associated with incremental increases in solar consumption when the market is already active but not yet saturated. In the United States, a plausible mechanism is a hedging and option value channel in which households, firms, and utilities place greater value on the price certainty of solar as a low marginal cost technology when macro policy conditions become noisy, especially when long lived contracts, corporate decarbonization commitments, and state level mandates keep project pipelines moving even if federal policy signals fluctuate.

This is consistent with evidence that uncertainty can stimulate renewable oriented technological responses and innovation, which can translate into faster deployment were enabling conditions already exist, and it also aligns with findings that uncertainty effects can be heterogeneous rather than uniform over time and states of the world [11]. At the upper tail at the 0.9 quantile, the marginal effect becomes significantly negative, indicating that when solar consumption is already high, additional uncertainty suppresses further solar use at the margin. This pattern fits a financing and bottleneck story where mature solar regimes rely heavily on stable tax equity, predictable permitting and interconnection timelines, and coordinated investment in transmission and storage, all of which become more fragile when policy uncertainty raises risk premia and encourages postponement of capital-intensive commitments. Empirically, this downside channel is strongly supported by US focused and G7 evidence showing that economic policy uncertainty tends to impede renewable energy consumption or investment by increasing irreversibility concerns and discouraging long horizon financing [10, 12, 33].

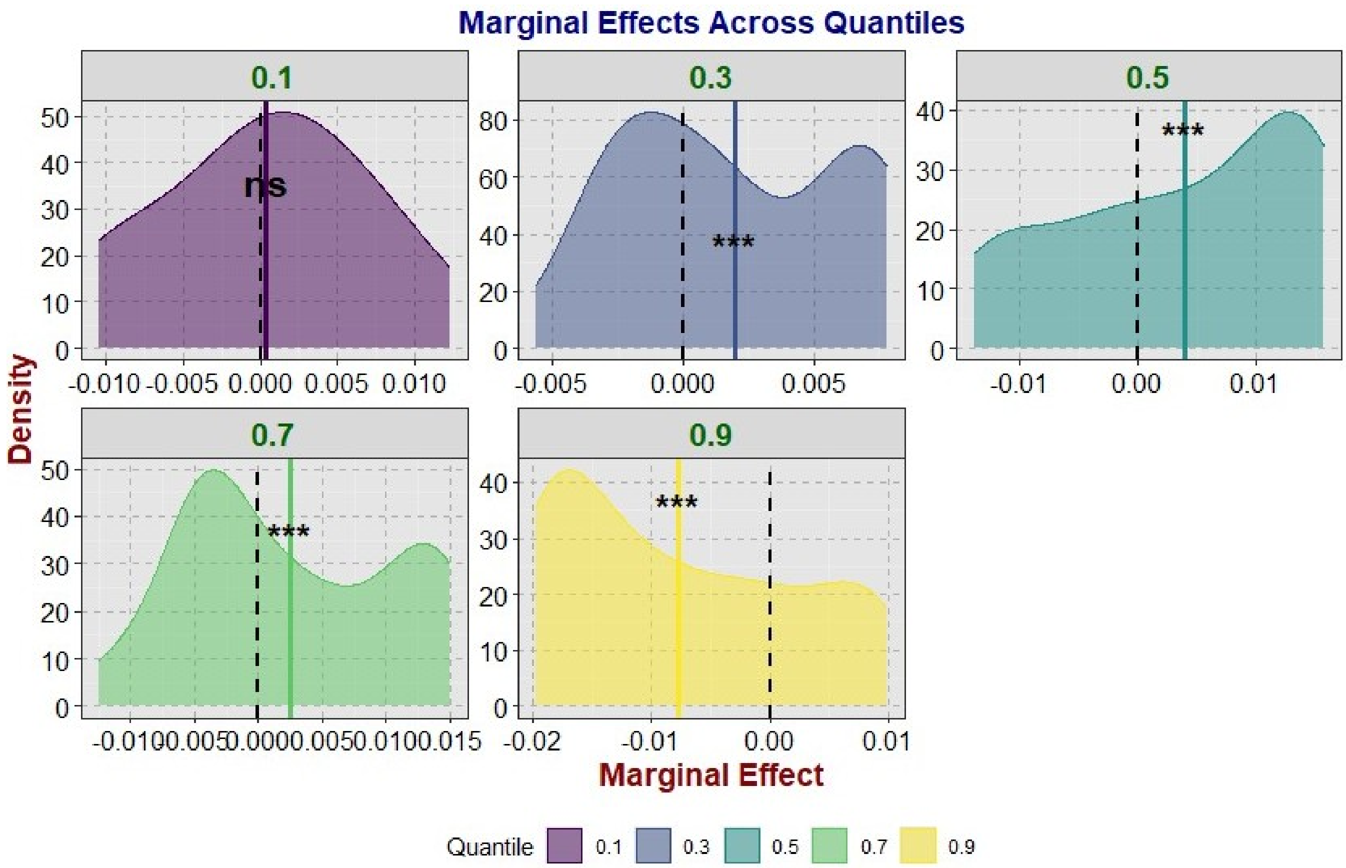

Figure 5. Impact of EPU on SOC. **Note:** The Y-axis shows how often each marginal-effect value occurs (its frequency) at the relevant quantiles, while the X-axis reports the marginal-effect magnitudes. Each subplot corresponds to a quantile (0.1, 0.3, 0.5, 0.7, 0.9) and displays the distribution of marginal effects at that quantile. ***$p \leq 0.01$, **$p \leq 0.05$, *$p \leq 0.10$.

Figure 6 explain how US–China trade tension (UCT) shape solar energy consumption (SOC) in the United States. The result indicates that higher US–China trade tension is associated with a consistently positive and statistically significant increase in US solar energy consumption across the distribution of SOC, with the effect already positive at the lower tail and becoming much larger as SOC moves into the middle and upper quantiles. Specifically at the 0.1 and 0.3 quantiles the estimated marginal effects are positive and highly significant, which implies that even when solar consumption is relatively low, periods of elevated bilateral tension tend to coincide with a measurable rise in solar adoption rather than a decline. The positive effect strengthens sharply at the median and upper quantiles, where the marginal effects are much larger and remain strongly significant, indicating that when the United States is already in a higher solar use regime, trade tension is linked with an even stronger expansion in solar consumption. A coherent US mechanism is a security and policy response channel in which heightened strategic competition and supply chain risk increase the perceived value of domestic and allied sourced clean electricity, motivating utilities, corporates, and households to lock in solar consumption as a hedge against external vulnerability and input price risk. At the same time, trade tension has triggered repeated trade actions and tariff episodes affecting solar components and supply chains, which can raise costs and create short run uncertainty in equipment procurement (https://cepr.org/voxeu/columns/beyond-tariffs-better-approach-green-industrial-policy (accessed on 4 January 2026)).

Tariffs and trade restrictions can push up module prices and harm parts of the US solar value chain, which would ordinarily weaken deployment (https://seia.org/research-resources/high-cost-tariffs/ (accessed on 8 January 2026)), so the positive relationship suggests that the demand and policy response in the United States has more than offset these cost headwinds for much of the sample, especially when solar consumption is already high and momentum and commitments are stronger. This is consistent with research showing that US–China solar trade measures reshaped upstream manufacturing and downstream installation outcomes, with welfare and incidence effects that run through the vertical structure of the solar supply chain [22], and with the study of [34] that tariff design and anti-dumping duties can materially alter PV demand conditions in the United States. It is also consistent with observed adjustments in global solar trade routes and sourcing patterns when the United States escalates tariff actions linked to Chinese owned supply chains, which reinforces the idea that tension can redirect supply and accelerate strategic deployment rather than simply suppress it (https://www.reuters.com/sustainability/boards-policy-regulation/us-tariffs-europe-slowdown-reshape-global-solar-panels-trade-2025-05-07/ (accessed on 4 January 2026)). In addition, US market updates during earlier tariff periods show that installations continued to grow strongly, supporting the view that deployment can remain resilient even when trade frictions intensify, particularly when underlying demand, state mandates, and procurement pipelines are robust (https://docs.nrel.gov/docs/fy19osti/74585.pdf (accessed on 23 March 2026)).

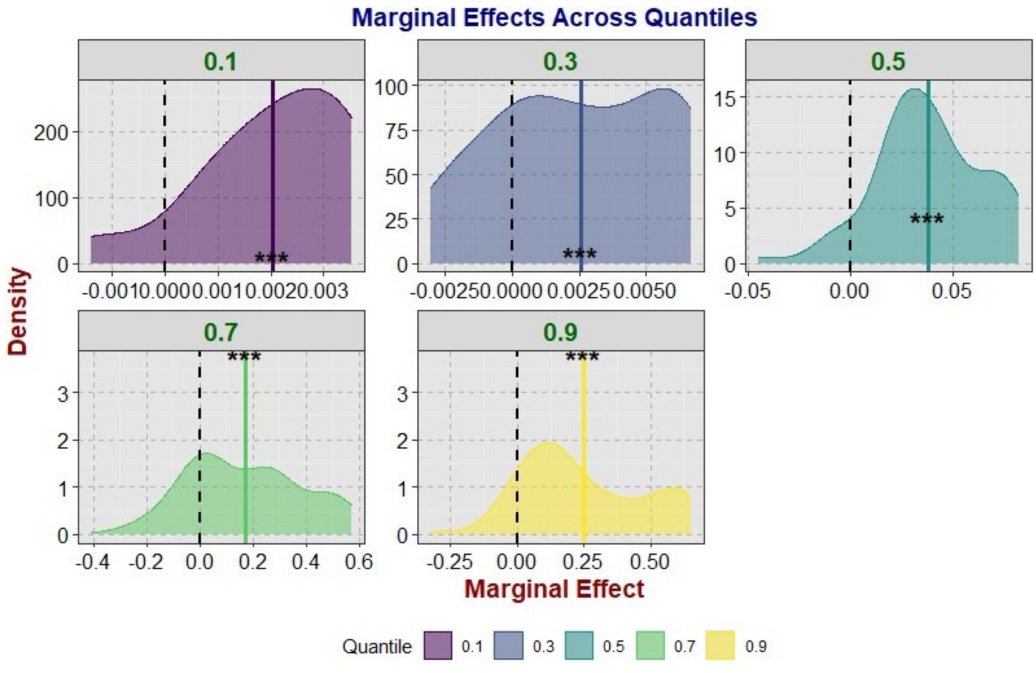

Figure 6. Impact of UCT on SOC. **Note:** The Y-axis shows how often each marginal-effect value occurs (its frequency) at the relevant quantiles, while the X-axis reports the marginal-effect magnitudes. Each subplot corresponds to a quantile (0.1, 0.3, 0.5, 0.7, 0.9) and displays the distribution of marginal effects at that quantile. ***$p \leq 0.01$, **$p \leq 0.05$, *$p \leq 0.10$.

The effect of oil price (OP) on solar energy consumption (SOC) is shown in Figure 7. At the lower quantiles of SOC at 0.1 and 0.3, the estimated marginal effects are small, positive, and statistically significant, meaning that when solar consumption is relatively weak, increases in oil prices still nudge SOC upward but only modestly because adoption in these states is often constrained by nonprice fundamentals such as installed capacity, interconnection queues, and the pace of household and utility investment decisions rather than by short-run energy price signals. At the middle and upper-middle quantiles at 0.5 and 0.7, the marginal effect becomes materially larger and remains strongly significant, which is consistent with a substitution and salience channel in which higher oil prices heighten economywide attention to fossil-energy cost risk, reinforce the perceived hedging value of low marginal cost renewable generation, and support greater solar offtake through utility procurement and corporate clean-power contracting. Even though US electricity generation competes more directly with natural gas than with oil, oil price increases still matter through correlated movements in broader energy inflation, expectations about future energy policy, and the risk premium embedded in long-horizon energy choices.

The nonlinear effect is expected for the case of United States since oil price shocks can raise clean energy use after certain shock types even while other demand-side shocks reduce investment temporarily, implying that the net effect depends on the macro regime and the underlying driver of oil price movements [35]. A complementary study by [36] also shows that the linkage between oil prices and renewable energy behavior is heterogeneous across the conditional distribution, reinforcing why the effects differ across quantiles rather than collapsing to one average slope. At the extreme upper tail at 0.9, the figure still indicates a statistically significant effect, and the distribution suggests that the relationship can weaken or tilt toward a less expansionary response when SOC is already very high. This is plausible in the US because very high solar regimes are more exposed to binding constraints such as transmission and storage bottlenecks, interconnection delays, and financing conditions, and these can deteriorate when oil-driven inflationary pressures raise interest rates and capital costs, offsetting the competitiveness channel [37].

4.4. Nonparametric Quantile Causality

The study proceeds to examine the predictive power of ESGUI, OP, EPU, and UCT for SOC. To this end, the study employs the nonparametric quantile causality (NQC) approach proposed by [38]. Figure 8 (Table 3) presents the NQC results. The result shows that ESGUI, EPU, UCT, and OP each exhibit statistically significant causality toward solar energy consumption in the mean across a wide range of quantiles. The blue curves represent the causality-in-mean test statistic over the conditional distribution of SOC. In all four panels, the blue line rises above the critical thresholds through the middle quantiles, indicating that these drivers matter most when SOC is in its typical operating range rather than at the extremes. Concretely, the mean-causality signal strengthens from the lower quantiles, peaks around the central quantiles (roughly $\tau \approx 0.4$–0.7), and then declines toward the upper tail where it often falls back toward or below the critical lines. This pattern implies that in the US, changes in ESG uncertainty, economic policy uncertainty, US–China trade tension, and oil prices are most informative for predicting normal-to-high SOC states, while their predictive power becomes weaker when SOC is already at very low or very high quantile states.

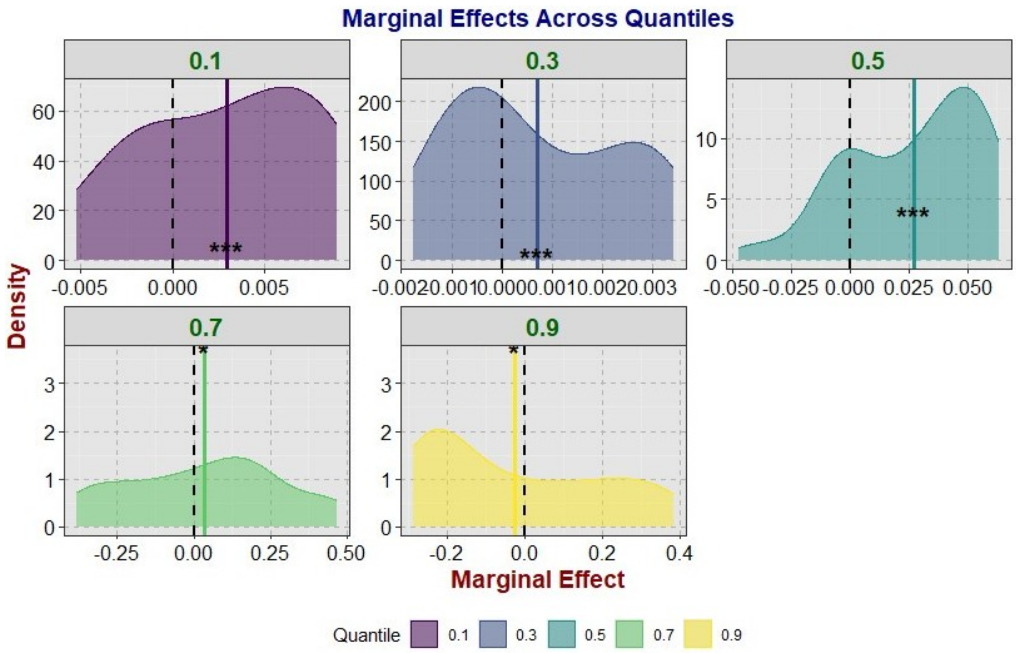

Figure 7. Impact of OP on SOC. **Note:** The Y-axis shows how often each marginal-effect value occurs (its frequency) at the relevant quantiles, while the X-axis reports the marginal-effect magnitudes. Each subplot corresponds to a quantile (0.1, 0.3, 0.5, 0.7, 0.9) and displays the distribution of marginal effects at that quantile. ***$p \leq 0.01$, **$p \leq 0.05$, *$p \leq 0.10$.

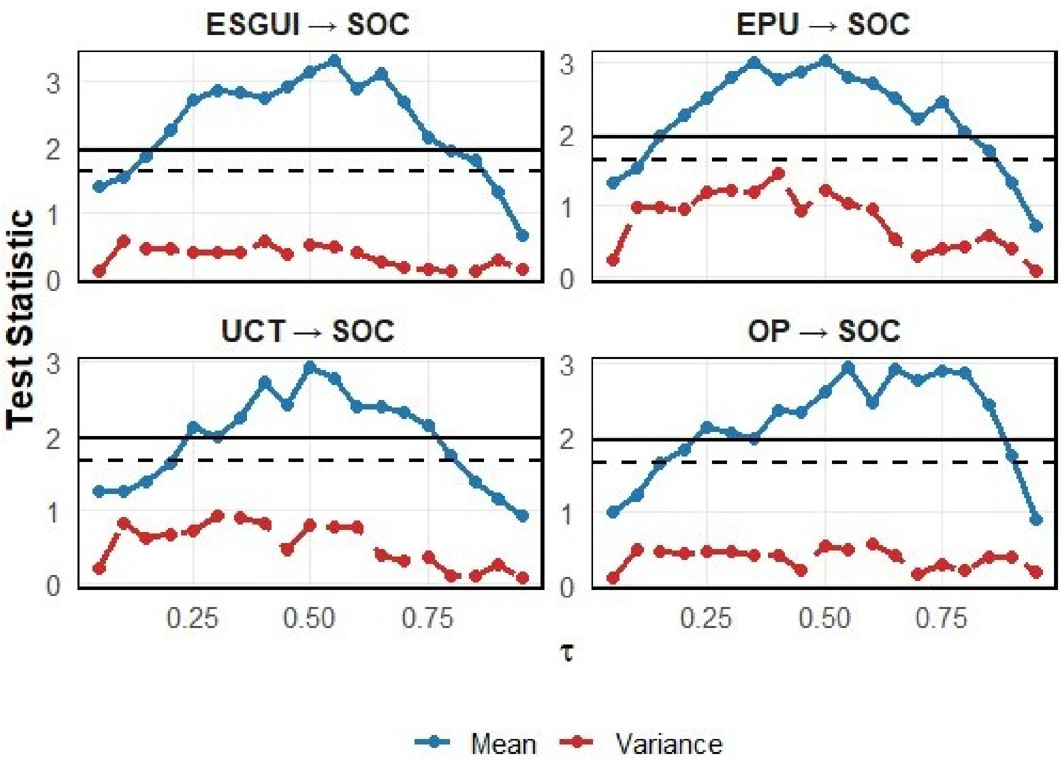

Figure 8. Nonparametric Quantile Causality Result. **Note:** The Y-axis and Y-axis report the test statistics and quantiles, respectively. The blue and red lines denote causality in the mean and in the variance, respectively.

Table 3. Nonparametric quantile causality.

	Causality in Mean				Causality in Variance			
Quantile	**ESGUI**	**EPU**	**UCT**	**OP**	**ESGUI**	**EPU**	**UCT**	**OP**
0.05	1.393	1.318	1.237	0.992	0.105	0.253	0.201	0.088
0.10	1.542	1.522	1.238	1.220	0.555	0.975	0.807	0.490
0.15	1.855*	1.982**	1.376	1.646	0.464	0.987	0.619	0.443
0.20	2.259**	2.274**	1.629	1.835	0.457	0.964	0.647	0.430
0.25	2.731**	2.493**	2.122**	2.137	0.406	1.201	0.698	0.461
0.30	2.884**	2.785**	1.995**	2.063	0.405	1.217	0.915	0.465
0.35	2.833**	3.005**	2.246**	1.995	0.407	1.192	0.879	0.400
0.40	2.749**	2.777**	2.726**	2.358	0.557	1.459	0.818	0.413
0.45	2.922**	2.866**	2.417**	2.346	0.371	0.919	0.446	0.210
0.50	3.165**	3.025**	2.922**	2.628	0.517	1.204	0.784	0.533
0.55	3.323**	2.798**	2.790**	2.941	0.477	1.036	0.762	0.488
0.60	2.913**	2.716**	2.402**	2.474	0.400	0.949	0.749	0.549
0.65	3.121**	2.495**	2.408**	2.935	0.260	0.536	0.379	0.413
0.70	2.689**	2.203**	2.311**	2.786	0.170	0.305	0.293	0.147
0.75	2.144**	2.465**	2.129**	2.906	0.140	0.408	0.354	0.275
0.80	1.938*	2.019**	1.722*	2.886	0.105	0.432	0.090	0.192
0.85	1.802*	1.768*	1.383	2.444	0.112	0.593	0.083	0.371
0.90	1.326	1.308	1.147	1.754	0.294	0.386	0.247	0.384
0.95	0.643	0.716	0.914	0.880	0.146	0.079	0.061	0.167

Note: Statistical significance is indicated when the test statistic exceeds the corresponding critical value: 1.645 for *$p \leq 0.10$ (10%) level and 1.960 for **$p \leq 0.05$ (5%) level. Values above these thresholds imply rejection of the null hypothesis of no quantile causality at the stated significance level.

In contrast, the red curves indicate causality-invariance, and they remain mostly below the critical thresholds in every panel, meaning these variables generally do not transmit volatility to SOC in a statistically strong way across quantiles. Put simply, for the US case the dominant channel is level effects rather than volatility spillovers. This suggests that shocks to ESG uncertainty, policy uncertainty, trade tension, and oil prices tend to shift the expected path of solar consumption more than they shift the uncertainty around that path. The fact that mean causality is strongest in the center of the SOC distribution also fits a practical interpretation, namely that when the US solar system is neither constrained by very low penetration nor capped by upper-tail bottlenecks, these macro and geopolitical signals are most able to influence planning, procurement, and consumption decisions, while at the tails structural constraints and saturation effects reduce the incremental predictability.

5. Conclusion and Policy Implications

5.1. Conclusion

This study explores the drivers of solar energy consumption in the United States using monthly data spanning 1/11/2002 to 1/2/2024. The employs Quantile-threshold Kernel Regularized Least Squares (QT-KRLS), thereby offering a methodological contribution and enabling more rigorous inference on distributional heterogeneity. In conclusion, the results show that solar energy consumption responds to ESG uncertainty, economic policy uncertainty, US–China trade tension, and oil price movements in a distinctly state dependent manner. The kernel regularized quantile estimates reveal that the direction and magnitude of effects vary across the SOC distribution, implying that uncertainty can suppress solar adoption most strongly in normal adoption regimes while, in high commitment regimes, it can coincide with stronger solar consumption through hedging and credibility motives. The nonparametric quantile causality results further confirm that these drivers predominantly influence SOC through mean effects across a broad range of quantiles, with limited transmission through variance, indicating that they shift the expected path of solar consumption rather than its volatility.

5.2. Central Policy Framework

As solar energy consumption in the United States reacts differently across low, normal, and high solar regimes, any uniform, one size fits all intervention might fail to deliver stable progress. Therefore, policymakers might adopt a phase wise solar acceleration approach that strengthens adoption when the market is weak, protects deployment when the market is normal, and removes bottlenecks when the market is already in a high penetration state. This phase wise approach is especially necessary because the results indicate that ESG related uncertainty tends to dampen solar consumption most strongly in the normal regime, while policy uncertainty and trade tension can stimulate solar adoption in some regimes but become restrictive once the system faces maturity constraints. Hence, sudden and uncoordinated policy shifts might raise financing frictions and induce a wait and see behavior, which can slow solar adoption in the regimes where most activity occurs.

In the first phase, policymakers should target the weak solar regimes where solar consumption is low and where adoption is constrained more by access, affordability, and administrative frictions than by long horizon expectations. In this phase, the government might provide standardized, low transaction cost adoption pathways through streamlined permitting, simplified interconnection procedures, and pro rata support mechanisms for households and small firms. The support could be delivered through subsidized loans, bill financing, and limited interest rate holiday periods that reduce upfront cost burdens without disrupting household liquidity. At the same time, the rules surrounding disclosure expectations, sustainability commitments, and verification standards should be clarified in a simple and enforceable form so that rising ESG uncertainty does not create confusion in early adoption environments. Once weak regimes begin to transition into active regimes, the demand for solar solutions becomes more durable, and the supply side can begin to expand installation capacity with greater confidence.

In the second phase, policymakers should concentrate on the normal regime where solar consumption sits in its typical operating range, because the findings indicate that this is the regime where ESG uncertainty reduces solar consumption most strongly. In this phase, the central policy instrument should be regulatory clarity and enforcement consistency. The policymakers might establish durable multiyear guidance on incentive eligibility, disclosure enforcement, and contract reliability for power purchase agreements, community solar subscriptions, and corporate procurement. This is because normal regime deployment is strongly dependent on stable financing structures and predictable implementation timelines, and uncertainty raises risk premia that can reduce incremental adoption. Alongside clarity, policymakers might adopt a differential support and compliance mechanism where firms and utilities with higher carbon intensive portfolios face stricter transition requirements, while cleaner actors receive lower financing costs and faster administrative processing. This differential treatment can be interpreted as a Pigouvian style internalization mechanism that gradually penalizes environmentally deteriorating choices while rewarding cleaner operational structures.

In the third phase, policymakers should target the high solar regimes where solar consumption is already elevated and where additional uncertainty becomes more harmful due to system integration constraints. In this phase, the focus should shift from adoption incentives toward infrastructure and reliability. Policymakers might accelerate transmission expansion, storage deployment, and interconnection queue reforms so that high penetration states do not experience deployment fatigue due to bottlenecks. In addition, because policy uncertainty becomes negative at the upper tail, the government might introduce countercyclical financing backstops and credit guarantees that activate when macro policy conditions deteriorate, so that long dated investments do not get postponed. These measures can stabilize the mature solar ecosystem and prevent high regime slowdowns that would otherwise reduce the speed of decarbonization progress.

Once these phases are implemented, the United States can simultaneously expand solar consumption, reduce reliance on external vulnerabilities, and protect economic activity. The gradual shift supports the attainment of SDG 7 by accelerating affordable clean energy access, while preserving investment stability. The reduced dependence on fossil fuel-based energy and the improved capacity for domestic clean supply chains can support SDG 12 through more sustainable consumption and production pathways. Furthermore, a stable and scalable solar expansion pathway strengthens job creation and domestic competitiveness in clean industries, which aligns with SDG 8. Lastly, rising solar reliance reduces emissions intensity and strengthens climate mitigation progress, helping to advance SDG 13.

5.3. Tangential Policy Framework

As the central policy framework can be derived directly from the study outcomes, the tangential policy framework can help the United States achieve additional objectives by sustaining the phase wise transition and strengthening its social acceptance. Now, in order to sustain the initiatives for expanding solar consumption, it becomes necessary to create an environmental and energy transition awareness among citizens, investors, and local decision makers. Therefore, policymakers should encourage people public private partnerships that can disseminate information on the benefits of solar adoption, the reliability of modern systems, and the long run cost advantages of low marginal cost clean electricity. These partnerships can also reduce misinformation and build trust in procurement models such as community solar, corporate offtake, and municipal aggregation programs.

To reach the grassroots level, policymakers might revise educational curricula and workforce training programs to reflect practical clean energy skills, solar installation standards, and energy literacy. This initiative can contribute to SDG 4 through quality education and skill development while strengthening the domestic labour pipeline needed for sustained deployment. Once the public awareness and workforce readiness improve, households will be more capable of embracing solar solutions, and local governments can provide standardized adoption packages at a pro rata rate with limited interest support mechanisms. Similar to the industrial sector, households might receive interest rate holiday options, tax rebates, or targeted subsidies so that the shift away from fossil fuel dependence does not impose short run financial stress on vulnerable groups.

Furthermore, since trade tension with China is associated with higher solar consumption across the distribution, policymakers might extend the central framework by building a resilience oriented clean supply chain strategy that is socially acceptable and economically efficient. In doing so, incentives can be structured to expand domestic manufacturing and allied sourcing without abruptly raising costs for installers and households. This can be achieved through gradual localization targets, procurement preference schemes for traceable components, and long-term supply agreements that reduce procurement uncertainty. Once such a supply chain transition becomes stable, the United States can sustain solar expansion even under geopolitical strain, while keeping adoption affordable for consumers.

Finally, as oil prices tend to coincide with higher solar consumption but can create financing stress through inflation and interest rate channels, policymakers should adopt a stabilizing support mechanism that protects clean energy investment during energy price shocks. This can be done by scaling up public credit guarantees, maintaining predictable incentive schedules, and ensuring that grid integration investment continues during high price periods. The short run fiscal burden borne by the government under these stabilizers can be compensated through broader economic gains from cleaner energy competitiveness, rising employment in clean sectors, and reduced exposure to fossil price volatility. In this way, the tangential policy framework sustains the central phases and enables the United States to strengthen progress toward multiple SDG objectives while maintaining economic stability.

5.4. Limitations of Study and Future Directions

A limitation of this study is that it focuses only on the United States and covers the period from 2002M11 to 2024M02, which means the findings may not be fully generalizable to other countries with different policy structures, market maturity, or energy transition pathways. The analysis is also restricted to a specific set of drivers—ESG uncertainty, economic policy uncertainty, US–China trade tension, and oil prices—so other relevant factors such as technological innovation, solar subsidies, electricity prices, financing conditions, and grid infrastructure are not explicitly incorporated. In addition, although the QT-KRLS approach provides a strong framework for capturing nonlinear and state-dependent heterogeneity, the results remain conditional on the selected variables and cannot fully rule out omitted influences or broader structural shifts in the energy market. Future research may extend this work by including additional institutional, financial, and technological determinants, comparing the US case with other developed and emerging economies, and examining whether the identified quantile-specific responses persist across alternative renewable energy sources such as wind or total clean energy consumption. Further studies may also explore regional or state-level evidence within the United States to uncover local heterogeneity in solar adoption dynamics.

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Informed Consent Statement

Not applicable.

Data Availability Statement

All data and code necessary to reproduce the results are available at request from the corresponding author.

Conflicts of Interest

The author declares that he has no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Use of AI and AI-assisted Technologies

Generative AI tools were not used to generate manuscript text or analyze data beyond standard grammar/spell-checking.

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