

**Inherent Risk Analysis of Power Supply Management in Small
Developing Countries: A Techno-Economic Study of Belize**
(小規模開発途上国における電力供給管理の固有
リスク分析：ベリーズの技術経済学的研究)

Khadija Sherece Usher

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Abstract

Power mix risk management is a crucial aspect of energy sector decision-making. Amidst disruptive events, emerging economies struggle to sustain recovery and long-term progress, necessitating a focus on mitigating the impact of major incidents. System operators (SOs) manage power supply, focusing on risk management. In small emerging economies, proactive risk management is crucial as major disruptions require SOs to redirect resources into recovery efforts. Therefore, SOs prioritize risk reduction, proactively minimizing the possibility of major disruption, to ensure the industry's long-term advancement.

However, power mix risk management often overlooks the pathways through which the system's structure is exposed to risks. In this study, the SO refers to the entity responsible for real-time management of electricity supply to meet demand while maintaining system reliability. A critical cause of risk oversight is that SOs frequently focus on residual risk mitigation—exposures that remain after protective measures such as hedging, reserve capacity, or demand-side management—while ignoring their exposure to inherent risk, which encapsulates the amount of risk present before any controls are applied, such as reliance on imported electricity from Mexico. Residual risk controls are protective, whereas inherent risk controls are preventative. Power supply management tends to emphasize residual risks, but these represent only a subset of the overall risk landscape. Moreover, smaller markets' risk-mitigation strategies have received less attention compared with those in larger economies.

This study focused on power generation mixes in emerging economies using Belize, on which limited research is published, as the case. This thesis performed a comprehensive techno-economic risk analysis, investigating the inherent risks associated with power supply management using the SO's operations and pertinent third-parties. The research was conducted in three (3) main phases:

Phase 1 used a qualitative three-step approach, this study investigated inherent risks of the structure and managerial practices Belize's power mix, mapping its structure and actors, identifying underlying causes and exposure pathways, classifying risks into five major dimensions, and characterizing each dimension as complex, uncertain, or ambiguous: complex risks involve multiple interdependent variables whose interactions are difficult to model or predict; uncertain risks are those for which the likelihood or magnitude of outcomes cannot be reliably estimated due to limited data or inherent variability; and ambiguous risks arise when there is a lack of shared understanding among stakeholders regarding the nature of the risk or the appropriate response.

Phase 2 progressed into the quantitative component of the risk analysis. Moreover, early in the research, it was revealed that a substantial proportion of Belize's power supply mix relied on a foreign third-party supplier (Mexico). Accordingly, phase 2 examined the price risk of the Belize–Mexico interconnection using ARMA-ARCH models to assess electricity pricing volatility and autoregression to determine the influence of conditional volatilities and import consumption.

Finally, Phase 3 included all inherent risk elements by investigating the interrelationship of quantity and price-related risk variables, which contribute to increased uncertainty in power supply management. Phase 3 investigated the inherent risks associated with power supply management using the SO's operations and pertinent third-parties. It used a seasonal multivariate strategy to identify risk factors, create univariate distribution models, and generate multivariate distributions using the copula method. Joint risk exposure was calculated using different percentile metrics for each scenario, allowing comparison of exposure levels.

In phase 1 (Chapter 2), results revealed that Belize's structural choices presented inherent paradoxes such as the application of fixed-cost models for volatile local renewable sources, the actor's ambiguity on key elements of the supply system, including reliance on electricity imports and the retirement of local supply assets, being perceived as a lack of commitment. The inconsistencies increased the threat of investing in the domestic supply market, and regulations seeking to attract investment and de-risk electricity supply projects that in turn locked-out new investment and technologies due to market size.

Phase 2 (Chapter 3) revealed that power imports were to be a contentious supply source, presenting the most significant impact on Belize's price risk component. Findings revealed that the volatility of the forward and spot pricing (especially spot pricing) of Belize's power import market showed rare high-impact shocks and prolonged periods of volatile clusters. The Volatile pricing tendencies, and forward pricing to a lesser extent, had positive effects on premiums. Premiums were largely dependent on pricing properties and system conditions of the supplier's (Mexico) side, with negligible influence from the buyer's (Belize) side. However, significant effects were found during certain hours with the buyer's loading and transmission loss patterns.

In Phase 3 (Chapter 4), the analysis of interdependencies among price and quantity-related inherent risks revealed that variables can either reinforce or offset each other, influencing overall exposure behavior. Exposure levels identified periods of heightened or reduced susceptibility to risk factors. The copula-based modeling captured higher exposure magnitudes but with lower unit likelihoods, offering less conservative forecasts for SO managers. Case 1 (forecasting inaccuracies vs. import premiums) showed the highest exposure in the early dry season (0.775 and 0.730 at the 95th and 90th percentiles, respectively). Case 2 (local RE unavailability vs. demand) peaked in the late wet season (1.009 and 0.948), followed by Case 3 (demand, RE unavailability, and premiums: 0.977 and 0.908) and Case 4 (all variables combined: 0.950 and 0.879).

Practical implications revealed the possibility of occasional losses caused mostly by information delays and misalignment of risk factors and premiums in the power import supply market, which could affect Belize's local supply planning. This posed economic impacts on the local power cost and scheduling of local generation. Further, system mitigation practices were limited and primarily based on regulatory interventions, with risk dimensions varying and sometimes related, suggesting a need for expanded and consolidated mitigation styles. Future research can broaden this current scope to enhance planning on local power supply by integrating current findings on the importation market behavior with the buyer's local power expansion plan.

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LIST OF ABBREVIATIONS

(in order of appearance)

EHS-	environment health and safety
TRI-	toxic release inventory
PDB-	performance-based design
SD-	system dynamics
SO-	system operator
SSI-	semi-structured interviews
ARMA-	auto-regressive moving average
ARMA-X-	auto-regressive moving average with exogenous variable
ARMA-ARCH-	auto-regressive moving average auto-regressive conditional heteroscedastic
PDF-	probability density functions
EVs-	electric vehicles
EU-	European Union
DERs-	distributed energy resources
RE-	renewable energy
PV-	photovoltaic
SWI-	Shannon-Wiener index
HHI-	Herfindahl-Hirschman index
EMCI-	Energy Mix Concentration Index
RESI-	Renewable Energy Security Index
NRF-	National renewability factor
FCEVs-	fuel cell electric vehicles
NEP-	National Energy Policy
PPA-	power purchase agreements
IRRP-	integrated resource & resilience plan
USD/kWh-	U.S. dollar per kilowatt hour
CCREEE-	Caribbean Centre for Renewable Energy and Energy Efficiency
EIR-	electricity import reliance
EFF-	electricity share from fossils
ERES-	share of electricity from renewable energy sources
RFP-	request for proposals
SOE-	state-owned enterprise
T&D-	transmission and distribution
IPPs-	independent power producers
EVs-	electric vehicles
SEN-	National Electric System of Mexico
SIN-	National Interconnected System of Mexico
AI-	artificial intelligence
LMP-	locational marginal price
VAR-	vector autoregression
SIM-	market information system
ADF-	Augmented Dickey–Fuller
ACF-	autocorrelation function
PACF-	partial-autocorrelation function
AIC-	Akaike information criterion

LM-	Lagrange Multiplier
ARCH-	autoregressive conditional heteroskedastic model
GARCH-	generalized autoregressive conditional heteroskedastic model
GJR-GARCH-	Glosten, Jagannathan, and Runkle-GARCH model
AIC-	Akaike information criterion
SST-	skewed Student's t
FPE-	final prediction error
HQIC-	Hannan–Quinn information criterion
tsa-	time-series analysis
NG-	natural gas
VRE-	variable renewable energy
UC-	unit commitment
GHGs-	greenhouse gases
NDCs-	nationally determined contributions
PPAs-	power purchase agreements
RSS-	residual sum of squares
GEV-	generalized extreme value distribution
LL-	log-likelihood
VaR-	value-at-risk
EE-	energy efficiency

LIST OF SYMBOLS

i -	interval (hour)
t -	interval (day)
S_i -	spot price
F_i -	forward price
FP -	forward premium
p -	autoregressive component of ARMA model
q -	moving average component of ARMA model
X_t -	value of variable in the current period i
X_{t-i}	value of variable in the previous period i
ε_t	baseline constant of ARMA model
φ_i	coefficient of the autoregressive (AR) component
θ_1	coefficient of the moving average (MA) component
ε_{t-i}	error terms for previous period i
η_i -	coefficient of the exogenous variable
d_{t-i} -	exogenous variable
p -	order of GARCH term <i>of GARCH model</i>
q -	order of ARCH term σ_{t-1}^2 <i>of GARCH model</i>
σ	unconditional variance <i>of GARCH model</i>
ε_{t-1} -	residual of the previous variance <i>of GARCH model</i>
α_i -	coefficient for the previous squared residual <i>of GARCH model</i>
β_i -	coefficient for the previous conditional variance <i>of GARCH model</i>
γ_i	leverage parameter <i>of GARCH model</i>
I_{t-1}	dummy variable
y_t -	endogenous time series variables VAR model
c -	k -vector of constants VAR model
Φ -	time-invariant ($k \times k$) matrix VAR model
e -	k -vector of error terms VAR model
IP -	percentage difference between the normalized electricity imports and Belize's total electricity supplied to the grid
D -	Energy Supply on the Buyer's (Belize) side
D_{Fi} -	Forecasted grid energy supply for an hourly interval, i
D_{Ai} -	Actual grid energy supply for an hourly interval, i
S_{Pi} -	Electricity supply by a power plant, P , for an hourly interval, i
FP_i -	Imported electricity day-ahead forward price of Xul-ha interconnection node for an hourly interval, i
SP_i -	Imported electricity day-of spot price of Xul-ha interconnection node for an hourly interval, i
PE -	prediction error
PU -	plant unavailability
PK -	peaking
FP -	forward premiums
y_i -	value of variable to be predicted in RSS
x_i -	explanatory variable in RSS
C_{Gauss} -	Gaussian copula
C_T -	t-copula
μ -	mean of copula

Σ -	shape matrix of copula
v -	degrees of freedom of copula
P -	probability
q -	percentile level

Chapter 1 Introduction

1.1 Background

This thesis investigates the inherent risks associated with power mixes in emerging economies. The power mix —the combination of energy sources used for electricity generation (Burke, 2010)- is a foundational component of energy security. Energy security is commonly defined as the reliable availability of energy in sufficient and affordable quantities, while maintaining acceptable economic and environmental impacts (De Rosa et al., 2022). Prior research highlights that a well-balanced power mix contributes significantly to this goal by reducing overdependence on any single source or supply pathway, thereby enhancing the system's resilience to disruptions (International Energy Agency (IEA), 2019). The transition toward more sustainable energy systems has increased the complexity of managing power mixes, requiring careful consideration of technical reliability, economic viability, and environmental sustainability (Irena, 2015). For this reason, stakeholders depend on strategic planning processes to navigate complexities and shape effective transition pathways.

This thesis was developed to bring specific real-world experiences and limitations to the forefront of strategic planning of smaller nations. In the context of small and developing power systems, the composition of the power mix becomes even more critical, as these systems often face additional challenges such as limited domestic resources, high import dependency, and exposure to external market fluctuations- each uncovered and analyzed in this study.

According to the International Energy Agency, to achieve long-term security, timely investments in energy supply are essential to satisfy economic growth and environmental demands, minimizing disruptions to industrial operations and fostering economic development (2023b). While significant progress has been made in improving electricity access and establishing regulatory frameworks, literature highlights that small developing nations continue to face substantial obstacles in achieving reliable, affordable, and sustainable energy systems (International Bank for Reconstruction and Development, 2017).

Smaller nations often contend with small market size, remoteness, and high exposure to climate-related events and natural disasters which complicate strategic energy planning (International Bank for Reconstruction and Development, 2017; Osazuwa-Peters et al., 2021). Their dependence on imported fossil fuels results in volatile and elevated energy costs, while limited economies of scale further hinder the viability of large-scale investments in energy infrastructure (Seetharaman et al., 2019). Moreover, dispersed and low-density populations challenge the expansion of national electricity grids, limiting equitable energy access. These combined factors place small developing nations at a distinct disadvantage in formulating long-term strategies compared to larger, better-resourced countries.

One possible reason for experiencing challenges in strategic planning may be the methodologies employed by stakeholders during the planning process. However, a preliminary review of the literature revealed that there was limited research into the root causes of these shortcomings, particularly for smaller nations, thereby presenting the first research gap and the need for further investigation. This thesis investigates the underlying factors contributing to the persistent challenges that stakeholders in small developing power systems face in executing effective strategic long-term energy planning. Both stakeholder awareness and response in strategic planning for disruptive events are theoretically linked to the core concept of risk management. By examining the definition, approaches and importance of risk across disciplines, this thesis gained deeper insight into the challenges and strategies involved in navigating an investigation on power mixes. A few commonalities were determined:

First, while the concept has been explored across diverse fields—from finance and engineering to public health and environmental studies—its fundamental meaning remains consistent. According to the Merriam-Webster Dictionary, risk is defined as "the degree of probability of loss" (2024). In application, generally, risk represents an entity's awareness—or lack thereof—of potential threats or uncertainties (Aven, 2012). For example, in environment health and safety (EHS), risk reflects uncertainty about stressors like pollutants. The pollutant can create harmful consequences of environmental change. The risk arises due to a lack of knowledge, inability to measure, identify trends, or assess the pollutant (Aldy & Viscusi, 2014). There-in lies the uncertainty of the stressor. In the field of climate-resilient infrastructure, the risk often reflects changes in weather patterns and extreme weather. The risk arises from increased variability and intensity of shifting weather and climate extremes (Auld & MacIver, 2006). Essentially, seeing that these shifts have the potential to damage infrastructure, it is uncertain how existing infrastructure will cope under the changing conditions. Each example demonstrates a common perspective, that the risk reflects uncertainty about the basic problem.

Second, risk awareness plays a critical role in decision-making, particularly in environments marked by complexity and ambiguity. As energy systems become increasingly interconnected and technologically advanced, the need to understand, assess, and manage risk becomes even more vital. For example, Laimon et al. (2019) found that in Australia's energy sector, uncontrolled growth has led to excessive extraction of fossil fuels, coal and gas – posing a significant risk to the country's ability to meet its long-term sustainability targets. Their findings provide awareness to stakeholders in planning for a highly complex energy system- made up of many interconnected parts that interact with each other in ways that are often unpredictable. These findings help Australian decision-makers better anticipate challenges, weigh alternatives, prioritize resources, and design more effective strategies.

Third, although the fundamental notion of risk is broadly consistent across disciplines, the methods for identifying, measuring, mitigating, and communicating risk differ considerably, and no single unifying framework currently exists (Aven, 2012).

Nevertheless, a recurring feature in technical disciplines is the focus on quantifying system vulnerability through an analysis of causal relationships among key variables. For instance, Laimon et. al. (2019) employed a system dynamics approach, constructing causal loops, stocks, and flows involving variables such as new renewable energy capacity, new non-renewable energy capacity, and the retirement of existing capacity to examine the long-term behavior of Australia's energy sector.

This thesis was motivated by these three observations to establish a clear conceptual framework for understanding risk for an increasing complex power system. Moreover, a framework that integrates the practical realities stakeholders face when operating in a small system. Given the research focus on strategic planning, the 'management' dimension of this study draws from principles in business administration and finance, particularly within an organizational context. This involved analyzing the risks associated with the current methods used by the organization to plan, direct, and manage system resources, and assessing how these risks could impact the system if the organization continues along its existing long-term energy plan.

In small developing systems, the system operator (SO) was identified as a key stakeholder actively involved in both strategic planning and risk management of the power supply system. SO refers to the entity responsible for real-time management of electricity supply to meet demand while maintaining system reliability. A critical cause of risk oversight is that SOs frequently focus on residual risk mitigation—exposures that remain after protective measures such as hedging, reserve capacity, or demand-side management—while ignoring their exposure to inherent risk, which encapsulates the amount of risk present before any controls are applied, such as reliance on imported electricity from Mexico. Residual risk controls are protective, whereas inherent risk controls are preventative. Power supply management tends to emphasize residual risks, but these represent only a subset of the overall risk landscape. Moreover, smaller markets' risk-mitigation strategies have received less attention compared with those in larger economies.

However, majority of the existing literature on small developing power systems adopts a macro-level focus, typically reflecting the government's perspective and emphasizing policy-related priorities such as electricity access and renewable energy targets. While this study acknowledges the value of these areas, it also highlights a critical gap: the limited attention given to strategic planning from the standpoint of operational stakeholders.

This thesis takes a distinct approach by examining the issue from the perspective of the SO, offering an academic lens that reflects realities of small developing power systems. The main purpose of a risk analysis is to support 'de-risking' of the system. De-risking refers to a strategy that is used to mitigate the risk to protect people, environment, physical assets etc. from potential threats (Benson & Sicilia, 2023). Essentially, the outputs of this study seek to improve both the quality and the adaptability of decisions for stakeholders when the future of the highly interconnected, complex power mix is uncertain and evolving in an environment marked with ambiguity.

This study adopts a unified conceptual focus developed progressively across Chapters 2 through 4, culminating in the overarching conceptual framework presented in Chapter 4. Chapter 2 establishes the theoretical foundation of the research, integrating actor analysis and risk governance principles to frame how systemic risks in the power mix can be identified, classified, and governed. Chapter 3 serves as the methodological component of the study, detailing the research design, data sources, and analytical approaches employed to operationalize the theoretical constructs. Building upon these foundations, Chapter 4 articulates the overarching conceptual framework that defines the study's key variables— independent, dependent, control, and moderating—and clarifies their interrelationships. This framework guided both the qualitative and quantitative assessment of inherent risk and exposure, thereby linking the study's theoretical orientation with its empirical execution.

The framework was tested on a novel case study: Belize, a country with limited existing academic research. Belize's power supply mix reflects the typical characteristics of a small, developing country - small and open economy, high exposure to climate-related risks, limited public sector capacity, but at the same time, strategic opportunities to leverage regional electricity trade and position itself as a leader in green transition -while featuring a diverse range of generation technologies. This offers a unique context for exploring how varying energy sources impact risk management and decision-making in power systems.

1.2 Thesis Objectives

Recognizing that stakeholders in small, developing countries' power systems continue to face challenges in strategic long-term energy planning—and in light of the gaps identified in the literature—this thesis pursued two primary objectives:

1. To develop a techno-economic conceptual framework for examining the inherent risks associated with strategic planning for small developing countries' power mixes;
2. To apply and validate this framework using the Belize power mix and its SO as a representative case study.

The rationales for objective 1 are threefold, primarily satisfying notable gaps in existing research. These are outlined as follows:

First, developing the framework bridges literature with the real-world realities of the stakeholders of the power mix. As outlined, the framework specifically integrates technical and economic dimensions. In that way, the analyses quantify the tradeoffs between cost and the realities - faced by the stakeholders. These realities refer to their small and trade-dependent economies with high vulnerability to climate impacts and limited institutional and financial capacity. At the same time, many of these states hold strategic opportunities to expand regional market participation and accelerate progress toward low-carbon and

climate-resilient development. This serves to translate the abstractness of risk concepts into variables, linkages and performance metrics for its validation and use in future research.

Second, the focus on inherent risk is emphasized. Existing studies often categorize—economic, technical, social, and so on—and analyze a full spectrum of risk. In contrast, the framework of this study first isolate vulnerabilities that predate any controls – inherent risk, then performs the risk analysis on this partial spectrum. The rationale in doing so is to steer strategic planners away from the predominant narrow focus of residual risk and toward preventative controls that can reshape the system from the outset.

Third, having no unified approach for small developing countries, objective 1 fills a critical research gap. Under this rationale, the framework ensures that the thesis not only provides novel theories on how to interpret and assess inherent risk in small power systems but also integrates the experiences of stakeholders, primarily government regulators and SO's who showed leading roles in long-term strategic planning, validating the practical relevance of the conceptual framework in a real-world setting.

Objective 2 carries key rationales for empirical grounding, transferability and novelty of the work conducted in the thesis. These are as follows:

Foremost, the rationale for objective 2 is to provide empirical grounding for the developed framework. By testing in Belize, this thesis demonstrates how the framework undergoes the process of uncovering the vulnerabilities, translating these vulnerabilities into variables, establishing linkages and estimating performance metrics for the power mix. Objective 2 thereby transforms the developed framework into a tool validated against the lived realities of the Belizean case study, enhancing both its accuracy and its relevance for strategic decision-making.

The second rationale is transferability of this thesis' methodology and findings. Insights from Belize can inform strategic planning in other small, developing countries, providing both validation of the framework's utility and guidance on adapting it to varying resource bases, regulatory environments, and interconnection arrangements. Moreover, by demonstrating how it works in Belize's real-world setting, it becomes easier to adapt and apply the same approach to other small, developing power systems in future research.

The final rationale concerns contextual novelty, selecting a non-typical power mix. Belize's case study features a mix of high penetration renewables, imported power via regional interconnections, and an emerging economic landscape. The case study presents renewable and non-renewable sources, both of which hold substantial shares in the national mix. Moreover, these energy sources are supplied through a combination of domestic generation and regional interconnections with third-party suppliers, offering a unique and underexplored context.

1.3 Layout and Structure

The thesis commenced with a qualitative exploratory study. The exploratory study was used to identify and understand the inherent risks. This first phase represented a fundamental stage in risk analyses (Buana et al., 2023). The purpose of phase 1 was to provide a preliminary assessment of the system. These included the system actors, technology & infrastructure, sub-systems, and the interactions between them.

The **Phase 1** analysis, presented in **Chapter 2**, consisted of three objectives: (i) to map the structure of the actors, (ii) to identify causes and exposure pathways of risks, and (iii) to classify risks into five major dimensions, and characterize each dimension as complex, uncertain, or ambiguous. Complex risks involve multiple interdependent variables whose interactions are difficult to model or predict; uncertain risks are those for which the likelihood or magnitude of outcomes cannot be reliably estimated due to limited data or inherent variability; and ambiguous risks arise when there is a lack of shared understanding among stakeholders regarding the nature of the risk or the appropriate response.

Multiple data collection techniques and sources were used in phase 1, including: semi-structured interviews, documented sources, and datasets. In-depth semi-structured interviews (SSI) were used to collect primary data from actors. Secondary data was acquired from documented sources and quantitative datasets. A top-down thematic approach was applied to analyze all collected data. Multiple data collection techniques also served to validate the findings of the phase 1 analysis. Validating findings was an especially essential process because the case study (Belize) was understudied in academia.

Phase 2, presented in **Chapter 3**, progressed into the quantitative component of the risk analysis. Early in the research, it was revealed that a substantial proportion of Belize's power supply mix relied on a foreign third-party supplier (Mexico). From one point of view, cross-border electricity trade with Mexico indirectly safeguarded Belize's electricity market from external price shocks (unexpected shifts) on rising global energy commodity prices. Price risk was selected for investigation because it represents a major source of inherent exposure for Belize, given its reliance on imported electricity from Mexico. This risk is quantifiable using historical market data and directly affects the cost of electricity, operational decisions, and investment planning. While other risks exist, price risk provides a tangible, data-driven dimension suitable for the techno-economic focus of this thesis. However, from another point of view, power trade with Mexico exposed the local power market to price risks associated with procuring power from a foreign market.

As a result, it was important to investigate the exposure by the power imports sub-system. **Phase 2** methodology examined the dynamic exposure of Belize's power system to the price risks associated with cross-border electricity trade with Mexico. The study used a volatility metric to represent dynamic exposure. The key datasets were electricity forward and spot pricing of the Belize-Mexico interconnection node. Data were analyzed using auto-regressive moving average auto-regressive conditional heteroscedastic (ARMA-

ARCH) models and hourly vector autoregressions. The ARMA–ARCH framework was chosen to capture both the serial dependence and time-varying volatility of electricity prices, which exhibit autocorrelation, volatility clustering, and mean-reverting behavior due to weather, demand, and market interventions. The ARMA component models the serial correlation, while the ARCH component captures conditional heteroscedasticity, reflecting dynamic exposure to price shocks at the Belize–Mexico interconnection. While alternatives like stochastic volatility models were considered, ARMA–ARCH provided the clearest, most robust, and computationally efficient approach for hourly data in a small, volatile market.

Phase 3, presented in **Chapter 4**, modelled the risks of the local power supply market during per season. This final phase explored the interdependence of quantity and price-related risk factors that can lead to higher uncertainties in power supply management. The analysis relied on probability distribution modelling to represent the likelihoods and distribution of univariate and multivariate factors.

Risk factors were synthesized and represented by a set of variables. Univariate distributions were developed by building and optimizing probability density functions (PDFs) for each variable. The copula method was adopted to build multivariate risk distributions per operating season which allowed for sampling. Levels of exposure to the risk factors were calculated and expressed using percentiles, allowing for scenarios to be compared. This approach allowed for efficient sampling of correlated risk scenarios and the calculation of exposure levels expressed as percentiles, facilitating comparative analysis across scenarios. Alternative multivariate techniques were considered, but copulas offered the advantage of flexibility in capturing non-linear dependencies and tail co-movements, which are critical in representing the joint exposure of the power system to inherent risks.

Chapter 5 presents the conclusions of this thesis. These include key take-aways on the validation and insights of the developed framework and application to Belize and its revealed vulnerabilities- such as cross-border dependence, hydropower seasonality, and fuel-price exposure. It highlights operational perspective by discussing the importance of integrating operational realities of the SO into strategic, long-term planning for more resilient system design. Further, through the analyses concluding discussion, the reemphasize the distinction between inherent and residual risk. Together, these conclusions demonstrate that a combined techno-economic, operator-centric approach—grounded in empirical data and attentive to inherent vulnerabilities—offers a robust path forward for small developing countries’ power systems navigating complexity and uncertainty.

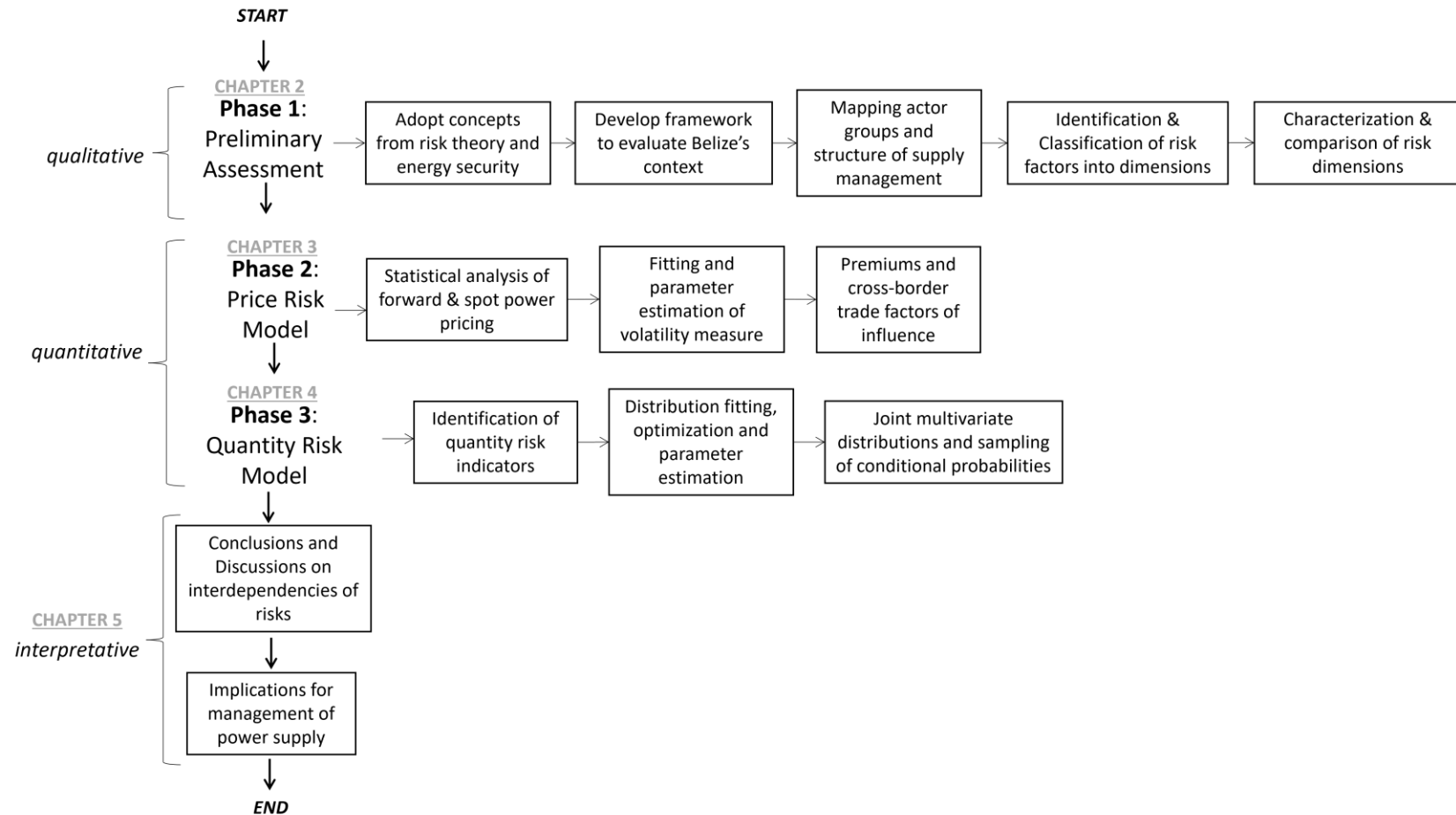


Figure 1-1 Layout of Thesis

1.4 Research Gaps

This thesis recognizes that stakeholders in small, developing countries' power systems continue to encounter significant challenges in strategic long-term energy planning. Gorzeń-Mitka and Wieczorek-Kosmala(2023) emphasize that local stakeholders must regularly reassess regulatory frameworks and market structures to facilitate the advancement of clean technologies. Their findings underscore the critical need for the power sector to systematically identify, measure, verify, and manage risks associated with increasing energy demands and the broader energy transition. Despite growing recognition of the need for improved risk management in energy systems, several research gaps remain:

First, prior studies have largely focused on technical or economic modeling for larger national power systems, overlooking the unique challenges faced by small developing countries, such as limited technological options and resource constraints. Findings from large markets often require significant adaptation to fit smaller contexts, where size remains a critical factor in risk exposure. Consequently, risk-mitigation strategies for small developing countries have received less attention. For example, while cross-border electricity trading can shield small economies from global price shocks, it also introduces risks tied to dependence on foreign power systems. Yet, cross-border trade and its role in facilitating energy arbitrage for small power systems and markets, particularly in emerging nations, remain underexamined in the current research.

Second, government-led research in developing nations often prioritizes system expansion, while risk management—particularly at the operational level—remains significantly underexplored. Essentially, this research gap lies in limitation of stakeholder perspective. Most existing literature on small developing countries' power systems adopts a macro-level focus, reflecting government perspectives that emphasize broad policy goals such as improving electricity access and meeting renewable energy targets. While these areas are undoubtedly important, this study identifies a critical gap: the limited attention given to strategic planning from the perspective of operational stakeholders, such as utility managers, SOs, and local planners. These stakeholders play a crucial role in ensuring system reliability, resilience, and efficient risk management on a day-to-day basis. Without integrating their operational insights into long-term planning, power systems may struggle to effectively manage uncertainties associated with demand fluctuations, supply interruptions, and broader energy transitions.

Third, there is a lack of diversity in the systems and countries explored in existing research. Many studies focus on either large national grids with single-source-dominant thermal systems (fossil-fuel based). Additionally, these studies typically reflect systems that have evolved within a country-centric framework, where power generation is largely sourced from local resources. However, systems that do not fit these commonly studied models—such as those relying on a combination of domestic generation and regional interconnections with third-party suppliers, or high-penetration renewable systems that are base-loaded—remain significantly underexplored. These alternative configurations introduce complexities that fundamentally alter risk profiles and decision-making needs. Systems combining domestic generation with regional interconnections expose operators to cross-border supply risks, price volatility in external markets, and coordination challenges across different regulatory regimes. High-penetration renewable base-

loaded systems, meanwhile, amplify variability and uncertainty in generation, necessitating novel approaches to balancing, storage integration, and real-time forecasting. Consequently, stakeholders planning these alternative systems cannot simply apply the research findings from typical power systems.

Fourth, while risk management has been widely applied within the field of strategic energy planning, existing studies have often overlooked the specific structural pathways through which power systems become vulnerable to risk. As a result, much of the literature has focused on managing outcomes rather than addressing the underlying systemic configurations that give rise to those risks. Stakeholders tend to concentrate on mitigating residual risks—those that remain after standard controls are applied—while paying less attention to inherent risks, which exist prior to the implementation of any mitigation measures. This imbalance has led to a focus on optimizing existing systems rather than developing strategies to prevent disruptions at their source. Residual risk controls are designed to limit the impact of adverse events, whereas inherent risk controls aim to reduce the likelihood of those events occurring in the first place. This thesis identified this imbalance as a critical research gap and established a conceptual link between this gap and the foundational distinction between residual and inherent risk.

1.5 Novelty

In satisfying the first research gap, this study offers a unique perspective by examining the role of planning methodologies and stakeholder practices within the context of smaller power systems. This novelty lies in highlighting the practical realities stakeholders face when operating in a small system and integrating these insights with existing theory to develop an analytical framework tailored to this context. This contribution enhances the understanding of potential consequences for power supply systems if these challenges remain unaddressed and informs more effective strategies for achieving energy security in underrepresented contexts—including small developing countries, small island developing states (SIDS), and other developing countries with large, dispersed populations and disaggregated power networks.

Second, this thesis presents a novel perspective in adopting the SO's perspective, providing an academic lens on the realities of small developing countries' power systems. As described, government-led research accounts for a majority of existing literature on small emerging economies. Their perspective often emphasizes system expansion, whereas risk management—particularly at the operational level—remains underexplored. As such, this thesis stems from the perspective of the SO who is central role in managing power supply, where the oversight of power delivery is closely tied to risk control. SOs prioritize reducing risk to minimize the likelihood of significant disruptions and ensure the sustained development of the power sector. The novelty of this study lies in its integration of real-world insights from the SO's professional experience with an analytical evaluation of the planning frameworks employed. This approach provides a deeper understanding of the root causes behind persistent failures in strategic energy planning.

Third, in addressing the research gap of contextual diversity in the prior explored power systems, this research contributes a novel case study to the field of strategic energy planning by focusing

on Belize—a country for which limited academic research currently exists. Belize’s power supply mix not only reflects the typical characteristics of a small, developing nation but also features a diverse range of generation technologies. Despite its scale, the diversity within Belize’s energy system allowed this thesis to explore the interaction between renewable and non-renewable sources, both of which hold substantial shares in the national mix. Furthermore, these energy sources are supplied through a combination of domestic generation and regional interconnections with third-party suppliers, offering a unique and underexplored context for analyzing energy dynamics in emerging economies. Unlike many studies that focus on either large national grids or single-source-dominant thermal systems, this thesis investigated a hybrid system where both types of energy sources are significant and supplied by a combination of domestic and regional third-party providers. The unique structure of Belize’s energy mix allows for a more nuanced analysis of strategic planning challenges, energy security concerns, and policy implications in small developing countries—an area that has been underexplored in existing literature.

Finally, to uncover the structural pathways that render power systems vulnerable, this thesis forges a conceptual link between these gaps and the essential distinction between inherent and residual risk. Whereas most power-planning research has focused on residual risk—the threats that persist after controls are applied—this study directs attention to inherent risks, those that exist before any mitigation. By doing so, it broadens the scope of analysis beyond the conventional emphasis on residual risk. This novelty lies in this reframing: rather than optimizing existing systems to reduce post-control threats, the research prioritizes strategies to prevent disruptions at their source, highlighting vulnerabilities that too often go unnoticed in stakeholders’ business-as-usual mode.

1.6 Practical Implications

One of the goals of this thesis was to adapt ideas and theories from the field of risk to the management practices of the SO. As a result, several real-world applications of this study’s findings can be used to improve the practices of SOs, inform energy policies, and develop trajectories for the development of the power sector. A key implication of the research findings is reducing the potential impact of risks. Through the processes carried out in the methodology, this study identified, analyzed and highlighted the inherent risks of the SO’s activities given its current structure and practices. In turn, these findings can be used as the basis for how these risks are likely to evolve if the SO continues in its given trajectory. Using this information, SO’s may leverage this study’s foundation and analytical insights to inform risk management strategies.

Because the study takes a specific focus on inherent risk, Practical implications may promote broader mitigating scope beyond regulations, incorporating a sector attitude of adaptability into power supply management. These implications also have the potential to impact future research that will improve local power supply planning and decision making, such as merging importation market behavior results with the buyer's local power development strategy. This study's findings can help to raise awareness of interconnectedness, resulting in better informed decisions and investments in preventative risk management control, particularly in small developing countries. By taking into account interdependencies and probable coincidences of risk factors, risk quantification may disclose a greater potential influence on the power industry. Practical implications indicate that preventative measures should be prioritized.

While this study examined key operational and structural risks in managing Belize’s power mix, it did not include risks from natural disasters or climate change. This exclusion was intentional, as the applied techno-economic and probabilistic framework was suited to power system operations rather than external environmental hazards. Addressing climate-related risks would require alternative methods—such as climate impact modeling or geospatial vulnerability analysis—supported by long-term data. Given the five-year dataset used, the study’s insights are limited to short-term weather variability rather than long-term climate trends.

Chapter 2 Power Mix Risk Analysis: An Exploratory Study

2.1 Introduction

Risk management is a crucial aspect of decision-making in the energy sector, involving strategies and tools to identify and control factors that can impact on operations in the short or long term (Gurtu & Johny, 2021a). Perhaps the most significant challenge in this field is that decision-makers must navigate a broad range of events that require consideration at local, national, and international scales. For example, studies like Zhou & Yang (2020) that identify high risks in distributed wind power investment in China and Jakimowicz (2022) that analyze the political, economic, social, technical, legislative, and environmental aspects of advancing electric vehicles (EVs) in the European Union (EU), may be grouped on the basis of ‘risk’ as it relates to the integration of new technologies from a multidisciplinary perspective on assessing the achievability of a higher presence of such distributed energy resources (DERs).

This study considers risk factors both in terms of geographical scope—from local to international—and analytical perspective, encompassing technological, social, and institutional dimensions. While prior studies have largely emphasized the latter, this framework explicitly integrates spatial and cross-border influences on Belize’s power system to capture a more comprehensive view of risk.

Meanwhile, recent global events have renewed interest in market risk studies that examine the risk of energy supply chain disruption, for example the following study (Jin et al., 2023) that confirmed the link between energy future prices, such as crude oil and natural gas, and geopolitical risk and climate risk, and another study revealed the highly nonlinear and asymmetric responses of spot prices on electricity power supply as a result of global-level uncertainties (Wadström et al., 2023). Risks in the energy sector can clearly be associated with a variety of internal or external factors, and this overarching challenge emphasizes the need for flexibility and deep understanding in the approaches used to manage the risks associated with fundamentally technological systems that play an important societal role.

As a result, the energy sector faces a pressing need to identify, measure, verify, and manage risks associated with these situations. However, according to Gorzeń-Mitka & Wieczorek-Kosmala (2023), who conducted a comprehensive review of risk management research in the energy sector, understanding and managing these risks remains a major challenge for the sector, as policymakers must deal with rising energy demand and the debate over the directions and methods of energy transition. This emphasizes the need to regularly review regulations, market structures and policy interventions, including environmental restrictions, tax benefits, utility regulations, and licensing standards, to enhance the potential and effectiveness of clean technology. Consequently, risk management represents a very timely issue for decision-makers to work towards a safer, affordable, and more sustainable energy sector (Andreev et al., 2021).

Previous studies on energy risk management identified three main research themes relating to energy risk management: accident issues, investment issues, with a focus on renewable energy investments and greenhouse gas emissions issues, and sustainability issues, with a focus on energy transition issues (Gorzeń-Mitka & Wieczorek-Kosmala, 2023). To investigate these areas, researchers have since relied on approaches that assess the complexity of the components and their interactions in energy systems (Nie et al., 2017), either by focusing on the risks associated with a specific technology, market instrument, etc., or by taking a system-wide approach that often includes a comprehensive evaluation of an energy sub-sector.

Alternative focuses can be seen between studies, for example Sridharan et al. (2019) that focuses on climate-related risks in the Eastern African Power Pool specifically relating to hydro-electric technology, versus Tehero et al. (2020) where a multitude of structural factors like regulation, government effectiveness, rule of law, and technology transfer are considered. Focused risk-based approaches tend to offer specific operational strategies, such as the proposed residential hybrid photovoltaic/solid oxide fuel cells by Cao et al. (2020). However, system-wide approaches capture a broader scope which is advantageous when evaluating trade-offs between risk and cost, as demonstrated by the multi-objective optimization approaches presented by Nie et al. (2017) and Unni et al. (2020) that reveals the impact of uncertainty and decision-making risk on strategy, planning and costs in energy systems.

Notably, while these studies exhibit contrasting techniques, both underscore the importance of being prepared to cope with contextual variables to conduct an effective examination. The methodology applied in this study is based on a systems approach, in which we analyze areas of regulations, technology, socioeconomic constraints, national goals, and global responsibilities of the local power sector, a choice justified primarily by the scarcity of research on Belize. In this regard, the system-wide approach complements the exploratory aspect of this study's methodology.

This study focused on power generation mixes in emerging economies using Belize, on which limited research is published, as the case. Unlike developed economies that can support economic recovery and advancement in the face of disruptive events, emerging economies must devote most of their resources to economic recovery (Khan et al., 2022), so it is crucial to mitigate exposure to risk factors. Additionally, developing nations are in the process of building the regulatory structures and electricity markets best fitted to support their power needs. Electricity is a critical input for development and progress (Tehero et al., 2020), but risk management research on power systems in developing nations is scarce. This lack of research may leave policymakers and stakeholders unable to modify the electricity system before it is subjected to change that it cannot successfully respond to (Molyneaux et al., 2012).

Power supply remains a critical focus of economies globally because stability in electricity supply minimizes disruption to industrial productions and supports economic advancement. The power mix comprises of a collection of sources used to generate electricity (Burke, 2010), and managing the simultaneous and varying impacts from these multiple sources pose challenges. Belize's peak demand is roughly 107 MW, while total installed capacity is at 172.8 MW (Belize Electricity Limited, 2022). The power grid has numerous centralized supply sources, the principal of which are hydroelectricity and co-generated biomass. Local supply renewable

energy (RE) is supplemented by Mexican electricity imports, which may be purchased on an hourly basis (Tillett, A; Locke, J; Mencias, 2011). Managing the simultaneous and varying impacts from these multiple sources pose inner-sector and inter-sectoral risk challenges.

This study aimed to explore the inherent risks of the structure and managerial practices of Belize's power mix through a qualitative three-step process based on a conceived framework that incorporates theoretical and conceptual notions on risk management, socio-technical systems and energy security. In doing so, we conducted a system-wide research that delved into numerous aspects of the sector, such as regulatory framework, legislation, technology, and governance.

In step 1, the electricity supply system's structure and actors are mapped from its installation to its current state. Inherent risks were identified and screened to identify underlying causes and exposure pathways in step 2. During this step, risks were also categorized into five main dimensions (economic, social, etc.). Finally, in step 3, risk dimensions were characterized based on their complexity, uncertainty, and/or ambiguity to more clearly unveil how their exposure pathways threaten long-term progress whilst coping with immediate societal demands.

The remainder of this chapter is divided into four sections: section 2.2 entails a review of the literature. The research methodology is detailed in section 2.3, and findings and analyses are presented in section 2.4. Section 2.5 finishes with conclusions and practical implications.

2.2 Literature Review

2.2.1 Assessing the Risks of the Power Supply Mix

The power mix (also known as the "power supply mix," "electricity mix," or "electricity generation mix") is the collection of sources used to generate electricity (Burke, 2010). There are various reasons why the power mix is considered in this study. Essentially, it is an important aspect in a country's energy security, which is defined as the consistent availability of energy in adequate and affordable quantities with acceptable levels of economic or environmental consequences (IEA, 2023b). Energy security is directly related to risk since it represents the likelihood of a disruption (De Rosa et al., 2022). Long-term security necessitates timely investment in energy supply to meet economic growth and environmental requirements.

Earlier studies have highlighted the environmental impact of the power mix due to concerns about greenhouse gas emissions (Burke, 2010). Particularly in the developing world, the electricity sector is rapidly expanding and innovating (Molyneaux et al., 2012), with global electricity demand expected to reach 50% of final energy consumption by 2050 under the Net Zero Emissions scenario (IEA, 2023a). The power mix has supply and demand characteristics that offer cost-effective strategies to reduce emissions.

For example, in (Pereira & Marques, 2020), the authors demonstrate France's power system's high level of flexibility to a diverse electricity mix proven primarily by its consumption patterns and realized by exploiting the utilization of solar PV power during various daily peaks to maintain electricity costs. Similarly, through a macro approach, Bonilla et al. (2022) reveals that

by 2040, the UK's power industry can achieve 85% decarbonization without increasing electricity costs and maintaining acceptable curtailments below tolerable ranges.

According to De Rosa et al. (2022), the power system, despite employing fundamentally identical technology across all countries, is heavily impacted by context since it is tied directly with national objectives and plans, which may vary over time. Recent studies highlight the importance of understanding these factors for policymakers in the energy sector. For instance, the policy implications reviewed in the case of France (Pereira & Marques, 2020), rationalized managing demand shifts between peak periods by combining conventional nuclear and fossil power with renewables. In France, the high proportion of nuclear power in the mix is a critical consideration, while the country's high interconnectedness with the European also delineates the contextual limits, constraints and degrees of freedom. Whereas in other contexts – such as Australia – there is no domestic nuclear power and no international interconnections, thus evidence-based policy for each of these countries requires different considerations. It is evident that the power mix is impacted by a nation's historical, sociopolitical, and economic characteristics.

Previous studies that have taken an economic focus have been able to integrate traditional financial variables and strategy into dynamic energy models, such as the subsidy-based model developed by Tso et. al. (2021) to improve the resilience of renewable energy supply networks by considering supply, demand, and payment risks through risk-sharing – a fundamentally financial strategy. Likewise the approaches of previous research including (Karatop et al., 2021) and (Sadeghi & Larimian, 2018) applied financial portfolio planning and strategy techniques to determine the optimal investment decisions, weights, and risks in renewable energy alternatives. Such economic assessments prioritize a set number of significant factors and their relationships; however, in reality, the influence of global and domestic uncertainty on electricity supply regarding power mix risk management in the energy sector involves a multitude of decision-making governed by complex and dynamic relationships. As a result, this research presented a system-wide view to increase awareness of nuances in the power supply structure in an emerging economy that can facilitate more focused mitigation practices.

Power mix studies often combine energy security concepts to measure system-wide risk from a macro perspective, the energy supply and potential disruptions, crucial for national security and economic stability (Molyneaux et al., 2012). These assessments evaluate factors like resource availability markets, and geopolitical variables, thereby assessing a risk typology (De Rosa et al., 2022), because while conventional economics suggests optimal resource allocation through markets, externalities, non-priced factors of the power mix, are often not associated with the traditional economic system (Wu & Rai, 2017). Researchers have used various indices to measure power mix security dimensions, focusing on understanding electricity system vulnerabilities.

The concept of diversification was developed to address dependency on a single energy source and is perhaps the most widely applied in power mix analysis, including studies such as (Akrofi, 2020; De Rosa et al., 2022; Rubio-Varas & Muñoz-Delgado, 2019b; Triguero-Ruiz et al., 2023). Diversifying provides additional options and risk sharing across many sources, lowering perceived risks. The term "dependence" implies that imported energy is less trustworthy than

native energy, resulting in greater risk (Molyneaux et al., 2012). The proportion of energy consumption met by renewable sources such as solar, wind, hydro, and geothermal is referred to as renewability (De Rosa et al., 2022), recognizing the threat to power networks that rely mainly on depleting resources (Molyneaux et al., 2012). This research utilized indices commonly used in previous studies to assess the power mix, as listed in Table 2-1. These indices serve to measure progress, performance, and system response to past events under comparable conditions (Molyneaux et al., 2012). The selection presented here represents only a sample of the broader body of available literature. The indices included were specifically chosen because they have been applied in contexts relevant to developing countries, making them particularly suitable for this study. The following section outlines the specific indicators selected to represent these fundamental concepts.

Table 2-1 Security indices used to assess the power mix

Key areas	Indices Applied in Past Studies	Reference
Variety	Number of sources	(Akrofi, 2020; Stirling, 1994)
Disparity	Descriptive	(Stirling, 1994, 2008)
Balance	Share per source	(Akrofi, 2020; Stirling, 1994; Wu & Rai, 2017)
Diversity	Shannon-Wiener index (SWIs)	(Chalvatzis & Rubel, 2015; Grubb et al., 2006)
	Herfindahl-Hirschman index (HHI)	
	Energy Mix Concentration Index (EMCI)	(Rubio-Varas & Muñoz-Delgado, 2019a, 2019b)
Reliance	Import reliance	(Molyneaux et al., 2012)
	Adjusted Shannon-Weiner index (De Rosa et al., 2022; Jansen, Van Arkel, et al., 2004)	(De Rosa et al., 2022; Jansen, Van Arkel, et al., 2004)
Dependence	Primary energy import Dependence	(Marong et al., 2018; Molyneaux et al., 2012)
	Adjusted Shannon-Weiner index	(Jansen, Van Arkel, et al., 2004)
	Renewable Energy Security Index (RESI)	(García-Gusano et al., 2017)
Renewability	National renewability factor (NRF)	(Molyneaux et al., 2012)
	Carbon intensity	

2.3 Methodology

2.3.1 Conceptual Framework

Phase 1 of this study employs a conceptual framework that combines actor analysis with risk governance principles to assess inherent risks in Belize's power mix. The framework involves three main steps: (i) mapping the system structure and relevant actors, (ii) identifying exposure pathways and classifying risks into major dimensions, and (iii) characterizing each risk dimension based on complexity, uncertainty, and ambiguity. This structured approach provides a foundation for subsequent methodological phases and situates the analysis within both socio-technical and institutional contexts. The framework is detailed as follows:

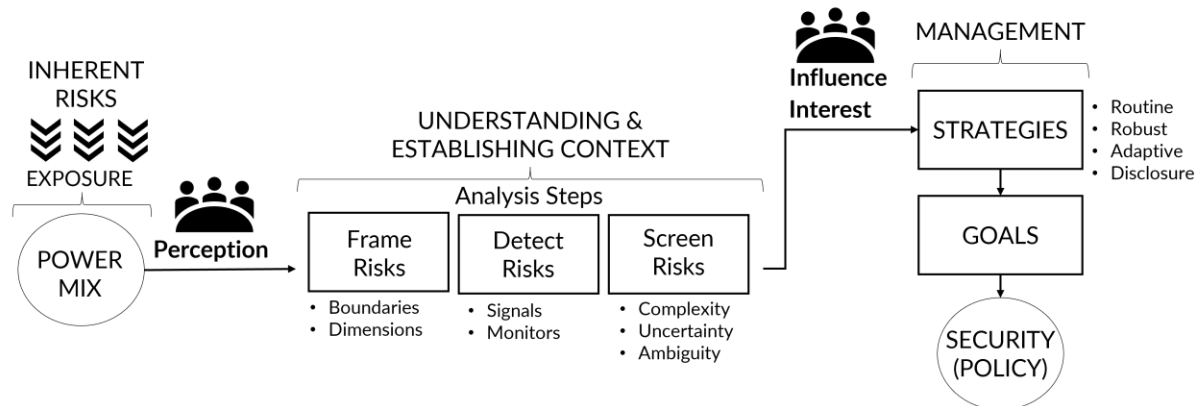


Figure 2-1 Conceptual Framework used to Assess Inherent Risk of Power Mix

This paper examines the power mix, which, while important for local energy security and global environmental ramifications, has received less attention than the energy supply mix. The power mix varies more than the energy supply mix over time and across nations, which increases its interest for comparing and extending existing work (Burke, 2010).

As presented in Figure 2-1. The power mix is considered as part of a complex socio-technical system exposed to inherent risks that could fully disrupt its functionality. These risks are embedded in the larger social, economic, environmental, political, and geopolitical contexts, and their perceptions and management are reliant on various invested actors to address these risks effectively (Bhatt & Singh, 2020a). As a result, understanding stakeholder values is crucial for effective risk management and the first step in this study's approach. Perceptions are influenced by concerns associated with risks. Actor groups are also guided by their roles, interests, and influence (IRCG, 2020a; IRGC, 2017a). These interlinks are explored and have been prior established in stakeholder assessments such as that of Bhatt and Singh (2020b). The author deploys an actor analysis approach that focuses on understanding action scenarios as well as the power, interests, and interdependence of the actors to help understand the barriers affecting technology adoption.

The next step involves understanding risk problems and establishing context. Framing, a concept from consensus, communication, and organizational management, is essential in risk governance frameworks (Stein et al., 2019b). It involves selecting and interpreting relevant risk topics,

clarifying perspectives, defining issues, and forming the baseline for risk management (IRCG, 2020b; IRGC, 2017b). The process aims to collectively reconstruct risk phenomena and organizing experiences through consensus (Stein et al., 2019b). Risk detection is critical for preventing disruptions and enabling decision-making based on evidence and transparent assumptions because if foresight is lacking, the subject is vulnerable. As such, risk detection is often conceptualized in terms of vulnerability and certainty of outcomes (Gurtu & Johny, 2021b). Risk theory suggests adequate information is needed to identify the damage of risk events and predict future loss (Jansen, Arkel, et al., 2004). Signals indicate problems, requiring action on existing knowledge. Monitoring is based on identified signals, foresight, and identifying emerging risks (IRCG, 2020b; IRGC, 2017b). The screening process selects, allocates, and prioritizes assessment routes based on collected risk-related information for addressing risks (Aven & Renn, 2010b).

Within the third and final step, the combined knowledge gathered is used to characterize the inherent risks based on complexity, uncertainty, and ambiguity (Wadström et al., 2023) to assess the appropriateness and adequacy of the existing risk management measures. Complex risks arise from multiple interconnected factors whose interactions are challenging to model or anticipate; uncertain risks occur when the probability or potential impact of outcomes cannot be reliably determined due to limited information or intrinsic variability; and ambiguous risks emerge when stakeholders lack a common understanding of the risk's nature or the suitable course of action. Actors are essential in creating and maintaining sustainable management options and institutionalizing these strategies in policy (Stein et al., 2019a), as a result, in this final step, it is also essential to draw parallels between the assessment of the actor's in step 1, and the characteristics of the risk dimensions.

In this study, data specific to Belize's power supply structure were collected via interview from its actors, along with documented sources policies, projects, annual reports, regulatory agreements and datasets as detailed in section 3.3. As a result, the evaluation of energy security reflected the specific features of the country under consideration, emphasizing contextual variations such as local resource endowments, as well as internal factors such as existing infrastructure, and decarbonization strategies (which may be external to both the energy system and the country in some cases).

2.3.2 Study Procedure

An exploratory case study was used to analyze Belize's power mix, which included semi-structured interviews as well as documented sources and datasets. The research's approach includes site identification, sampling, data collection, processing and presentation, ensuring a thorough coverage of the inherent risks of the power mix. In accordance with the conceptual framework, the processes for this study were divided into three steps, each of which included a collection of topics for which data was acquired and evaluated, as presented in the figure below:

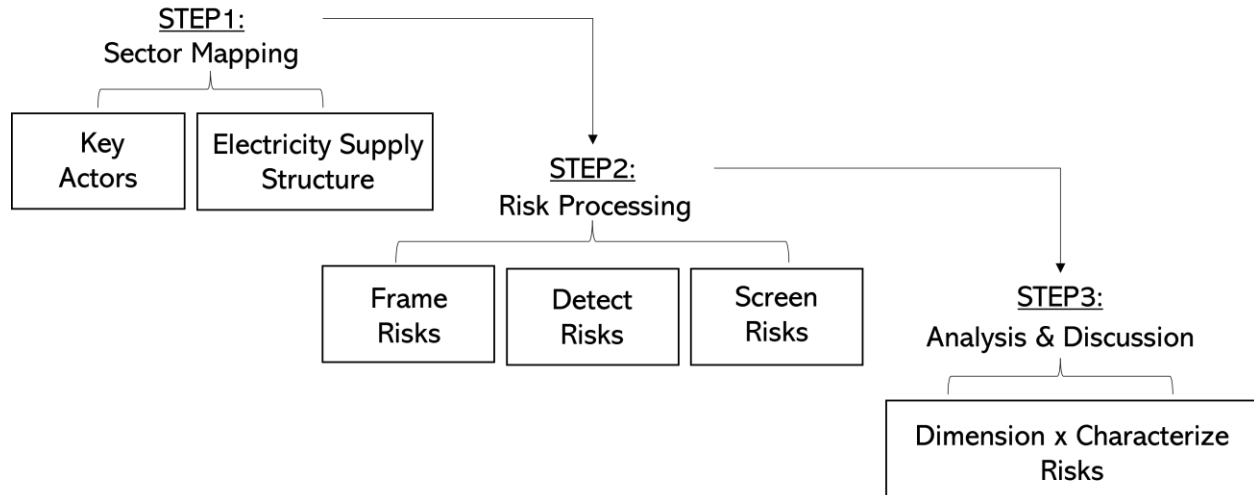


Figure 2-2 Methodological flow used to analyze exploratory case study of Belize's power mix

Step 1 – Mapping the Key Actors & Structure of the Electricity Supply System

The first step was to conduct a thorough review of the participant groups and the structure of the power mix, based on the provision of the electricity supply resource and their trade mechanisms, adopting from frameworks on actor roles in the electricity sector (Bhatt & Singh, 2020a; Moallemi & de Haan, 2019). As a result, the goal in this step was to address the following themes:

- Who are the actors and what are the relationships between them;
- Their responsibilities, values and resources;
- Their level of interest and influence in risk management;
- The electricity supply technologies;
- Overview of supply system's structure.

The research design prioritized sampling to involve participants using selection criteria based on their roles, functions, and experiences in decision-making, planning, or implementation (Haque et al., 2020; Landegren et al., 2019; S. Shadman, C. M. Chin, E. H. Yap, N. . Sakundarini, 2021; Whiston et al., 2022). The study involved experts from Belize's public organizations, including the Public Utilities Commission, energy unit, and utility, and regional representatives from the Caribbean Community and the Caribbean Centre for Renewable Energy and Energy Efficiency.

The study was limited to a small sample size due to a lack of institutional capacity for this topic. The three key local organizations (utility, regulatory commission, and government) had dedicated units for expert matters on power mix (each having 3 to 5 personnel). The grounded theory of qualitative research (Vasileiou et al., 2018) suggests the optimal sample size for a single case study is 15-30 participants, but this may vary due to study context constraints. In this study, 17 stakeholders were approached and 12 agreed to participate. Data saturation is crucial in such cases (S. Shadman, C. M. Chin, E. H. Yap, N. . Sakundarini, 2021; Vasileiou et al., 2018),

whereby the same themes were discovered again throughout data gathering, particularly through diverse collecting approaches.

To define the roles, influence, and linkages of each actor group, we created a stakeholder map - a commonly used tool in stakeholder management (Bourne & Walker, 2005; Walker et al., 2008; Xia et al., 2018; Zedan & Miller, 2017). Based on the data acquired, the researcher demonstrated a view of their respective amount of influence and interest on risk problems (Bhatt & Singh, 2020a).

Step 2 – Framing, Detecting and Screening Risks using Dimensions

Risks were classified using economic, social, technological, environmental, and legal/political dimensions (IRGC, 2017a). The legitimacy of the selection based on the analysis of a broad, comprehensive knowledge of collective consensus grounded in such sociological viewpoints (Parsons, n.d., 1939; Schwartz & Sagie, 2000), determined whether a sector-wide consensus was established concerning the description of each risk dimension. Second, this step aimed to capture evidence based on the indicators and conventions of the risk problems to establish the causal relationships as sources of the risk's exposure pathways and the stakeholder's responses to mitigate the exposure to the risks, by addressing the following.

- Sources of the exposure (causal relationship with source)
- The risks and their various dimensions;
- Possible damages, impacts, persistency;
- Concerning areas of vulnerability;
- Key measures and indicators;
- Actor's response and trade-offs of response.

Step 3 – Characterization of Risk Dimensions

The final step uses the knowledge accumulated in the previous stages to characterize across each dimension as predominantly complex, uncertain, ambiguous, or a combination thereof (Aven & Renn, 2010a; IRGC, 2017a). The risk characterization included three categories – complexity, uncertainty and ambiguity. Generally, simple risks can be managed with routine strategies, while complex risks require field-specific expertise and scientific models for robustness to withstand threatening events (IRGC, 2017a; Wadström et al., 2023). Higher uncertainty leads to adaptive strategies against unknown outcomes, management strategies for ambiguous risk involve discourse for mutual understanding and cooperation.

In the prior steps, the study observed how attributes like values and roles govern the selection of frames, how detecting and screening used signals and monitoring for evidence to regulate causal interpretations (Aven & Renn, 2010a), of the risk's dimension (economic, technical, etc.). As a result, the final element of the third step established causal interpretations between risk dimensions and compared their differences within the causal connection. The following themes were addressed:

- Complexity of the risk dimension – identifying or quantifying the causes of specific adverse effects of the risk pose challenges;
- Uncertainty of the risk dimension- lack of scientific or technical data, or the inconsistency or quality of the data, can significantly impact its accuracy and reliability;
- Ambiguity of the risk dimension - various perspectives on risk, lack of clarity on possible outcomes and conditions for conflict;
- Causal connection between risk dimensions;
- Comparison of risk dimension characteristics within the causal connection

The case study approach is a method used to understand complex issues in real-life contexts (Crowe et al., 2011). A single-case study investigates one site or case (Chopard & Przybylski, n.d.). Many recent studies have used the single-case study technique to address difficulties related to diverse energy systems, to gain a more in-depth understanding than investigating multiple situations. For instance, Landegren et al. (2019) investigates the impact of Swedish quality of electricity supply regulations on the Styrel system, a national power supply system, revealing that critical customers are not given sufficient attention in current regulations. In the transport sector, Whiston et al. (2022) reveal that fuel cell electric vehicles (FCEVs) could significantly reduce carbon emissions in China but emphasize that they are expensive to manufacture and lack widespread refueling infrastructure. Meanwhile, Haque et al. (2020) investigate the constraints and prospects for energy trading in South Asia, focusing on Bhutan, Bangladesh, India, and Nepal, finding vulnerabilities and risks while also proposing solutions to address them.

These studies demonstrate the efficacy of case studies in tackling a wide range of energy policy issues, with the specific local conditions of national or sub-national contexts being important in identifying both opportunities and challenges.

Belize presents an interesting case study. The electricity supply system evolved during a time when climate challenges were becoming more prominent and renewable innovation was gaining traction (1990's). In response, local actors devised a supply structure based on domestic and non-domestic resources to provide an affordable level of service for the local public through integrating a significant amount of renewable supply into the power system for base load capacity and outsourcing ancillary services to manage power quality and shortages via its interconnection with Mexico's electricity grid. This is an unorthodox strategy, considering that industrialized countries prioritized self-sufficiency during the development of their electricity systems.

The National Energy Policy in Belize (Tillett, A; Locke, J; Mencias, 2011) aims to reduce refined fuel oils and electricity imports from Mexico. Belize commits to an 85% share of renewable energy for electric power generation under revised Nationally Determined Contributions (NDCs) by 2030 (UNFCCC, 2021). With the transportation sector, including mass and road transport, and domestic cooking and heating expected to shift towards electricity as the primary energy carrier in the medium to long term (UNFCCC, 2021), electricity will be key to the decarbonization of the overall sector (Tillett, A; Locke, J; Mencias, 2011). The topic presented in this study is timely as Belize prepares to renew its national energy policy in 2024.

2.3.3 Data Collection

The study used multiple data collection techniques and sources, including: semi-structured interviews, documented sources, and datasets.

In-depth semi-structured interviews (SSI) were used to collect primary data from actors. SSI have been widely applied in previous works to investigate risk phenomena related to the power mix among participants (Dadzie et al., 2018; Mirzania et al., 2019; Trencher et al., 2020). This qualitative technique is valuable for confirming, validating, refuting, and elaborating upon existing knowledge (McIntosh & Morse, 2015), such as presented in (Mirzania et al., 2019; Trencher et al., 2020). In the exploratory research on risk and its management, SSI were used to better understand proposed phenomena, related actions, and actors' perspectives, while also addressing validity and credibility issues.

The research design prioritized purposive sampling to include participants based on roles, functions, and experiences in decision-making, planning, or implementation (Haque et al., 2020; Landegren et al., 2019; S. Shadman, C. M. Chin, E. H. Yap, N. . Sakundarini, 2021; Whiston et al., 2022), namely, experts from Belize's Public Utilities Commission, energy unit, and utility, and regional representatives from the Caribbean Community and the Caribbean Centre for Renewable Energy and Energy Efficiency. With a relatively small sample size of 12 experts in this Belize case study, data saturation was achieved to demonstrate credibility (S. Shadman, C. M. Chin, E. H. Yap, N. . Sakundarini, 2021; Vasileiou et al., 2018). Saturation was observed as recurring themes and patterns emerged consistently across the interviews regarding risk perceptions, actor influence, and decision-making processes within Belize's energy sector. For example, multiple participants independently highlighted similar challenges in coordination between regulatory and operational actors, concerns regarding hydropower variability, and the prioritization of affordability and reliability in system operation. The convergence of these themes across interviews supports the assertion that additional interviews were unlikely to yield substantially new insights, thereby providing a basis for data saturation.

During the SSI, participants were allowed to introduce new ideas while still having the freedom to answer open-ended questions (Dadzie et al., 2018). The key themes covered through the in-depth SSI process in this study are fully described in section 3.1. These themes were not covered verbatim but provided structure and focus to the conversation.

Secondary data was acquired from documented sources and quantitative datasets. The National Energy Policy (NEP) of Belize was developed in 2012 (Tillett, A; Locke, J; Mencias, 2011). From 2012 until the present, various energy-related initiatives, studies, and development plans have been developed. Table 2-2 provides a chronological list of each document.

Findings on the electricity industry, particularly the power mix, are presented from various perspectives. As a result, data on the power mix were gathered from these documented sources, which, when combined, provide a 10-year historical history of Belize's energy industry. In addition, annual utility reports, and power purchase agreements (PPAs) of existing suppliers were utilized as supplementary secondary material.

Table 2-2 Documented sources used in this study, including: policies, projects, annual reports and regulatory agreements with relevancy to Belize's power mix

Title	Year(s)	Source
'National Energy Policy (NEP)'	2012	(Tillett, A; Locke, J; Mencias, 2011)
'Belize Sustainable Energy Strategy	2015	(Castalia Limited, 2015)
'Belize Consolidated Project Plan'	2018	(Bunker & Torbert, 2018)
'Assessment of Electricity Generation System & Investment Alternatives of Belize 2020-2035'	2019	(Montouliu et al., 2019)
'Sustainable Energy Roadmap 2021-2040'	2021	(Ministry of Energy & Public Utilities, 2020)
'Belize Integrated Resource & Resilience Plan (IRRP)'	2022	(CCREE, 2022)
Belize Electricity Limited (Utility) Annual Reports	2009-2022	(Belize Electricity Limited, 2009, 2010, 2011, 2012, 2013, 2014, 2015, 2016, 2017, 2018, 2019, 2020, 2021, 2022)
PPAs	1995-2022	(BECOL / BEL, 1991, 2007; BELCOGEN / BEL, 2007; CFE Calificados, 2016; HML / BEL, 2006)

Belize Electricity Limited provided assistance in collection of datasets for quantitative assessment, including annual kWh and cost of electricity supplied to the grid and total annual kWh electricity demand for 14 years from 2009 to 2022 (Appendix, Table A-1 to A-3). The company used internal auditing techniques to verify the data, ensuring high-quality data with no gaps or outliers. Electric utility representatives were provided with a detailed description of the quantitative assessment, and the datasets were approved for use in assessing the power mix indices.

2.3.4 Data Analysis

A top-down thematic approach was chosen for this research, processing data based on commonalities and similar characteristics (Adeoye-Olatunde & Olenik, 2021; McIntosh & Morse, 2015). This approach is particularly useful when theoretical or conceptual frameworks guide data collection (Adeoye-Olatunde & Olenik, 2021). Thematic analysis involves comparing data from various sources across each theme, known as 'triangulation', to identify patterns, conflicting implications, and other characteristics of a phenomenon and its context (Chopard & Przybylski, n.d.). Causal interpretations are based on agreement among data and rationally rejecting alternative explanations (Chopard & Przybylski, n.d.). The frequency of recurring themes does not necessarily indicate the degree of impact (Adeoye-Olatunde & Olenik, 2021).

The study utilized data collection techniques and triangulation to reduce bias, but multiple data streams may not guarantee objectivity, as such participant validation confirmed the risk descriptions' consistency with their experience. The framework can be applied to various settings and socio-technical systems to explore risk problems. Although the findings' transferability is limited, participants' socioeconomic and cultural descriptions can be used to assess its appropriateness in other contexts (Birt et al., 2016; Hamilton, 2019; Motulsky, 2021).

Power mix risks were evaluated using energy security measures to support the thematic analysis. Four dimensions were analyzed: diversity, reliance, dependence, and renewability. These dimensions, presented in Table 2-3, were crucial in assessing Belize's power mix vulnerability and providing insights for hedging against observed or unforeseen risks.

Table 2-3 Description and definition of indices applied to assess Belize's power mix.

Indices ¹	Description	Definition
Diversity – 'Stirling's variety, disparity & balance concept'	- greater number of sources, greater variety leads to more contingency permutations, lowering risk (Jansen, Van Arkel, et al., 2004; Stirling, 1994, 2008)	- changes in energy source variety (e.g. fuel oils, natural gas, coal, nuclear, hydro, wind, solar, and biomass) from 2009 to 2022
	- the more distinct categories, the greater disparity, the greater the diversity (De Rosa et al., 2022)	- number of distinct categories of sources from 2009 to 2022
	- the more even the distribution of categories, the greater the balance, the stronger diversity (Stirling, 1994, 2008; Wu & Rai, 2017)	- annual share of each electricity source (kWh) from 2009 to 2022
Reliance – 'electricity import reliance (EIR)'	- the amount of electricity generated from imported sources (Molyneaux et al., 2012). The lower the reliance, the lower the technical & geopolitical risk (De Rosa et al., 2022; Jansen, Van Arkel, et al., 2004; Wu & Rai, 2017)	- % ratio of annual net imported electricity to total electricity from all sources from 2009 to 2022

¹ ; Calculations can be accessed in Appendix Table A-1 to A-3 'Study's Worksheet of Indices using gross electricity generation by power supplier from 2009 to 2022'

‘Dependence – ‘electricity share from fossils (EFF)’	- the lower the dependence, the lower the vulnerability to depleted fuels, the lower the geopolitical risk (De Rosa et al., 2022; Molyneaux et al., 2012)	- % ratio of annual net electricity generated using fossil fuels to total electricity from all sources from 2009 to 2022
Renewability – ‘share of electricity from renewable energy sources (ERES)’	- higher renewability, lower vulnerability to climate-related and geopolitical constrictions, the lower the risk (De Rosa et al., 2022; Paravantis et al., 2020)	- % ratio of annual net electricity generated using renewables to total electricity from all sources from 2009 to 2022

2.4 Results and Discussion

2.4.1 Mapping the Key Actors and Structure of the Power Supply System

This section conveys the findings of the extensive study of the participant groups and the structure of the power mix, based on the provision of the electricity resource and their trading mechanisms. Five actor groups were identified, namely, the Government of Belize's energy unit, the Public Utilities Commission, Belize Electricity Limited, domestic and non-domestic independent power producers, and civil society actors, and presented in Table 2-4 according to state/government, state-owned enterprise, private enterprise, and consumer.

Table 2-4 Findings based on value, responsibility, and resource of actors categorized by affiliations of government, state-owned, private, or customer

Affiliation	Actor	Values	Responsibilities	Resources
State/ Government	Energy Unit, Government of Belize	Electricity access	Policymaking	Decision-making authority
		Affordability	Funding including development loans and grants	Financial assets
	Public Utilities Commission of Belize (regulator)	Sustainability		
		Security		
		Electricity access	Tariffs & regulations	Rulings
		Affordability	Licensing	Regulations
		Efficiency	Adjudicator of sector actors	Licensing
		Service quality	Request for proposals (RFP) of suppliers	Service standards
State-owned enterprise (SOE)	Belize Electricity Limited (utility)	Safety	Transmission and distribution	T&D assets
		Reliability and service quality	(T&D) operation Central coordination and dispatch	Skills and technical capital
		Innovation		Data / information
Private enterprise	Domestic & non- domestic independent power producers (IPPs)	Recover cost of investment	Electricity generation	Financial capital
		Meet performance expectations	Manage localized performance and financial risks	Generation assets
Customer	Civil Society Actors	Affordability		
		Service quality	No formal role	Social capital

The study revealed that the electricity sector was structured using formal relationships, laws, and procedures for decision-making, strategy implementation, and resource allocation. Although participation in this study occurred at an individual level, perceptions of risk factors varied at the group level according to the interest, role, and understanding of the actors.

Mapping highlighted conflicting interests among actors. For example, state and government-owned actors showed both prioritizing economic and universal access to power, technological efficiency, and service quality. However, the state actor was inclined towards sustainability and energy security through initiatives like off-grid solar PV projects, while the government-owned actor focused on safety, dependability, and innovation, such as automated metering and electric vehicle charging infrastructure. The IPP actor group included the domestic and foreign (Mexico) electricity suppliers. These private enterprises aimed at recovering the costs of investment in generation assets from the sale of electricity. However, performance expectations were partially restricted by operating protocols implemented by the regulator or government actor.

This analysis noted that it may be difficult to see how actors who are state, government or state-owned can have conflicting interests that create risks, particularly in a small developing country with actor groups of limited sizes. Arguably, these actors stem from the same entity. Despite shared institutional affiliations, these actors differed in the type, magnitude, and deployment of resources, which shaped their power, interests, and influence on risk outcomes. As shown in Table 2-4, actors categorized by affiliation (government, state-owned, private, or customer) exhibited measurable differences in value, responsibility, and resources, providing a concrete basis for understanding how resource endowments define actor distinctions and their potential impact on system risks. The author found that clear distinction between these actor groups was primarily established through the distinguishing features of their resources. Resources showed as the defining variable of the actor's power and interest.

Similar to findings by (Bhatt & Singh, 2020a; S. Shadman, C. M. Chin, E. H. Yap, N. . Sakundarini, 2021), this Belize study found power hierarchies among actors and an indirect relationship between power and interest of actors. Unsurprisingly, this research showed civil society actors valued affordability and quality service but maintained no formal power in deciding and managing the power mix. However, outside the hierarchy, the civil society actor group was strongly influential over decisions of state and government-owned actors, especially in tariff reviews and opened consultations on power supply expansion projects. This research thereby defined their resource as social capital, referring to the networks of relationships, shared norms, and trust that enable collective action and cooperation among civil society actors in the governance of the power sector.

In contrast, operators like IPPS and utilities in the power hierarchy remained risk focused in alignment with responsibilities to maintain uninterrupted electricity supply, but these enterprises exhibited little involvement and influence over sector policies and regulations that guide risk mitigation. Figure 2-3 depicts a hybrid map of actor network based on levels of influence and interest found in the Belize power mix. This figure was constructed based on qualitative data collected through interviews and document review, where respondents provided insights on the levels of influence and interest of various actors in the Belize power mix. Actor significance was assessed using their resources, responsibilities, and decision-making authority, while interest was

inferred from the extent to which actors actively engage in or seek to shape power sector outcomes. The circle sizes and positioning were therefore grounded in qualitative evidence. The larger the circle, the more significant the actor, and interest grows from left to right.

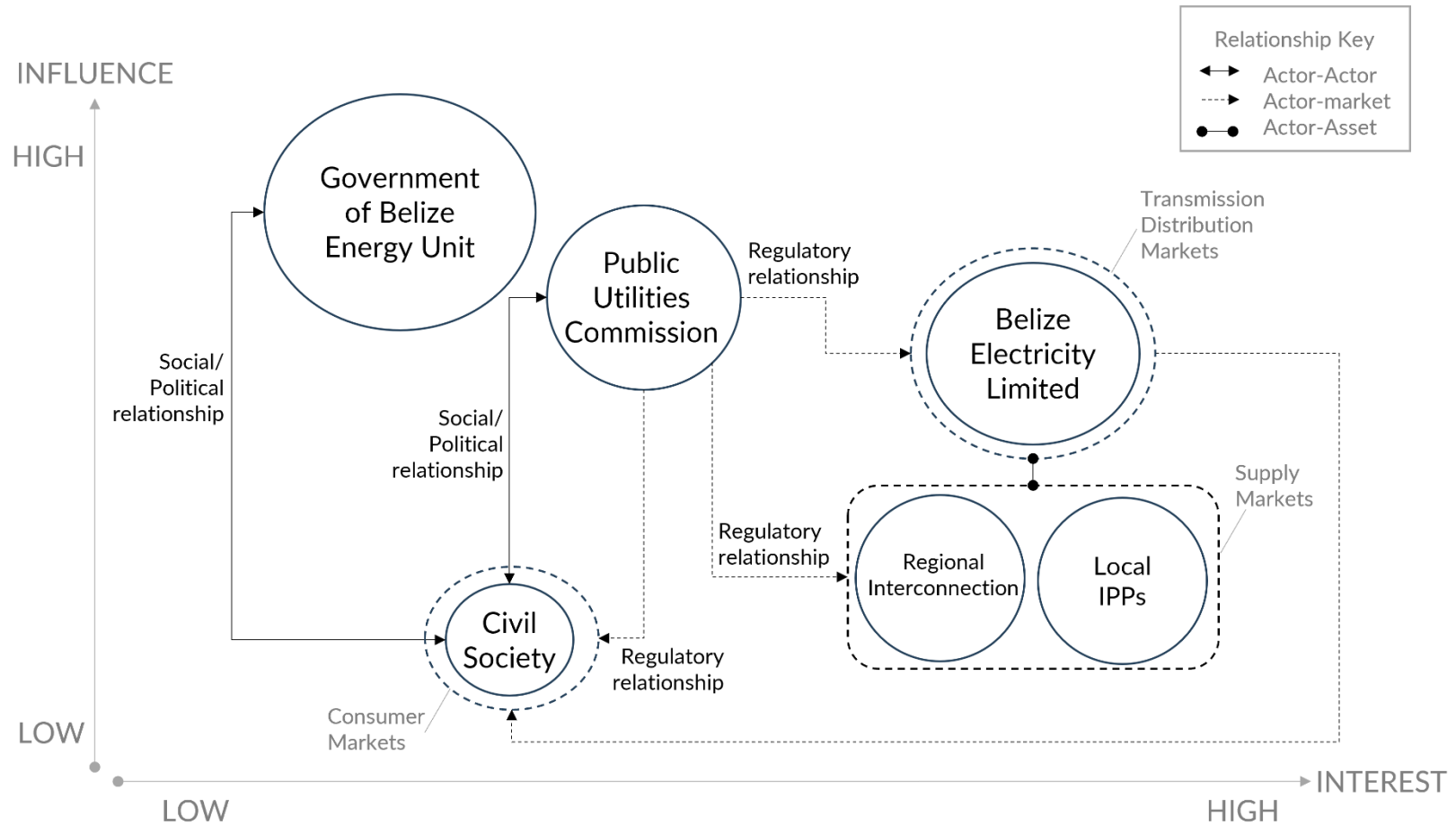


Figure 2-3 A hybrid map of actors in Belize's power supply structure depicting relationships, interests, and levels of influence (Usher & McLellan, 2024)

2.4.2 Framing of Themes in Main Risk Dimensions

Themes emerging from the data were framed in five dimensions of risks to which the sector was exposed: economic, social, technological, environmental, and legal/political. Calculated indices on diversity, reliance, dependence, and renewability are presented in the analysis of this section for which calculations can be accessed in Appendix Table A-1 to A-3.

Economic

For both the short and long term components of planning, the economic dimension highlighted concerns regarding the system's reliance on imported power and the susceptibility of Belize's strictly regulated local supply market to the liberal and dynamic Mexican market. The price of imported power was highly volatile. Prices in 2022 varied from \$0.0139 US/kWh to \$0.87 US/kWh. Nonetheless, while being the single greatest source of supply, electricity imports have a low yearly proportion of supply per cost when compared to indigenous suppliers. In 2021 and 2022, electricity imports accounted for 59% and 47.2% of total power costs, respectively, and averaged approximately 44% over the last 14 years, thereby, indicating that despite the price volatility, electricity imports remained a competitive and affordable source in the power mix. Importing power also pressured availability of foreign currency and incurred foreign exchange costs, as payment was made in US dollars, while still remaining competitive.

Secondly, exposure to hurricane and flooding has heightened concerns about the vulnerability of supply infrastructure. Over the last 12-year period, Belize witnessed 10 major hurricanes, which caused days of power disruptions and up to \$100 million in infrastructure damages, for example, in 2020, Hurricane Eta overwhelmed the hydro-electric reservoir spillway and ruptured transmission cables. Belize's economic risk is also exposed to Mexico disasters. Mexico experienced four major natural gas pipeline incidents in 2010, 2012, 2019, and 2021 that stimulated severe price shocks. Belize turned to indigenous renewables and local thermal sources until importation costs stabilized. Nevertheless, power imports accounted for more than half of overall electricity supply from 2019 to 2021.

Social

The informal influence of civil society actor group identified in this study and discussed under Section 2.4.1 was consistent with the Belize government's objective to lower power imports (Tillett, A; Locke, J; Mencias, 2011; UNFCCC, 2021). However, at the time of this study, Belize's daily capacity was unaffected, and the geopolitical relationship with Mexico remained stable.

Developing power supply technologies such as solar and wind requires substantial land area; however, the availability of suitable space is increasingly constrained by the expansion of hazard-prone zones. With social capital identified as a key resource for this actor group, the study detected potential spatial conflicts between actors advocating for renewable energy development and those supporting urbanization. Civil society actors—including communities, non-governmental organizations, and interest groups—have, in past instances, demonstrated the

capacity to engage collectively and constructively with policymakers to influence decision-making processes that steer the power sector's trajectory.

For example, Belize has witnessed large-scale public mobilization on power supply related issues, such as the Chalillo hydroelectric project lawsuit in the 1990s, and the 2018 offshore oil drilling ban in Belize. These conflict resolutions highlighted public interest and influence and solidified civil society as an actor group in Belize's power supply structure, despite not being empowered formally in the risk management hierarchy as discussed in Section 4.1. This Belize study finding contrasted with findings in other jurisdictions where minimal community involvement was reported (Bhatt & Singh, 2020a; S. Shadman, C. M. Chin, E. H. Yap, N. . Sakundarini, 2021). This Belize situation could be attributed to an unrelated interest of the public in maintaining biodiversity for tourism and agriculture.

Technological

The study identified challenges with the availability of indigenous resources used in Belize's power mix. Hydroelectricity and biomass co-generation contributed an average of 50% of total electricity supply across the 14-year research period. In years with regular weather, the renewable share approximated the long-term average but considerably exceeded it in years with above-average precipitation, such as 2010 (65%). However, during the dry season with protracted heat waves as reported from 2019 to 2021, the renewable share of total supply resulted in annual amounts of 25%, 46%, and 33%, respectively. Similar effects resulted for the largest biomass power plant, which accounted for 10% of total electricity supply. The said plant experienced a decrease in supply following the 2012 drought from 12.4% to 8.9%, then recovered slightly in 2014, and maintained a share of 3.4% during the 2019-2021 dry period.

In addition, Belize faced a shortage of essential ancillary supply functions, which are important for system stability and quality, reactive power management, second-order regulation, system backup, and storage (Castalia Limited, 2015; CCREE, 2022; Montouliu et al., 2019). Connection to a larger grid (Mexico) had reduced the need for domestic ancillary functions, but these shortages in ancillary services become vastly evident and threaten the stability and quality of electricity supply during events whereby the interconnection with Mexico is disrupted. Further, experts agreed that the effects of these shortages will grow as Belize integrates distributed energy resource (DER) technologies, such as electric vehicles (EVs) as per planned conversion across the transportation sector.

Environmental

Belize is a low-lying coastal nation. Rising sea levels and flooding posed threats to indigenous resources, especially hazardous zones, for supply infrastructure. For example, a 2017 feasibility study determined a number of terrestrial zones inappropriate for installation of commercial-scale solar PV due to vulnerability to floods. This finding is consistent with Rostam et al. (2020), which study suggested that site-appropriate areas for expanding domestic power supply sources have decreased in other countries and will continue to threaten prospective supply.

Local shifts in weather patterns exposed water and agricultural resources. This altered availability in indigenous electricity supply and created a quantity risk in the supply balance of

imports versus indigenous renewables. For example, during the 2019 to 2021 drought, imports accounted for 57%, 50%, and 58.9% of total electricity supply, respectively, as imports increased to compensate for shortages in indigenous supply. Such compensation fostered a more dominant position for imports in the power mix and occurred with less consideration for cost, although, as reported in Section 2.4.1, these state and government-owned actors prioritized economics under normal circumstances.

Legal/Political

Regulatory arrangements used PPAs and such agreements guaranteed sale and return on capital investments to attract investors in the developing country. Regulatory arrangements can stimulate de-risking of projects to enable low-cost financing (Tehero et al., 2020)(Tehero et al., 2020), but in the case of Belize, long term guarantee on sales and returns presented technical implications for expansion. This Belize case study found that regulatory arrangements can manage invested supply within a range of 51% (2011) and 64% (2022) demand peak per total installed capacity, while maintaining acceptable reserved capacity. According to Tehero et al. (2020), these arrangements can balance technological advancement and sociopolitical pressure, influencing operating costs and improving quality electricity service.

However, this Belize case study identified slow market growth in Belize and regulatory arrangements could limit capacity for investment until peak demand growth fosters opportunities for new entry. This risk carried an important practical challenge. Generally, power supply investment options exist in discrete quantities. It followed that a system, which is quite small with a slow-growing peak, is limited in the physical number of possible configurations as it relates to technological choices of supply. There was also an economic implication that any possible arrangement would be unable to attain the cost advantage that larger systems can obtain due to the scale of their operation versus that of a small developing country's system.

2.4.3 Characterizing identified Risk Dimensions and Linkages

Table 2-5 reflects the primary dimensions of the five risks identified in the study data. Descriptions of the dimensions are shown in Section 3.2.2.

Table 2-5 Risk dimension using categories of complexity, uncertainty and ambiguity, and identifies the causal relationships based on this study findings

Index	Description	Complexity	Uncertainty	Ambiguity	Causal Relationship (with)
E1	Exposure of domestic supply market to price volatility and foreign exchange risks of electricity imports market	x	x		T1 EN1
E2	Vulnerability of existing and prospective domestic supply infrastructure to climate-related impacts	x		x	T1 LP1 LP2
S1	Social pressures to reduce reliance on non-domestic supply based on risk to energy security			x	T2 LP1 LP2
S2	Competing interest of indigenous resources, such as land, amongst domestic supply expansion, ecosystems, urbanization, and industry	x	x	x	S3 EN2
S3	Public acceptance of domestic supply expansion initiatives	x		x	S2 EN2
T1	Volatility of hydro and biomass resource availability for power generation	x	x		E1 E2
T2	Lack of in-country ancillary power functions e.g. reactive power management & storage			x	S1 LP1 LP2
EN1	Indirect cost of emission from electricity imports	x	x		E1
EN2	Loss of site appropriateness for the expansion of domestic supply		x		S2 S3
LP1	Lack of market capacity for supply investment		x	x	S1 T2 E2 LP2
LP2	Lack of clear positions and guidelines for the retirement of existing supply contracts		x	x	S1 T2 E2 LP1

Risk dimension of the volatile market for electricity imports (E1) was complexity and uncertainty observed on the side of the Mexican retailer. Several participants hypothesized underlying reasons for the observed market behavior, with state-affiliated actors highlighted the availability of natural gas delivered to power plants in the Mexican region of the interconnection (Ministry of Energy & Public Utilities, 2020). Other issues included grid congestion, shifting demand, and global market trends. Because of the highly linked systems and non-domestic players, understanding the dynamics to quantify and validate the indirect cost of emission from electricity imports (EN1) was challenging. Still, it was observed that the level of exposure to these market conditions (from the perspective of the importer) was based on a causal relationship with the volatility of domestic hydro and biomass supply (T1).

The anticipated steps necessary to reduce the power mix's vulnerability to geophysical effects (E2) were complex and ambiguous, with limited technical data to address the underlying conditions created by the seasonal volatility of their power generation (T1). A recent study suggests that Belize's supply expansion will result in higher total costs, requiring a net present cost expenditure anywhere between US \$988 and US \$795 million over 20 years to limit the system's vulnerability to economic and climate shocks (CCREE, 2022). As for ambiguity, participants emphasized the need for a robust and adaptable future power mix, considering asset mitigation, such as presented by (Rostam et al., 2020).

However, they disagreed with the widely held notion ((Dadzie et al., 2018; Mirzania et al., 2019; S. Shadman, C. M. Chin, E. H. Yap, N. . Sakundarini, 2021; Trencher et al., 2020)) that renewables will significantly improve Belize's power mix security due to the current constraints of indigenous supply. Additionally, seeing as the primary cause was linked to the technical aspect of T1, the possibility of both economic (E2) and technical (T1) repercussions revealed uncertainty due to the lack of scientific knowledge on the climatic effects on the local supply, such as investigated by (Sridharan et al., 2019; Wieczorek-Kosmala, 2020).

Social pressure concerning the reliance on electricity imports (S1) was the only problem of the three risks under the social dimension addressed in policy, albeit with ambiguity. While the policy framework (Tillett, A; Locke, J; Mencias, 2011) called for less reliance on imports, real-world developments suggested otherwise. Subsequent to the policy, three technical reports (Castalia Limited, 2015; Ministry of Energy & Public Utilities, 2020; Montouliu et al., 2019) suggested a second interconnection with Mexico or the Central American regional transmission market, 'SIEPAC,' could be economically and technologically beneficial for local consumers' long-term affordability, where the technological benefit supports the lack of in-country ancillary supply functions (T2). From a technical perspective, on its own, T2 was a simple risk (IRGC, 2017a) because there was ample high-frequency data available on the grid's power quality, and little uncertainty as to the level of in-country installation that would be necessary to assume this ancillary role domestically. However, from an inherent perspective, the range of its possible outcomes was heavily tied to the ambiguity of Belize's continued interconnection with Mexico.

However, from a broader energy security perspective, Belize's continued dependence on imported electricity presents significant long-term vulnerabilities dependent on the energy trajectory of Mexico. For example, such reliance exposes the power system to external shocks, policy shifts, and price volatility in Mexico's electricity market — risks that could escalate under future carbon pricing schemes or supply constraints. Moreover, sustained reliance on imported fossil-fuel-based electricity is fundamentally inconsistent with Belize's national climate commitments and the broader global transition toward net-zero emissions. Mexico's generation portfolio contains a substantial proportion of liquefied natural gas (LNG)-fired generation (Sarmiento et. al., 2021), such that continued dependence on these imports is inherently misaligned with Belize's decarbonization objectives and long-term energy sustainability strategy.

From a techno-economic standpoint, while cross-border imports may appear cost-effective in the short run, the long-term risks undermine both economic sovereignty and energy resilience. Comparatively, several South East Asian economies have adopted energy strategies grounded in economic nationalism — prioritizing domestic generation capacity through solar PV, wind, and battery storage to strengthen national self-sufficiency (Andreev et. al., 2021; Do & Burke, 2023). A similar approach could guide Belize's long-term strategy, focusing on the gradual expansion of domestic renewable energy resources to reduce import dependence, enhance system resilience, and align with sustainable development goals.

Conflicts over resource consumption with other social sectors (S2), like urban planning and industrial development, as well as data informing public acceptance matters (S3) were minimal, and thus primarily based on isolated incidents with electricity supply projects in the past. As a result of their interdisciplinary nature, difficulty in scoping, quantifying, and the conflicting conditions that these risks created, S2 and S3 were complex, ambiguous, and logically heightened by the uncertainty of further loss of appropriate sites for the expansion of domestic supply (EN2) due to the hazards of flooding, natural disaster and other climate-related unknowns.

Belize's supply market is a high-risk investment environment (Tehero et al., 2020; Zhang et al., 2022) due to uncertainty and ambiguity in its limits on market capacity for investment (LP1) and lack of defined views and rules for the retirement of current supply contracts (LP2). Both risks are intertwined in the ambiguous posture of policy and regulation on disposing of existing supply assets. Moreover, their effects may have been perceived as a lack of commitment, increasing the dangers of investing in the domestic supply market (Tehero et al., 2020), contributing to the low level of domestic finance observed across the electricity supply projects - where only two of the eight projects in the power mix were locally financed.

The implications of this ambiguity and uncertainty extended socially, unto pressures to reduce reliance (S1), technologically, unto the persistent lack of in-country ancillary supply functions (T2), and economically, unto the vulnerability of existing and prospective domestic supply infrastructure to climate-related impacts (E2).

It is noteworthy that the influence of external actors—such as international aid agencies, donor governments, and regional trading partners as it relates to investment in Belize’s supply market—did not emerge from the stakeholder interviews. This absence may highlight a methodological limitation related to the institutional scope and representativeness of participants. Given the reliance of small developing countries on international financial institutions (IFIs) and development partners for energy infrastructure financing, institutional bias may also play a role, whereby government participants are reluctant to acknowledge the extent of foreign influence on national energy decisions.

As this research was grounded in an inductive, participant-driven design, the analysis was deliberately confined to themes that stakeholders themselves identified. However, the lack of discussion on external geopolitical and donor influences presents an analytical gap, as such actors likely exert substantial influence over Belize’s future energy diversification and import strategies. Future research should therefore expand the stakeholder scope to systematically examine the perspectives of international and bilateral agencies, as well as Mexico’s strategic role in regional electricity trade. Doing so could provide deeper insight into how external financing, geopolitical relations, and transboundary energy dependencies shape the resilience and autonomy of small developing countries’ power systems.

The figure below illustrates the interconnected nature of Belize’s electricity-sector risks across economic (E), social (S), technical (T), environmental (EN), and market/legislative (LP) domains. Each index in the diagram is linked exactly as defined in the analytical table, showing how vulnerabilities in one area propagate through the wider system.

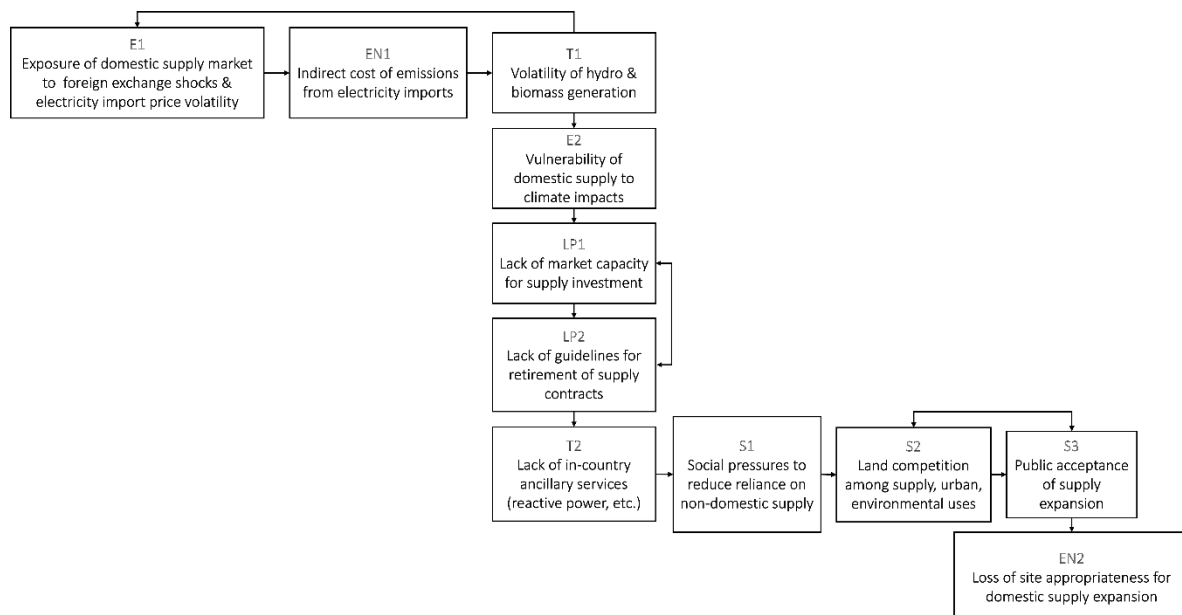


Figure 2-4 Causal Loop Diagram of Inherent Risk Factors Affecting Domestic Supply Expansion and Energy Security

On the economic side, exposure to import-driven price volatility (E1) influences both technical resource availability (T1) and environmental emissions costs (EN1). Similarly, the climate vulnerability of domestic infrastructure (E2) feeds directly into technical risks (T1) and the investment and contract-planning constraints represented by LP1 and LP2.

The social drivers—public acceptance (S3), resource competition (S2), and security-driven preferences for domestic supply (S1)—shape both environmental risks (EN2) and key system requirements such as ancillary services and investment planning (T2, LP1, LP2). Notably, S2 and S3 form a reinforcing loop that captures the dynamic between land-use pressures and social acceptance.

On the technical side, variability in hydro and biomass resources (T1) is influenced by external exposures (E1, E2), while limitations in in-country ancillary functions (T2) link back to social expectations (S1) and investment constraints (LP1, LP2).

Environmental risks (EN1, EN2) similarly integrate with technical and social drivers, completing the cross-sector feedback structure.

Finally, a bidirectional loop between LP1 and LP2 reflects the mutually reinforcing nature of investment capacity and contract-retirement clarity—two core structural conditions that shape long-term system planning.

2.5 Chapter Summary and Practical Implications

This study aimed to investigate the inherent risks of the structure and managerial practices of Belize's power mix using a qualitative three-step method based on a developed framework that integrated theoretical and conceptual notions on risk management, socio-technical systems, and energy security. In so doing, a system-wide scope was applied, examining regulatory framework, legislation, technology, and governance. It mapped the structure and actors of the electricity supply system, framed, detected, and screened risks to identify underlying causes and exposure pathways, categorized the risks into five main dimensions (economic, social, etc.), and characterized each dimension as complex, uncertain, or ambiguous. This case study found similarities of Belize power supply mix with literature available on other jurisdictions, but that peculiarities in Belize supply mix influenced conflicting and uncommon management decisions, though achieving immediate degrees of adequacy and service quality.

Examples of paradoxes included a fixed-cost model of domestic supply to stabilize cost, while using volatile resources. Likewise, reliance on electricity imports and retirement of local supply assets to boost opportunities but limiting domestic options in a small developing country with limited purchasing power. Also, regulatory arrangements to attract investments but de-risking of electricity supply projects to attract low-cost financing could instead deter new investment and technologies locally for prolonged periods.

This study conceived that values and roles influenced varying perceptions of risks among the actors, with an implication on how the risks are managed. For example, heavy reliance on regulation to mitigate risks being established by regulators in the ‘high-influence-low-interest’ actor group. Though much of the risks were due to uncertainty, for which theory prior promoted adaptive strategies against unknown outcomes to address uncertainties, while championed regulations to manage complexities. Based on said theory prior, ambiguity best aligned with mutual understanding, involving discourse and cooperation management style.

Influenced by theory, practical implications encourage broader mitigation scope beyond regulations to incorporate a sector mindset of adaptability in power supply management. Also, Belize could stimulate greater involvement of low-influence-high-interest actor groups to reduce ambiguity through co-creation of mitigation options. While Figure 2-3 was developed using qualitative data from interviews and document analysis, future research could complement this approach with a quantitative-based methodology. Such an approach would enable a more precise scaling of actor circles and spatial plotting of interest and influence, providing additional rigor and clarity to the visualization of actor networks in the Belize power sector.

While complexity and uncertainty have been widely explored in extant research, this Belize study highlighted ambiguity as a risk characteristic and proved the breadth of its impact through causal interpretations with other risk dimensions. This study evaluated Belize’s power supply mix and contextualized the analysis of data in Belize setting. Nevertheless, detailed descriptions, analogies with literature in other situations, and application of theories were made to facilitate transferability of the findings to power supply mix in other nations. Also, the study offers opportunity for further research on quantifying the risk dimensions, building mitigation models based on the risk characteristics, and evaluating effects on the system.

Chapter 3 Price Risk Exposure of Small Participants in Liberalized Multi-National Power Markets: The Belize–Mexico Interconnection

3.1 Introduction

Studies on energy security have emphasized implementation of strategies to achieve reliable and affordable quantities of energy supply under acceptable environmental consequences (De Rosa et al., 2022). Strategies seek to diversify and weatherize the power supply mix, the collection of sources used to generate electricity (Burke, 2010), including locally installed power plants and supply chains of fuel imports. Less discussion was noted in the literature on cross-border trade, a centrally dispatched international electricity transmission system that directs energy from various stations to supply specific loads from a common power pool (F. Chen et al., 2019; Do & Burke, 2023).

This gap in the literature is particularly significant considering the importance of such mechanisms for small developing countries. For these nations, energy security challenges are compounded by structural constraints such as limited market size and restricted economies of scale. As a result, non-traditional approaches—including regional integration and coordinated system operation—offer critical pathways for enhancing energy resilience and security in the context of small developing countries.

Oseni and Pollitt (Oseni & Pollitt, 2016) found national electricity markets in advanced countries had evolved from (and for the purpose of supply to) local markets. Countries were reluctant to trade electricity across borders, but with limited resources and rising demand, jurisdictions like Bangladesh and India (Haque et al., 2020), Nepal (Dhakal et al., 2021), Switzerland (Thaler & Hofmann, 2022), and regions across ASEAN (Do & Burke, 2023) and North America (Yuan et al., 2021) identified opportunities in cross-border trade as alternative sources of potentially cleaner and lower-priced electricity supply, alongside local generation.

For example, Mexico reported a power capacity of 87,130 MW (iea, 2024) and operated in the North American network with the United States and Canada, under the provision of the USMCA (United States–Mexico–Canada Trade Agreement) (Office of the United States Trade Representative, 2023; Sarmiento et al., 2021), and in Central America with interconnectivity to Belize.

Small developing countries face additional challenges, which threaten affordable self-sufficiency, given the scale of their power systems. The smaller nations are limited in their range of technological choices and opportunities for energy resource exploration. For

example, Belize, with approximately 172 MW installed power capacity (Belize Electricity Limited, 2022), has been supplementing its domestic power supply with electricity imports from Mexico since the early 1990s, via a physical interconnection as presented in Figure 3-1.



Figure 3-1 Regional map of northern Central America, including Mexico, adapted from Guderjan et al. [14], whereby the authors highlighted the 115 kV transmission line that interconnects the power grids of both countries

For Belize, like other small developing countries, cross-border electricity trade indirectly safeguarded the economy from external price shocks (unexpected shifts) on rising global energy commodity prices (IEA, 2023a) but also exposed the local power market to price risks associated with procuring power from a foreign market. Belize's local suppliers sold power on annualized fixed-cost pricing (Tillett, A; Locke, J; Mencias, 2011), but since Mexico liberalized its sector in 2013, electricity was sold under variable market-based pricing (De la Torre et al., 2024; Percino-Picazo et al., 2021). Belize imports averaged approximately 40% of the annual power supply, indicating significant price risks that could influence local supply investments and operational savings and spending due to deflationary and inflationary price volatility.

This Belize study expanded empirical research findings in the field of electricity contract pricing, including electricity forward and spot pricing, and market volatility (Algieri et al., 2021; Wei & Lunde, 2022). This research also provided insights into the effects of cross-border electricity trade on small developing countries.

3.1.1 Empirical Analysis of Electricity Forward and Spot Pricing

The efficient market hypothesis (Fama, 1970) in financial economics suggests that the commodity price incorporates all available market information and fosters trading at fair value in the absence of market inefficiency. However, empirical studies have identified information asymmetry in electricity prices (Longstaff & Wang, 2004), making some power markets less efficient. Consequently, it is important for small developing countries like Belize, who would be more exposed to asymmetric information, to understand the inefficiencies often embedded in pre-determined forward and spot pricing. Figure 3-2 presents a relationship of spot and forward pricing, highlighting how differences in expected pricing factors influence the level of basis risk.

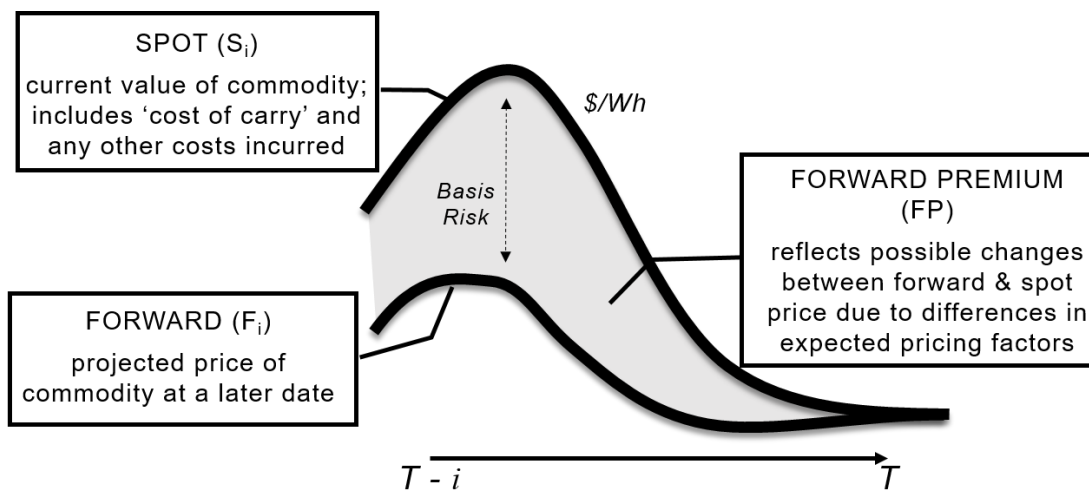


Figure 3-2 Time-dependent relationship between forward and spot pricing strategies and their influence on basis risk. Property of the authors

Electricity is not directly storable (as electricity itself), so consumption and generation occur simultaneously (Koten, 2020). Therefore, differences between forward and spot prices are strongly influenced by factors such as disruptions, congestion, demand surges, supply deficits, and with recent RE integration, intermittent supply. Such characteristics result in the price of electricity exhibiting higher volatility and jumps than prices of conventional commodities (Ramírez-García et al., 2022).

Forward purchases allow buyers to mitigate adverse impacts of potential price increases. Forward premiums are the difference between spot and forward prices (Algieri et al., 2021). However, the effectiveness of this strategy for Belize depends on the country's ability to anticipate precisely the amount of power required—because any excess is subject to real-time spot pricing, and shortfalls trigger penalties. Avoiding regular spot purchases is extremely challenging because of the number of factors stated earlier, which can result in differences between predetermined and real-time power supply and demand levels.

Consequently, Belize's deficit purchases also exhibit volatile tendencies and spikes over time. Similarly, forward contracts do not fully insulate Belize from risks associated with volatility and surges, which are inherent in forward pricing over time.

The discussed literature findings motivated this Belize study aiming to develop a methodological approach using time-series analyses. The current study investigated volatility and surges specific to electricity forward and spot pricing and assessed the effects on premiums favorable to Belize.

Extant research has previously examined pricing time series of various markets in Mexico, where the National Electric System (SEN) comprises four subsystems. The largest subsystem, the National Interconnected System (SIN), covers 94% of federal entities. Seven control regions integrate SIN, with 101 load zones and 2356 nodes for electricity distribution (Cruz May et al., 2022), of which Belize's power system interconnects at SIN's 'Xul-Ha' node (Tillett, A; Locke, J; Mencias, 2011).

Rodriguez-Aguilar et al. (2019) and De la Torre et al. (2024) concentrated on developing modeling tools, including alpha-stable regressions and deep-learning models to generate price forecasts for Mexico's wholesale power market. With a similar objective, Livas-García et al. (2022) and Ramírez-García et al. (2022) looked at the southeastern region of SIN and subsystems of SEN, respectively, but applied artificial intelligence (AI) approaches to generate price forecasts. The objectives of these four past studies focused on obtaining highly accurate short-term predictions; however, this Belize study investigated the properties of the pricing series to gain insight into the long-term behavior of the power market.

Quantitative analysis in this current study included two power systems, Belize and Mexico. However, using the Mexico system only, Rodriguez-Aguilar (2019) identified qualitatively that congestion and loss were two components that determined the locational marginal price (LMP) of a SIN power node. Each component was based on the effect of increasing or reducing consumption on transmission line loadings, and the incidental line losses that accompanied the change. On the other hand, in this Belize study, patterns of consumption depended on electricity Belize imported, while the time-series analyses considered how technical conditions of the Xul-Ha Mexican node were influenced by Belize's consumption and any statistically significant effect on the node's LMPs.

3.1.2 Study Aim and Structure

The aim of this paper was to examine the dynamic exposure of Belize's power system to the price risks associated with cross-border electricity trade. This study hypothesized that price risk exposure will be largely dependent on the pricing properties and system conditions of the supplier's (Mexico) side with negligible influence from the buyer's (Belize) side because of the huge difference in country size.

This current research demonstrated the following relationships in the Xul-Ha node's local marginal price: (i) an overall positive correlation with volatile tendencies of forward and spot pricing, (ii) the presence of premiums (if any) having a positive correlation with the volatile tendencies, and (iii) the presence of premiums (if any) having a weak correlation with the loading and transmission loss patterns of the buyer's (Belize) electricity import consumption.

Focusing on nodal data, analysis occurred for the trading node of the buyer, relying on information made public or accessible to foreign power purchasers. With derivative contracts increasing in popularity as financial risk management tools for electricity suppliers and as a potential discount medium for purchasers, this study incorporated forward premium, which received less attention in previous studies on Mexico's power system.

Furthermore, the analysis employed hourly measurements to improve the understanding of how pricing and nodal conditions varied during the day. Evaluating system conditions in the two nations simplified the assessment of the implications for Belize and Mexico's intra-day trends on an hourly basis.

The remainder of this paper is divided into three sections, namely the research methodology in Section 2, findings and analyses in Section 3, and Section 4 consists of the study conclusion, limitations, and practical implications.

3.2 Methodology

3.2.1 Study Design

The research design was composed of four stages, depicted in Figures 3-3 to 3-6. Data were collected and summarized in Stage 1, using descriptive statistics that highlighted variability and distribution frequency in hourly electricity price per day, as shown in Figure 3-3.

STAGE 1 DATA PROCESSING & STATISTICAL SUMMARIES

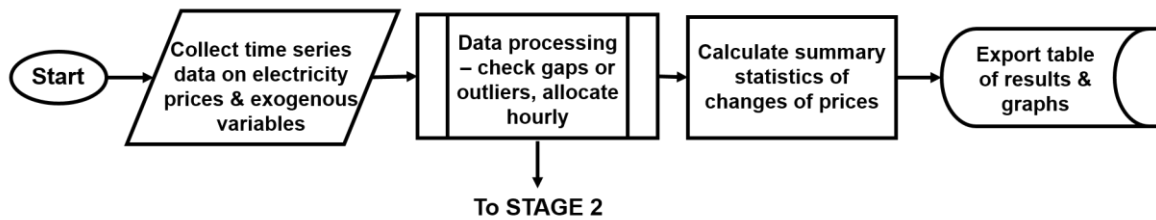


Figure 3-3 Stage 1 of the methodological approach consisting of data pre-processing and calculating summary statistics of hourly allocated forward and spot pricing

While descriptive statistics provided a useful summary of basic price patterns, they were insufficient to capture the dynamic behavior and interdependence of risk factors over time. Therefore, modeling techniques such as ARMA–ARCH and copula methods were applied to analyze temporal dependencies and joint distributions among variables.

Model estimations (Stage 2), depicted in Figure 3-4, were used to draw generalized data-driven conclusions on each market’s characteristics and to develop a model for predicting electricity prices. This study applied a series of ARMA (Box, G. E., Jenkins, G. M., Reinsel, G. C., & Ljung, 2015) for each hour of the day to construct an acceptable mean model of the historical price data, based on fundamental factors of electricity, with separate models for the forward and spot prices.

STAGE 2 MODEL ESTIMATION OF MEAN EQUATION (ARMA-X)

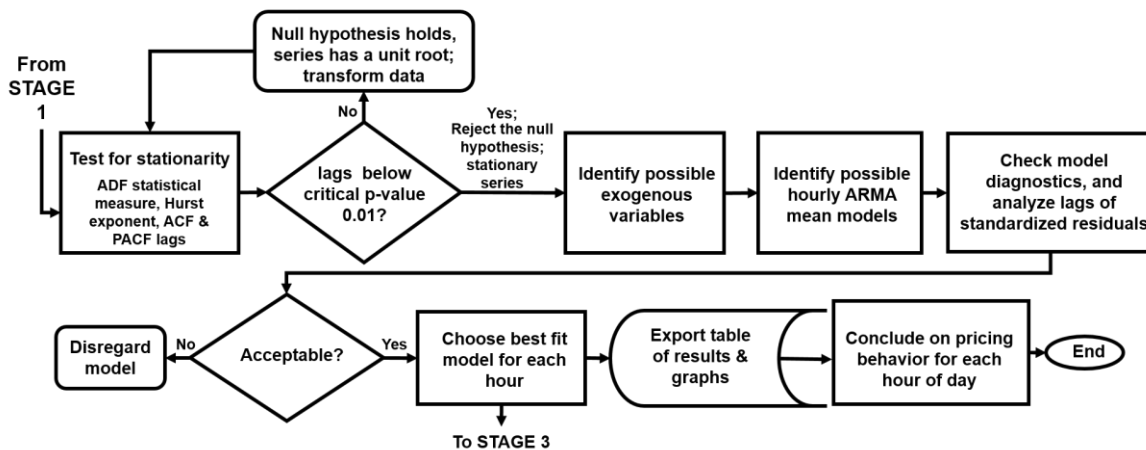


Figure 3-4 Stage 2 of the methodological approach consisting of the development of ARMA-X models for changes in forward and spot pricing to construct mean models.

Price risks specific to the simulated ARMA-X electricity forward and spot pricing time series were captured in Stage 3 by modeling the conditional volatilities of the standardized residuals of each time series using ARCH (autoregressive conditional heteroscedastic) simulations (Bollerslev, 1986), as depicted in Figure 3-5. A similar pairing of techniques was applied to analyze electricity price data in past work, including (Ahmad et al., 2023; Ioannidis et al., 2021; Janczura & Puć, 2023; Viehmann, 2011; D. Wang et al., 2022), and is detailed in Section 3.3.

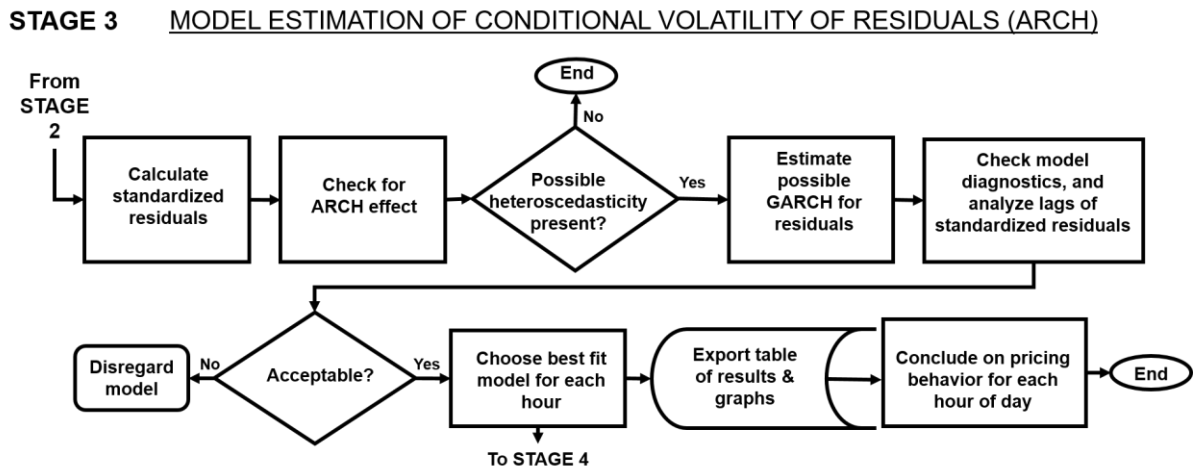


Figure 3-5 Stage 3 of the methodological approach consisting of the development of ARCH models for the standardized residuals of ARMA-X models to construct conditional volatility

Investigating the relationship between the forward premium and price risk factors associated with the Xul-Ha node using a series of hourly VAR (vector autoregression) models occurred in Stage 4 and is depicted in Figure 3-6. Assessment was performed on four risk factors, including the volatile tendencies and spikes specific to the forward and spot pricing, and variables reflecting potential effects on the nodal condition due to the buyer's consumption activity.

STAGE 4 REGRESSION OF FORWARD PREMIUMS (FP) & CONDITIONAL VOLATILITY (VAR)

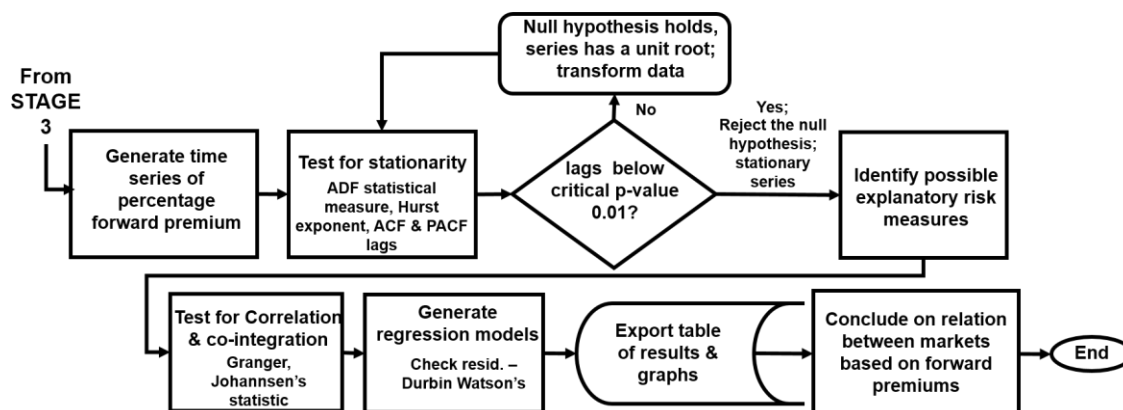


Figure 3-6 Stage 4 of the methodological approach consisting of the development of VAR models.

3.2.2 The Data

The primary study data were hourly day-ahead forward and spot prices for electricity at the Xul-Ha node from 1 January 2018 to 31 December 2022. It is important to note that the Belize–Mexico electricity market does not currently trade futures beyond the day-ahead forward market. As such, all price data and analyses in this study are based exclusively on day-ahead forward contracts. The dataset comprises the price for the day-ahead forward market where power delivery is made at the relevant hour the next day for each of the 43,824 intervals in the sample period. In each hourly period, the dataset included a spot price, allowing for real-time purchase. Also, the hourly electricity imported by Belize and Belize’s total electricity supplied to the grid were collected for the same study period. The price and power data were shared by Belize Electricity Limited (the buyer) after receiving a comprehensive description of the quantitative assessment for this research (data not publicly available).

Secondary research data were collected on daily weather conditions, natural gas price index, and electricity usage. Extant studies, such as (Rodriguez-Aguilar et al., 2019), determined significant fluctuations in prices due to factors like seasonal demand, fuel availability, network congestion, and natural hazards. Similarly, another study (Cruz May et al., 2022) in Yucatan federal entity identified electricity generation (17.06%), fossil fuel costs (12.54% and 8.63%), load zone (11.17%), and day of the year (8.51%) as factors that affected locational marginal prices. It should be noted that natural gas is a key fuel source for power generation in Mexico, whereas Belize does not utilize natural gas in its domestic generation mix. This distinction is relevant to understanding cross-border price dynamics and exposure behavior.

This Belize study retrieved daily average temperature data from the National Centers for Environmental Information (National Centers for Environmental Information, 2024) open-source portal for historical weather information from the Felipe Carrillo Puerto weather station and the Henry Hub Natural Gas Spot Index from the U.S. Energy Information Administration data portal (eia, 2024). Background information, which served advisory purposes, on Mexico's network structure was obtained from CENACE's (the seller) market information system (SIM) public information on the wholesale electricity markets (CENACE, 2024).

The collected data were analyzed for gaps and irregularities. The primary data, power pricing time series obtained directly from Belize's electric utility, were deemed to be of good quality, with no gaps or abnormalities. A few gaps were discovered in the secondary data, specifically the web-based meteorological and natural gas index time series. Previous-day values were substituted into missing data fields to address the gaps.

3.2.3 Data Analysis

Data analyses for each stage of the methodological approach are undertaken as follows:

Stage 1:

This study generated the commonly applied measures, including mean, minimum, maximum, skew, and standard deviation. Rodriguez-Aguilar et al. (Rodriguez-Aguilar et al., 2019) provided similar summary statistics for the wider SIN wholesale electricity market's average LMP based on observations from January 2016 to 2017. Though the study period preceded this Belize study and was generated for the wholesale market, findings of both studies are comparable.

Stage 2:

The modeling estimations used daily changes in forward and spot price data, with an hour as the fundamental unit of analysis. This allowed for dampening extremities while maintaining data integrity. An ARMA model (Box, G. E., Jenkins, G. M., Reinsel, G. C., & Ljung, 2015) was used to fit an acceptable mean model that predicted average outcome value based on predictor variables, as defined in Equation (1).

$$X_t = \varepsilon_t + \sum_{i=1}^p \varphi_i X_{t-i} + \sum_{i=1}^q \theta_i \varepsilon_{t-i} \quad (1)$$

where p is the autoregressive component, q is the moving average component, X_t and X_{t-i} are the values in the current period and previous i period, ε_t is the baseline constant, φ_i is the coefficient of the autoregressive (AR) component, θ_i is the coefficient of the moving average (MA) component, and ε_{t-i} is the error terms for the current period.

The data were divided into training and validation parts, 80% training and 20% validation. The data were split by time, using the first 80% of the observations to estimate the model and the last 20% to test it. This approach kept the natural time order of the data. Before developing the model, changes in electricity prices were examined for stationarity using the Augmented Dickey–Fuller (ADF) test (Perktold et al., 2024) to determine if there was a unit root, based on likelihood ratio statistics to reject the null hypothesis of non-stationarity in time series (Dickey & Fuller, 1981).

This study used autocorrelation and partial-autocorrelation functions (ACF and PACF) to assess the influence of lagged endogenous variables in the time series, using a correlogram to examine the ACF’s response to immediate impacts (the AR component) and PACF’s response to secondary impact (the MA component). This procedure was used to identify the appropriate AR (p) and MA (q) orders for the ARMA model, ensuring that the lag structure accurately captured both immediate and delayed dependencies in the electricity price series. The analysis incorporated exogenous factors of natural gas price index and average daily temperature (For the hourly analysis, the daily average temperature was applied to each hour of the corresponding day, reflecting a limitation in the dataset, as daily observations represented the finest temporal resolution available), along with dummy variables for the month, day of the week, weekday, and weekend, as defined by the ARMA-X (with exogenous variable, X) (Box, G. E., Jenkins, G. M., Reinsel, G. C., & Ljung, 2015) function in Equation (2).

$$X_t = \varepsilon_t + \sum_{i=1}^p \varphi_i X_{t-i} + \sum_{i=1}^q \theta_i \varepsilon_{t-i} + \sum_{i=1}^b \eta_i d_{t-i} \quad (2)$$

where η_i is the coefficient of the exogenous input d_{t-i} .

The time-series models, with and without exogenous factors, were optimized using the Auto Arima Python module (Smith, 2023), with values of p and q ranging from 1 to 10, based on minimization of the Akaike information criterion (AIC) using the Box–Jenkins approach (Box, G. E., Jenkins, G. M., Reinsel, G. C., & Ljung, 2015). The AR and MA components were deemed statistically significant with coefficients of p -values less than 0.05 and robust with total coefficients of less than one. The residuals’ ACF and PACF, and square of the residuals of the ARMA model residuals, were examined to confirm no autocorrelations, thereby suggesting the presence of the ARCH effect, deeming the mean model acceptable. In addition to the correlogram, the ARCH Lagrange Multiplier (LM) test (Breusch & Pagan, 1980) was applied to determine the presence of the heteroscedastic effect (Bollerslev, 1986) of the residuals. The model estimation results were compared with real testing data using overall fit based on the lowest AIC.

Stage 3:

The ARMA estimates took into consideration autocorrelated aspects of power price, resulting in residuals associated with volatility. The volatility of these residuals was

predicted using ARCH models, basic GARCH, and GJR-GARCH to account for possible asymmetry and leveraging, as specified in Equation (3).

$$\begin{aligned} \text{GARCH: } \sigma_t^2 &= \omega + \sum_{i=1}^p \alpha_i \epsilon_{t-i}^2 + \sum_{i=1}^q \beta_i \sigma_{t-i}^2 \\ \text{GJR-GARCH: } \sigma_t^2 &= \omega + \sum_{i=1}^p (\alpha_i + \gamma_i \mathbb{I}_{t-i}) \epsilon_{t-i}^2 + \sum_{i=1}^q \beta_i \sigma_{t-i}^2 \end{aligned} \quad (3)$$

where p is the order of GARCH term ϵ_{t-i}^2 ; q is the order of ARCH term σ_{t-i}^2 ; σ is unconditional variance; σ_t^2 and σ_{t-i}^2 are current and previous conditional variances, respectively; ϵ_{t-i}^2 is the squared residual of the previous variance; α_i is the coefficient for the previous squared residual; β_i is the coefficient for the previous conditional variance; γ_i is the leverage parameter; and $\mathbb{I}_{t-i}$ is a dummy variable with the following stationary constraint:

$$\mathbb{I}_{t-i} = 0 \text{ if } \epsilon_{t-i} \geq 0, \text{ and } \mathbb{I}_{t-i} = 1 \text{ if } \epsilon_{t-i} < 0$$

Overall, four modeling combinations were used to determine volatility (GARCH and GJR-GARCH) and residual distribution (normal and skewed Student's t , SST (Nugroho et al., 2021)). Model adequacy, overall fit, and accuracy were evaluated using information criteria (AIC), out-of-sample testing, and estimating the average and squared error, respectively. p -values were used to determine the importance of each model parameter. The coefficients of GARCH models were deemed statistically significant if they had p -values less than 0.05 and robust based on reviewing the ACF and PACF of their associated standardized residuals, which suggested that GARCH (1, 1) and GJR-GARCH (1, 1, 1) class models, where the order of p and q is 1, adequately captured the volatility in each hour.

Stage 4:

The final stage examined the relationship between electricity forward and spot prices, focusing on hourly time-varying forward premiums' economic features and risk factors, estimating VARs using percentage forward premiums (FP_{it}) as defined by Equation 4, where $F_{i,t-1}$ reflects the day-ahead forward price, and S_{it} reflects the day-of spot price for a daily interval, i , of a particular hour of day series.

$$FP_{it} = \frac{S_{it} - F_{i,t-1}}{F_{i,t-1}} \quad (4)$$

The fundamental VAR assumption is that each variable, y , influences others within the hourly interval consisting of k time series, with the lagged values of all k time series serving as regressors (Hacker & Hatemi-J, 2008). As such, the VAR is defined in matrix form with a collection of endogenous variables, k , with p lags as follows:

$$\begin{bmatrix} y_{1,t} \\ y_{2,t} \\ \vdots \\ y_{k,t} \end{bmatrix} = \begin{bmatrix} c_1 \\ c_2 \\ \vdots \\ c_k \end{bmatrix} + \begin{bmatrix} \phi_{11}^1 & \phi_{12}^1 & \dots & \phi_{1k}^1 \\ \phi_{21}^1 & \phi_{22}^1 & \dots & \phi_{2k}^1 \\ \vdots & \vdots & \ddots & \vdots \\ \phi_{k1}^1 & \phi_{k2}^1 & \dots & \phi_{kk}^1 \end{bmatrix} \begin{bmatrix} y_{1,t-1} \\ y_{2,t-1} \\ \vdots \\ y_{k,t-1} \end{bmatrix} + \dots + \begin{bmatrix} \phi_{11}^p & \phi_{12}^p & \dots & \phi_{1k}^p \\ \phi_{21}^p & \phi_{22}^p & \dots & \phi_{2k}^p \\ \vdots & \vdots & \ddots & \vdots \\ \phi_{k1}^p & \phi_{k2}^p & \dots & \phi_{kk}^p \end{bmatrix} \begin{bmatrix} y_{1,t-p} \\ y_{2,t-p} \\ \vdots \\ y_{k,t-p} \end{bmatrix} + \begin{bmatrix} e_1 \\ e_2 \\ \vdots \\ e_k \end{bmatrix} \quad (5)$$

where vector y_t is the endogenous time series variables, c is the k -vector of constants, Φ is the time-invariant ($k \times k$) matrix, and e is the k -vector of error terms.

The optimal lag, p , was determined by fitting increasing orders from 1 to 7, minimizing AIC, BIC, FPE (final prediction error), and HQIC (Hannan–Quinn information criterion) (Hacker & Hatemi-J, 2008). In this stage, multiple information criteria were used due to the complexity of the multivariate VAR, reducing the likelihood of overfitting. The highest-performing lags were ranked and selected based on each criterion's scoring. Appendix Figure A-4 presents the excerpt script and sample of results for the process for data of the 23rd hour. The VAR of the optimal order was fitted using Python's StatsModels library, `tsa` (time-series analysis) module VAR (statsmodels 0.14.1, 2024). The Durbin–Watson statistic (DURBIN & WATSON, 1950) was calculated to detect residual patterns. These values ranged from 0 to 4, whereby a value close to 2 indicated no significant correlation, while values closer to 0 or 4 indicated positive or negative correlation, suggesting the need for model enhancements by altering the model's order or predictor set, k .

The time series were tested for stationarity using the ADF test. The presence of causality and cointegration were assessed using Granger's causality test (Granger, 1969) and Johansen's statistic (Johansen, 1991). Granger's causality test was used to examine the link between time series, with a p -value less than 0.05 indicating that a plausible correlation is present. Johansen's test for cointegration was used to identify if the link between time series was statistically significant, determining if a linear combination of the series indicated a long-term significant link based on a 95% confidence interval.

In total, the study evaluated four risk variables. Following previous studies that performed similar empirical analyses on electricity prices, including (Algieri et al., 2021; Valitov, 2019; Wei & Lunde, 2022) and past findings on Mexico's SIN, this study determined that the pricing volatilities appropriately reflected real-time corrections of congestion, operating reserves, and transmission losses (Rodriguez-Aguilar et al., 2019) by the supplier. Consequently, the time series of the simulated GARCH volatilities of the standardized residuals of spot and forward price changes, σ^2_S and σ^2_F , respectively, were chosen as the first two components to reflect the uncertainties associated with the supplier's operations and system conditions at the Xul-Ha node.

Like any consumer, Belize's consumption patterns affect the power flows and physical constraints at the delivery point interface. Further, the study considered that increasing and decreasing the output of local generation affects Belize's transmission line loadings, incidentally varying the transmission line losses.

Therefore, to determine the statistical significance of the buyer's (Belize) relationship with the percentage forward premium, the analysis relied on two variables, namely (i) the hourly consumption of electricity imports, normalized between 0 and 1, delineated as *IP*, and (ii) the percentage difference between the normalized electricity imports and Belize's total electricity supplied to the grid, *D*. Both indicators were adopted to represent complementary dimensions of Belize's interaction with the regional grid.

While *IP* captures the magnitude of Belize's import demand at the interconnection node, *D* reflects the relative balance between imports and domestic generation, which can influence internal transmission loadings and losses. Including both variables provides a more complete view of how system conditions at the delivery interface may shape congestion and pricing behavior. The fundamental pricing elements of SIN's LMPs suggest that both activities can affect congestion and incidental transmission loss components (Rodriguez-Aguilar et al., 2019) at the Xul-Ha node, potentially impacting pricing. These variables represent variability in system conditions at the delivery node, which is fully concerned with the buyer's activities.

3.3 Results and Discussion

3.3.1 Data Analysis of Forward and Spot Market Conditions

The time series plots for electricity imports forward and spot prices, allocated by hour of day, are presented in Figure 3-7. The figure presents the visualization of the primary dataset used in this phase of the analysis, illustrating the hourly time series of electricity forward and spot prices. This figure provides an overview of the data patterns that underpin the subsequent modeling, including the identification of alternating periods of volatility central to the study's focus. The data depicted alternating periods of volatility and calm, exhibiting a heteroskedastic effect, with rises in volatility particularly in late 2018, which coincided with the most recent reform revision restructuring of Mexico's electricity sector (Percino-Picazo et al., 2021).

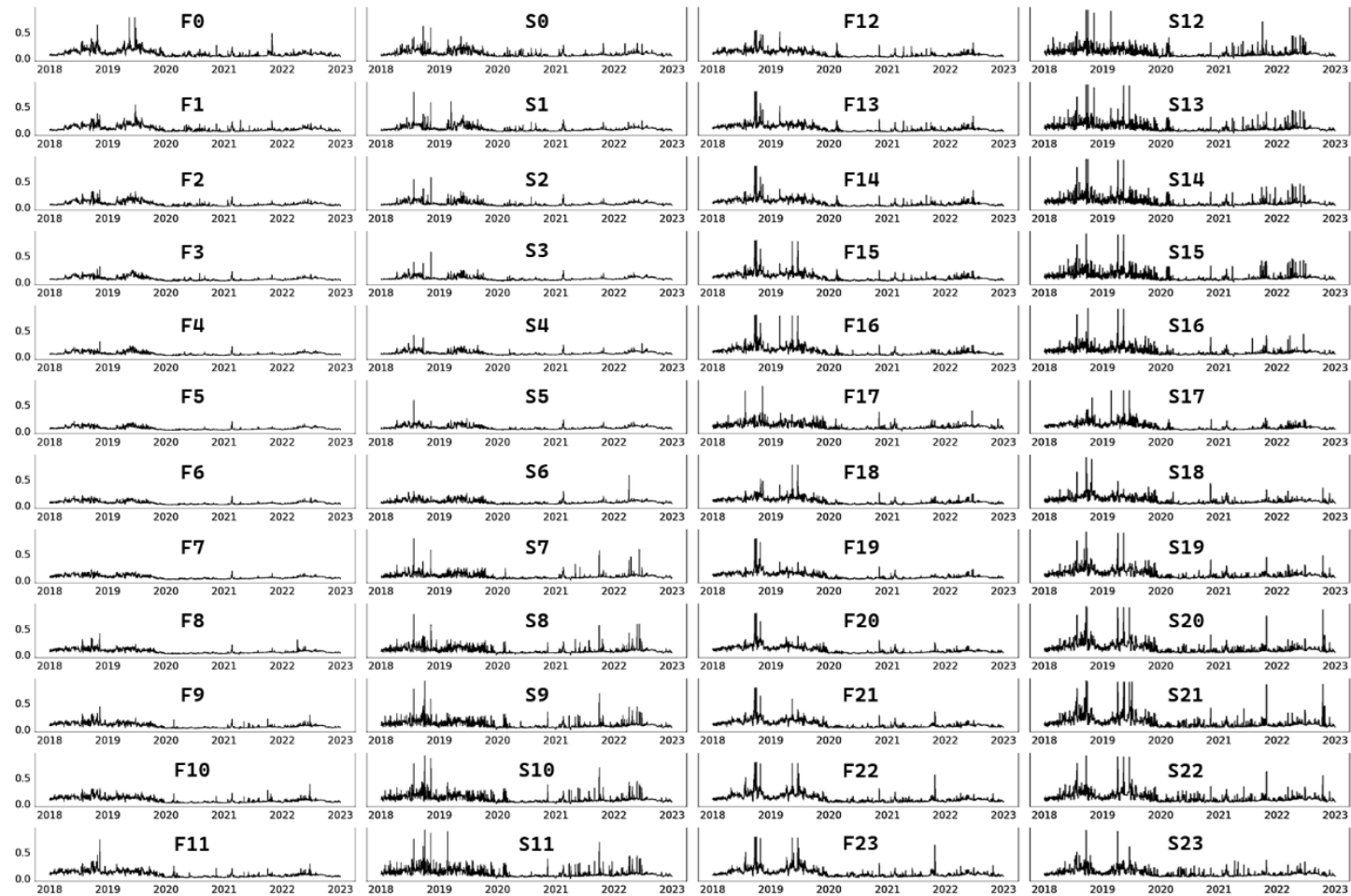


Figure 3-7 Time series of day-ahead electricity forward prices ('F') and day-of electricity spot prices ('S') received by the buyer (Belize) from the Mexican export market at interconnection node, Xul-Ha, allocated by hour of day ('0' to '23') for 2018 to 2022. Prices are expressed in US dollars per kilowatt hour

Appendix Table A-4 reports the summary statistics for the electricity imports forward and spot prices. All prices are quoted in US dollars per kilowatt hour (USD/kWh). As shown, the average forward price fluctuated throughout the day, ranging from 0.057 USD/kWh in the 4th hour to 0.111 USD/kWh in the 21st hour. Overall, the lowest prices were observed in the early-morning hours, with average prices falling below the overall average of 0.083 USD/kWh from 0 to 9 h, gradually increasing throughout the remaining hours from the 10th to the 22nd hour and then decreasing during the final hour of the day.

Forward prices all returned positive skewness, indicating asymmetric tailing extending to more positive values for each hour's distributions, with the most significant right-skewed tailing occurring during the afternoon-to-night-time hours, showing a high of 4.107 during the 18th hour. This finding was consistent with the right skewness reported in past studies of dynamic electricity pricing.

Based on standard deviations, forward prices, like other markets, displayed high intra-day variance. When the relative hourly ratios between the standard deviation and the mean value were compared, the highest variations occurred in the early afternoon from roughly the 12th to 15th hour and at night from the 20th to 22nd hour. For example, during the 15th hour, the standard deviation increased to almost 86% of its corresponding hourly mean value (0.096 USD/kWh) and was equal to the total mean for all hours of the forward prices (0.083 USD/kWh). The standard deviation exceeded this overall mean in the 20th and 21st hours. These results suggested that forward prices are particularly volatile during these hours.

Overall, forward price movements suggested an early-afternoon and night-time peak, consistent with extant findings (Cruz May et al., 2022) that linked the region's climatic and geographical characteristics, as high temperatures prevail in the early afternoon, and demand for power increases once more during the last hours of the day for public, commercial, and residential lighting and air conditioning.

On an hourly basis, spot prices averaged around 0.015 USD/kWh higher than forward prices, resulting in a minimum of 0.07 USD/kWh in the 3rd and 4th hours, a maximum of 0.132 USD/kWh in the 21st hour, and an overall average of 0.098 USD/kWh. Overall, the average spot prices followed a similar hourly profile to average forward prices. Similarly to previously analyzed markets (Algieri et al., 2021; Viehmann, 2011), spot prices showed higher overall right skewness than future prices; however, the maximum observed skewness of 4.088 in the 16th hour was less than the highest skew observed in forward prices.

The pattern of the magnitude of skewness also varied, occasionally appearing high in non-consecutive hours such as the 1st, 7th, and 13th hours, as opposed to future pricing, which showed larger skewness throughout successive afternoon and night-time hours. These findings demonstrated that contrary to the typical expectation, maximum forward prices may not be lower than maximum spot prices, particularly during odd hours such as the

14th, 15th, and 18th, with substantially right-skewed forward price distributions. This finding was not surprising as previous authors, including Ramírez-García et al. (Ramírez-García et al., 2022), emphasized that preconceptions on spot-to-forward relationships should be avoided by market participants, as electricity cannot be stored, and there is no specific formula for estimating the cost-of-carry difference between markets.

In contrast, the standard deviations of spot prices were uniformly greater than the equivalent standard deviations for forward prices, suggesting that spot prices are more volatile than forward prices and supporting the finding that, overall, spot prices are more right-skewed. However, analyzing the ratios of standard deviations and hourly means revealed that the variances fell more or less in line with those of the forward market, indicating that both markets are highly comparable in terms of volatility. The greatest variance was seen during the 21st hour, when the standard deviation (0.111 USD/kWh) matched the hourly mean while exceeding the overall mean by around 13%.

3.3.2 Time -Series Analysis for Determining Conditional Mean Equations for Pricing Series

The following section presents the analysis using the ARMA–ARCH model. As introduced earlier, the ARMA models serve as the mean equations within this framework, capturing the conditional mean of price changes, while the ARCH component models conditional variance to reflect time-varying volatility. Together, these components form the complete ARMA–ARCH structure applied to evaluate the dynamic exposure of Belize’s electricity market to price risk. In Appendix, Table A-6a & b contains the estimation results for the conditional mean equations on the change in electricity prices for day t to $t - 1$ using a system of autoregressive moving averages (ARMAs) based on information provided to the buyer for the forward and spot pricing, respectively.

For each hourly model, the sum of the autoregressive (AR) and moving average (MA) coefficients was less than one, suggesting that the ARMA process was stationary. Furthermore, the ACF and PACF of their standardized residuals revealed that no autocorrelated or partial autocorrelated lags (up to 30) exceeded the critical 5% level of significance. Additionally, all ARMA coefficients were statistically significant at the 1% level in each model. Notably, in addition to showing the validity of each equation for the conditional mean, these characteristics were also necessary for the subsequent volatility estimation of the residuals.

The study found that exogenous variables, average daily temperature, and the natural gas price index did not improve the mean models, as presented in Appendix, Table A-5. The coefficient for average temperature was positive but statistically insignificant. Likewise, the natural gas energy index did not carry statistical significance on changes in forward pricing. For example, simulations showed the average daily temperature and gas price index had a directly proportional impact on the changes in forward prices, 1.17×10^{-5} and 5.77×10^{-5} , respectively. However, both factors were insignificant (p -value = 0.56 and 0.88,

respectively), and the base ARMA model resulted in a better overall fit in both cases ($AIC_{ARMA} = -7645.10$ versus $AIC_{ARMA-X} = -7579.08$). Therefore, estimating the electricity price change without the exogenous factors, when considering a full day's profile, resulted in a better fit under the model selection criteria.

The insignificance of natural gas prices was in contradiction to Livas-García et al. (2022) and Cruz May et al. (2022), who previously determined that natural gas had the second-largest impact of 35.1% and 12.5%, respectively, on the value of the LMP using artificial intelligence and sensitivity analysis. This disparity may be due to the data analysis of this current study being conducted at the nodal level, unlike earlier studies that used regional estimates. The time difference between the reporting of the daily NG index and intra-day electricity pricing series must also be considered. With respect to the temperature indicator, average daily temperature might not have been as effective an indicator for the hour-by-hour analyses; however, due to data constraints, the study was limited to daily values.

Working versus non-workday variables were highly significant for a number of hours in both forward and spot markets. The weekend variable coefficient revealed both direct and inverse relationships in the forward and spot markets. Though highly statistical, these impacts were low in absolute terms, yet higher than the estimated impact of the workday dummy variable in the hourly models for which these variables were found to be significant.

Interestingly, the weekend variable's coefficient did not consistently show a negative trend, contradicting the assumption that weekend prices are lower than weekday prices due to reduced congestion and reserves. Instead, individual hourly spot regressions showed a significant negative relation for 6 h and positive for 7 h, with the most significant negative relation occurring during the 0th hour, and the most significant positive relation occurring during the 21st hour.

Changes in forward prices reflected the information provided to the buyer on day $t-1$, hence, at the start of the buyer's decision making process. The AR component suggested a directly proportional average impact of 0.40 on the price difference by its day-ago (lag 1) observation. Although highly statistically significant, this revealed a relatively low first-order correlation for a financial time series, but is consistent with extant findings and speaks to the volatile properties of the electricity commodity (D. Wang et al., 2022). In turn, based on the MA component, the regressed residual of the day-ago observation revealed a significant inversely proportional average impact of 0.93 on changes in electricity price.

Spot prices reflected the information provided to the buyer on day t , hence, at a secondary stage of the buyer's decision-making process. Its AR component suggested a considerably higher autocorrelation average impact of 0.79 compared to the changes in forward prices and for a financial time series for an electricity commodity when compared to previous market findings (Longstaff & Wang, 2004; D. Wang et al., 2022). Similar to the changes in

forward prices, the MA component of the day-ago observation revealed a significant inversely proportional average impact of 0.94 on the changes in spot prices.

3.3.3 Modelling the Volatility of Residuals as a Risk Measure for Pricing Series

In Appendix Table A-6 presents the estimation results for conditional volatility models on the residuals of the change in forward and spot prices using an hourly system of generalized autoregressive conditional heteroskedastic (GARCH) models.

Reviewing the ACF and PACF of their associated standardized residuals suggested that GARCH (1, 1) and GJR-GARCH (1, 1, 1) class models adequately captured the volatility, and in all but one hourly model of forward residuals, the model fit and accuracy were improved by an assumed SST distribution of the residuals, as compared to a normal distribution.

The alpha and beta parameters (whereby the α (alpha) parameter measures the impact of recent shocks on current volatility, while β (beta) captures the persistence of past volatility. Together, they describe how volatility clusters over time, reflecting periods of higher or lower price fluctuations) were positive and highly statistically significant, suggesting that an increase in the lagged squared residuals (α) and lagged conditional variance (β) leads to an increase in the volatility. Moreover, the estimations observed that the beta effect was greater than that of the alpha for all hours of both the forward and spot changes in price residuals, suggesting that generally, there should be greater concern for the persistence of volatile periods versus the magnitudes of this volatility.

Figures 3-8 and 3-9 provide depictions of sample hours of identical periods and comparative years for these simulations relative to the actual calculated volatility and stationary volatility. Stationary historical volatilities based on the value of standard deviation were estimated to measure the dispersion of daily fluctuations from 2018 to 2022 (a useful indicator for assessing risk over time and comparing it to dynamic volatilities generated by the estimated models).

Visualizations of the ARCH-simulated volatilities showed presence of the clustering effect of price volatility. For example, following the simulated volatility line with the actual standard deviations, Figure 3-8 showed the simulated volatility increased across periods of high volatility and leveled off during periods of low volatility. This contrast was observed more clearly during less volatile hours such as the 5 a.m. hour, and as shown in Figure 3-9, which reflects the same hour and period, but for differing years. Further, the visualizations demonstrated that reconstructed ARCH volatilities effectively captured the clustering effect, surpassing the use of information gathering based on stationary volatilities.

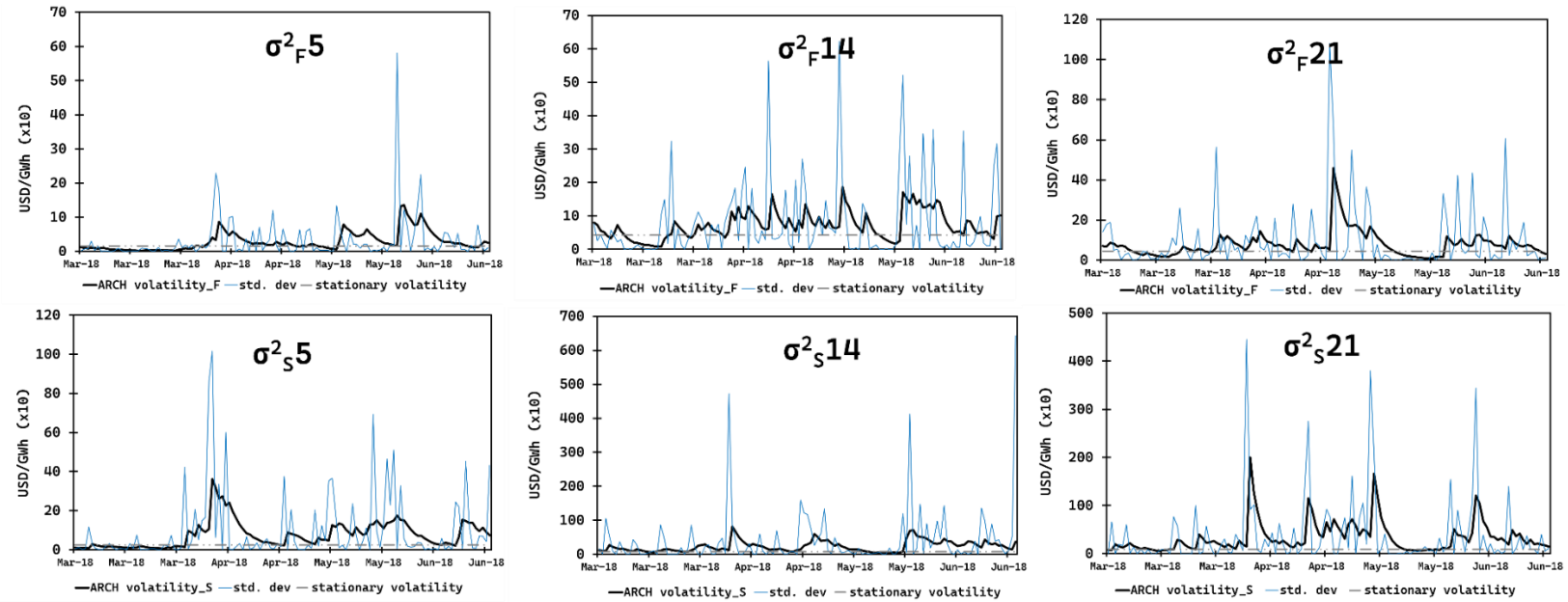


Figure 3-8 Simulated GARCH conditional volatility and standard deviations of daily changes in prices during certain hours from March to June of 2018 (corresponding to Belize's dry season). Results are expressed in US dollars per kilowatt hour scaled by 10^4

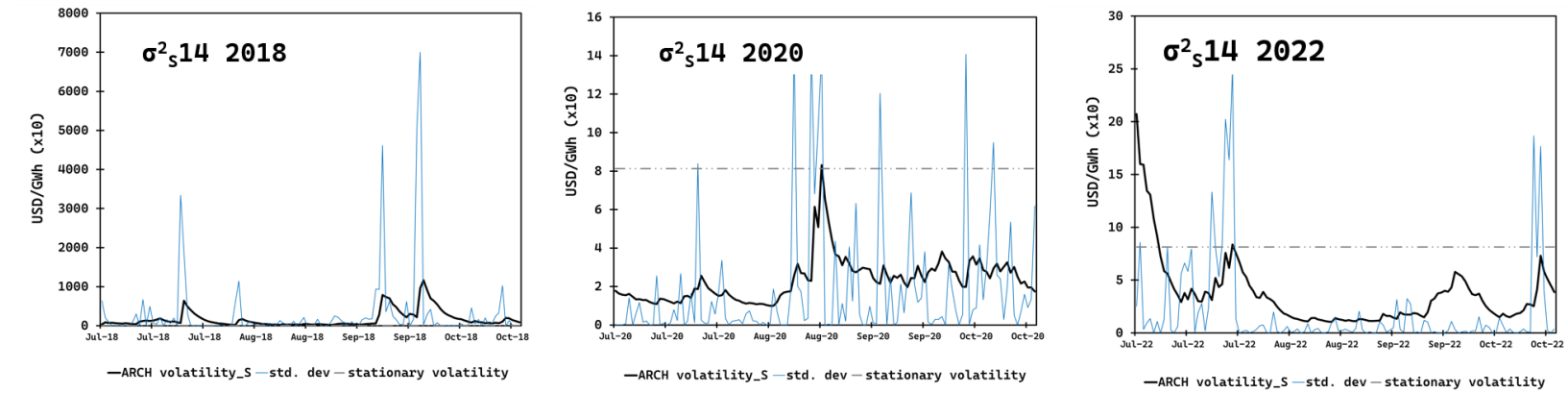


Figure 3-9 Simulated GARCH conditional volatility and standard deviations of daily changes in spot prices during the 2 p.m. hour from July to October (coinciding with Belize's wet season) for different years. Results are expressed in US dollars per kilowatt hour scaled by 10⁴

In cases where the GJR-GARCH outperformed the GARCH class, the gamma coefficients (represents the asymmetric effect of shocks on conditional volatility. This term allows the model to capture leverage effects, where negative shocks (price decreases) can have a larger impact on volatility than positive shocks of the same magnitude, reflecting the market's tendency to react more strongly to adverse events) were all statistically significant and all negative for the forward price models but varied between positive and negative for the spot price models, suggesting a varied asymmetric response to positive and negative shocks across these hours. The negative relation of gamma in the forward price change models implied that positive changes in price (a daily electricity price increase) consistently caused larger variance, while the spot prices would experience the inverse effect for 11 of the 16 h where the asymmetrical effect proved significant.

The volatility of spot price changes was significantly higher than forward price changes, indicating greater long-term risk in the spot market. For hours from 7 to 16, and 20 to 21, spot volatilities were over 90% higher. Notably, an overlap was observed between these 12 h and the hours of gradual mean price increases in both markets, as per Appendix Table A-4. Overall, the historical data revealed variations between the volatilities of forward and spot prices, in addition to their individual series' intra-day variations, suggesting evidence of forward pricing compensating market participants for assuming risk. In this regard, risk premiums were present and primarily concentrated in the late-morning and late-night hours, averaging 12 h per day.

3.3.4 VAR Analysis for Determining the Presence of and Factors Influencing Premiums

The final set of results assessed the behavior of the relationship between electricity forward and spot prices, investigated by way of the percentage forward premiums (FPs). As depicted in Figure 3-10 and indicated in Appendix Table A-7, similar to the average forward and spot prices, the average FP fluctuated throughout the day, ranging from a maximum of 51.3% during the 20th hour to a minimum of 7.3% during the midnight hour. The average FP and hourly skewness were all positive, large, and experienced significant variation across hours, as supported also by the changes in standard deviation. For example, on average, 19 of the 24 h showed an FP greater than 20%.

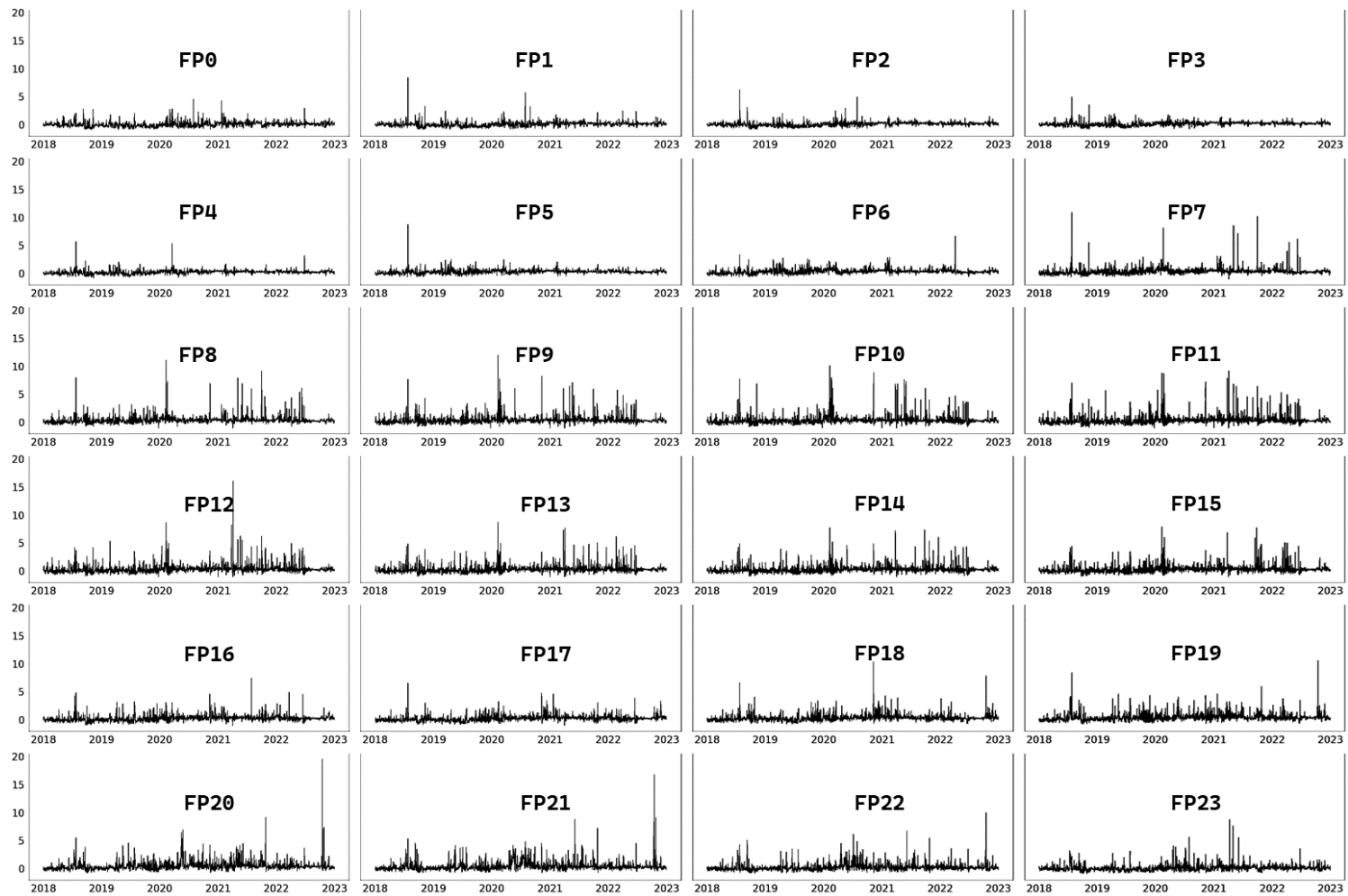


Figure 3-10 Time series of the percentage forward premiums ('FPs') received by the buyer (Belize) from the Mexican export market at the interconnection node 'Xul-Ha' allocated by hour of day ('0' to '23') from 2018 to 2022

The magnitudes of the percentage premiums in this study may be most comparable to those seen in the German market (Bessembinder & Lemmon, 2002; Koten, 2020) and the PJM market (Longstaff & Wang, 2004), while differences in datasets should be emphasized. Nonetheless, in this Belize study, positive risk premiums for certain hours were significantly larger than in other studies, suggesting that electricity markets are not yet fully settled into the restructured operating patterns following liberalization, especially for markets with short time frames like forward and spot, where pricing is observed within a day.

Additionally, unlike the other studies, this Belize study found negative premiums were not observed, even during off-peak hours, suggesting a persistent presence of risk factors like fuel availability and congestion at this particular node, and in turn, participants were highly risk-averse and rationally willing to pay significant premiums having understood these locational risk conditions. Premiums were not a focus of earlier research on the Mexican electricity market, making this element of the nodal findings difficult to relate to other nodes, or the regional or SIN level.

There were some peculiarities primarily concerned with a lack of the FP's coincidence with unexpected shifts in the forward and spot markets. For example, the FP exhibited its first peak around the 8th hour and once more at the 20th hour, preceding the peak areas of the average forward and spot prices by approximately 2 to 3 h. Additionally, the skewness was found to be erratic, depicting sharp increases and decreases from hour to hour, unlike the heavy right-skewed tailing concentrated in the late-afternoon and night-time hours of the forward and spot electricity prices.

Seeing as the FP originated from a percentage of observations where the realized spot price is higher than the forward price, it was expected that the positive skewness of the forward and spot electricity data would drive the periods when the FPs were significantly impacted, as underlined by the models of (Bessembinder & Lemmon, 2002; Koten, 2020). However, the observed inefficiencies suggested timing concerns between the actual changes in the nodal system's conditions and when their effects were reflected in the pricing series.

Further, these information time lags showed significant increases with volatility. Such findings implied that forward pricing does not move in steady correlation with the spot pricing. From Belize's perspective, concerns can be raised over the adequacy of the hedging instrument that is applied in the forward market, whereby adequacy is indicative of the appropriateness of hedge timing and magnitudes, seeking to perfectly offset the forward-trade losses associated with its delivery node.

This study's interpretations revealed that contrary to previous studies that investigated regional price averages, the highly locational aspect of the trade of electricity impacts the appropriateness of the applied hedging methodology and becomes more apparent in the analysis at the nodal level.

As the Xul-Ha node interfaces two independent power systems, its technical conditions are dependent on the patterns of generation, loading, and physical limitations of transmission as characterized by the operation and rated specifications of the two systems, but its hedging instrument may be largely reliant on the supplier's side, as originally hypothesized.

For example, Belize's power consumption data revealed high electricity import consumption between the hours of one and four, particularly during the dryer months of the year, to conserve water availability of the local hydropower plants during these very early morning, low-demand hours. In effect, the technical conditions of SIN's Xul-Ha node may vastly vary compared to other local nodes that display standard intra-day patterns of loading.

With that key difference in mind, if Mexico's regional operator applies a strategy in which localized hedging is relative to its larger geographic zone, such as the generation patterns and physical limitations of the node's wider peninsula region, the disparity created by Xul-Ha's unique loading pattern as a result of Belize's consumption behavior creates the potential for a hedging practice that is, at times, excessive or too moderate.

As imperfect offsets (in magnitudes and timing) between forward and spot pricing at the node are observed, a plausible concern is the compatibility of the hedging methodology with the loading pattern's physical limitations of a node that facilitates cross-border exchange and, in turn, identifies the factors on either sides of the interface that play the most influential roles in Xul-Ha's local marginal pricing.

The VAR analyses explored this theory by modeling two sets of variables: pricing factor (conditional forward and spot volatilities) and nodal conditions (percentage power import, IP, and domestic generation factor, DF). The optimal FP VAR function for each hour is provided in Table 3-1, and matrices summarizing all variables are found in Appendix Figure A-5 and A-6. The analysis revealed significant links across variables, with premiums causally linked to forward and spot volatilities for all hours. Cointegration analysis revealed long-term, statistically significant relationships with both price factors. Full correlation and cointegration matrices are also available in Appendix Figures A-7.

Table 3-1 VAR analysis coefficients for the four factors (forward pricing volatility σ_2F , spot pricing volatility σ_2S , electricity import percentage IP, and percentage variation in local generation support D)

Hour	ϕ_1	ϕ_2	ϕ_3	ϕ_4
0	-9% Δ^*	32% Δ^*	-10%*	-4%
1	-11% Δ^*	52% Δ^*	-11% Δ^*	0%
2	-8% Δ^*	32% Δ^*	-5%*	4%

3	-10%Δ*	38%Δ*	-2%*	4%
4	-10%Δ*	44%Δ*	-4%*	4%
5	-16%Δ*	54%Δ*	-3%*	7%
6	-18%Δ*	38%Δ*	0%Δ*	13%Δ
7	-9%Δ*	63%Δ*	-6%Δ*	8%Δ
8	-8%Δ*	53%Δ*	-8%Δ*	7%Δ*
9	-10%*	46%Δ*	-7%Δ*	10%Δ*
10	-10%Δ*	46%Δ*	-9%Δ*	1%Δ*
11	-4%Δ*	44%Δ*	-13%Δ*	-2%Δ*
12	-8%Δ*	38%Δ*	-14%Δ*	-4%Δ*
13	-9%Δ*	40%Δ*	-12%Δ*	0%*
14	-9%Δ*	40%Δ*	-13%Δ*	-2%Δ*
15	-7%Δ*	41%Δ*	-13%Δ*	2%Δ*
16	-11%Δ*	35%Δ*	-14%Δ*	-1%*
17	-10%Δ*	35%Δ*	-6%*	2%*
18	-9%Δ*	41%Δ*	-9%*	-4%
19	-7%Δ*	42%Δ*	-11%Δ*	-6%
20	-9%Δ*	39%Δ*	-9%Δ*	-4%Δ
21	-8%Δ*	42%Δ*	-11%*	-7%Δ*
22	-16%Δ*	32%Δ*	-7%*	-2%*
23	-10%Δ*	29%Δ*	-9%*	-4%*

¹ (Δ) *plausible correlation based on Granger's causality test; (*) statistical cointegration based on Johansen's statistic.*

The study found a direct relationship between premiums and unexpected shifts in spot pricing, but inversely linked to volatile forward pricing tendencies. The highest influence on the forward price (FP) was observed in hour 7 with 63%, suggesting that market participants may benefit most at this hour from forward purchases.

Further, based on the main cost components of spot pricing described by Rodriguez-Aguilar (Rodriguez-Aguilar et al., 2019), this relationship can be linked to unexpected shifts in real-time system conditions, including deficiencies in operating reserves, congestion effects from increasing or decreasing supply resources or consumption, and the

incidental effect on transmission losses. These corrections can be characterized by activities on both the supplier and buyer's side, depending on the variables involved.

Consequently, we assessed nodal conditions from the perspective of the buyer's load specifications and considered incremental energy transactions from the cross-border exchange (IP), as well as a variable measure of complementary generation from the buyer's side (D). In turn, these relationships can lead to unexpected shifts in nodal conditions, influenced by congestion associated with consumption. These changes, unlike price factors, were primarily influenced by buyer activities, rather than price factors.

An underlying theory suggested that price factors and supplier nodal conditions often overshadow buyer activity variation, leading to the assumption that Belize's loading patterns, which were a variable of the Xul-Ha node's power flows, will not significantly influence FP due to the significant size disparity between SIN and Belize's power system.

However, the study found that Xul-Ha's premiums decreased with higher electricity import consumption during certain hours, with the IP factor inversely correlated with FP. This effect was most significant during daytime hours 7–16 and night-time hours 19–20, with a maximum effect of 14% occurring during hours 12 and 16. Conversely, the nature of the relation between FP and D varied.

For example, during the hours from 8 to 12, whereby D revealed plausible causality and long-term correlated significance, its impact on FP varied between positive and negative, suggesting that as Belize adds more local generation to complement power imports, premiums may reveal increases or decreases depending on the time of day. This activity, from the buyer's side, is likely reflected in pricing through the varied nodal conditions of congestion and, incidentally, transmission losses. Still, both the impacts of IP and D, the resultant of the buyer's activities, were significantly lower than the supplier's, particularly the supplier's activity as represented through the spot price factor.

An interesting aspect of the observed relationships were the high premium hours of 7 to 10 that were characterized by low demand on the supplier's system, which coincided with highly volatile tendencies of spot pricing but low impact as a result of varying nodal conditions from the buyer's side. Generally, the intra-day profiles assume higher system corrections during periods when the system is highly stressed (Valitov, 2019). However, this period neither aligned with the peak hours of SIN nor peak electricity imports from Belize's system.

The volatile tendencies and high premiums during low-demand hours were likely due to supply resource and operating reserve corrections, which are entirely associated with the supplier's system. According to Livas-García et al. (2022) and Rodríguez-Aguilar et al. (2019), SIN's price volatility increases are generally caused by peak demand resulting from meteorological conditions, which causes high congestion (Rodríguez-Aguilar et al., 2019),

and to a lesser extent, increased power generation from renewable sources, which results in higher intermittent supply, particularly during peak conditions.

In contrast, more recent studies on FP have emphasized the uncertainties associated with capacity, particularly variable renewable energy (VRE) like (Valitov, 2019; Viehmann, 2011) found that VRE, like wind power, shifts intra-day variations by supplying high production during low-demand hours, thereby linking economic risk to potential supply surplus and variability. Cruz May et al. (2022) found that VRE has considerably influenced Mexico's LMP price over time, and this behavior is linked to the recent start-up of wind power facilities in several load zones. As such, this VRE phenomenon presented a plausible source of the unexpected real-time shifts that resulted in relatively high FP during low-demand hours in this Belize study.

3.4 Chapter Summary and Practical Implications

This study proposed a methodological approach for understanding the associative effect of the cross-border supply on Belize's price risk exposure. This methodology can be used by small developing countries to conduct price analyses in liberalized electricity markets worldwide. Most crucially, the research design was based on the quality and timing of information received during the two major decision-making stages, allowing the findings to be readily integrated into the greater body of evidence on decision making and the costs associated with risk exposure of electricity imports compared to alternative power sources. This approach is reproducible for other participants and bidding zones, considering the differences in each zone (e.g., other nodes) and time intervals.

Data analysis highlighted that forward and spot pricing were lowest in early-morning hours, increasing gradually from the 10th to the 22nd hour and decreasing in the final hour. Price changes showed positive skewness, with the most significant right-skewed tailing occurring during afternoon-to-night-time hours. These behaviors proved consistent across both forward and spot pricing series; as such, from the perspective of an intra-day profile, we can first conclude that price risk exposure shows an overall positive association with expected price trend, which varies in magnitude across a given day.

Initially, we predicted a positive link between price risk exposure and the unexpected fluctuations in forward and spot pricing. Time-series analysis adequately captured autoregressive and moving-average trends, revealing unexpected shifts that may be analyzed using volatility models. Having established the latter, it was justifiable to proceed with the development of ARCH models to forecast and depict the conditional volatilities of the residuals of forward and spot price trends.

The market's volatility revealed rare high-impact electricity price shocks, along with prolonged periods of volatile clusters, indicating that Belize's reliance on this market mostly generated favorable economic returns, but occasional losses could potentially impact the affordability of local power costs, and the predicted association with price risk

exposure was affirmed. Comparing the effects of recent shocks versus the persistence of volatility over time suggested that the duration of volatile periods tends to be of greater concern than the magnitude of individual shocks in assessing price risk for the Belize–Mexico interconnection.

Evidence of hedging was determined. Estimates highlighted that Belize is compensated 7% to 51%, on average, via forward premiums for bearing intra-day risks, whereas trading in the spot market showed increased risk and procuring at higher price margins, which would likely magnify its economic losses. However, findings revealed the unexpected behavior observed across the changes in spot and forward prices does not transmit efficiently to the percentage forward premiums; thus, there are delays in the impact on these variables. Hence, in many instances, the Belize buyer could trade at a loss or not benefit economically because of mistiming when purchasing a substantial volume of electricity supply or, inversely, when purchasing a small quantity or not at all.

The study found that unexpected price shocks during morning hours had a greater impact on prices than the variation in nodal conditions due to electricity import consumption and local generation activities by the buyer. This suggested that real-time corrections on the supplier's side have significantly greater influence on nodal conditions reflected in pricing than the buyer.

The VARs noted periods with high FPs during low system demand and low import consumption that could be linked to uncertainties due to VRE's introduced supply surplus and variability risks, thereby potentially impacting prior notions of premiums that primarily coincided with system peaks and high congestion. Still, contrary to the initial hypothesis, the buyer's activities revealed a statistically significant effect associated with premiums during certain hours.

The practical implications of these findings revealed that both forward and spot prices can change rapidly, changes in supply and demand, and a host of other factors. However, the evidence identified that these risks were associated more highly with spot pricing. Purchasing electricity imports via the forward market provides the opportunity to profit from or hedge against price movements, particularly during hours where the percentage forward premiums are highest.

Perfect foresight into markets is hindered by information lags, which were shown to misalign with heightened periods of risk factors and heightened periods of premiums. However, hedging does not necessarily imply buying electricity forward (like the case for power purchase agreements) but can be instituted as a purely financial instrument through contracts for difference or futures. These implications can influence future research that could further enhance planning and decision making on local power supply, for example, integrating the findings on the importation market behavior with the buyer's local power expansion plan.

Future research could revisit the inclusion of exogenous variables such as temperature and natural gas prices using higher-resolution data. In this study, only daily averages were available, which may have limited the model's ability to capture short-term variations affecting hourly electricity price movements. Access to hourly or sub-hourly datasets would allow for a more precise estimation of their influence and potentially improve model performance and fit criteria. In future refinements, the model can be strengthened by trying different optimization methods, lag selections, or regularization tools. This will help ensure the model is stable and confirm whether the higher AIC values reflect real performance issues or simply a technical convergence limitation.

The analysis relies on a five-year dataset spanning 2018–2022. This period was chosen to ensure relevance to current operational and regulatory conditions at the Xul-Ha node, while maintaining data consistency. Although longer historical datasets could capture additional variability, structural changes in the market prior to 2018 may confound model assumptions. Hence, the five-year period is considered sufficient to represent the characteristics of Belize's cross-border electricity market, with potential for future studies to incorporate extended datasets if available.

Notably, the findings of this analysis are dependent on the provisions defined by the power purchase agreement of the Belize–Mexico interconnection during the period of this study (2018 to 2022). As a result, possible changes in the local or bi-lateral market situations can cause the results to differ. In turn, future work can address this limitation by conducting model-based studies in contrast to econometric analyses, whereby various market conditions can be defined and simulated through multiple scenarios.

Chapter 4 Inherent Risk Analysis of Power Supply Management: Case on Belize's System Operator and Third-Party Actors

4.1 Introduction

System operators (SOs) (Hong et al., 2022) oversee power supply management, including considerations of risk. Effective risk management enables SOs to make informed decisions on power supply (Kadir et al., 2023). In small developing countries, proactive risk management is a top priority. This is because major disruption events require SOs to re-direct a significant portion of their resources into recovery efforts (Tehero et al., 2020). Short-term redirection of resources delay medium and long term advancement for the power industry. Consequently, SOs in small developing countries prioritize risk reduction, thereby, proactively minimizing the possibility of a major disruption.

RE technologies have increased the focus of SOs on risk management. SOs are concerned with the emerging threats from these technologies. For example, Wang, Rousis, and Strbac's (2020) study on improving power system resilience using DERs found that interconnectivity with DERs creates new challenges for restoring power to an area after an outage.

Changes in the natural environment have also increased SOs' focus on risk management (L. Chen et al., 2020; Huang et al., 2023; Qiu et al., 2021; Zhong et al., 2020). In Qui et. al.'s (Qiu et al., 2021) work on water reservoirs, the authors showed that the effects of warming climate led to greater uncertainty of the hydrological state of water. The uncertainties created new challenges for the existing manner in which water resource are managed for power generation, flood management and environmental protection.

The discipline of power supply tends to focus on residual risks, but this accounts for only a subset of risk (Miller et al., 2012). In contrast, inherent risk encapsulates the amount of risk that exists prior to the implementation of routine controls (Gupta & Bhatia, 2023; Miller et al., 2012). Residual risk controls are protective, while inherent risk controls are preventative (IRCG, 2020a).

The distinction between residual and inherent risks remains largely unaddressed in power supply management. Consequently, an abundance of methodologies and tools, such as unit commitment (UC) optimization (Buraimoh & Park, 2022; Hong et al., 2022), has emerged to target residual risks and influenced a bias of SO towards protective controls.

Researchers in other technical fields have highlighted similar shortcomings. In Bachev's (2013) analysis of risk management in the agri-food industry, the author identified that a predominant focus on technological tools in technical industries have limited the scope of

risk analyses. Technical industries have largely ignored risk based on managerial decision-making. Although in practice, managerial decisions that depend on factors like the regulatory condition, mode of transaction (via market, public resource etc.), and human aspects (resource mismanagement, ignorance), carry highly consequential risks (Bachev, 2013).

Understanding inherent risks would help SOs to extend their approaches to preventative controls (IRCG, 2020a). However, the lack of research on inherent risks associated with power supply management has created a critical gap in this field.

The primary goal of SOs is to ensure availability of sufficient quantities of supply to meet demand (Zambrano, 2022). However, layered on this fundamental goal (to match power supply with demand) are sub-objectives to allocate and schedule power supply to achieve the lowest possible cost, maintain high power quality, and prioritize renewable or clean energy sources (Yang et al., 2022).

In addition, power supply sources vary in technology type. This means that SOs must remain attentive to how the respective constraints of the differing sources interact with each other (Buraimoh & Park, 2022). Ultimately, the decisions of SOs to reduce events of unmet demand and unwanted consequences associated with daily scheduling and allocation evolved primarily from managing residual risk. Together, inherent and residual risk form the SO's complete risk profile, however, based on literature reviewed, inherent risk assumed a secondary status in power supply risk management.

While this study focused on SOs, it recognized that much of an SO's operation relies on third-parties. SOs procure power that is generated by various external suppliers. This is a critical transaction that has introduced a highly interconnected power input-output relationship between SOs and third-party suppliers (Gupta & Bhatia, 2023). This meant that SOs also must be attentive to the inherent risks faced by third-party suppliers in addition to the SO's inherent risks.

SOs should decide whether the combined inherent risks of their operation and that of relevant third-parties are material to warrant mitigating actions. To do so, SOs require reliable information and effective tools to identify threats and evaluate the levels of exposure.

This study aimed to fill the identified gap by developing a methodology to investigate inherent risks associated with power supply management based on the operations of the SO and relevant third-parties. Two primary objectives were defined: (i) identify inherent risk factors and variables to appropriately represent power supply related exposures, and (ii) evaluate the SO's level of exposure from these risk factors.

To achieve objective (i), inherent risk factors were qualitatively synthesized based on SO and relevant third-party operations. To achieve objective (ii), a multivariate analysis was

undertaken to measure exposure level of power supply management in Belize. Variables were selected to represent risk factors. Descriptive statistics were calculated to highlight variability and distribution frequency. Univariate distribution models were developed for each risk factor. Lastly, the copula method was adopted to build multivariate risk distributions per season for four scenarios. A joint exposure level was calculated at varying percentiles for each scenario, allowing comparison of exposure under both conditions.

The remainder of this research paper is organized into the literature review with background of the study problem, related literature and this study's conceptual framework, the methodology, the results and discussion, and lastly, the conclusion outlining the study's limitations and practical implications.

4.2 Literature Review

4.2.1 Background on Case Study

Research in power supply risk management often focuses on residual risks, neglecting inherent risks. This results in methodologies focusing on protective controls, and largely ignoring preventative controls. This study used the case of Belize, a country that exhibited a scarcity in published literature, to assess the problem.

At the center of power supply management was the power mix system, which is comprised of the collection of sources used to generate electricity (Burke, 2010). Figure 4-1 maps Belize's power mix system by technology type and estimated average percentage supply contribution to the power grid. Peak demand was roughly 107 MW, while total installed capacity was at 172.8 MW (Belize Electricity Limited, 2022).

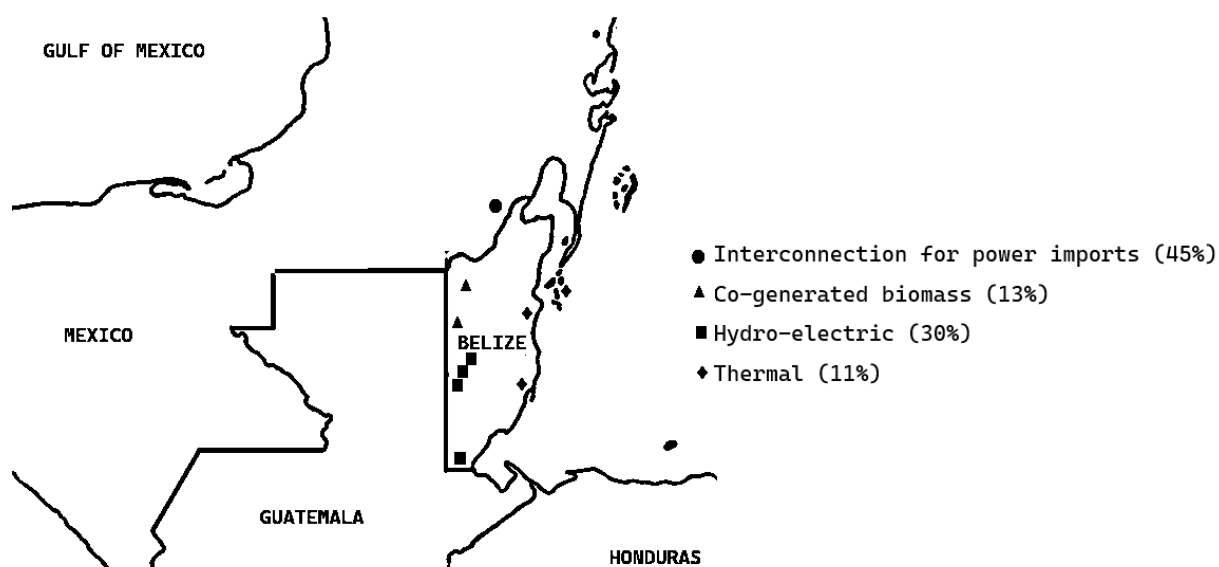


Figure 4-1 Map of Belize's power mix system by technology type and their average percentage supply to the power grid.

Belize's SO oversaw the management of all supply sources with the principal ones being hydroelectricity and co-generated biomass. Local supply from RE was supplemented by Mexican electricity imports with purchases on an hourly basis (Tillett, A; Locke, J; Mencias, 2011).

In early 2024 consumer demand for electricity exceeded power supply capability, so the SO in Belize performed a series of rotating outages from one area to the next to reduce demand on the power grid. Rotating outages were used to purposively balance power demand with supply to avoid system overload which would lead to an uncontrollable outage. Rotating outages were also implemented in early 2011. Essentially, rotating outages could signal unexpected shifts in the managed levels of residual risks and necessitate deeper evaluation of the inherent risks to warrant a useful tool as proposed in this study.

4.2.2 Residual versus Inherent Risk Contextualized for the Operations of an SO

The SO's primary goal is to ensure adequate quantities of electricity supply to meet demand. SOs purchase power from a number of suppliers on an hourly basis and schedule an allocated quantity per supplier each hour (Yang et al., 2022). To achieve their goal, SOs set operational objectives, summarized as follows:

- (a) The most widely discussed is to schedule and allocate at the lowest possible cost and maintain affordability of power for consumers. The energy industry uses the

term 'merit order' (Buraimoh & Park, 2022) to describe the sequence by which power supply is allocated and scheduled on an economic basis like lowest-cost.

- (b) Schedule and allocate achieve high power quality (Tehero et al., 2020). High power quality means the combined supply remains steady and within prescribed voltage, frequency and waveform standards (Al-Shetwi et al., 2020). By maintaining high power quality, SOs also ascertain compatibility with electrical devices of consumers. Poor power quality can cause devices to malfunction.
- (c) The most novel is to prioritize renewable and clean energy sources. SOs incorporate climate goals to reduce sources, like fossil fuels and coal, which contribute to greenhouse gases (GHGs) or other major pollutants. Notably, VRE are prioritized in the merit order having zero marginal cost (Barrera-Zapata et al., 2023).

Supply sources have varying constraints, and SOs must manage a mix of technologies simultaneously. For example, solar power supply is subject to weather disruption (Guerra et al., 2022). Assuming no or limited storage, cloudy periods reduce the amount of electricity solar facilities can supply. Similarly, hydropower is constrained by weather conditions, though on a longer timescale. During periods of low rainfall or drought, power supply can significantly decrease (Zhong et al., 2020). In turn, during periods of heavy rainfall, SOs can be required to maximize hydropower output to avoid reservoir spillage.

Thermal facilities are flexible in that they can be turned on and off when required (Guerra et al., 2022). However, if the heat rate of thermal power plants decrease below its optimal operating range, the cost to generate electricity increases below a specified output (Jian et al., 2022). SOs remain attentive to how constraints of the various sources interact. For example, power generated from biomass can experience large fluctuations due to natural inconsistencies in its feedstock – the organic material used as fuel. SOs can utilize a flexible alternative source, like thermal or large hydro, in conjunction with biomass supply to counter the effect of fluctuations on the power grid.

SOs seek to reduce chances of unmet demand and unwanted consequences on affordability, quality and environment. However, daily scheduling and allocation of power supply is a form of residual risk management that ignores inherent risks. As shown in the biomass example immediately above, SOs can respond to threats (like fluctuations) using in-place measures (such as supplementary flexible generation) in an established process (day-to-day scheduling and allocation).

Simply put, each hour, the SO engages in a repetitive, ongoing process of identifying, assessing and controlling the threats to power supply. Unit commitment (UC) optimization techniques (Abdi, 2021; Buraimoh & Park, 2022; Guy, 1971) have been developed to address the day-to-day residual risks of supply management. These deterministic techniques model a system of various suppliers, the technical and economic constraints, and

define either a single or multiple objectives to solve for an optimal solution. Such a solution, or model output, is an optimized scheduled allocation of power supply for each supplier.

SOs often focus on residual risk because corresponding measures can readily be established in the daily routine. For example, SOs can regularly adjust the spinning reserve (the amount of extra power supply held to respond quickly when another supplier fails unexpectedly) (Hong et al., 2022). In modern power systems, SOs rely on predictive models to determine possible shortfalls from VRE, like solar power supply, to proactively adjust spinning reserve (Buraimoh & Park, 2022; Hong et al., 2022). This is yet another control response around the residual risk of VRE supply shortfalls with no obvious consideration to inherent risk.

This study recognizes the importance of residual risk management. The SO's responses during the scheduling and allocation process represent a robust residual risk management mechanism. In this light, because residual risk management has the benefit of routine controls, residual risk is less likely to create severe problems. However, residual risk accounts for only a subset of risk (Ewertowski & Butlewski, 2021; IRGC, 2017a).

Unlike residual risk, inherent risk reflects the level of risk prior to implementing routine controls (Ewertowski & Butlewski, 2021). Inherent risk influences effective control measures for SOs to achieve its primary goal. The SO's fundamental goal was ensuring sufficient quantities of supply to meet electricity demand. SOs devise controls, like scheduling and allocation and spinning reserves, to minimize the possibility of not achieving this goal. Therefore, SOs are simply left with residual risk to manage day-to-day.

Together, inherent and residual risk form the SO's complete risk profile. Yet, based on the availability of literature, inherent risk is treated secondary in power supply risk management. SOs might assert that evidencing stable, quality, and affordable supply equates to low inherent risk. However, disruption occurs, and power outages are recorded in advanced systems when residual risk is managed effectively. Consequently, in this current study, focus was on developing a tool to strengthen the management of inherent risk, which appeared to receive much less focus than residual risk in power supply systems in developing economies.

Another support for additional study on inherent risk is that residual risk controls are protective, while inherent risk controls are preventative (Ewertowski & Butlewski, 2021) and the two sets of controls can serve complementary roles. For example, hydropower is the largest and most mature source of renewable electricity (Zhong et al., 2020). SOs harness power by managing the flow of water that passes through hydro-electric turbines from a river. During seasons with low precipitation, SOs can regulate the flow of water such that a stable stream is maintained upstream and downstream of the powerhouse. This response presents a temporary protective control to safeguard against dangerously low stream levels.

In contrast, warming climate increases extreme weather events (Val et al., 2019). Higher frequencies of droughts, dry-spells, and high temperatures affect the basic hydrology of the river (Zhong et al., 2020). If the amount of water in the stream is significantly reduced due to the impact of warming climate, simply regulating flow will not be sufficiently effective. Instead, SOs can decide on preventative controls that could better serve power supply.

For instance, existing hydropower infrastructure can largely be utilized for pumped storage services to capture surplus electricity from VREs (Hong et al., 2022; Nasab et al., 2022). This response serves two controls. First, hydropower's main role is converted from power supply to power storage. This means that while warming climate impacts on hydrology will persist, its ability to influence supply will significantly lessen. Second, SOs reduce the amount of power supply surplus from VREs that would have otherwise been wasted.

SOs need to decide if the inherent risks are substantial enough to warrant their attention. SOs can properly address uniqueness of inherent risks by implementing preventative controls. Therefore, a tool or methodology, as formulated in this current study, to identify threats and evaluate the levels of exposure can be valuable to SOs. Research (Kadir et al., 2023; Sambo et al., 2023) also demonstrated instances where inherent risk controls require more time and resources to implement than residual risk controls, thereby, emphasizing a need for a tool that can identify varying levels of risks for SOs to more appropriately direct efficient use of resources.

Interestingly, SOs procure power supply and become reliant on third-parties. Essentially, the generation of power is outsourced. Therefore, SOs must understand the inherent risks also of third parties. For example, through a physical interconnection between the power grids of two or more countries, electricity can be procured from foreign power suppliers (Oseni & Pollitt, 2016). If a foreign power market lacks sufficient controls to manage spikes (Uniejewski et al., 2018) in electricity prices, a price spike can create unwanted consequences on affordability locally.

As such, it is important for SOs to have a methodology that facilitates evaluating inherent risks of SOs and their third-parties to gain a comprehensive understanding of potentially adverse situations. This current research developed a tool to investigate inherent risks associated with power supply management based on the operations of the SO and relevant third-parties. A conceptual framework was devised to develop an appropriate method, as presented in the next section.

4.2.3 Conceptual Framework

Figure 4-2 provides a depiction of the conceptual framework applied in this study. The SO was the main actor of the framework.

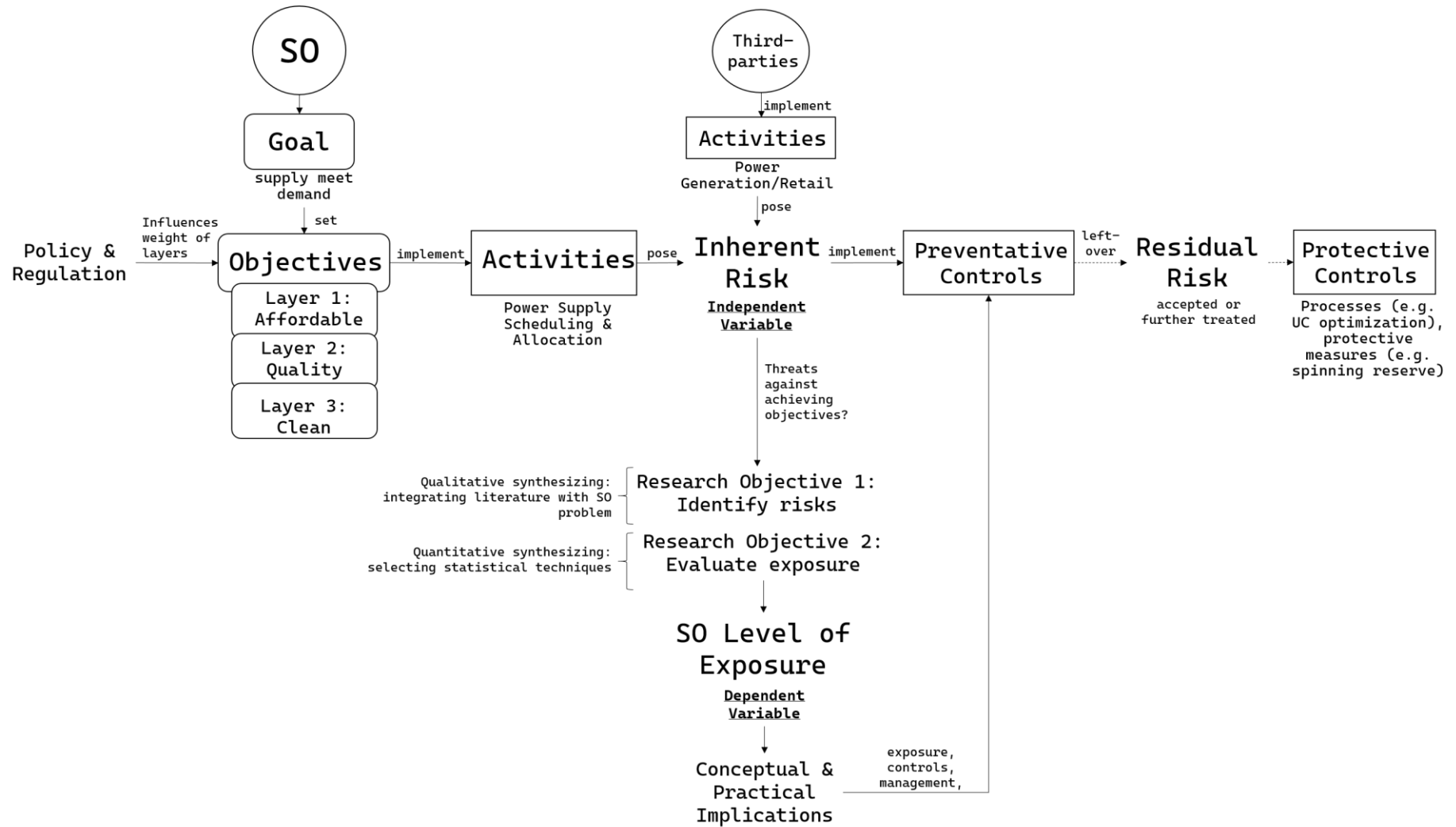


Figure 4-2 Conceptual framework devised and used to analyze the inherent risks of power supply management

The study conceived that risk which threatens the SO from achieving their objectives is categorized into two types: inherent and residual. Risk types were distinguished based on the absence/presence of protective controls. While inherent and residual risk form the complete risk profile of the SO, this work focused on the assessment of inherent risk. Hence, risk in the absence of protective controls represented the study's independent variable, and exposure level represented the study's dependent variable.

The goal and objectives of the SO represented control variables that remained constant. However, policy and regulation could influence the weighting of importance placed on each objective layer. For example, recently, the Government of Belize committed to an increased share of 85% RE in electricity supply by 2030 in the nationally determined contributions (NDCs) (UNFCCC, 2021). While Belize's SO prioritized affordability (layer 1) and quality (layer 2) ahead of environmental friendliness (layer 3), this hierarchy is prone to changes in the future to meet the NDC goal. For simplicity, the methodology was not concerned with the weighting of each objective. Rather, risks that could possibly prevent the SO from achieving all objectives were equally considered.

Activities represented moderating variables that could influence the relationship between the inherent risk (independent variable) and exposure level (dependent variable). Based on the reviewed literature, the activities of third-parties relevant to the inherent risk of the SO were also identified as moderating variables. Relevant third-party activities included power generation or the re-selling of power through retail markets to the SO.

The study used qualitative and quantitative synthesizing to establish the relationship between inherent risk and exposure level. In qualitative synthesizing, inherent risk factors were identified. Appropriate variables were selected as indicators that can predict changes in exposure for the SO. In quantitative synthesizing, the study selected statistical techniques fit to measure the level of exposure. Synthesizing relied on lessons acquired from literature and an understanding of the activities of the SO and third-parties.

Statistical findings were internally validated based on model validation. Their extended conceptual and practical implications were externally validated by comparing findings with information available on the practical setting from case-specific documentation, including: power purchase agreements (PPAs) (BECOL / BEL, 1991, 2007; BELCOGEN / BEL, 2007; CFE Calificados, 2016), and SO annual reports (Belize Electricity Limited, 2018, 2019, 2020, 2021, 2022). As prior discussed, the main outcomes of the study supplied implications on preventative control measures.

4.3 Methodology

4.3.1 The Data

The study utilized five time-series datasets from January 1, 2018 to December 31, 2022, each presented in hourly times-steps, as detailed in Table 4-1.

Table 4-1 List and descriptions of datasets that were collected and utilized in the analysis of this study

Data	Unit	Description
D_{Fi}	kWh	Forecasted grid energy supply for an hourly interval, i
D_{Ai}	kWh	Actual grid energy supply for an hourly interval, i
S_{Pi}	kWh	Electricity supply by a power plant, P , for an hourly interval, i
FP_i	USD/kWh	Imported electricity day-ahead forward price of Xul-ha interconnection node for an hourly interval, i
SP_i	USD/kWh	Imported electricity day-of spot price of Xul-ha interconnection node for an hourly interval, i

The study collected forecasted (D_{Fi}) and actual (D_{Ai}) aggregate grid supply for 43,824 hourly intervals of the sample period, as well as hourly electricity supplied by hydro-electric and biomass co-generation facilities (S_{Pi}). Secondary data on the maximum rated capacities of these facilities was also collected. The study also collected the price for purchasing electricity imports from the day-ahead forward market (FP_i) and the spot market (SP_i) for real-time purchase. The forward and spot pricing of power imports accounted for unit cost variability of the system's power supply, as local power supply was regulated by annualized fixed-cost pricing.

Datasets were shared by Belize Electricity Limited (the utility) after receiving a comprehensive description of the quantitative assessment for this research (data not publicly available). The collected data was analyzed for gaps and irregularities; however, no gaps or abnormalities were found.

4.3.2 Study Design

4.3.2.1 Objective 1- Qualitative synthesis of inherent risk factors

A total of four risk factors were considered with relation to its effect on the vulnerability of the power supply. A variable was assigned and defined for each risk factor, as per Table 4-2.

Table 4-2 Definition of the variables that was used to assess each supply management risk factor and their generalized inferences as applied by this study

Risk Factor	Variable	Definition	Inference on vulnerability
Prediction Error	PE	$\left \frac{D_{Fi} - D_{Ai}}{D_{Ai}} \right $ Normalized [0,1], The absolute value of the fractional difference between the forecasted and actual total grid supply, normalized between 0 and 1 using the maximum and minimum values observed in the entire dataset before splitting for training from 2018 to 2022. Provided that the cost is the same for over-forecast and under forecast., this study focused on the magnitude of the error, versus direction.	The higher the PE, the greater the perceived quantity and price risk due to supply manager's forecasting error
Plant Unavailability Factor	PU	$1 - \left[\frac{\sum S_i}{Total\ RE\ Capacity} \right]$ Normalized [0,1], The fractional proportion of the aggregate supply not available from all RE plants per aggregate rated capacity of all RE plants, normalized between 0 and 1 using the maximum and minimum values observed in the entire dataset before splitting for training from 2018 to 2022	The higher the PU, the greater the perceived quantity risk due to lack of supply availability by local hydro & biomass co-gen facilities
Peaking	PK	D_{Ai} Normalized [0,1], The actual grid demand requirement, normalized between 0 and 1 using the maximum and minimum values observed in the entire dataset before splitting for training from 2018 to 2022	The higher the PK, the greater the perceived price and quantity risk due to high demand requirement
Forward Premiums	FP	$\left \frac{SP_i - FP_i}{FP_i} \right $ Normalized [0,1],	The higher the FP, the greater the perceived price risk due to larger

		The absolute value of the fractional difference between the spot and forward price of electricity imports, normalized between 0 and 1 using the maximum and minimum values observed in the entire dataset before splitting for training from 2018 to 2022	price differences between the day-ahead and real-time purchasing price of imported power
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A factor (prediction error, 'PE') was included to account for the quantity and pricing uncertainties that occur as a result of the manager's capacity to predict exactly what the total supply requirements will be hour by hour. Understanding the importance of forecasting accuracy (Mir et al., 2020; Nti et al., 2020), the study used the difference between predicted and actual total grid power supply requirement to calculate this risk.

Warming climate presented a significant risk to water availability for hydropower production and crop availability for co-generated biomass. This analysis used the inverse of renewable energy plant availability, focusing on the variability of supply output. This approach holistically captures ex-ante ecological conditions, enacted management protocols for renewable energy facilities, and the scheduling and allocation decisions by the SO manager, unlike previous studies that primarily focused on purely ecological or commodity variables (Huang et al., 2023; Qiu et al., 2021).

Thirdly, the study looked at risk of total power demand approaching of possibly exceeding the capacity limits of power supply (peaking, 'PK). Extreme demand conditions tend to reflect concerns of a quantity shortage of supply, as well as, potential price spikes or fluctuations in price (Jabir et al., 2018; Janczura & Puć, 2023) as less efficient or costly generation is operated to meet the supply requirement and the congestion of the physical infrastructure increases (Torriti et al., 2017). To measure PK, the study relied on the difference between the actual total grid power supply and peak supply.

Finally, a factor (FP) was incorporated to reflect a major concern of an SO manager, which is that the cost of sourcing power may exceed their ability to recoup costs. Economic risk is extensively addressed by scholars that specialize on trading in liberalized power markets (Çanakoglu & Adıyeke, 2020; Koten, 2020; Wei & Lunde, 2022). To measure the potential severity of this risk, the study relied on the difference between the spot and forward price of electricity imports to reflect the most significant cost uncertainty tied to power supply.

Risk factors were addressed using four seasonal categories: early dry (December-February), late dry (March-May), early wet (June-August), and late wet (September-November). This allocation reflects locally recognized seasonal periods relevant to hydropower inflows and operational planning. While monthly precipitation or biomass harvest data could further justify this classification, such climatological datasets were not comprehensively available. The seasonal allocation served to take into consideration the different characteristics of

inflow and discharge associated with hydropower as done by past authors who focused on power-water-ecology interdependencies, like (Qiu et al., 2021). In this study, the seasonal allocation was also applicable for differentiating between in-crop and out-of-crop periods for the biomass sources.

4.3.2.2 Objective 2- Quantitative assessment of exposure level

Figure 4-3 provides a depiction of the quantitative assessment synthesized to measure exposure level. Time-series datasets were collected and pre-processed per season for each variable. Data was categorized into four seasons: early dry (December-February), late dry (March-May), early wet (June-August), and late wet (September-November). Descriptive statistics were calculated to highlight the variability and distribution frequency of the datasets for each variable per season.

Parametric estimation was used to fit theoretical distributions to each variable per season, relying the optimal marginal distributions to draw data-driven conclusions on individual variables. Parameter estimations were validated by bootstrapping 10,000 iterative re-samples and comparing the bootstrapped samples and empirical data using an RSS score (residual sum of squares). The marginal distribution of each variable was selected based on the lowest RSS score.

Variables were analyzed using univariate and joint distribution sampling to compute the relative exposure based on percentiles. 10,000 random samples were generated from each variable's marginal distributions. Theoretical Gaussian and t-copulas were used to define a correlation structure for multivariate distributions. Joint distributions were fitted and assessed per season. The copula that best modelled the multivariate distribution was determined using log-likelihood as a fitness measure.

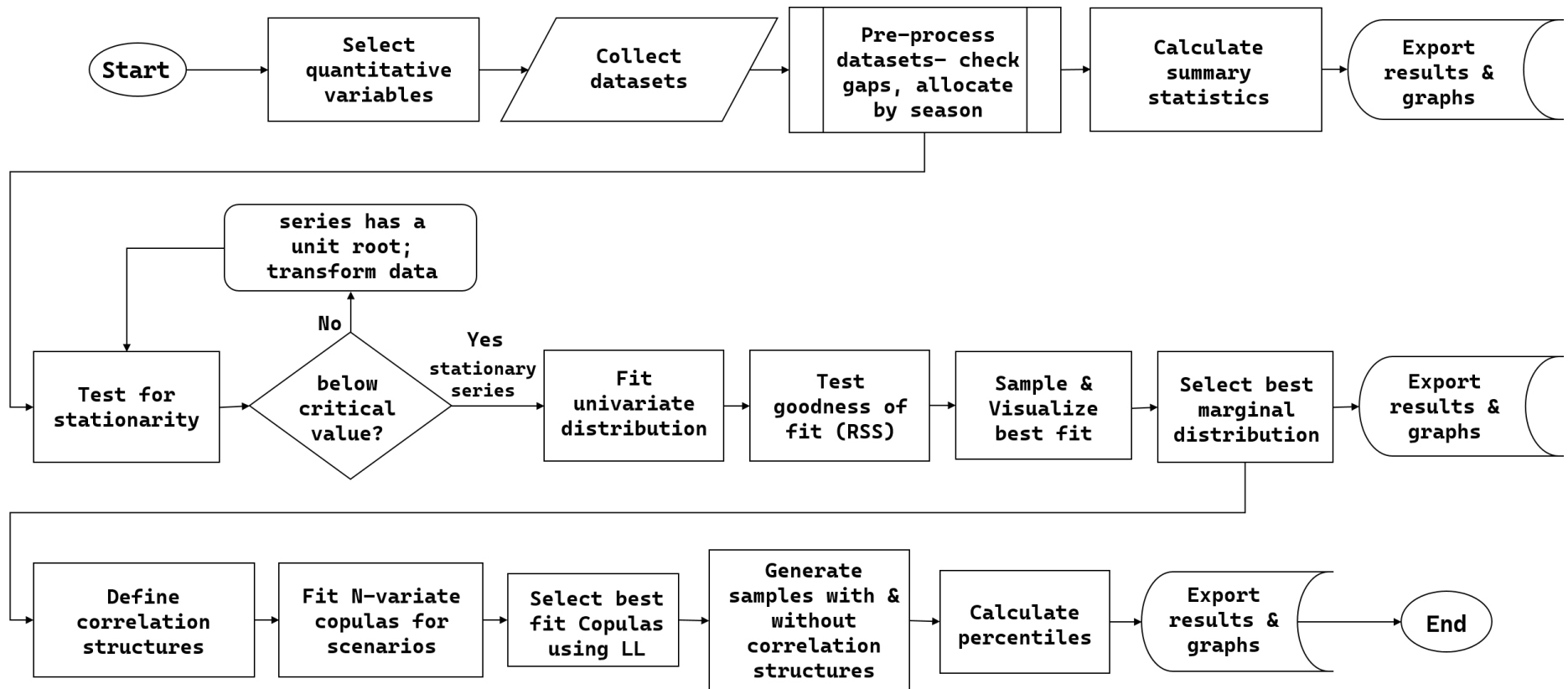


Figure 4-3 Steps of the quantitative assessment synthesized in this study to measure the exposure level of Belize's SO

Random samples (10,000) were generated from the copula and re-transformed. The normalized risk index was calculated at varying percentiles of the re-transformed data, thereby incorporating correlation structures between variables. For comparison, percentiles were similarly computed for samples from the marginal distributions. Equal weightings were assumed for each variable in the 'n'-dimension distribution. Findings on exposure level were compared for each season.

4.3.3 Description of statistical analyses applied in this study

4.3.3.1 Summary statistics and marginal distribution

A few commonly utilized descriptive statistics were generated for the seasonal datasets, including mean, minimum, maximum, skew and standard deviation. Prior to developing the distribution models, datasets were examined for stationarity using the Augmented Dickey-Fuller (ADF) test [38] to determine if there was a unit root, based on likelihood ratio statistics to reject the null hypothesis of non-stationarity in time series [39].

The study used a probability distribution to describe each variable for a specific season, hence repeating the process 16 times (4 variables for 4 seasons). This research examined a variety variables and their interdependencies. Previous studies have used distribution types like GEV and log-normal for hydrological evaluations (Kousar et al., 2020a; Qiu et al., 2021). In Ji et al.'s (2018) study involving agricultural commodities, the authors applied skewed student-t density distributions to account for asymmetric features in comparable data. This research built on previous studies that have used similar distributions for ecological assessments, agricultural commodities, and power markets.

The study selected 11 commonly applied density distributions (Appendix Table A-9). Optimal parameters were determined by minimizing the residual sum of squares (RSS). The RSS represented the deviation between predicted and empirical data values, as defined in equation 1. RSS was chosen not only as a conventional goodness-of-fit measure but also because it emphasizes the accurate representation of extreme values, which is critical in assessing exposure to high-impact events in the power system.

$$RSS = \sum_{i=1}^n (y_i - f(x_i))^2 \dots\dots\dots (1)$$

, where y_i is the value of variable to be predicted, x_i is the explanatory variable, and $f(x_i)$ is the predicted value of y_i .

The RSS was used as the main score to rank the best theoretical distribution for empirical variables. To validate the ranking, bootstrapping was applied to resample the fitted distribution and compare with the empirical values. This step was repeated 10,000 times, and computations were performed in Python using the 'distfit' version 1.8 (*Distfit* · *PyPI*, n.d.) package for probability density fitting of univariate distributions.

4.3.3.2 Joint distributions based on copula technique

To support specific insights as it relates to the overview of supply management, we considered the following bi-variate, tri-variate and multivariate cases. The variables modelled in each case, their expected insights on supply management, and level of dimension of the required joint distribution model ('n') are outlined in Table 4-3.

Table 4-3 Interdependencies analyzed using the copula technique in this study to support various inferences on the management of Belize's power supply

Case	Variables	Expected Insight(s) on	'n'-distribution
1	[PE, FP]	Correlation structure between forecasting inaccuracies, which would be subject to higher spot prices as a result of real-time adjustments, and premiums, which reflect the additional cost incurred from real-time purchases	n =2
2	[PU, PK]	Correlation structure between local RE unavailability and the system's demand requirements as a function of peak demand	n =2
3	[PK, PU, FP]	Correlation structure between the system's demand requirements, local RE unavailability, and the additional costs incurred from real-time purchases	n =3
4	[PE, PK, PU, FP] (All)	Unit score risk based on correlation structure between all four factors	n =4

Gaussian and t-copula were used to generate multivariate distributions for each season, demonstrating their ease of application in describing multivariate dependency among variables. Both Gaussian and t-copulas were employed to generate multivariate distributions for each season. The Gaussian copula models linear dependencies efficiently, whereas the t-copula accounts for tail dependencies, enabling better representation of extreme co-movements among risk variables. Using both copulas allows for comparison of dependency structures and assessment of the potential impact of extreme events on exposure. This proved useful as the cases increased in dimensions, with the 'n'-dimension as large as 4, as was in the case of case 4. According to Sklar's theorem (Durante et al., 2013), multivariate distributions can be expressed in terms of their univariate marginal

functions. In n -dimensions, for H , an n -dimensional distribution function for n -variates, $(x_1, x_2, \dots, x_n)$, with marginal, $(F_1, F_2, \dots, F_n)$, there exists an n -copula, C , such that,

$$H(x_1, x_2, \dots, x_n) = C(F_1(x_1), F_2(x_2), \dots, F_n(x_n)) \dots (2) \text{ (Nelson, 2006)}$$

For Gaussian copula, C_{Gauss} , the main parameter is a covariance matrix, Σ , that defines the model's dependence structure between variables. Its theoretical probability density function is defined by equation (3):

$$C_{Gauss}(x) = \frac{1}{\sqrt{(2\pi)^n \det \Sigma}} \exp\left(-\frac{1}{2}(x - \mu)^T \Sigma^{-1}(x - \mu)\right) \dots (3) \text{ (Genz \& Bretz, 2009)}$$

,where μ represents the mean and n denotes the number of variables (rank of model). For t-copula, C_T , the main parameter is a covariance matrix, also referred to as a shape matrix, Σ , and the degrees of freedom, ν . Its theoretical probability density function is defined by equation (4):

$$C_T(x) = \frac{\Gamma(\nu+n)/2}{\Gamma(\frac{\nu}{2})^{\frac{n}{2}} \pi^{\frac{n}{2}} |\Sigma|^{1/2}} \left[1 + \frac{1}{\nu}(x - \mu)^T \Sigma^{-1}(x - \mu)\right]^{-(\nu+n)/2} \dots (4) \text{ (Arellano-Valle et al., 2013)}$$

,where μ represents the mean, n denotes the number of variables, and denotes Euler's gamma function.

A theoretical Gaussian and t-copula was fitted to each case per season, and the model which best represented the data was selected based on the estimated log-likelihood (LL). Random variate samples of 10,000 were generated from the selected copula, and transformed from uniform variables to their prior defined optimal marginals using the inverse of their respective cumulative density functions (CDF). All computations were carried-out in Python using scipy.stats version 1.14.0 (SciPy, n.d.).

The copula method captures statistical dependency rather than causal relationships, meaning it identifies how risk variables co-vary but not whether one causes changes in another. Therefore, expressions such as "reinforce" or "offset" are used in this study to describe the direction and strength of dependency, not causation. The findings should thus be interpreted as patterns of joint behavior among risks rather than evidence of deterministic influence.

Each case was scored based on varying percentiles of the distribution, estimated in increments of 5 from 70th to 95th. Percentiles provided a widely understood statistical metric for scoring the distributions. The percentile at a level q of a cumulative distribution function, $F(y) = P(Y \leq y)$, of probability measure, P , was defined by the value x that met the conditions in equation (5):

$$P(Y < x) \leq q/100 \text{ and } P(Y \leq x) \geq q/100 \dots\dots (5) \text{ (Numpy Statistics, n.d.)}$$

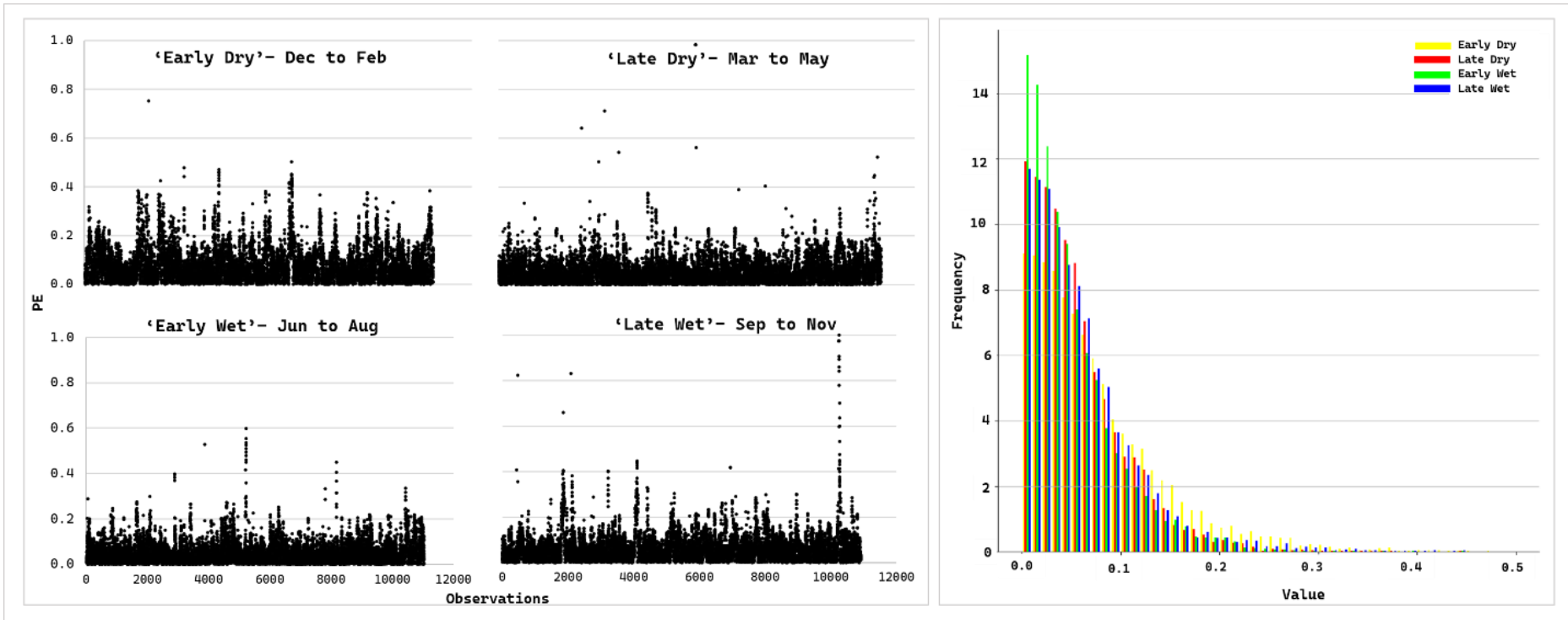
A similar principle is the traditional value-at-risk (VaR) used in financial applications which is a typical percentile-based score generated over a given period and for a given probability level (Burchi & Martelli, 2016; Mensi et al., 2017; Zhang et al., 2020). For example, a generalized inference of the VaR at the 95th percentile models the possible loss or deficits that may occur in a 1 in 20 worst-case scenario. However, in this analysis, the percentile returns a multivariate risk index between 0 and 1. As its variables, this score was dimensionless, and percentiles were computed under the assumption that the variables were of equal weighting.

Percentile scores were used to compare case-by-case risk and its variation across seasons, with and without incorporating the correlation structure between variables. The copula technique was used to calculate percentiles for case variables, allowing comparison of perceived risk increases or decreases when considering interdependencies of variables. The analysis relied on sets of contour plots to assist with the visualization of the bi-variate and multivariate cases in 2-dimensional space.

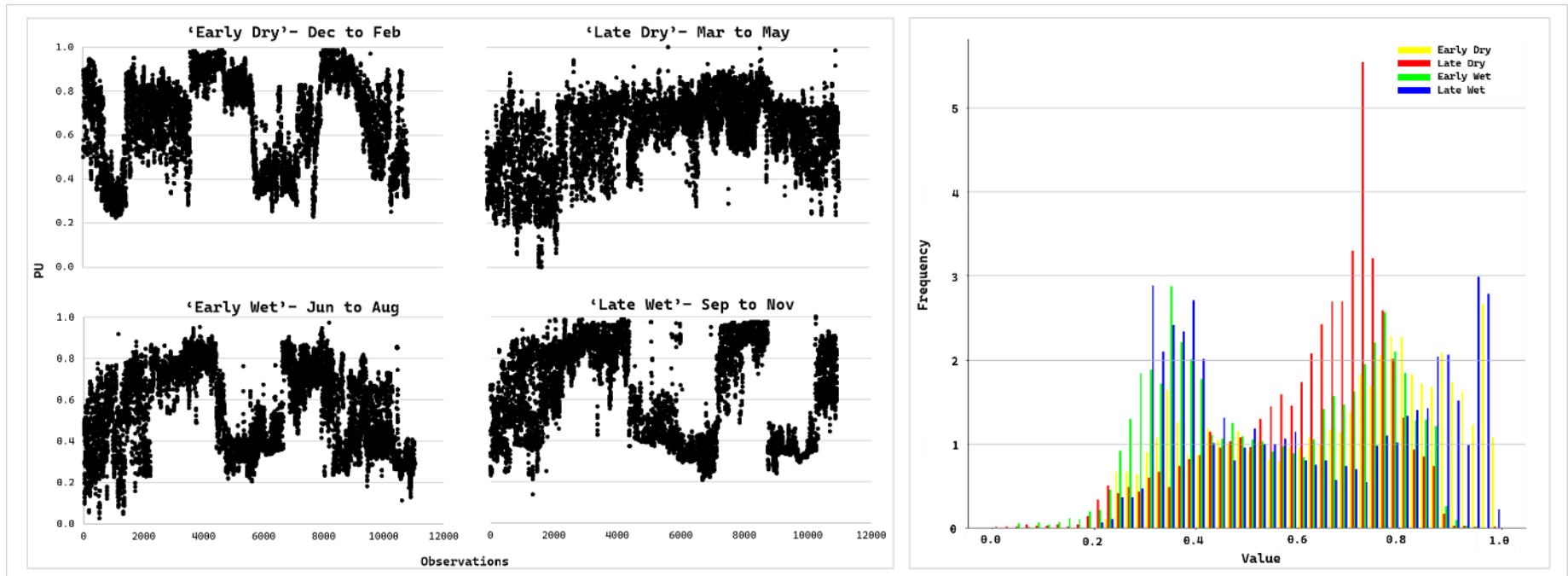
4.4 Results and Discussion

4.4.1 Summary Statistics

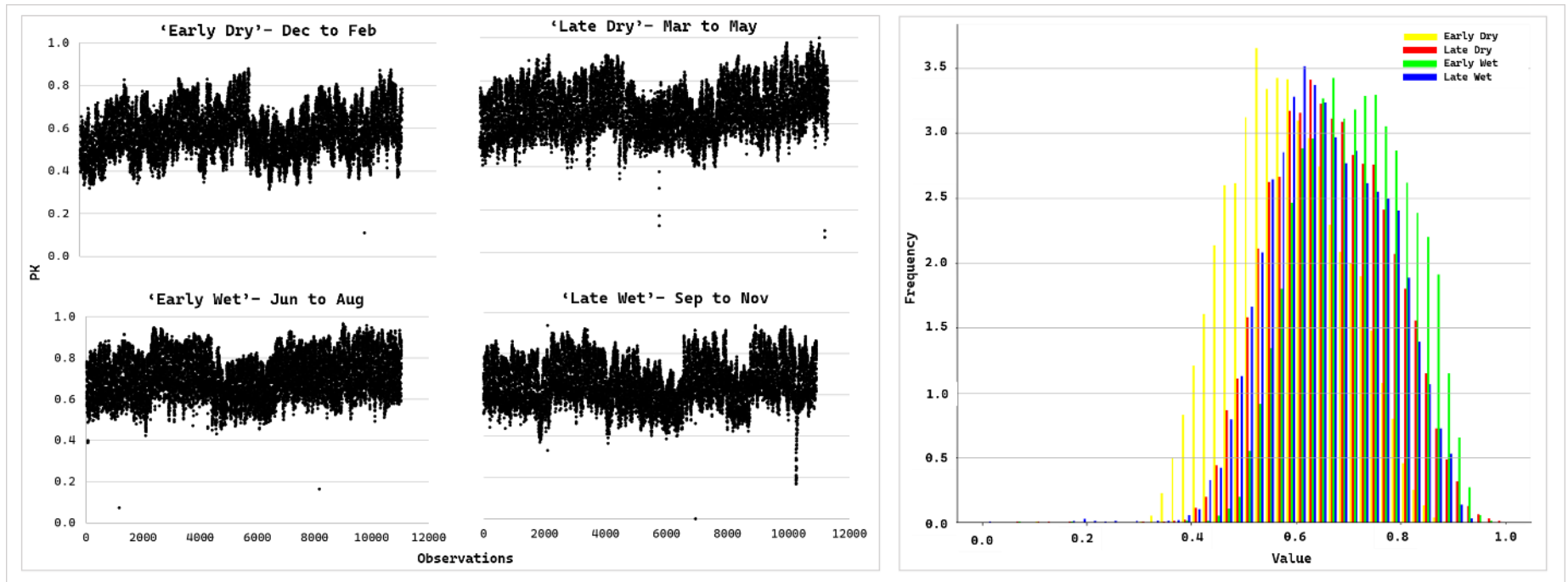
The time series datasets for each variable were pre-processed and allocated seasonally as presented in Figure 4-4, (a) through (d). For clarity, the figure lays out five consecutive years side by side per season. Due to the use of previously unassessed data, it was challenging to compare numerical findings with prior studies. However, data patterns and descriptive statistics were compared with expected behavior across different seasonal conditions, as per literature.



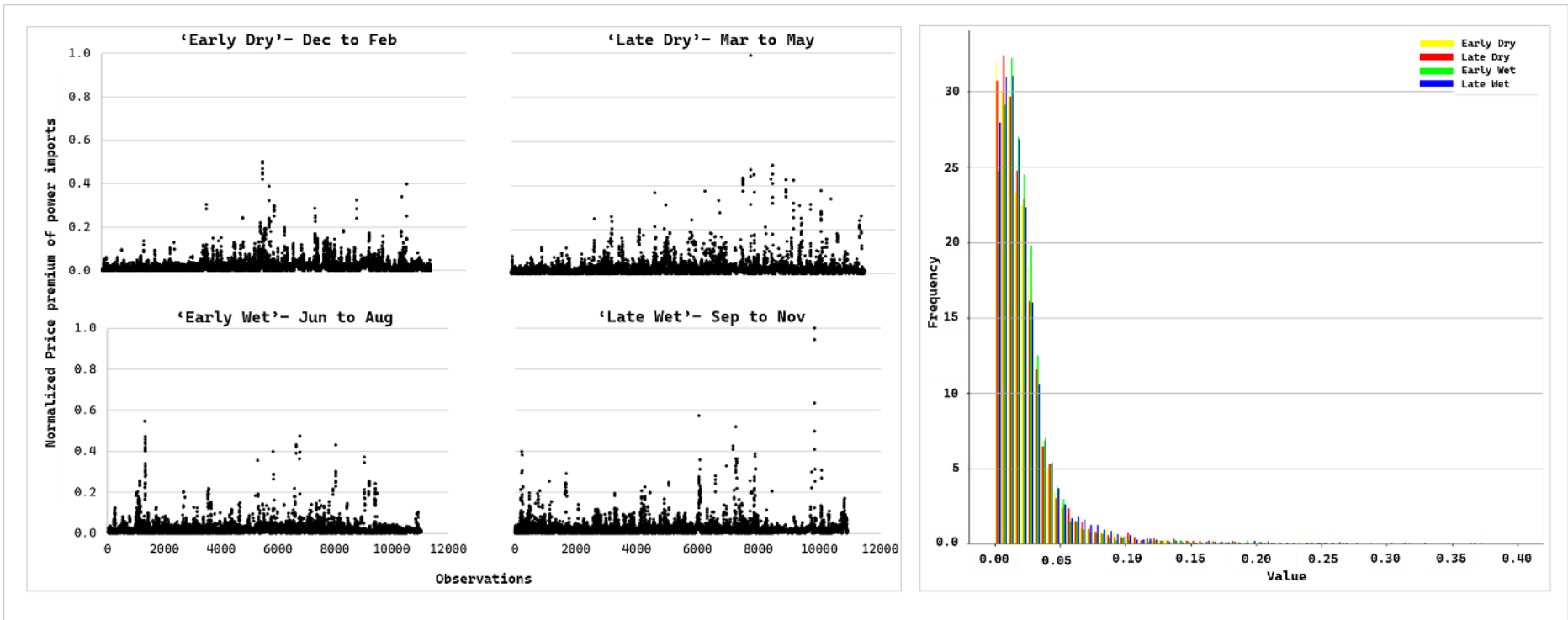
(a) PE



(b) PU



(c) *PK*



(d) FP

Figure 4-4 Scatter plots for each risk variable per season for each variable from 2018 to 2022

The data showed varying shapes per variable, suggesting different optimal probability distributions. However, the shape per season was relatively consistent, except for the unavailability factor of local renewable plants (PU). This inconsistency in intra-seasonal patterns suggested that PU can account for the greatest shifts in risk across seasons in supply management. PU skewed towards the right-end of the normalized scale, indicating that it can also account for larger effects on the system.

Overall, none of the variables exhibited symmetry in these preliminary visualizations, suggesting that the optimal distributions possessed asymmetric properties. This suggested that simple normal distributions may not be suitable for marginal distributions. Table 4-4 (a) through (d) provides further insight into individual risk factors.

Table 4-4 Summary statistics for each risk variable per season. The sample includes hourly observations for each variable from 2018 to 2022.

(a) PE

Season	Mean	Median	Max	Min	Skew	Kurtosis	Std. dev
Early Dry	0.077	0.059	0.753	0.000	1.709	4.341	0.068
Late Dry	0.057	0.045	0.985	0.000	3.476	36.528	0.052
Early Wet	0.051	0.038	0.599	0.000	2.395	11.671	0.049
Late Wet	0.062	0.047	1.000	0.000	3.977	35.140	0.063

(b) PU

Season	Mean	Median	Max	Min	Skew	Kurtosis	Std. dev
Early Dry	0.677	0.728	0.992	0.223	-0.385	-1.083	0.215
Late Dry	0.624	0.668	1.000	0.000	-0.875	0.151	0.161
Early Wet	0.553	0.552	0.974	0.028	-0.042	-1.331	0.201
Late Wet	0.622	0.595	1.000	0.140	0.082	-1.519	0.236

(c) PK

Season	Mean	Median	Max	Min	Skew	Kurtosis	Std. dev
Early Dry	0.583	0.578	0.880	0.110	0.135	-0.597	0.107
Late Dry	0.666	0.662	1.000	0.071	0.063	-0.416	0.109
Early Wet	0.713	0.712	0.965	0.076	-0.044	-0.581	0.101
Late Wet	0.662	0.656	0.937	0.000	-0.053	-0.241	0.109

(d) FP

Season	Mean	Median	Max	Min	Skew	Kurtosis	Std. dev
Early Dry	0.023	0.017	0.502	0.000	5.825	59.705	0.029
Late Dry	0.024	0.017	0.989	0.000	7.268	100.715	0.034
Early Wet	0.024	0.017	0.546	0.000	6.508	63.070	0.032
Late Wet	0.025	0.017	1.000	0.000	8.160	131.325	0.036

The system's supply requirement (PE) forecasting accuracy was highest during the early dry season (0.077), with the highest absolute error occurring in the late wet season, followed by the late dry season (0.985). The distribution of PE showed right-skewness and kurtosis, with the late wet season showing the highest positive skewness (3.977) and the largest kurtosis (36.528), suggesting higher probabilities of large prediction inaccuracies during the late dry period.

The study found that PE's intra-seasonal variations were high, amounting to as high as 93% of the corresponding seasonal mean value during dry season and exceeding the mean value during wet seasons, indicating a volatile accuracy in predicting demand requirements and in turn, the quantity and price risks tied to this factor.

The risks associated with supply shortages due to ecological and commodity interdependencies (PU) were highest during the dry seasons (0.677 and 0.624 for early and late seasons, respectively). Surprisingly, the risk level was similar in the late wet season, despite hydro-electric facilities' anticipated higher capacity reducing this risk factor during the out-of-crop season for lesser capacity biomass supply.

The distribution of PU showed greater symmetry and thinner tails than PE, with low intra-seasonal variation across all seasons. The lowest deviation was observed in the late dry season (0.161), likely due to supply constraints tied to ecological run reflecting a management protocol to conserve water the availability during the driest period of the year.

The study found that the late dry season had the highest peak supply requirement, while the early wet season had the highest average requirement. The PK variable showed the least skew and asymmetry, suggesting the lowest probability of extreme lows or highs. Intra-seasonal variations were relatively consistent across all four seasons, indicating that a single theoretical distribution may be suitable for this variable across all seasons.

The mean values of seasonal premiums were fairly similar (between 0.023 and 0.025), with the largest premiums observed in the late wet season and the late dry season (0.989). The skew and kurtosis of the FP were larger in the late dry and wet seasons, suggesting that extreme price spikes associated with FP were more likely to occur during these periods.

Overall, FP showed high positive skewness and heavy asymmetric tailing, indicating that spot or real-time purchase prices were generally larger than forward prices. This finding held economic implications, as any unforeseen adjustments to supply requirements were subject to more expensive real-time pricing.

It is acknowledged that using min–max normalization over the full five-year period can be sensitive to extreme outliers, which may stretch the scale and compress the majority of observations into a narrow [0,1] range, potentially increasing apparent skewness and kurtosis. However, this approach was chosen to preserve the relative magnitudes of extreme deviations, consistent with the study's focus on inherent risk exposure. Future refinements could consider robust normalization techniques that reduce the influence of outliers while maintaining the interpretability of exposure metrics.

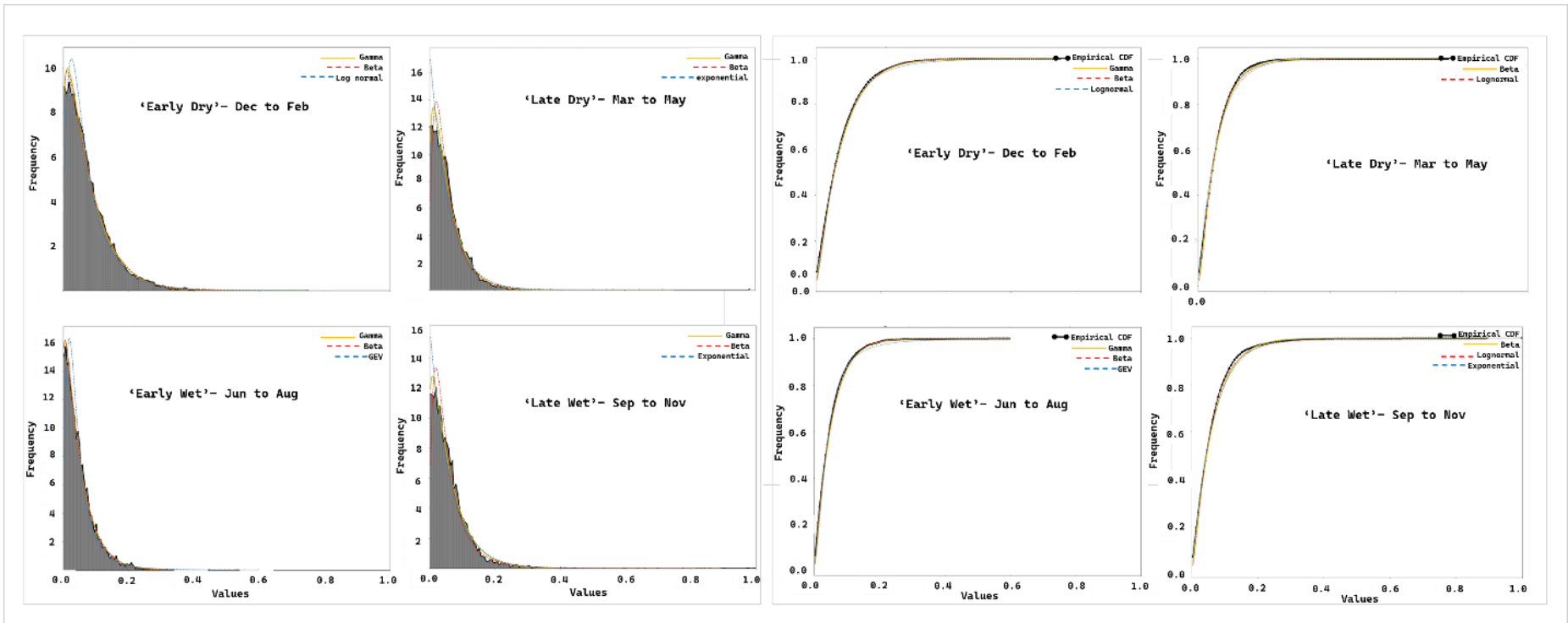
4.4.2 Marginal distributions – parameter estimation and fitting

The ADF test was applied to test for randomness and stationarity. Results are summarized in Table 4-5. The datasets were found to be random and stationary, making them suitable for statistical analysis and fitting of probability distributions. A process of curve fitting, parameter estimation, and scoring was conducted for each variable per season.

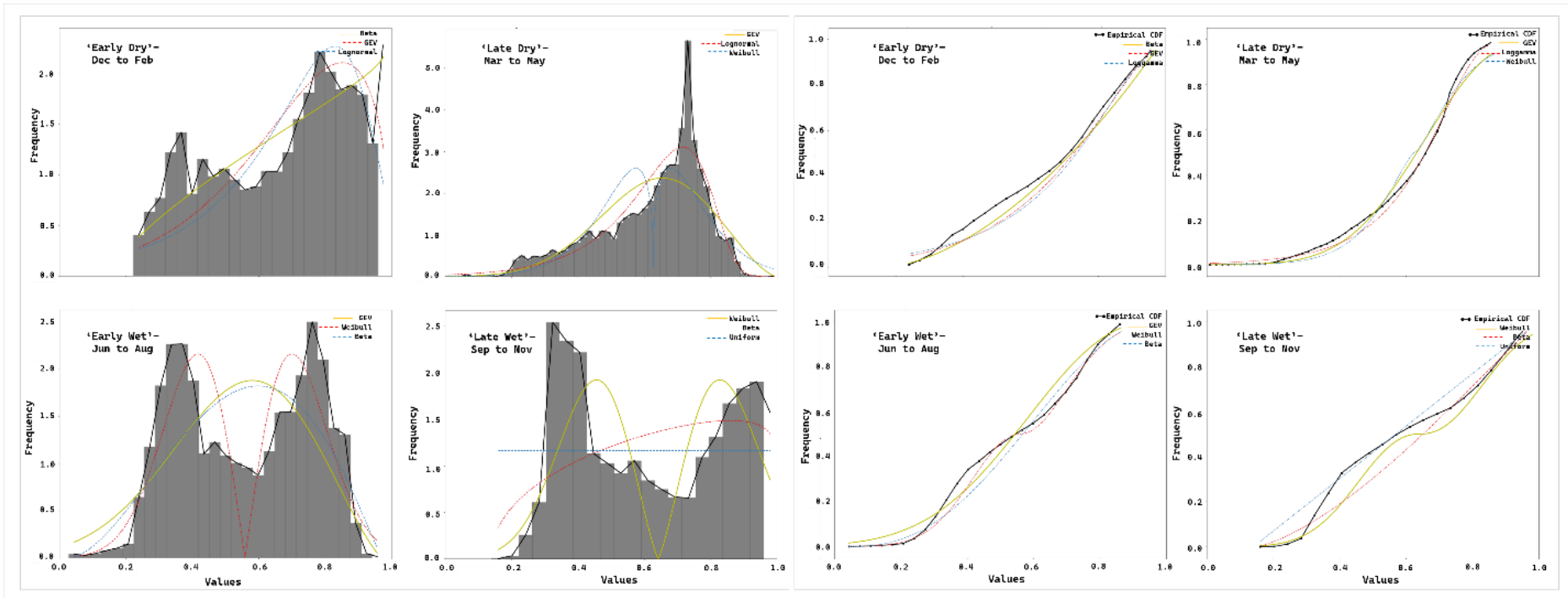
Appendix Table A-10 presents the scores and ranking of marginal distribution models for each variable per season, with probability density functions and cumulative distribution functions plotted alongside empirical data provided in Figure 4-5 (a) through (d). Based on scoring and visualization, the selected marginal distribution models and their parameters were identified, as summarized in Table 4-6.

Table 4-5 Results of the Augmented Dickey Fuller (ADF) test performed on each dataset prior to distribution fitting to determine randomness and stationarity, whereby (**) and (*) highlights that the test statistic had an observe significance at 1% and 5% level based on critical values

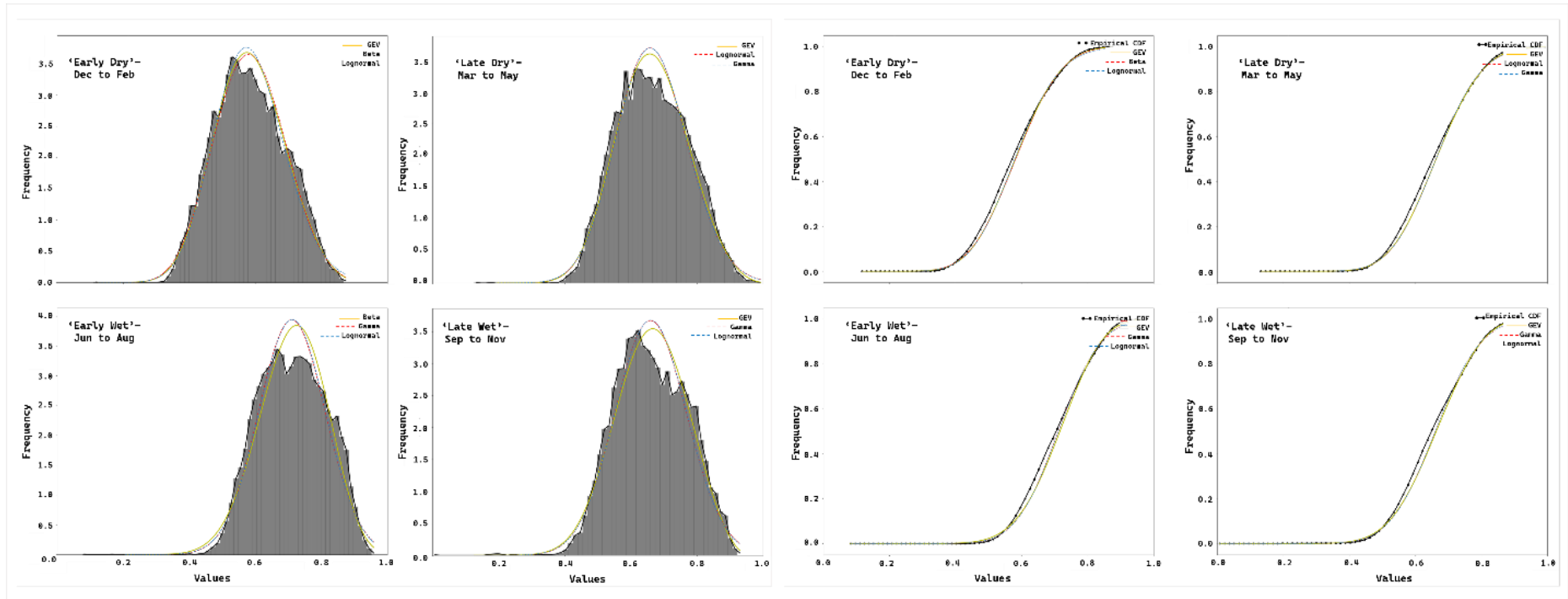
Variable	ADF statistic				p-value			
	Early Dry	Late Dry	Early Wet	Late Wet	Early Dry	Late Dry	Early Wet	Late Wet
PE	12.48**	-15.22**	-15.10**	-12.22**	6.91×10^{-20}	1.74×10^{-22}	1.13×10^{-22}	1.71×10^{-19}
PU	-3.26*	-7.49**	-4.36**	-3.48**	1.70×10^{-02}	1.09×10^{-09}	2.54×10^{-03}	8.64×10^{-03}
PK	-8.38**	-9.92**	-11.32**	-8.75**	2.49×10^{-13}	2.97×10^{-17}	5.69×10^{-18}	1.33×10^{-12}
FP	-14.79**	-14.23**	-14.22**	-11.92**	2.85×10^{-22}	6.96×10^{-22}	7.17×10^{-22}	5.18×10^{-19}



(a) PE



(b) PU



(c) PK

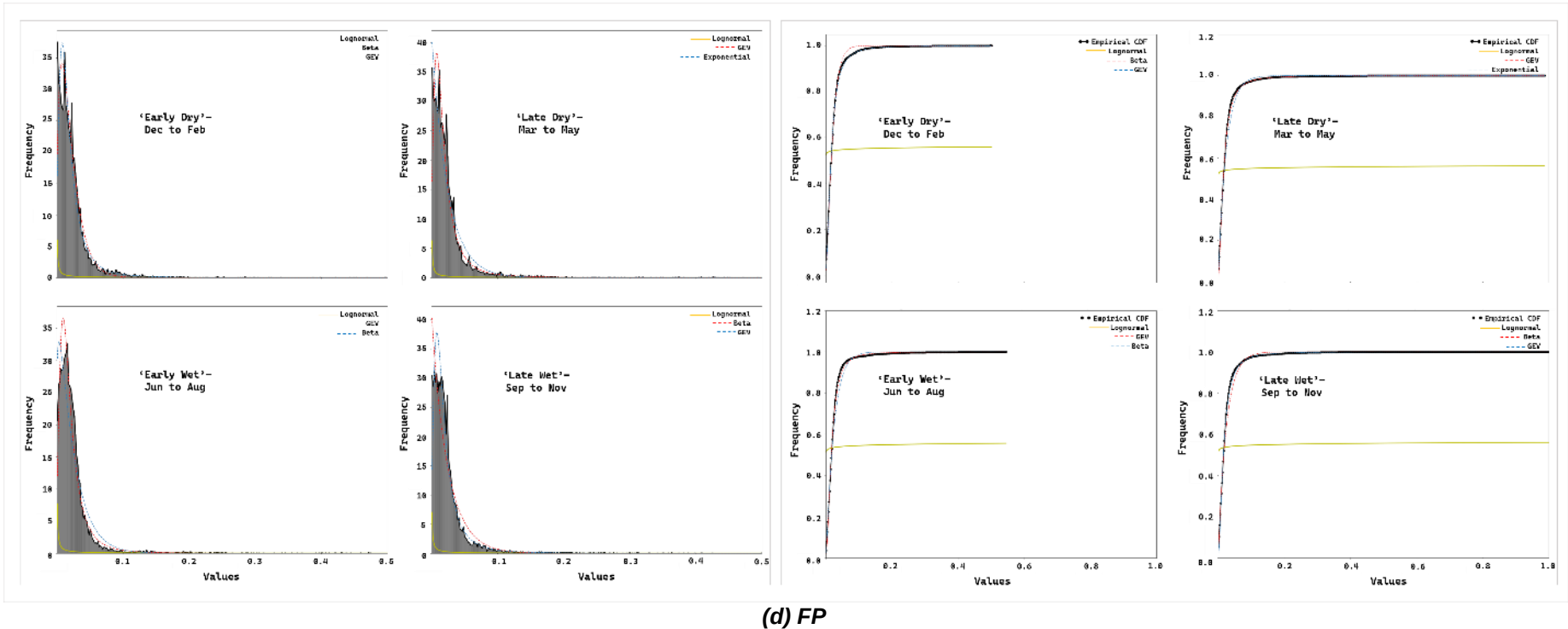


Figure 4-5 PDF and CDF plots of the top ranked distribution fits with the histogram (in bars) of the empirical data for each risk variable per season, based on RSS scoring

Table 4-6 Results of parameter estimation of the selected marginal distributions for each variable per season

Season	Variable	Marginal dist.	a ¹ or c	b	loc	scale
Early dry	PE	beta	1.182	64.949	0.000	4.310
	PU	beta	1.673	1.028	0.153	0.378
	PK	GEV	0.257	na ¹	0.547	0.103
	FP	beta	1.628	128.834	-0.001	1.673
Late dry	PE	beta	1.249	75.286	0.000	3.493
	PU	log gamma	4.708	na	0.142	0.334
	PK	GEV	0.258	na	0.624	0.106
	FP	GEV	-0.422	na	0.011	0.010
Early wet	PE	beta	1.113	181.039	0.000	8.231
	PU	weibull	1.300	na	0.528	0.179
	PK	beta	14.388	7.840	0.054	1.021
	FP	GEV	-0.338	na	0.012	0.011
Late wet	PE	beta	1.114	73.828	0.000	4.221
	PU	weibull	2.248	na	0.641	0.242
	PK	GEV	0.325	na	0.625	0.110
	FP	GEV	-0.407	na	0.012	0.010

¹ 'a' & 'b' reflects the shape parameters of beta distributions, 'c' reflects the shape parameter of all other distribution types, 'loc' is the locational parameter and 'scale' is the scale of the fit

²¹ 'na' - not applicable parameter for distribution definition

The study found that a single distribution was not the best fit for all variables. Though preliminary visualizations suggested that a single distribution could describe PE, PK, and FP, only PE was best described by a single marginal distribution (beta).

The distributions of PU reflecting the level of unavailability of Belize's renewable power supply showed the greatest variability, with a beta profile best describing its behavior during the early dry season, log gamma during the late dry season, and Weibull during the wet seasons. This was somewhat expected as seasonality significantly impacts hydropower generating capacity in river basins, requiring consideration of temperature, rainfall, evaporation, soil moisture, and runoff under changing conditions (Zhong et al., 2020).

The relationship between optimal marginal distribution and data properties were not clear. GEV distributions were well suited for higher asymmetries and heavy tailing, suggesting its appropriateness for data with greater extremities (Huang et al., 2023). However, GEV also best described three of the four seasons of PK with low skew and light negative tailing. Similarly log normal distributions that are known to be more suitable for positive values of kurtosis and skewness (Kousar et al., 2020b), performed poorly for all seasons of FP and received an average ranking for PE.

In contrast, the optimal marginal distribution of a risk factor was influenced by the nature of the risk factor. For instance, PE, an actor-related variable, was best modelled by a beta distribution. FP, an economic variable (Bessembinder & Lemmon, 2002; Korten, 2020; Usher & McLellan, 2024), and PK, a market variable reflecting Belize's grid power consumption pattern, were largely described by GEV. On the other hand, the main generalization we were able to draw on seasonal conditions, including ecological and commodity shifts, was that these variables can result in vastly different distributions across time intervals as short as 3 months.

Seasonal behavior variability among variables offered insights into individual variables and had quantitative implications for risk interdependencies, suggesting the presence of similar shifts in their dependence structures. For example, the likelihood of heavy positive tailing of FP and PE is higher during the late wet season (kurtosis 131.3 and 35.1, respectively) compared to the early dry season (kurtosis 59.7 and 4.3, respectively). By considering the dependence structure of these variables and allowing seasonal conditions to switch, estimation and expectations on tail risk can be improved (Qiu et al., 2021), allowing risk managers to adjust the probabilities and extremities of variables' effects periodically.

4.4.3 Joint distribution parameter estimation and fitting

The copula technique was used to analyze the dependency structure between samples, developing a multivariate probability distribution with uniform marginal probability distributions. The theoretical Gaussian or t-copula was selected based on the LL criterion. The evaluation results are presented in Appendix Table 0-11. Table 4-7 summarizes the selected theoretical copula, correlation matrix, and degrees of freedom for the t-copula.

The Gaussian copula was found to be the most suitable for 9 out of 16 models, while the t-copula was best for the remaining cases. This was surprising given its limitations in modeling tails and extreme observations (Durante et al., 2013; Nelson, 2006). The Gaussian performance indicated that dependencies were concentrated in the center of joint distributions, and extreme values were mostly independent (Wei & Lunde, 2022). The t-copula, on the other hand, best defined the multivariate distribution of case 1 during most seasons, indicating significant tail dependencies.

Case 1 found a positive relationship between PE and FP during early dry and late wet seasons (0.008972 and 0.0220, respectively), but an inverse relationship during late dry and early wet seasons (-0.0121 and -0.0087, respectively). The late wet season showed the strongest correlation (0.022082), followed by the late dry season, both exhibiting the heaviest tailing and positive skew. These findings suggested that while the indicated linkages were fairly weak, there was a tendency for the extreme values of PE and FP to occur together. It is noted that the observed correlations are relatively small in magnitude, suggesting that the variables are largely independent. However, even small correlations were retained in the analysis to capture subtle seasonal dependencies, particularly since extreme values and tail behavior may still influence exposure levels. These small correlations should be interpreted cautiously and not as strong linear dependencies, but as indicative of minor co-movement under certain seasonal conditions. As such, these results hold financial implications, as forecasting inaccuracies were subject to higher spot prices as a result of real-time supply adjustments. However, the inverse correlation of the late dry season revealed that there was a possibility that the resultant exposure reduced as the risk in one variable offsets the risk in the other.

Notably, since the PE index is expressed in absolute values, the directional relationship between forecast errors and spot prices is not fully captured. Overestimations of demand could indeed correspond to lower spot prices, while underestimations could correspond to higher prices. Consequently, the observed co-occurrence of extreme values reflects the magnitude rather than the direction of exposure. As such, correlations should be understood in terms of risk magnitude rather than sign, preserving the focus on inherent risk exposure rather than directional effects.

In contrast, PU and PK revealed a positive relationship in all seasons of case 2, indicating a dependence on the degree of unavailability of local renewable supply as the system's supply requirement increased. This dependency is likely due to the link between electricity supply and demand, where high demand can strain supply resources (Longstaff & Wang, 2004; Mir et al., 2020).

Table 4-7 Summary of the selected theoretical copula, the correlation matrix, and in the case of the t-copula, degrees of freedom

Case	Variables	Season	Copula	Correlation Matrix	Degrees of Freedom
1	[PE , FP]	Early dry	gaussian	$\begin{bmatrix} 1 & 0.008972 \\ 0.008972 & 1 \end{bmatrix}$	na ¹
		Late dry	t	$\begin{bmatrix} 1 & -0.012128 \\ -0.012128 & 1 \end{bmatrix}$	71.425
		Early wet	t	$\begin{bmatrix} 1 & -0.008733 \\ -0.008733 & 1 \end{bmatrix}$	50.005
		Late wet	t	$\begin{bmatrix} 1 & 0.022082 \\ 0.022082 & 1 \end{bmatrix}$	76.781
2	[PU , PK]	Early dry	gaussian	$\begin{bmatrix} 1 & 0.003132 \\ 0.003132 & 1 \end{bmatrix}$	na
		Late dry	gaussian	$\begin{bmatrix} 1 & 0.003516 \\ 0.003516 & 1 \end{bmatrix}$	na
		Early wet	t	$\begin{bmatrix} 1 & 0.005431 \\ 0.005431 & 1 \end{bmatrix}$	75.3014
		Late wet	gaussian	$\begin{bmatrix} 1 & 0.126815 \\ 0.126815 & 1 \end{bmatrix}$	na
3	[PK ,PU , FP]	Early dry	t	$\begin{bmatrix} 1 & 0.003237 & -0.026092 \\ 0.003237 & 1 & 0.021153 \\ -0.026092 & 0.021153 & 1 \end{bmatrix}$	157.532
		Late dry	gaussian	$\begin{bmatrix} 1 & 0.003517 & 0.010746 \\ 0.003517 & 1 & -0.010254 \\ 0.010746 & -0.010254 & 1 \end{bmatrix}$	na

		Early wet	t	$\begin{bmatrix} 1 & 0.005377 & -0.001673 \\ 0.005377 & 1 & -0.0115 \\ -0.001673 & -0.0115 & 1 \end{bmatrix}$	126.136
		Late wet	gaussian	$\begin{bmatrix} 1 & -0.005044 & -0.003733 \\ -0.005044 & 1 & 0.003792 \\ -0.003733 & 0.003792 & 1 \end{bmatrix}$	na
4	[PE, PK, PU, FP] (all)	Early dry	gaussian	$\begin{bmatrix} 1 & 0.010742 & -0.00567 & 0.009111 \\ 0.010742 & 1 & 0.002987 & -0.026331 \\ -0.00567 & 0.002987 & 1 & 0.021241 \\ 0.009111 & -0.026331 & 0.021241 & 1 \end{bmatrix}$	na
		Late dry	gaussian	$\begin{bmatrix} 1 & -0.016632 & 0.008526 & -0.012621 \\ -0.016632 & 1 & 0.003571 & 0.010668 \\ 0.008526 & 0.003571 & 1 & -0.010186 \\ -0.012621 & 0.010668 & -0.010186 & 1 \end{bmatrix}$	na
		Early wet	t	$\begin{bmatrix} 1 & -0.00149 & -0.008739 & -0.008215 \\ -0.00149 & 1 & 0.005264 & -0.001767 \\ -0.008739 & 0.005264 & 1 & -0.011523 \\ -0.008215 & -0.001767 & -0.011523 & 1 \end{bmatrix}$	120.770
		Late wet	gaussian	$\begin{bmatrix} 1 & 0.010845 & -0.007552 & 0.022146 \\ 0.010845 & 1 & -0.005045 & -0.003733 \\ -0.007552 & -0.005045 & 1 & 0.003792 \\ 0.022146 & -0.003733 & 0.003792 & 1 \end{bmatrix}$	na

¹ 'na' - not applicable parameter for copula definition

Yet, the strongest dependency (0.1268) was seen during the late wet season. As per Table 4-4, the mean values of PK and PU were near average (0.662 and 0.622, respectively). The risk factors were not significantly high during this period, suggesting a possible individual dependence on environmental factors. Previous literature identified that increases in temperature and humidity are linked to peaking (Mir et al., 2020) and decreases in ecological resources needed for renewable power production (Sridharan et al., 2019; Zhong et al., 2020). Therefore, PU and PK may not be related. Instead, their dependency was defined by environmental conditions - a confounding variable.

Environmental conditions may play a role in confounding variables, as evidenced by the ranking of local renewable energy resources in the merit order of supply. The SO must prioritize scheduling and allocating available resources to minimize waste or mismanagement of water and biomass (BECOL / BEL, 1991; BELCOGEN / BEL, 2007). Assuming that RE supply is mainly responsible for the grid's base load requirement, as it cannot fully meet the grid's supply requirement (43% on average, see Figure 4-1). Peaking is less likely to affect supply sources like hydropower and biomass, which are primarily satisfying the grid's base load. Instead, peaking may influence the utilization of sources used as supply reserves, such as thermal supply (11% on average, see Figure 4-1) in Belize.

In case 3, PK and PU maintained positive relationships of similar strengths as case 2 (example, early dry case 2 was 0.003132, while case 3 was 0.003237) across all seasons except the late wet season, which was defined by an inverse relationship (-0.005044) of considerably lower strength than the late wet season of case 2 (0.1268).

This structure of dependencies presented an interesting potential correlated offset, seeing as PK and FP also exhibited an inverse relationship (-0.003733), while FP positively reinforced PU during the late wet season (0.003792). In contrast, during the late dry season, PK shared a positive association with PU and FP (0.003517 and 0.010746, respectively). Meanwhile, the dependence between PU and FP was negative (-0.010254).

Case 4 expanded the joint distribution model by incorporating all study variables. It revealed a mix of relationships between variables, with positive and negative types varying across seasons. For instance, the early dry season showed the strongest positive linkage between PU and FP (0.021241), changing to an inverse relationship in late dry (-0.010186) and early wet (-0.011523) seasons before reverting to a weaker positive relationship in late wet season (0.003792).

The study found that high-dimensional distributions have a complex dependence structure, with intra-seasonal variations in relationship types and strength. Based on the variations observed across the strengths and type of correlation between risk factors from season to season, the dependence structure of high-dimension distributions were complex. This observation highlighted a few key insights about the behavior of exposure levels. First, the varying relationship types meant that one risk factor might sometimes reinforce or counteract another. In effect, reinforcement can increase the overall degree of exposure. In such instances, the SO's chances of meeting an undesired occurrence grew when risk variables converged. In contrast, counteractions resulted in the offsetting of risk factors. Offsets showed that the degree of

exposure may be reduced. As a result of offsets, the SO's likelihood of experiencing an undesired occurrence decreased as risk variables coincided.

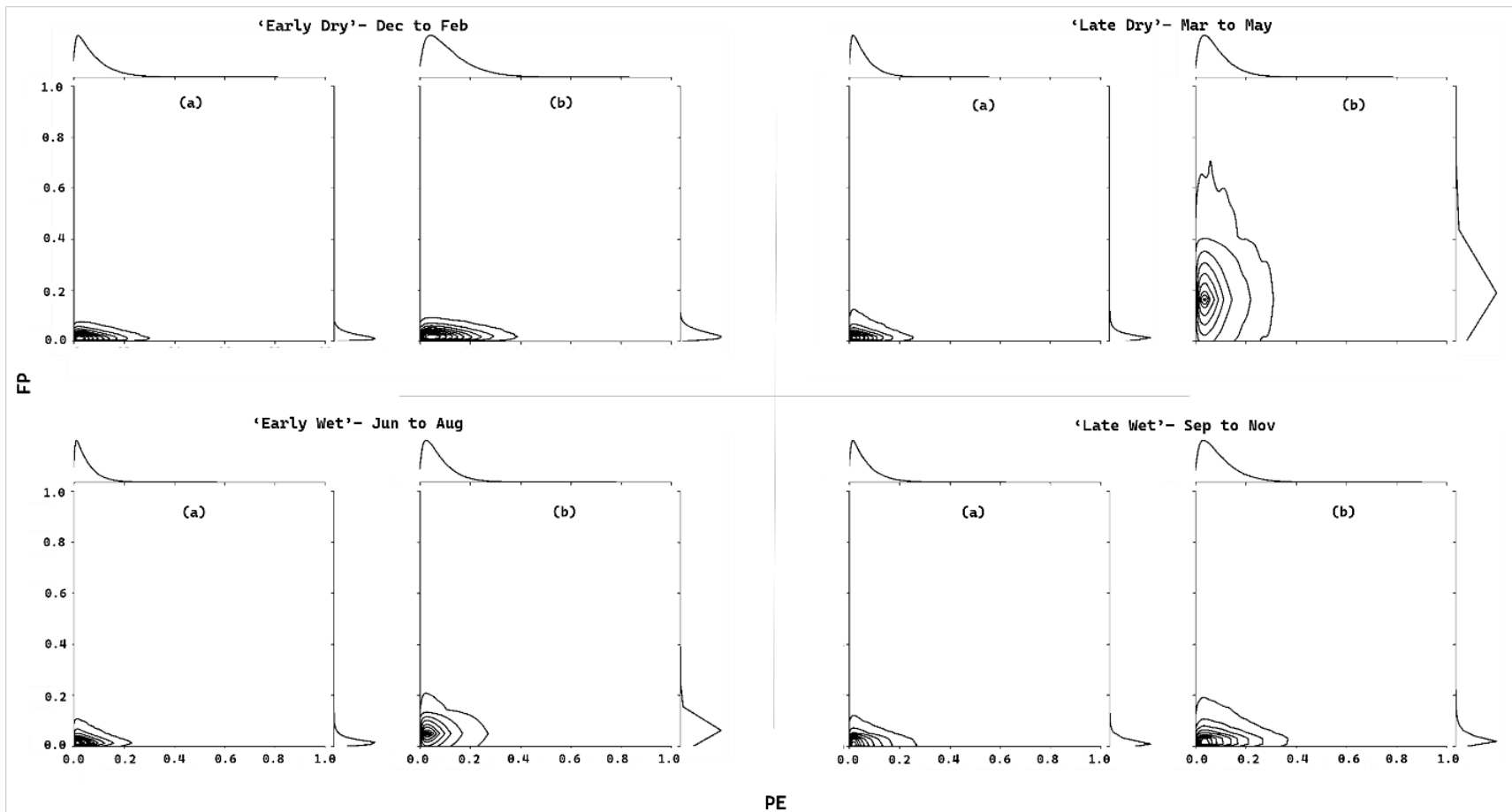
Second, the resultant level of exposure depended on the strength of the individual factors and their relationship. This meant that while a risk factor can reinforce another risk factor, lower strength relationships during periods whereby the risk of an unwanted event occurring for each risk factor is medium to low, resulted in insignificant shifts to exposure level. In turn, The SO may deem the resultant as inconsequential, although their overall exposure to unwanted events increased as a result of the correlation.

In such cases, SOs may respond by building on protective controls. In contrast, significant correlations might lead to considerable reinforcing of risk variables. As a consequence, the SO's exposure level exceeds the calculated combined exposure to risk variables. If the likelihood of undesirable outcomes is substantial, the SO may regard the resulting exposure as significant and choose to take preventative actions. The final steps of the analysis gained a deeper understanding of these interpretations.

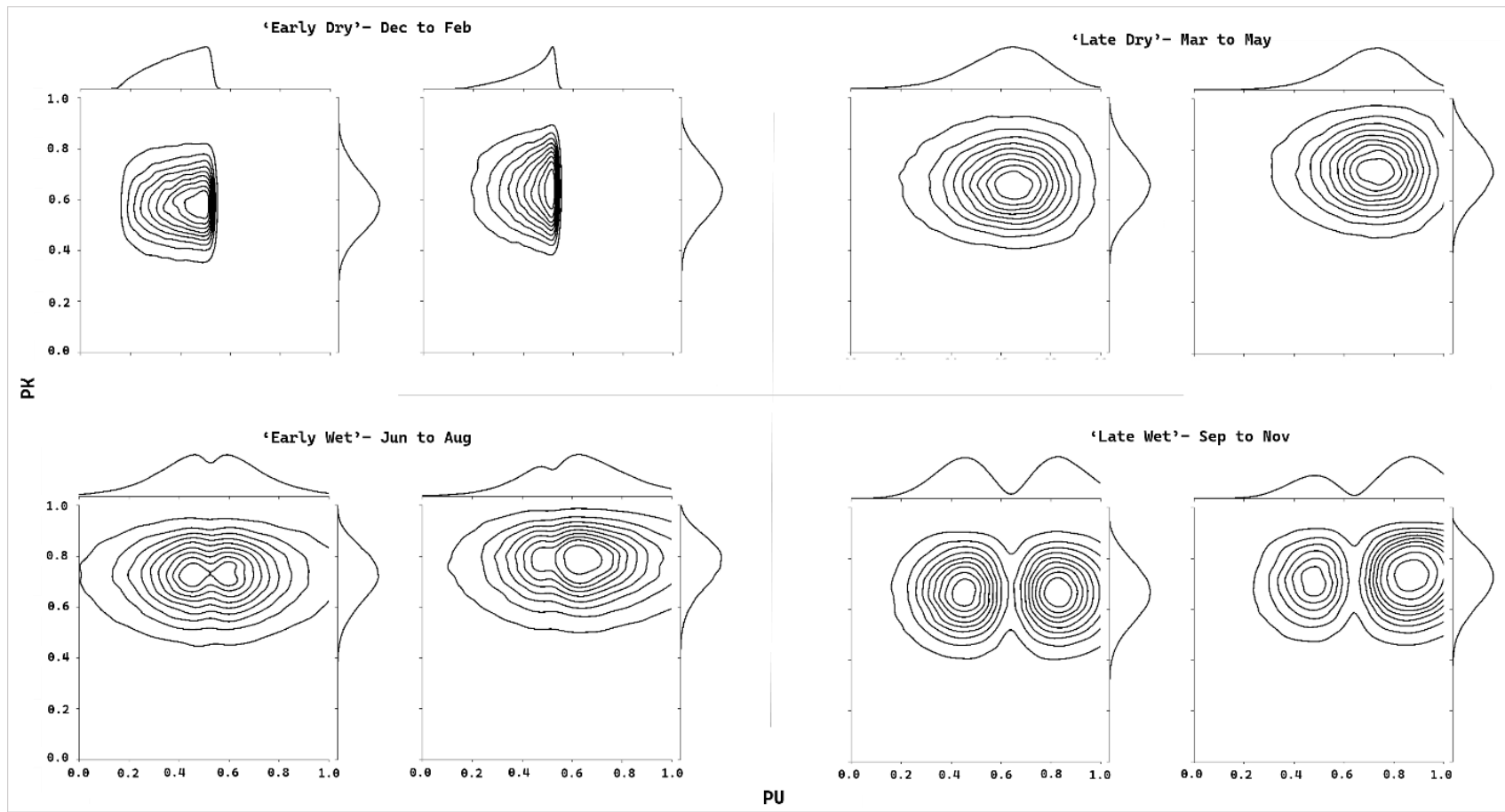
4.4.4 Relative levels of exposure per season and inferences on preventative controls

The analysis used contour plots to visually compare multivariate distributions, presenting the relationship between samples from marginal distributions and those from re-transformed marginal distributions that included copula-modelled dependencies, as shown in Figure 4-6 (a) through (d).

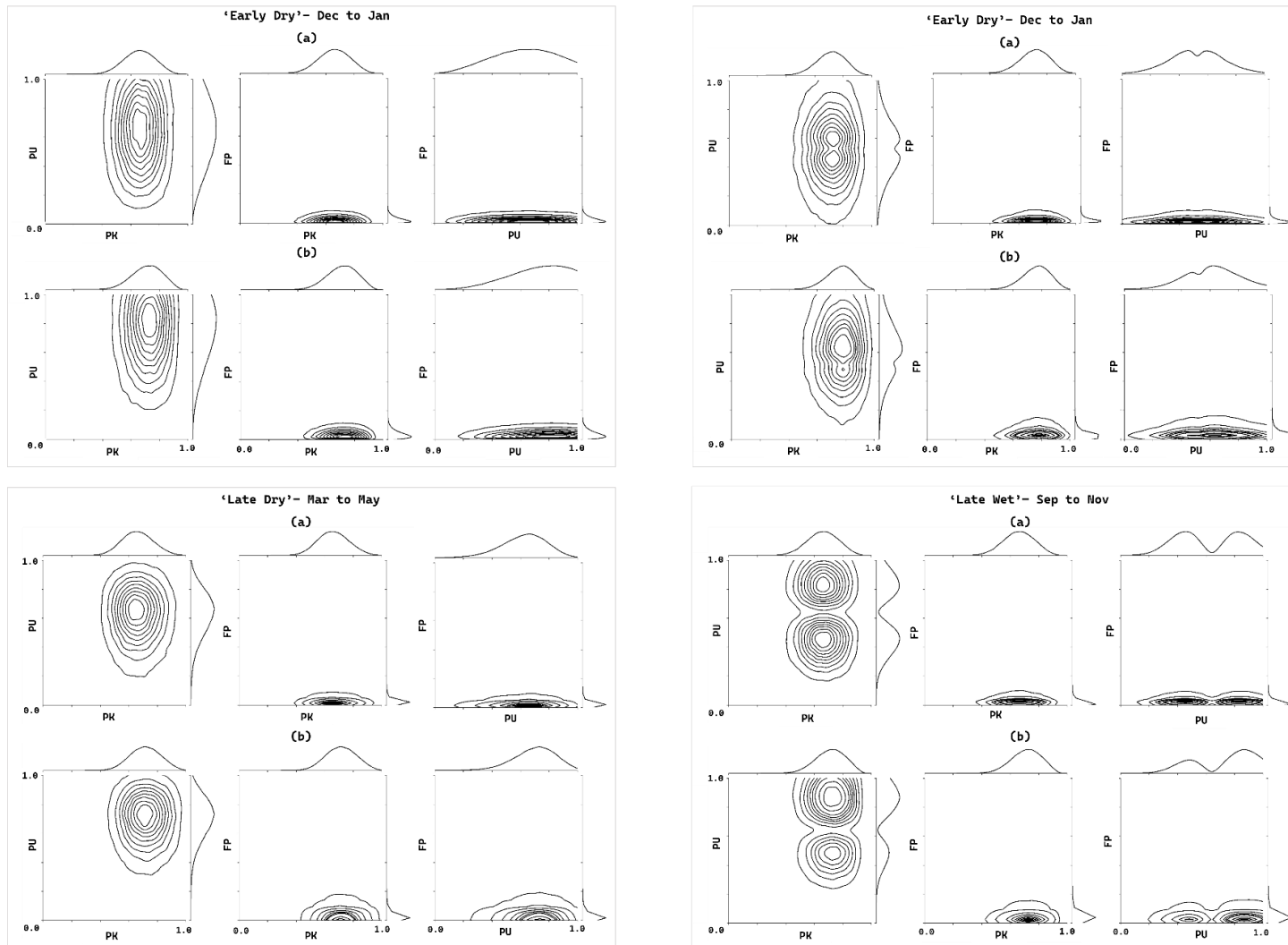
The left-hand plots in Figure 4-6 present samples drawn from the marginal distributions under the assumption of independence, without incorporating the copula-modeled dependencies. The right-hand plots show the same variables after applying the copula, which introduces the estimated interdependencies among the risk factors. This comparison allows visualization of how accounting for dependency structures modifies the joint behavior of the variables, highlighting potential scenarios of concurrent extreme outcomes that would not be captured under an independence assumption.



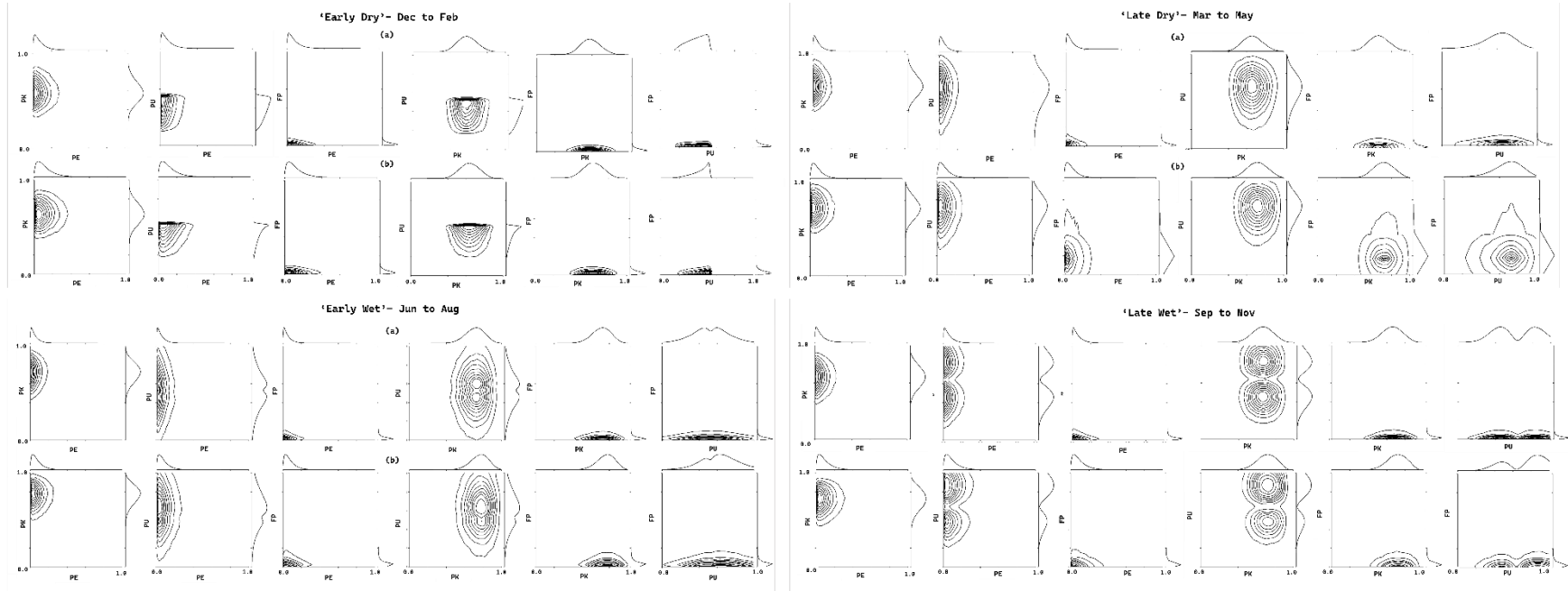
(a) Case 1



(b) Case 2



(c) Case 3



(d) Case 4

Figure 4-6 Contour plots comparing the multivariate joint distributions whereby the correlation structures between variables are (a) not included in the joint modelling, and (b) included in the joint modelling for cases 1-4 per season

Figure 4-6 (a) provides a visual representation of the relationship between PE and FP showing side-by-side results with and without the copula-modelled correlation structure. In contrast to the plots without the copula-modelled dependencies, the elongated tailing perpendicular to the x-axis (higher exposure occurrence due to FP) in the case of the copula-modelled late dry season, and parallel to the x-axis (higher exposure occurrence due to PE) in the case of the late wet season was shown.

This result suggested that although most likelihood of incidents were centrally concentrated, extreme values of PE and FP can occur together, especially when reinforcing dependencies are accounted for. The contour planes also showed that the area of exposure widened towards the upper and right-end of the plot when interdependencies were considered, indicating that despite the presence of offsets in relationships between variables, the correlated dependencies were generally positive when the copula-modelled interdependencies were considered, and thereby reinforcing supply management risk.

The study found that models without copula-modelled dependencies had slightly smaller distances between outer contour spacing, indicating that while copula-modelled interdependencies captured higher exposure levels, their unit likelihoods were less than those in models without interdependencies. As such, an SO manager can interpret the latter as a less conservative representation of risk level.

Table 4-8 presents the relative exposure results based on sampled data from marginal distributions and re-transformed marginal distributions of copula modelled dependencies. The measure denotes the exposure not exceeded by levels below the value presented in the chart, allowing for better comparison of various bounds of risk exposure levels per case and per season.

Table 4-8 Relative exposure effect of inherent risks per case ('C1'- 'C4') per season, based on joint distribution percentiles.

	Percentile	70	75	80	85	90	95
Early dry	C1	0.078	0.095	0.116	0.142	0.179	0.237
	C1 (nc) ¹	0.051	0.061	0.075	0.094	0.122	0.169
	C2	0.610	0.638	0.665	0.695	0.730	0.775
	C2 (nc)	0.555	0.583	0.610	0.640	0.675	0.722
	C3	0.527	0.565	0.610	0.651	0.695	0.749
	C3 (nc)	0.501	0.522	0.555	0.596	0.640	0.696
	C4	0.495	0.518	0.545	0.609	0.664	0.728
	C4 (nc)	0.454	0.454	0.515	0.555	0.610	0.675
Late dry	C1	0.073	0.085	0.099	0.118	0.145	0.145
	C1 (nc)	0.045	0.054	0.064	0.078	0.098	0.133
	C2	0.780	0.799	0.819	0.841	0.869	0.909
	C2 (nc)	0.717	0.736	0.757	0.781	0.811	0.855
	C3	0.730	0.755	0.780	0.808	0.842	0.887

Early wet	C3 (nc)	0.666	0.691	0.718	0.747	0.782	0.830
	C4	0.682	0.714	0.747	0.780	0.818	0.870
	C4 (nc)	0.617	0.650	0.682	0.717	0.757	0.811
	C1	0.065	0.075	0.089	0.106	0.131	0.173
	C1 (nc)	0.040	0.047	0.057	0.069	0.086	0.118
	C2	0.797	0.816	0.836	0.860	0.890	0.939
	C2 (nc)	0.732	0.753	0.775	0.800	0.829	0.871
	C3	0.741	0.768	0.796	0.825	0.859	0.909
	C3 (nc)	0.675	0.704	0.733	0.764	0.800	0.848
Late wet	C4	0.682	0.722	0.760	0.796	0.836	0.889
	C4 (nc)	0.608	0.653	0.693	0.732	0.775	0.829
	C1	0.076	0.090	0.107	0.128	0.158	0.208
	C1 (nc)	0.047	0.056	0.068	0.084	0.108	0.148
	C2	0.831	0.853	0.878	0.908	0.948	1.009
	C2 (nc)	0.760	0.785	0.812	0.843	0.882	0.942
	C3	0.771	0.800	0.831	0.865	0.908	0.977
	C3 (nc)	0.688	0.724	0.759	0.797	0.841	0.906
	C4	0.710	0.752	0.791	0.832	0.879	0.950
	C4 (nc)	0.607	0.663	0.712	0.759	0.811	0.881

¹ joint percentile estimation; no correlation structure included.

The study compared cases across seasons, based on the 95th and 90th percentiles (representing the exposure level that could arise in the worst 1 in 20 and 1 in 10 situations across a given season), case 1 had the highest exposure level during the early dry season (0.237 and 0.179), and case 2 had the highest exposure level during the late wet season (1.009 and 0.948), along with cases 3 (0.977 and 0.908) and 4 (0.950 and 0.879).

Overall implications for management were that joint exposure due to a lack of local RE and high supply requirement during the wet season were the highest inherent risk, followed by early wet and late dry seasons due to joint distribution of PU and PK. The early dry season had the lowest inherent risk for supply management. The conceptual and practical implications of the main findings were reinterpreted back to the study's conceptual framework.

Conceptually, the maximum joint exposure of PK and PU suggested that the greatest inherent risk were posed by shared SO and third-party activity. The practical implication of the share of exposure posed by PK is that there is a lack of implemented control to reduce the electricity consumed during peak demand. This implication proved consistent with the existing operation of Belize's SO. The SO had not implemented preventative control measures for demand-side management (DSM), such as demand response or energy efficiency (EE) strategies (Bakare et al., 2023). Thermal generation or additional power imports were used to meet sharp increases in demand by local agriculture and aquaculture industries. Relying on additional power generation in this situation, represented a protective control, implying that only the residual risk of peaking was managed.

The share of exposure posed by PU was largely third-party related. Possible unavailability of power generation by local RE suppliers significantly contributed to the inherent risk of the SO. Similar to PK, the protective controls of PU, including protocols for water management of the existing PPAs, were inadequate in mitigating the inherent risk impact. As previously reviewed, Belize's SO can decide on preventative control like re-purposing the RE asset (Hong et al., 2022; Nasab et al., 2022) to reduce the effect climate warming has on third-party RE supply.

At the same time, it should be noted that the large values observed in the exposure analysis indicate that certain combinations of risk variables are statistically more likely to occur, rather than being inherently dangerous. These high-exposure scenarios highlight situations that may require attention in risk management, but do not, by themselves, signify severity or imminent harm. Consequently, mitigation strategies should consider both the probability and the potential impact of these events.

Further, while the analysis identified that third-party unavailability contributes substantially to the SO's inherent risk, the adequacy of protective or preventative measures cannot be conclusively determined from this study alone. References to controls, such as water management protocols or potential re-purposing of RE assets (Hong et al., 2022; Nasab et al., 2022), are presented as general observations from the literature rather than direct conclusions drawn from the present results.

The quantitative findings revealed certain unexpected seasonal dynamics, notably higher renewable unavailability during the late wet season and comparatively greater market stability during the dry season. At first glance, these outcomes appear counterintuitive, given that hydropower output typically increases with wet-season inflows and system stress tends to rise during the dry months. Initially, the study predicted the late dry season to have the highest inherent risk. This was because Belize experienced a series of planned load-shedding due to supply shortages during the most recent late dry season. This inconsistency was likely due to the challenge of isolating preventative from protective controls in the quantitative synthesis.

The study conceived that risk which threatens the SO from achieving their objectives is categorized into two types: inherent and residual. Risk types were distinguished based on the absence/presence of protective controls. From a practical modelling perspective, accounting for actor response was a challenge. This was because actor response resulted in tangible controls, as well as intangible controls. For example, the scheduling decisions of hydropower could be influenced by the SO manager's favorable or unfavorable outlook on the season's weather conditions, which is an intangible factor that goes beyond the standard management protocols of reservoirs.

This dynamic helps explain why the model reflected higher renewable unavailability in the late wet season: operators may have exercised precautionary withholding of generation,

resulting in apparent underutilization of hydropower capacity. Conversely, the observation of greater stability during the dry season may reflect the compounding effects of proactive management, including early dispatch planning, import scheduling, and demand moderation measures implemented ahead of expected stress conditions.

These findings underscore the challenge of representing behavioral and institutional responses within quantitative risk frameworks. Literature had prior highlighted the challenge of quantifying aspects like mismanagement or optimism (Bachev, 2013). Further, while this study's models neatly categorize management into seasonal groups, it was acknowledged that actor response may not always align with these boundaries. For example, supply decisions made during the early parts of the year can impact the inherent risks of the late wet season, which contractually, occurs at the end of an annual cycle. The methodological approach can be improved by introducing a time-varying supply expectation variable to capture actor response. Accordingly, future research could strengthen methodological robustness by incorporating a time-varying supply expectation variable or similar behavioral proxy, capable of capturing the evolving influence of actor response and strategic management decisions across seasonal cycles.

Conversely, including variable dependency in the quantitative synthesis proved valuable. The study found that modelled interdependencies led to higher exposure levels in different seasons. The largest difference was observed in case 4 during the late wet season (0.103), while the smallest difference was observed in case 1 during the late dry season (0.012). It should be noted that while the observed difference of 0.103 in case 4 during the late wet season indicates some amplification of exposure due to the modeled dependency structure, the magnitude is relatively small. This suggests that the reinforcing effect of risk factors exists but may be modest in practical terms, and the discussion emphasizes the presence of dependency rather than implying a critically large impact. This confirms the reinforcing effect of risk factors due to their dependency structures. At the same time, the analysis showed that negative relationships between variables can reduce risk, as seen with case 4's four-variable model resulting in a lower exposure level than the bivariate case 2 for all seasons.

It was evident that identifying and selecting risk factors was crucial for quantifying interdependencies. Previous literature suggested that risks can be under-estimated due to ignorance of inherent interdependencies. Results also showed that if risk factors are not comprehensively identified, and their dependencies not adequately captured, exposure level can result in overly conservative estimates, resulting in inconsistencies between empirical estimations and field evidence.

4.5 Chapter Summary and Practical Implications

This study examined inherent risks associated with power supply management based on the operations of the SO and relevant third-parties. Two primary objectives were defined, namely (i) identify inherent risk factors and variables to appropriately represent power

supply related exposures, and (ii) evaluate the SO's level of exposure from these risk factors.

Its findings aimed to enhance awareness of interdependence, leading to more informed decisions and investments in preventative risk management control, particularly among small developing countries. We proposed that by considering interdependencies and possible coincidences of risk variables, the quantification of risk may reveal a larger potential impact on the power sector.

To fulfill the research objectives, the study developed a seasonal multivariate approach identifying risk factors and selecting variables, developing univariate distribution models for each risk factor, and generating multivariate distributions using the copula method to define the dependency structures for four scenarios. Joint risk exposure were computed based on varied percentile measures for each scenario, allowing comparison of exposure level.

Beta distributions were the most effective way to model the actor-related variable. GEV largely provided suitable descriptions of economic and market characteristics. Meanwhile, the variable extensively impacted by seasonal factors, including ecological and commodity variations, resulted in greatly varying distributions between seasons.

The Gaussian copula was determined to be the best fit for the majority of the models, demonstrating that dependencies were concentrated in the center of joint distributions and extreme values were mostly independent. However, the t-copula best described case 1's multivariate distribution during most seasons, showing that the PE-FP joint distribution had large tail dependencies. Joint distributions showed that, despite the weak links, extreme values might occur simultaneously.

Risk factors can sometimes reinforce or offset each other, influencing the behavior of exposure. This was observed in exposure levels, revealing periods of increased or decreased exposure to risk factors. Copula-modelled interdependencies capture higher exposure levels but have less unit likelihoods, making them a more conservative representation of risk level for SO managers.

Findings suggested that inherent risk posed by the joint distribution of PK and PU presented the highest inherent risk. These results implied that protective measures were no longer sufficient in mitigating the threats associated with peaking and climate impact on RE power generation. Practical implications highlight that preventative controls should be prioritized in the areas of demand-side management and incremental re-purposing of RE infrastructure.

A limitation of the methodology was incorporating intangible aspects of actor response, like optimism or making management decisions under varying levels of information. Moreover, the limitation extended to accounting intangible factors vary SO response over

time. For example, hydropower scheduling decisions may be influenced by the SO manager's favorable or negative outlook on weather conditions, as well as how this outlook evolves over time. Future study can enhance the methodological approach by using a time-varying supply expectation variable to capture cross-seasonal exposure.

Further, for the purposes of this study, risk factors were analyzed across four seasonal categories—early dry (December–February), late dry (March–May), early wet (June–August), and late wet (September–November). This allocation reflects locally recognized seasonal periods relevant to hydropower inflows and operational planning. While monthly precipitation or biomass harvest data could further justify this classification, such climatological datasets were not comprehensively available. Consequently, the seasonal categorization should be interpreted as a practical approximation, suitable for capturing broad seasonal variations in hydropower availability, with the understanding that future studies could refine this categorization using empirical hydrological data.

Chapter 5 Conclusion

5.1 Overview

This thesis developed and conducted a comprehensive risk analysis of Belize's power supply system from the perspective of the SO. SOs manage power supply operations, considering risk factors. Effective risk assessments enable SOs to make informed power supply decisions. In small developing countries, managing risks is crucial due to disruptive events that divert resources from long-term progress. Consequently, SOs prioritize risk reduction to mitigate the likelihood of significant disruptions.

SOs aim to ensure sufficient supply to meet demand, with sub-objectives for allocating and scheduling power supply to achieve the lowest cost, maintain excellent power quality, and favor renewable or clean energy sources, enhancing overall efficiency. However, the industry lacks comprehensive study on inherent hazards in power supply management, highlighting a significant gap in understanding and implementing preventative measures for SOs.

The research demonstrated that risk analyses are critical components of energy sector decision-making. Through the investigations carried out in this body of work, the study formulated frameworks based on socio-econometric techniques and tools for identifying and measuring risk factors that can enable SOs to develop the appropriate management strategies to mitigate the exposure of their systems in the medium and long term through system change.

One of the most significant achievements of this thesis' outputs were the frameworks which allow decision-makers to identify and measure a wide range of risks at regional and global levels for a small developing country with little global influence, yet was able to bring the concepts and interpretations down to the local level for the SO.

For example, in Phase 1, the study uncovered how trends in RE technologies, a global phenomenon, can have significant impacts on the local sector. These possible impacts have shifted SOs' attention to risk analyses to understand the hazards these novel technologies pose.

This phase also highlighted how changes in the natural environment have also enhanced SOs' attention to risk analysis. Local weather patterns have exposed water and agricultural resources, altered indigenous electricity supply and created a quantity risk in the balance between imports and indigenous renewables.

Another important consideration of this thesis, observed in phase 3, was the interconnected input-output relationship between SOs and third-party suppliers, emphasizing the need for SOs to be aware of the inherent risks faced by these suppliers, thereby emphasizing the importance of a comprehensive system investigation.

One of the strongest illustrations of this relationship was seen through the Belize—Mexico interconnection, explored in phase 2. While findings revealed that hourly market premiums were largely dependent on the pricing properties and system conditions of the supplier's (Mexico) side, with negligible influence from the buyer's (Belize) side. Yet, results also demonstrated that the rare high-impact price shocks and prolonged periods of volatile clusters of the Mexican market can significantly affect the price exposure of Belize's local power costs. These findings affirmed the association between a third-party's activity and the inherent risk faced an SO.

While the techno-economic scope of this study necessarily limited the analysis of Belize's reliance on Mexico to primarily economic considerations, the qualitative findings underscore the substantial uncertainty and ambiguity surrounding the country's future dependence on imported electricity, as perceived by key stakeholders. These insights highlight the potential for future research to examine how governance structures, institutional capacity, and the strategic mindset of actors can critically shape national energy planning.

Continued reliance on imported electricity from Mexico exposes Belize to long-term energy security risks, including external shocks, price volatility, and misalignment with national climate commitments due to Mexico's LNG-heavy generation mix. While imports may seem economically advantageous in the short term, they undermine energy resilience and sovereignty. A long-term strategy focused on expanding domestic renewable generation—such as solar PV, wind, and battery storage—could reduce import dependence, enhance system reliability, and support Belize's climate and sustainable development objectives.

Phase 3 demonstrated how incorporating third-party activity increased the complexity of the framework. A part of the reason for the increased complexity was due to the multiple classes of relationships between the SO and third-parties. While the most recognizable classification of relationships between SOs and third-parties was technological, it was important to understand that the SO carried-out its activity within Belize's regulatory environment. Consequently, this study developed multi-faceted frameworks that can delve into numerous aspects of the sector:

Phase 1 focused on assessing the structural and managerial risks of Belize's power mix through a qualitative three-step process. An exploratory case study was employed, incorporating semi-structured interviews and documented sources. The methodology included site identification, sampling, data collection, processing, and presentation, aiming to address inherent risks. Step 1 involved mapping the electricity supply system's structure and key actors. In Step 2, inherent risks were identified, categorized into five dimensions (e.g., economic, social), and their underlying causes were screened. Finally, Step 3 characterized risk dimensions based on complexity, uncertainty, and ambiguity, highlighting their threats to long-term progress amid immediate societal demands.

Phase 2 focused on analyzing Belize's power system exposure to price risks from cross-border electricity trade. The hypothesis suggested that price risk exposure primarily

depends on Mexico's pricing properties and system conditions, with minimal influence from Belize due to the significant size difference. The study introduced a methodological approach to investigate the impact of cross-border supply on Belize's price risk exposure, employing hourly ARMA-ARCH models for pricing volatility and vector autoregressions to assess factors affecting forward premiums at the delivery exchange node.

Phase 3 arrived at the measured exposure to inherent risks. This phase developed a methodology to assess inherent risks in power supply management concerning the SO and third parties. Two key objectives were set: (i) to identify inherent risk factors representing power supply exposures, and (ii) to evaluate the SO's exposure from these factors. To address (i), risk factors were qualitatively synthesized from operations, while (ii) used multivariate analysis to measure exposure in Belize. Selected variables represented risk factors, with descriptive statistics calculated to show variability. Univariate distribution models were created, and the copula method was applied to formulate multivariate risk distributions for various scenarios, enabling exposure comparison.

5.2 Gaps Addressed

The multi-faceted frameworks addressed methodological research gaps. First, this study identified that the power sector urgently needs to identify, measure, verify, and manage risks linked to rising energy demands and the energy transition debate.

Second, policymakers face new challenges from the external environment and must regularly review regulations, market structures, and policies, like environmental restrictions and utility regulations, to advance clean technology.

Third, and most essential, the review of past literature identified that there was primarily a focus on residual risks, which represent only a subset of the actual risks. Addressing only a subset of risk, hinders effective management. Inherent risk, which exists before routine controls are applied, is crucial yet often overlooked.

This gap leads to a preference for methodologies targeting residual risks, such as unit commitment (UC) optimization in addressing wholesale power supply management, thereby biasing perspectives towards protective rather than preventative controls.

The selected case study addressed contextual research gaps. The case study examined power generation mixes in emerging economies, specifically Belize, due to limited existing research. Unlike developed nations, emerging economies focus their resources on recovery from disruptions, necessitating risk mitigation. This reflects a common reality of small developing countries globally.

Small developing countries face unique challenges that threaten affordable energy self-sufficiency and have limited technological options and resource exploration opportunities.

Often-times, studies are conducted based on the context of larger nations. The findings of which small developing countries attempt to customize to fit their local contexts. The problem with this approach is twofold:

First, size remains a significant factor. Experiences shared by small developing countries are not factored in the analysis of large markets. Some of these experiences can carry significant implications on risk. Stage 1 of this study revealed decisions and strategies that were unique experiences to Belize's small power market.

In stage 1, it was shown that Belize's strategies carried significant impact on the structure and management of power supply resources. For example, findings showed that Belize's small electricity market size limited its purchasing power in procuring new capacity to expand the market.

In response, the sector implemented stringent regulations that guarantee cost-recovery. Results revealed that the guarantees helped to de-risk investment opportunities for new entrants. However, the guarantees also caused prolong periods of limited investment opportunity due to the slow growth of the power demand market. Such experiences are unique to the small developing nation's context. Further, this strategy forms the regulatory framework under which power supply is managed. Clearly, risk management options for nations that are not subject to similar conditions would differ.

Second, the strategies used by smaller markets to mitigate the inherent risks are less explored than the strategies used by larger markets. For example, in stage 2, this study examines the dynamic exposure of Belize's power system to the price risks associated with cross-border electricity trade. A strategy that includes cross-border electricity trade can protect small developing countries from external price shocks linked to global energy commodity prices while simultaneously exposing them to risks from reliance on foreign power markets.

Still, literature revealed that for larger markets, energy security strategies conventionally take a country-centric approach, whereby large markets emphasize self-sufficiency rather than interconnectivity. This means lesser studies on cross-border interconnection strategies, leaving a contextual gap for markets of small developing countries that may consider implementing this strategy.

5.3 Key Findings

The study analyzed Belize's supply structure, identifying five actor groups: the Government of Belize's energy unit, the Public Utilities Commission, Belize Electricity Limited, domestic and non-domestic independent power producers, and consumers. The wholesale supply market was structured using formal relationships, laws, and procedures for decision-making, strategy implementation, and resource allocation.

Perceptions of risk factors varied at the group level, with conflicting interests creating risks in small developing countries with limited actor groups. The authors found clear distinction between these actors was primarily established through their resources, which shaped their power and interest.

The study highlighted economic risks in Belize, including reliance on imported power and vulnerability to the Mexican market. Imports pressured foreign currency availability and incurred foreign exchange costs. The study also highlighted social risks related to power supply technologies like solar and wind, which require space due to rising hazard-prone zones. The study also highlighted potential disputes between urbanization growth and development actors, as well as the public's interest in biodiversity. Technological risks included challenges with indigenous resources and a shortage of essential ancillary supply functions, which are crucial for system stability, quality, reactive power management, second-order regulation, system backup, and storage.

Rising sea levels and flooding posed environmental risks to indigenous resources, particularly hazardous zones, and alter the availability of indigenous electricity supply. Local weather patterns exposed water and agricultural resources, creating a quantity risk in the supply balance of imports versus indigenous renewables. Regulatory arrangements to stimulate de-risking of projects for low-cost financing presented legal and political risks due to long-term guarantees on sales and returns.

Slow market growth in Belize limited investment capacity until peak demand growth fosters new entry. Conflicting management decisions, such as a fixed-cost model of domestic supply and reliance on electricity imports, limited domestic options in a small developing country with limited purchasing power. Regulatory arrangements to attract investments also deterred new investment and technologies for extended periods.

Power imports which accounted for, on average 40%, of Belize's wholesale power supply was determined to carry significant inherent price risk. The study revealed that market volatility, particularly spot pricing, had rare high impact shocks and prolonged periods of volatile clusters. Premiums largely depended on the supplier's pricing properties and system conditions, with negligible influence from the buyer's loading patterns and local generation output. Significant effects were found during certain hours with buyer's loading and transmission loss patterns. Practical implications suggested occasional losses due to information delays and misalignment of risk factors and premiums.

Price changes showed positive skewness, with the most significant right-skewed tailing occurring during afternoon-to-night hours. These behaviors were consistent across forward and spot pricing series, indicating a positive association between price risk exposure and expected price trends, which vary in magnitude across a given day. Moreover, volatile clustering is more significant than the impact size, as indicated by comparisons of alpha and beta parameters.

Belize was compensated 7% to 51% via forward premiums for intra-day risks, while spot market trading increased risk and higher price margins, potentially magnifying economic losses. Unexpected behavior in spot and forward prices did not efficiently transmit to percentage forward premiums, leading to delays in their impact. This resulted in Belize buyers trading at a loss or not benefiting economically due to mistiming when purchasing large volumes of electricity supply or small quantities.

Distribution analyses revealed that risk factors can influence exposure behavior, with periods of increased or decreased exposure. Risk factors can either reinforce or offset one another, affecting exposure behavior. In Case 1, early dry and late wet seasons showed a reinforcing relationship (PE: 0.008972, FP: 0.0220), whereas late dry and early wet exhibited an inverse correlation (PE: -0.0121, FP: -0.0087). Case 2 exhibited the strongest dependency (0.1268) between PK and PU in the late wet season. Case 3 identified a negative correlation between PK and FP (-0.003733), with FP positively reinforcing PU (0.003792). The late dry season showed positive associations of PK with PU (0.003517) and FP (0.010746), while Case 4 indicated complex intra-seasonal relationships.

Copula-modelled interdependencies capture higher exposure levels but have less unit likelihoods, making them conservative for SO managers. The highest inherent risk was found in the joint distribution of PK and PU, suggesting protective measures are insufficient in mitigating threats from peaking and climate impact on renewable energy generation. While this analysis identified that third-party unavailability contributes substantially to the SO's inherent risk, the adequacy of protective or preventative measures cannot be conclusively determined from this study alone. Controls, such as water management protocols or potential re-purposing of RE assets are presented as general observations from the literature rather than direct conclusions drawn from the present results, warranting considerations for future work.

5.4 Theoretical & Practical Implications of Research

Findings provided implications on how values and roles shaped risk perceptions among different actors, impacting risk management strategies. For instance, regulators in the 'high-influence-low-interest' group heavily relied on regulations for risk mitigation. Although uncertainty highlighted the need for adaptive strategies, regulations were emphasized for managing complexities.

The practical significance of the thesis lies in its contribution to strengthening evidence-based policymaking in Belize's power sector by identifying critical areas of inherent risk and proposing proactive, preventative management approaches. The findings highlight that addressing ambiguity, foreign market exposure, and interdependent risk variables—such as peak demand (PK) and renewable energy unavailability (PU)—is essential for enhancing energy security and long-term system resilience.

Several policy recommendations derived from the study are practicable within the national context. These include expanding risk mitigation strategies beyond regulatory compliance to promote adaptability in power supply management, incorporating stakeholder participation in co-creating risk solutions, and employing financial hedging instruments such as contracts for difference or futures to manage import price volatility. Furthermore, prioritizing preventative risk controls in demand-side management, load-shifting initiatives, and renewable energy infrastructure planning can strengthen both operational stability and sustainability outcomes.

Risk coincidences and offsets can Improve understanding of interdependence for better decision-making and investments in preventative risk management, especially in small developing countries. Addressing risk variables could highlight broader impacts on the power sector, emphasizing the need for prioritizing preventative controls in demand-side management and RE infrastructure repurposing.

It should be noted that while the joint distribution of PK and PU indicates a relatively high probability of co-occurrence, this alone does not provide direct evidence regarding the adequacy of existing protective measures. The discussion of potential mitigation strategies—such as demand-side load management for PK or supply-side infrastructure considerations for PU—is therefore presented as a general recommendation based on observed risk exposure patterns, rather than a conclusion directly drawn from this analysis. A proactive and institutionalized risk governance framework in Belize can be feasibly implemented by allocating clear mandates and establishing structured coordination across the power sector. The Ministry of Energy and Public Utilities would serve as the central authority responsible for strategic oversight, formalizing a Power System Risk Governance Committee tasked with conducting periodic risk reviews, endorsing scenario analyses, and ensuring alignment with national energy security objectives.

The Public Utilities Commission (PUC) can operationalize the study’s findings by embedding quantified joint-risk indicators into regulatory instruments — including procurement approvals, reserve margin requirements, and tariff determinations — particularly during seasons identified as high-exposure in the copula-based models.

BEL, in its role as SO, would implement the operational dimension of risk mitigation through dynamic reserve thresholds, enhanced load and renewable forecasting, and activation of pre-defined contingency procurement protocols once jointly modeled risk triggers are reached.

Independent Power Producers (IPPs) would be obligated, through updated licensing conditions or standardized PPAs, to provide timely generation availability and operational data necessary for risk quantification.

To reinforce accountability, Cabinet could require annual reporting of system risk exposure, mitigation actions taken, and progress toward climate-resilient capacity expansion. Collectively, these measures transform the study’s analytical outputs into

institutional practice — shifting Belize from reactive crisis response toward anticipatory energy system governance that reduces vulnerability to correlated supply disruptions and market volatility.

While this study is grounded in the Belizean context, several findings demonstrate potential transferability to other small developing countries with comparable energy and governance characteristics. The structural features examined—such as limited generation capacity, dependence on imported fuels, regulatory capacity constraints, and fiscal vulnerability—are common among small power systems in the Caribbean and Central America. In this regard, the findings may hold relevance for countries such as Barbados, Jamaica, Saint Lucia, and Honduras, where similar institutional and infrastructural challenges shape energy policy and diversification efforts.

The broader applicability lies not in direct generalization, but in analytical transferability (Lincoln & Guba, 1985), whereby the mechanisms and interdependencies identified—such as stakeholder coordination, regulatory responsiveness, and external financing influence—reflect systemic conditions characteristic of small developing countries. This aligns with the World Bank’s recognition that ‘Small States’ share structural challenges—small domestic markets, vulnerability to external shocks, and high exposure to climate and economic risks—that require tailored policy and institutional approaches. Consequently, the insights derived from Belize’s case may inform comparative analyses or policy learning among other small island and small-grid economies navigating the transition toward more sustainable, diversified energy systems.

Future research on the aspect of these countries’ current and future development stage by examining how the institutional fragility of governance systems, often characteristic of small developing countries, affects strategic energy planning. Governance capacity serves as a critical determinant of the effectiveness and continuity of risk management frameworks. Investigating this relationship could yield deeper insights into how institutional robustness shapes strategic planning.

While the study identified and analyzed key inherent risks related to Belize’s power mix management, a key limitation is that it did not extend to risks arising from natural disasters or climate change impacts. The exclusion of these dimensions was deliberate, as the methodological framework applied—comprising techno-economic modeling and probabilistic risk analysis—was specifically designed to assess operational and structural risks within power supply management, rather than exogenous environmental hazards. Incorporating climate and disaster-related risks would require a fundamentally different analytical approach, such as climate impact modeling, geospatial vulnerability assessment, or integrated resilience modeling, supported by long-term meteorological and infrastructural data. This study utilized a five-year data period and was therefore limited to providing insights on short-term weather patterns rather than long-term climate shifts.

Nonetheless, recognizing the increasing frequency and severity of climate-related events in the region, future research could expand on this work by integrating climate vulnerability and disaster resilience dimensions into the inherent risk framework. This would allow for a more holistic understanding of how climate-induced shocks may compound existing operational risks and influence long-term energy security and planning in small developing countries such as Belize.

Finally, while the quantitative analysis provides valuable insights into the dependency patterns among key supply variables, the findings are interpreted as indicative of statistical dependency rather than causal influence. The applied methods—such as correlation and copula-based modeling—capture the strength and direction of associations but do not establish causation. This methodological limitation constrains the ability to infer directional or underlying causal mechanisms driving these relationships. Future research could address this by employing causal inference frameworks, such as time-series regression or structural equation modeling, to validate and deepen the understanding of the directional relationships suggested by the current results.

While copula-based multivariate assessment principally reproduces dependency structures observed in historical data, the results nonetheless point to practical policy levers that the SO and regulators can deploy to reduce inherent exposure going forward. Building on the identified co-dependences and seasonal exposure peaks, the SO should pursue a two-track strategy of preventative structural change and adaptive operational measures.

For instance, preventative changes include accelerating domestic renewable capacity deployment (with paired storage) to reduce import dependence and price exposure; diversifying import sources and hedging arrangements (e.g., forward contracts, contracts-for-difference) to mitigate spot-market volatility; and embedding resilience criteria into procurement (minimum availability, penalties for prolonged underperformance).

Meanwhile, adaptive operational measures can include raising targeted reserve margins during identified high-exposure seasons, deploying demand-side management and price signals (TOU/critical-peak pricing) to blunt peak risk, and expanding routine preventative maintenance and redundancy on critical local units. Complementary institutional actions are also required: improve short-term forecasting and real-time monitoring (AMI and hydro inflow telemetry), formalize information-sharing protocols with major third-party suppliers to reduce ambiguity, and design contingency procurement protocols that prioritize rapid, contractually clear emergency responses.

Together, these changes — informed by the multivariate exposure patterns highlighted in this study — would shift emphasis from solely protective (residual) controls toward preventative controls that reduce the system's inherent exposure to correlated price and quantity shocks.

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Appendix

Table A-1 Gross electricity generated (kWh) by suppliers, percentage share reliance, renewability and dependence from 2009 to 2022

Gross generation (kWh)														
Supplier	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Electricity imports	216,233,228	159,876,375	170,611,926	237,864,369	234,069,725	233,150,422	254,857,688	243,429,443	230,138,201	235,154,984	383,726,057	239,368,146	381,188,451	324,074,736
Mollejon (Hydro)	146,847,868	138,861,210	122,517,000	107,129,130	127,465,440	128,178,740	120,173,391	129,591,050	120,521,948	122,087,890	34,231,414	68,867,040	77,411,007	117,636,949
Chalillo (Hydro)	33,224,938	37,200,126	30,192,113	19,608,752	31,826,852	34,330,128	31,601,216	35,490,720	38,578,978	31,854,641	6,959,863	15,426,525	19,740,833	34,649,075
Vaca (Hydro)		73,662,738	79,541,038	72,300,756	83,998,425	82,846,507	74,105,413	82,003,836	89,121,308	78,593,927	23,838,496	42,085,853	50,054,726	73,156,276
HML (Hydro)	7,783,000	13,586,800	12,524,100	9,556,200	15,458,900	10,520,800	10,229,000	13,499,500	14,517,605	15,133,000	9,966,400	8,780,867	9,937,298	12,914,209
BAPCOL (Thermal)	48,782,377	4,460,857	-	3,578,370	954,241	2,807,734	11,948,176	17,497,111	19,436,138	37,050,810	85,217,040	10,845,178	40,218,174	15,070,354
Belcogen (Biomass)	1,370,067	48,174,788	70,719,975	64,506,362	48,858,655	66,355,490	83,174,842	78,983,037	63,938,501	71,896,967	68,877,718	47,668,297	24,414,054	59,061,755
Santander (Biomass)									18,400,703	21,937,155	23,522,191	34,299,493	33,083,342	34,742,852
JICA (solar)				255,000	590,649	623,470	560,084	622,379	581,808	602,369	657,974	462,861	595,000	470,000
PSF (solar)														454,000
CCK / GT (Thermal)	18,760,000	7,608,000	6,910,000	13,632,000	8,439,000	8,108,000	11,732,124	14,354,000	15,514,000	16,848,000	33,173,000	8,943,000	10,858,000	14,226,000
Total	473,001,478	483,430,893	493,016,152	528,430,939	551,661,887	566,921,291	598,381,933	615,471,076	610,749,190	631,159,743	670,170,152	476,747,260	647,500,886	686,456,206
% share reliance	45.7%	33.1%	34.6%	45.0%	42.4%	41.1%	42.6%	39.6%	37.7%	37.3%	57.3%	50.2%	58.9%	47.2%
% share RE	40.0%	64.4%	64.0%	51.7%	55.9%	56.9%	53.5%	55.3%	56.6%	54.2%	25.1%	45.6%	33.2%	48.5%
% share dependence	14.3%	2.5%	1.4%	3.3%	1.7%	1.9%	4.0%	5.2%	5.7%	8.5%	17.7%	4.2%	7.9%	4.3%

Table A-2 Installed capacity (MW) by suppliers, from 2009 to 2022

Capacity (MW)	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Electricity imports	50.00	50.00	50.00	50.00	50.00	50.00	50.00	50.00	50.00	50.00	50.00	50.00	50.00	50.00
Mollejon (Hydro)	25.20	25.20	25.20	25.20	25.20	25.20	25.20	25.20	25.20	25.20	25.20	25.20	25.20	25.20
Chalillo (Hydro)	7.00	7.00	7.00	7.00	7.00	7.00	7.00	7.00	7.00	7.00	7.00	7.00	7.00	7.00
Vaca (Hydro)		19.00	19.00	19.00	19.00	19.00	19.00	19.00	19.00	19.00	19.00	19.00	19.00	19.00
HML (Hydro)	2.40	2.40	2.40	2.40	2.40	2.40	2.40	2.40	2.40	2.40	2.40	2.40	2.40	2.40
BAPCOL (Thermal)	15.67	15.67	15.67	15.67	15.67	15.67	15.67	15.67	23.50	23.50	23.50	23.50	23.50	23.50
Belcogen (Biomass)	12.50	12.50	12.50	12.50	12.50	12.50	12.50	12.50	12.50	12.50	12.50	12.50	12.50	12.50
Santander (Biomass)									8.00	8.00	8.00	8.00	8.00	8.00
JICA (solar)				0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.45
PSF (solar)														1.00
CCK / GT (Thermal)	23.80	23.80	23.80	23.80	23.80	23.80	23.80	23.80	23.80	23.80	23.80	23.80	23.80	23.80
Total	136.57	155.57	155.57	156.02	156.02	156.02	156.02	156.02	171.85	171.85	171.85	171.85	171.85	172.85

Table A-3 Total electricity sold (kWh) by Belize's grid per customer class and peak grid demand (MW), from 2009 to 2022**Electricity sales
(kWh)**

	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Residential	234,595,636	241,777,168	251,764,491	250,883,593	159,333,460	164,709,482	181,455,059	199,843,234	209,180,223	218,989,240	239,191,669	245,265	252,092	239,852
Commercial	129,305,069	128,762,715	132,755,713	148,906,754	255,345,762	262,185,837	274,985,851	281,892,182	286,663,831	289,712,492	305,645,684	249,848	265,033	299,249
Industrial	29,146,574	31,157,835	19,483,238	37,597,181	43,698,510	42,380,747	50,551,601	32,567,382	30,466,150	20,835,912	19,527,474	19,511	18,742	37,855
Streetlights	24,325,754	24,534,903	24,486,190	24,781,203	25,516,352	26,115,977	26,237,909	26,618,585	26,167,883	24,895,928	23,986,498	24,645	24,926	24,858
Own Use	-	-	-	-	-	2,437,666	2,474,086	2,446,836	2,266,561	2,057,656	2,261,610	-	-	-
Total	417,373,033	426,232,621	428,489,632	462,168,731	483,894,084	497,829,709	535,704,506	543,368,219	554,744,648	556,491,228	590,612,935	539,269	560,793	601,814
Peak demand (MW)	76.2	80.6	79.3	82.0	84.3	87.7	96.0	96.0	104.5	104.2	105.6	102.7	103.5	110.3

Table A-4 This table provides summary statistics for the hourly forward and spot electricity prices for each of the 24 h from 2018 to 2022.

All Prices are expressed in US dollars per kilowatt hour

Hour	Mean		Min.		Max.		Skew		Std. Deviation	
	Forward	Spot	Forward	Spot	Forward	Spot	Forward	Spot	Forward	Spot
0	0.076	0.091	0.017	0.028	0.372	0.619	1.598	2.423	0.047	0.056
1	0.068	0.082	0.016	0.019	0.343	0.784	1.796	3.798	0.042	0.052
2	0.062	0.075	0.015	0.016	0.296	0.579	1.602	3.271	0.035	0.043
3	0.058	0.070	0.013	0.015	0.288	0.579	1.549	3.192	0.031	0.037
4	0.057	0.070	0.015	0.014	0.188	0.410	1.193	2.224	0.030	0.035
5	0.060	0.073	0.015	0.014	0.200	0.593	1.146	2.670	0.032	0.037
6	0.064	0.077	0.012	0.016	0.290	0.587	1.090	2.289	0.035	0.040
7	0.070	0.083	0.014	0.017	0.409	0.801	1.563	4.002	0.041	0.053
8	0.076	0.091	0.006	0.008	0.439	0.777	1.537	3.159	0.048	0.062
9	0.081	0.097	0.013	0.017	0.302	0.927	1.114	3.237	0.052	0.069
10	0.086	0.102	0.012	0.015	0.744	0.927	1.986	3.464	0.059	0.077
11	0.089	0.105	0.012	0.021	0.535	0.927	1.907	3.249	0.063	0.081
12	0.091	0.107	0.012	0.021	0.801	0.927	3.338	3.384	0.071	0.082
13	0.093	0.107	0.012	0.022	0.800	0.927	3.820	3.823	0.078	0.086
14	0.094	0.108	0.012	0.008	0.801	0.927	3.578	3.558	0.079	0.087
15	0.096	0.110	0.012	0.021	0.801	0.925	3.552	3.186	0.083	0.087
16	0.090	0.103	0.012	0.016	0.781	0.927	3.194	4.088	0.067	0.076
17	0.085	0.099	0.013	0.027	0.512	0.864	1.682	2.896	0.054	0.061
18	0.092	0.107	0.020	0.027	0.802	0.926	4.107	3.279	0.069	0.071
19	0.101	0.118	0.021	0.030	0.802	0.926	3.289	3.346	0.074	0.084
20	0.108	0.127	0.021	0.031	0.802	0.934	3.486	3.769	0.084	0.098
21	0.111	0.132	0.023	0.031	0.802	0.934	3.365	3.762	0.091	0.111
22	0.103	0.120	0.022	0.030	0.802	0.926	3.760	3.691	0.081	0.089
23	0.089	0.106	0.021	0.031	0.641	0.926	2.097	3.081	0.060	0.074

```

model = VAR(df_train)
for i in [1,2,3,4,5,6,7,8,9]:
    result = model.fit(i)
    print('Lag Order =', i)
    print('AIC : ', result.aic)
    print('BIC : ', result.bic)
    print('FPE : ', result.fpe)
    print('HQIC: ', result.hqic, '\n')

```

VAR Order Selection (* highlights the minimums)

	AIC	BIC	FPE	HQIC
0	15.16	15.17	3.820e+06	15.16
1	12.16	12.22	1.906e+05	12.18
2	12.06	12.18*	1.728e+05	12.10*
3	12.05	12.22	1.718e+05	12.12
4	12.03	12.26	1.684e+05	12.12
5	12.02*	12.29	1.654e+05*	12.12
6	12.02	12.35	1.655e+05	12.14
7	12.03	12.41	1.669e+05	12.17
8	12.03	12.47	1.681e+05	12.19
9	12.04	12.53	1.694e+05	12.22
10	12.05	12.59	1.705e+05	12.25
11	12.04	12.64	1.700e+05	12.26
12	12.03	12.68	1.680e+05	12.27

Figure A-0-1 Optimization procedure for selecting the highest-performing lags executed in VAR module, sample script and results for hour 23.

Steps used to arrive at best fit ARMA, sample using hour 11.

```

1. ARMA
# Model WITHOUT Exogenous
# Fit ARIMA WITHOUT EXOGENOUS
model = SARIMAX(train1['diff_1'],order=(2,0,1),enforce_invertibility=False)
results = model.fit()
results.summary()

# predict
predictions = results.predict(start=start1, end=end1).rename('ARIMA(1,0,2) Predictions')
print(results.summary())
SARIMAX Results
=====
Dep. Variable:      diff_1  No. Observations:      1658
Model:              SARIMAX(2, 0, 1)  Log Likelihood      3352.156
Date:              Wed, 15 May 2024  AIC      -6696.312
Time:              14:25:20  BIC      -6674.658
Sample:            01-01-2018  HQIC      -6688.286
                  - 07-16-2022
Covariance Type:    opg
=====
              coef  std err      z  P>|z|  [0.025  0.975]
-----
ar.L1      0.3480   0.017  20.814   0.000   0.315   0.381
ar.L2      0.0991   0.020   5.030   0.000   0.060   0.138
ma.L1     -0.9372   0.008 -112.528   0.000  -0.953  -0.921
sigma2      0.0010  6.72e-06  152.506   0.000   0.001   0.001
=====
Ljung-Box (L1) (Q):      0.00  Jarque-Bera (JB):      231441.03
Prob(Q):                 0.95  Prob(JB):              0.00
Heteroskedasticity (H):   0.24  Skew:              3.81
Prob(H) (two-sided):      0.00  Kurtosis:          60.38
=====

2. ARMA w/dummies
# Fit ARIMAX WITH Dummies
model2 = SARIMAX(train1['diff_1'],exog=exog_train,order=(2,0,1),enforce_invertibility=False)
results2 = model2.fit()
results2.summary()

# predict
predictions2 = results2.predict(start=start1, end=end1, exog=exog_forecast).rename('ARIMAX(1,0,2) Predictions')
print(results2.summary())
SARIMAX Results
=====
Dep. Variable:      diff_1  No. Observations:      1658
Model:              SARIMAX(1, 0, 1)  Log Likelihood      2570.877
Date:              Mon, 05 Feb 2024  AIC      -5131.753
Time:              07:18:46  BIC      -5104.687
Sample:            01-01-2018  HQIC      -5121.721
                  - 07-16-2022
Covariance Type:    opg
=====
              coef  std err      z  P>|z|  [0.025  0.975]
-----
0      -0.0006   0.001  -0.579   0.563  -0.003   0.002
1       0.0016   0.003   0.567   0.571  -0.004   0.007
ar.L1     0.5267   0.011  49.817   0.000   0.506   0.547
ma.L1    -0.9317   0.006 -159.243   0.000  -0.943  -0.920

```

```
sigma2      0.0026 2.58e-05 102.193  0.000  0.003  0.003
```

```
=====
Ljung-Box (L1) (Q):      4.02 Jarque-Bera (JB):      102059.05
Prob(Q):                0.05 Prob(JB):              0.00
Heteroskedasticity (H):  0.24 Skew:                3.36
Prob(H) (two-sided):    0.00 Kurtosis:             40.84
=====
```

3. ARMA with dummies & temp exog

```
# Fit ARIMAX WITH Dummies and temp exog
model3 = SARIMAX(train1['diff_1'],exog=exog_train,order=(2,0,1),enforce_invertibility=False)
results3 = model3.fit()
results3.summary()

# predict
predictions3 = results3.predict(start=start1, end=end1, exog=exog_forecast).rename('ARIMAX(1,0,2) Predictions')

print(results3.summary())
```

SARIMAX Results

```
=====
Dep. Variable:      diff_1  No. Observations:      1658
Model:              SARIMAX(2, 0, 1)  Log Likelihood      3327.096
Date:              Wed, 15 May 2024  AIC              -6642.192
Time:              14:30:35  BIC              -6609.712
Sample:            01-01-2018  HQIC              -6630.153
                  - 07-16-2022
Covariance Type:    opg
=====
```

```
=====
              coef  std err      z  P>|z|  [0.025  0.975]
-----
is_weekend      0.0012   0.001   1.493   0.135  -0.000   0.003
Imports_norm    -0.0006   0.000  -1.647   0.100  -0.001   0.000
ar.L1           0.5151   0.015  33.259   0.000   0.485   0.545
ar.L2           0.1743   0.016  11.206   0.000   0.144   0.205
ma.L1          -0.9799   0.006 -174.706   0.000  -0.991  -0.969
sigma2          0.0011  1.02e-05 103.352   0.000   0.001   0.001
=====
```

```
=====
Ljung-Box (L1) (Q):      16.35 Jarque-Bera (JB):      222389.27
Prob(Q):                0.00 Prob(JB):              0.00
Heteroskedasticity (H):  0.25 Skew:                3.57
Prob(H) (two-sided):    0.00 Kurtosis:             59.29
=====
```

4. ARMA with dummies and all exog (temp & HH)

```
# Fit ARIMAX WITH Dummies and all exog
model4 = SARIMAX(train1['diff_1'],exog=exog_train,order=(1,0,1),enforce_invertibility=False)
results4 = model4.fit()
results4.summary()

# predict
predictions4 = results4.predict(start=start1, end=end1, exog=exog_forecast).rename('ARIMAX(1,0,2) Predictions')

print(results4.summary())
```

SARIMAX Results

```

=====
Dep. Variable:      diff_1  No. Observations:      1658
Model:              SARIMAX(1, 0, 1)  Log Likelihood      2513.621
Date:              Mon, 05 Feb 2024  AIC              -5013.243
Time:              07:19:31  BIC              -4975.349
Sample:            01-01-2018  HQIC             -4999.197
                  - 07-16-2022

```

```

Covariance Type:      opg
=====

```

	coef	std err	z	P> z	[0.025	0.975]
temp_avg	0.0002	0.000	0.837	0.403	-0.000	0.001
HH	-5.838e-06	0.001	-0.008	0.993	-0.001	0.001
0	-0.0161	0.019	-0.845	0.398	-0.053	0.021
1	-0.0138	0.019	-0.728	0.467	-0.051	0.023
ar.L1	0.1041	0.032	3.291	0.001	0.042	0.166
ma.L1	-0.4527	0.032	-14.083	0.000	-0.516	-0.390
sigma2	0.0029	2.84e-05	101.321	0.000	0.003	0.003

```

=====
Ljung-Box (L1) (Q):      1.22  Jarque-Bera (JB):      92186.07
Prob(Q):                  0.27  Prob(JB):              0.00
Heteroskedasticity (H):    0.23  Skew:              2.15
Prob(H) (two-sided):      0.00  Kurtosis:          39.27
=====

```

Summary:

```

ARIMA MSE Error: 0.0006274451597
ARIMA_dummies MSE Error: 0.0006264368661
ARIMA_temp MSE Error: 0.0006249755175
ARIMAX MSE Error: 0.0006249739728

```

Table A-5 Summary of results training ARMA to determine best fit model for each hourly interval.**(a) Forward Prices**

Hour	Mean	Min	Max	Skew	Std. Dev	AR1	AR2	MA1	MA2	temp_avg	HH	is_weekend	MSE
0	0.076	0.017	0.372	1.598	0.047	0.2232		-0.6447		0.0002**	0.0001	-0.0219**	8.58E-05
1	0.068	0.016	0.343	1.796	0.042	0.4215		-0.8049		0.0001	5.66E-05	-0.0104	5.59E-05
2	0.062	0.015	0.296	1.602	0.035	0.5152		-0.899		0.0001**	-8.78E-06	-0.0109**	6.46E-05
3	0.058	0.013	0.288	1.549	0.031	0.5152		-0.8964		0.0001**	1.29E-05	-0.0125**	6.32E-05
4	0.057	0.015	0.188	1.193	0.03	0.3607		-0.7791		9.075e-05*	-4.42E-06	-0.0103*	6.31E-05
5	0.06	0.015	0.2	1.146	0.032	0.39		-0.802		7.20E-05	-3.07E-05	-0.0104*	6.28E-05
6	0.064	0.012	0.29	1.09	0.035	0.3468		-0.7966		0.0001**	8.77E-05	-0.0162**	7.86E-05
7	0.07	0.014	0.409	1.563	0.041	0.2846		-0.7709		0.0001**	0.0001	-0.0213**	8.47E-05
8	0.076	0.006	0.439	1.537	0.048	0.2207		-0.718		0.0002*	6.16E-05	-0.0249**	9.56E-05
9	0.081	0.013	0.302	1.114	0.052	0.5858		-1.1714	0.2157	No exog	No exog	-0.0281**	7.76901E-05
10	0.086	0.012	0.744	1.986	0.059	0.2632		-0.8848		No exog	No exog	-0.0115**	8.18427E-05
11	0.089	0.012	0.535	1.907	0.063	0.348	0.0991	-0.9372		0.0002*	6.28E-05	-0.0248**	0.000111543
12	0.091	0.012	0.801	3.338	0.071	0.2687		-0.8396		No exog	No exog	-0.0246	0.000101694
13	0.093	0.012	0.8	3.82	0.078	0.4256	0.0962	-0.8177		0.0002	7.18E-05	-0.0238	0.000107517
14	0.094	0.012	0.801	3.578	0.079	0.1663	0.0897	-0.6497		0.0003	7.85E-05	-0.0316*	0.0001275
15	0.096	0.012	0.801	3.552	0.083	0.4644	0.2363	-0.9607		0.0003**	6.71E-05	-0.0340**	0.000144562

16	0.09	0.012	0.781	3.194	0.067	0.3923		-0.911		No exog	No exog	-0.0256**	0.00013018
17	0.085	0.013	0.512	1.682	0.054	0.23		-0.8923		No exog	No exog	-0.0259**	0.000138892
18	0.092	0.02	0.802	4.107	0.069	0.5564	0.2047	-0.9443		0.0002**	6.05E-05	-0.0284**	0.00016931
19	0.101	0.021	0.802	3.289	0.074	0.5452		-0.9224		No exog	No exog	-0.0292**	0.00013222
20	0.108	0.021	0.802	3.486	0.084	0.5287	0.103	-0.9465		No exog	No exog	-0.0409**	0.000168697
21	0.111	0.023	0.802	3.365	0.091	0.5033	0.1017	-0.8409		No exog	No exog	-0.0391**	0.000156622
22	0.103	0.022	0.802	3.76	0.081	0.2049		-0.7564		No exog	No exog	-0.0332**	0.000402816
23	0.089	0.021	0.641	2.097	0.06	0.255		-0.7534	0.0246	0.0002**	0.0002	-0.0224**	0.000215331
All hours	0.083	0.006	0.802	3.59	0.063	0.4018		-0.8917		No exog	No exog	-0.0037**	8.60757E-05

	AIC (lowest)				MSE (lowest)				AR				MA				Exog	<0.03	0.03< p<0.05	
Hou r	AR MA	with dum mies	with dum mies & tem p	with dum mies & all exog	AR M A	with dum mies	with dum mies & tem p	with dum mies & all exog	L1	L2	L3	AR_a bs_su m	L1	L2	L3	MA_a bs_su m	tem p_a vg	HH	is_we eken d	is_w eekd ay
0	-582 2.47 7	-5826 .561	-5719 .085	-5717 .218	2.7 4E- 04	2.75 E-04	2.73 E-04	2.74 E-04	0.22 93			0.229 3	-0.82 52			0.8252			-0.004 7	0.001 9
1	-698 2.91 8	-6992 .997	-6940 .706	-6939 .021	2.0 0E- 04	2.14 E-04	2.14 E-04	2.14 E-04	0.34 15			0.341 5	-0.86 68			0.8668			-0.004 5	0.001 8

2	- 771 4.81 6	- 7737 .854	- 7682 .454	- 7680 .509	8.5 7E- 05	9.82 E-05	9.90 E-05	9.90 E-05	0.38 56			0.385 6	- 0.89 45			0.8945				
3	- 838 4.22 8	- 8399 .072	- 8378 .184	- 8376 .452	5.5 4E- 05	5.98 E-05	6.00 E-05	6.01 E-05	0.37 15			0.371 5	- 0.86 93			0.8693			- 0.003 4	0.001 4
4	- 838 4.22 8	- 8399 .072	- 8378 .184	- 8376 .452	5.5 4E- 05	5.98 E-05	6.00 E-05	6.01 E-05	0.37 15			0.371 5	- 0.86 93			0.8693			- 0.003 4	0.001 4
5	- 932 6.21 1	- 9362 .952	- 9347 .373	- 9346 .053	6.4 2E- 05	6.78 E-05	6.81 E-05	6.83 E-05	0.28 65			0.286 5	- 0.82 94			0.8294			- 0.003 7	0.001 5
6	- 923 3.15	- 9250 .036	- 9228 .782	- 9227 .474	6.3 2E- 05	6.39 E-05	6.39 E-05	6.41 E-05	0.36 33			0.363 3	- 0.86 19			0.8619			- 0.002 8	0.001 1
7	- 896 5.56 9	- 8967 .444	- 8939 .732	- 8938 .024	6.2 8E- 05	6.24 E-05	6.20 E-05	6.20 E-05	0.40 48			0.404 8	- 0.89 45			0.8945			- 0.001 6	7.00 E-04
8	- 795 0.44 3	- 7951 .286	- 7891 .293	- 7889 .523	7.3 5E- 05	7.38 E-05	7.32 E-05	7.32 E-05	0.36 18			0.361 8	- 0.92 01			0.9201				
9	- 745 2.76	- 7436 .025	- 7423 .819	- 7422 .054	7.7 7E- 05	7.84 E-05	7.77 E-05	7.77 E-05	0.58 58			0.585 8	- 1.17 14	0.21 57		0.9557				
10	- 722 7.68 2	- 7229 .208	- 7178 .569	- 7177 .028	8.1 8E- 05	8.28 E-05	8.19 E-05	8.20 E-05	0.25 88			0.258 8	- 0.88 25			0.8825			- 0.002 6	0.001
11	- 669 6.31 2	- 6685 .269	- 6547 .482	- 6555 .733	9.8 3E- 05	9.78 E-05	9.75 E-05	9.82 E-05	0.34 8	0.09 91		0.447 1	- 0.93 72			0.9372				
12	- 644 7.54 5	- 6440 .069	- 6387 .503	- 6385 .599	1.0 2E- 04	1.03 E-04	1.01 E-04	1.01 E-04	0.69 64			0.696 4	- 1.30 7	0.34 15		0.9655			- 0.003 6	0.001 4

13	- 587 9.38 5	- 5876 .358	- 5753 .612	- 5751 .685	1.0 1E- 04	1.00 E-04	1.00 E-04	1.00 E-04	0.42 84	0.13 68	0.09 27	0.657 9	- 0.96 89			0.9689				
14	- 596 0.35 8	- 5957 .818	- 5877 .726	- 5875 .764	1.0 3E- 04	1.03 E-04	1.02 E-04	1.02 E-04	0.49 86	0.14 73		0.645 9	- 0.96 24			0.9624				
15	- 542 0.87 4	- 5417 .208	- 5341 .911	- 5339 .933	1.0 6E- 04	1.05 E-04	1.05 E-04	1.05 E-04	0.47 69	0.11 12		0.588 1	- 0.95 65			0.9565				
16	- 516 9.59 8	- 5165 .592	- 5095 .774	- 5093 .815	1.3 0E- 04	1.31 E-04	1.30 E-04	1.31 E-04	0.70 17			0.701 7	- 1.26 67	0.29 73		0.9694				
17	- 554 5.72 4	- 5417 .134	- 5417 .134	- 5415 .365	1.4 0E- 04	1.43 E-04	1.43 E-04	1.43 E-04	0.23			0.23	- 0.89 23			0.8923				
18	- 615 4.84 3	- 6150 .888	- 6011 .129	- 6009 .212	1.2 8E- 04	1.28 E-04	1.28 E-04	1.28 E-04	0.20 29	0.16 39	- 0.08 46	0.282 2	- 0.91 68			0.9168				
19	- 616 5.15 3	- 6161 .43	- 6116 .4	- 6114 .368	1.3 2E- 04	1.32 E-04	1.31 E-04	1.31 E-04	0.50 6	0.16 07		0.666 7	- 0.95 76			0.9576				
20	- 620 4.52 2	- 6201 .259	- 6149 .96	- 6147 .984	1.6 9E- 04	1.69 E-04	1.68 E-04	1.68 E-04	0.52 87	0.10 3		0.631 7	- 0.94 65			0.9465				
21	- 576 9.92 6	- 5698 .932	- 5713 .295	- 5696 .929	1.5 7E- 04	1.56 E-04	1.56 E-04	1.56 E-04	0.34 21			0.342 1	- 0.80 51			0.8051				
22	- 506 0.97 9	- 5057 .081	- 4996 .412	- 4994 .412	4.0 3E- 04	4.03 E-04	4.02 E-04	4.02 E-04	0.20 49			0.204 9	- 0.75 64			0.7564				

23	-513 5.27 2	-5131 .753	-5015 .247	-5013 .243	6.2 7E- 04	6.26 E-04	6.25 E-04	6.25 E-04	0.52 7			0.527	-0.93 18			0.9318				
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(b) Spot Prices

	AR				MA				Exog	<0.03	0.03<p<0.05	
Hour	L1	L2	L3	AR_abs_sum	L1	L2	L3	MA_abs_sum	temp_avg	HH	is_weekend	is_weekday
0	0.3454			0.3454	-0.9306			0.9306			-0.01	0.004
1	0.2788			0.2788	-0.9228			0.9228			-0.0087	0.0035
2	0.3015			0.3015	-0.91			0.91			-0.0094	0.0038
3	0.3305			0.3305	-0.912			0.912			-0.0091	0.0037
4	0.4355			0.4355	-0.9133			0.9133			-0.0074	0.003
5	0.4442			0.4442	-0.9169			0.9169			-0.004	0.0016
6	0.3784			0.3784	-0.9227			0.9227				
7	0.2565			0.2565	-0.9366			0.9366			0.0002	-4.31E-05
8	0.2407			0.2407	-0.9506			0.9506				
9	0.1211			0.1211	-0.9438			0.9438				
10	0.2358			0.2358	-0.9563			0.9563				
11	0.1481			0.1481	-0.9505			0.9505				
12	0.1346			0.1346	-0.9484			0.9484				
13	0.232			0.232	-0.9576			0.9576			0.006	-0.0024
14	0.2565			0.2565	-0.9523			0.9523			0.0094	-0.0038
15	0.3473	-0.1252	0.0768	0.2989	-0.9525			0.9525				
16	0.2738			0.2738	-0.9533			0.9533			0.0089	-0.0036
17	0.271	0.108		0.379	-0.9566			0.9566				
18	0.637			0.637	-1.2405	0.2723		0.9682				

19	0.4601			0.4601	-0.9496			0.9496				
20	0.3255			0.3255	-0.753	-0.178		0.931			0.0075	-0.003
21	0.4665			0.4665	-0.9458			0.9458			0.0101	-0.004
22	0.2784			0.2784	-0.7285	-0.2065		0.935			0.0077	-0.0031
23	0.6065			0.6065	-1.2121	0.2491		0.963				
All hours	0.7926			0.7926	-0.9863			0.9863			-0.0003	0.0001
2018	0.7909			0.7909	-0.9868			0.9868			-0.0006	0.0003
2019	0.8192			0.8192	-1.0108			1.0108				
2020	0.748	0.105	-0.0865	0.7665	-0.9834			0.9834				
2021	0.7216				-0.9706			0.9706				
2022	0.7721				-0.9879			0.9879			-0.0002	0.00007551

	AIC (lowest)				MSE (lowest)			
Hour	ARMA	with dummies	with dummies & temp	with dummies & all exog	ARMA	with dummies	with dummies & temp	with dummies & all exog
0	-6020.703	-6054.29	-5975.938	-5973.537	1.74E-04	1.65E-04	1.67E-04	1.67E-04
1	-6092.382	-6118.96	-6058.161	-6056.003	0.00011314	0.000106053	0.000108153	0.000108285
2	-6791.751	-6841.491	-6771.643	-6769.661	9.39E-05	8.92E-05	9.26E-05	9.26E-05
3	-7400.57	-7466.079	-7420.726	-7417.832	8.16E-05	7.81E-05	8.01E-05	8.04E-05
4	-7988.635	-8049.935	-8016.218	-8012.484	8.47E-05	7.78E-05	7.95E-05	7.98E-05
5	-7879.022	-7892.758	-7855.877	-7850.978	8.54E-05	8.00E-05	8.05E-05	8.08E-05
6	-7373.349	-7363.178	-7294.263	-7285.364	9.07E-05	8.84E-05	8.93E-05	9.26E-05
7	-5740.782	-5733.383	-5627.081	-5624.83	1.11E-04	1.12E-04	1.15E-04	1.16E-04
8	-5145.6	-5141.837	-5034.368	-5624.83	1.35E-04	1.34E-04	1.37E-04	1.39E-04

9	-4784.63	-4780.685	-4685.511	-4683.56	1.80E-04	1.83E-04	1.86E-04	1.86E-04
10	-4439.572	-4435.548	-4327.574	-4325.601	2.02E-04	2.02E-04	2.07E-04	2.07E-04
11	-4199.537	-4195.583	-4087.396	-4085.394	1.57E-04	1.60E-04	1.67E-04	1.67E-04
12	-4194.46	-4190.888	-4089.978	-4087.502	0.0001184	0.000124173	0.000133749	0.000134157
13	-4090.245	-4089.631	-3979.296	-3977.312	0.00012682	0.000145204	0.000154926	0.000154932
14	-4147.214	-4152.502	-4058.641	-4056.553	0.00018544	0.000226442	0.000241381	0.00024155
15	-4205.521	-4201.005	-4039.034	-4037.045	0.00018098	0.000229179	0.000247645	0.000247597
16	-4634.608	-4642.552	-4555.07	-4552.031	0.00018979	0.000228459	0.000237529	0.000238306
17	-5614.79	-5608.428	-5493.121	-5490.752	0.00043347	0.000451488	0.000459982	0.000460708
18	-5261.492	-5261.325	-5183.333	-5180.779	0.00124397	0.001267449	0.001281582	0.001282812
19	-4799.068	-4796.686	-4716.465	-4712.651	0.00219732	0.002215548	0.002217311	0.002218831
20	-4276.491	-4278.162	-4231.432	-4228.96	0.0071566	0.007169272	0.007172775	0.007174049
21	-3758.077	-3762.707	-3712.996	-3710.617	0.00945434	0.009506137	0.009513281	0.009514141
22	-4429.667	-4432.173	-4384.347	-4381.265	0.0039289	0.003994058	0.003999176	0.004001726
23	-5028.352	-5024.886	-4935.181	-4932.172	0.00058498	0.000592223	0.000602606	0.000606022
All hours	-171047	-171074.476	-168054.122	-168052.126	2.05E-05	2.03E-05	2.02E-05	2.02E-05
2018	-27413.03	-27421.354	-26800.265	-26798.265	0.00027176	0.000271554	0.000270717	0.000270717
2019	-29664.07	-28955.613						
2020	-43910.14							
2021	-38705.18							
2022	-38932.79	-38934.608						

Table A-6 These tables contain the final parameter values for the conditional mean equations of the change in electricity forward (a) and spot (b) prices using an hourly system of ARMA models

Selection criteria based on prediction error and quality of fit (Akaike information criterion, 'AIC'), out-of-sample testing (mean square error, 'MSE'), and parameter significance using the critical p-value (1% 'very significant', as indicated by (**) and 5% 'significant', as indicated by (*)). (–) Coefficient result provided 'if applicable' to the selected model

(a) Forward Pricing

Hour	AR			MA		Dummy Variables	
	Lag 1	Lag 2	Lag 3	Lag 1	Lag 2	D_weekend	D_weekday
0	0.229 **			–0.825 **		–0.005 **	0.002 **
1	0.342 **			–0.867 **		–0.005 **	0.002 **
2	0.386 **			–0.895 **			
3	0.372 **			–0.869 **		–0.003 **	0.001
4	0.372 **			–0.869 **		–0.003 **	0.001
5	0.287 **			–0.829 **		–0.004 **	0.002
6	0.363 **			–0.862 **		–0.003 **	0.001
7	0.405 **			–0.895 **		–0.002 **	7 x 10 ^{–4} *
8	0.362 **			–0.920 **			
9	0.586 **			–1.171 **	0.216 **		
10	0.259 **			–0.883 **		–0.003 **	0.001 *
11	0.348 **	0.099 **		–0.937 **			
12	0.696 **			–1.307 **	0.342 **	–0.004 **	0.001 **
13	0.428 **	0.137 **	0.093 **	–0.969 **			
14	0.499 **	0.147 **		–0.962 **			
15	0.477 **	0.111 **		–0.957 **			
16	0.702 **			–1.267 **	0.298 **		
17	0.230 **			–0.892 **			
18	0.203 **	0.164 **	–0.085 **	–0.917 **			
19	0.506 **	0.161 **		–0.958 **			
20	0.529 **	0.103 **		–0.947 **			
21	0.342 **			–0.805 **			
22	0.205 **			–0.756 **			
23	0.527 **			–0.932 **			

(b) Spot Pricing

Hour	AR			MA		Dummy Variables	
	Lag 1	Lag 2	Lag 3	Lag 1	Lag 2	D_weekend	D_weekday
0	0.345 **			−0.931 **		−0.010 *	0.004 *
1	0.279 **			−0.923 **		−0.009 *	0.004 *
2	0.302 **			−0.910 **		−0.009 *	0.004 *
3	0.331 **			−0.912 **		−0.009 *	0.004 *
4	0.436 **			−0.913 **		−0.007 *	0.003 *
5	0.444 **			−0.917 **		−0.004 *	0.002 *
6	0.378 **			−0.923 **			
7	0.257 **			−0.937 **		2 x 10 ^{−4} e-4	−4 x 10 ^{−5} e-5
8	0.241 **			−0.951 **			
9	0.121 **			−0.944 **			
10	0.236 **			−0.956 **			
11	0.148 **			−0.951 **			
12	0.135 **			−0.948 **			
13	0.232 **			−0.958 **		0.006 *	−0.002 *
14	0.257 **			−0.952 **		0.009 *	−0.004 *
15	0.347 **	−0.125 **	0.077 **	−0.953 **			
16	0.274 **			−0.953 **		0.009 **	−0.004 **
17	0.271 **	0.108 **		−0.957 **			
18	0.637 **			−1.241 **	0.272 **		
19	0.460 **			−0.950 **			
20	0.326 **			−0.753 **	−0.178 **	0.008 **	−0.003 **
21	0.467 **			−0.946 **		0.010 **	−0.004 *
22	0.278 **			−0.729 **	−0.207 **	0.008 **	−0.003 **
23	0.607 **			−1.212 **	0.249 **		

Table A-7 Parameter values for the conditional volatility models on the residuals of the change in forward (a) and spot (b) prices using an hourly system of GARCH models

Selection criteria based on prediction error and quality of fit (based on AIC), out-of-sample testing (based on MSE), and parameter significance using the critical p-value (1% 'very significant', as indicated by (**) and 5% 'significant', as indicated by (*)). Volatility model types included 'GARCH'—basic GARCH and 'GJR'—GJR-GARCH; assumed distribution of residuals included 'Normal' and 'SST'—skewed Student's T

(a) Forward Pricing

Hour	Model	ω	α	β	γ
0	GJR_SST	1.9×10^{-1} **	0.287 **	0.750 **	-0.075 *
1	GJR_SST	1.0×10^{-1} **	0.277 **	0.764 **	-0.082 **
2	GARCH_Normal	9.3×10^{-2} *	0.106 **	0.876 **	
3	GARCH_SST	2.0×10^{-2} **	0.248 **	0.752 **	
4	GJR_SST	1.9×10^{-2} **	0.290 **	0.759 **	-0.096 **
5	GJR_SST	9.4×10^{-3} **	0.261 **	0.795 **	-0.113 **
6	GJR_SST	1.0×10^{-2} **	0.252 **	0.796 **	-0.095 **
7	GJR_SST	7.7×10^{-3} **	0.229 **	0.816 **	-0.090 **
8	GARCH_SST	1.3×10^{-2} **	0.185 **	0.815 **	
9	GARCH_SST	3.6×10^{-2} **	0.210 **	0.790 **	
10	GARCH_SST	4.6×10^{-2} **	0.223 **	0.778 **	
11	GARCH_SST	4.0×10^{-2} **	0.188 **	0.813 **	
12	GARCH_SST	1.2×10^{-1} **	0.251 **	0.750 **	
13	GJR_SST	1.3×10^{-1} **	0.318 **	0.739 **	-0.114 **
14	GJR_SST	1.4×10^{-1} **	0.338 **	0.730 **	-0.136 **
15	GJR_SST	1.0×10^{-1} **	0.276 **	0.760 **	-0.073 **
16	GARCH_SST	6.0×10^{-2} **	0.198 **	0.802 **	
17	GARCH_SST	4.0×10^{-2} **	0.188 **	0.813 **	
18	GARCH_SST	3.3×10^{-2} **	0.172 **	0.83 **	
19	GJR_SST	4.2×10^{-2} **	0.267 **	0.787 **	-0.108 **
20	GJR_SST	6.4×10^{-2} **	0.315 **	0.755 **	-0.140 **

21	GJR_SST	$1.2 \times 10^{-1} **$	0.330 **	0.760 **	-0.180 **
22	GJR_SST	$2.8 \times 10^{-1} **$	0.351 **	0.734 **	-0.169 **
23	GJR_SST	$4.3 \times 10^{-1} **$	0.345 **	0.724 **	-0.139 **

(b) Spot Pricing

Hour	Model	ω	α	β	γ
0	GARCH_SST	0.166	0.288 *	0.712 **	
1	GJR_SST	0.097 *	0.251 **	0.694 **	0.109 **
2	GARCH_Normal	0.065 *	0.289 **	0.711 **	
3	GARCH_SST	0.046 **	0.272 **	0.728 **	
4	GARCH_SST	0.040 **	0.225 **	0.775 **	
5	GJR_SST	0.030 **	0.231 **	0.799 **	-0.060 **
6	GARCH_SST	0.029 **	0.188 **	0.812 **	
7	GJR_SST	0.131 *	0.170 **	0.767 **	0.126 **
8	GJR_SST	0.166 **	0.152 **	0.791 **	0.113 **
9	GARCH_SST	0.220 **	0.178 **	0.822 **	
10	GJR_SST	0.329 **	0.156 **	0.777 **	0.134 **
11	GJR_SST	0.309 **	0.101 **	0.807 **	0.185 **
12	GJR_SST	0.260 **	0.010 **	0.814 **	0.174 **
13	GJR_SST	0.268 **	0.148 **	0.772 **	0.159 **
14	GJR_SST	0.207 *	0.175 **	0.762 **	0.127 **
15	GJR_SST	0.167 **	0.187 **	0.778 **	0.070 **
16	GJR_SST	0.115 **	0.156 **	0.791 **	0.105 **
17	GJR_SST	0.063 *	0.155 **	0.823 **	0.045 *
18	GARCH_SST	0.116 *	0.234 **	0.766 **	
19	GARCH_SST	0.498 **	0.318 **	0.682 **	
20	GJR_SST	1.510 **	0.442 **	0.621 **	-0.126 **
21	GJR_SST	1.450 **	0.453 **	0.627 **	-0.159 **
22	GJR_SST	1.930 **	0.561 **	0.525 **	-0.172 **
23	GJR_SST	1.040 **	0.509 **	0.557 **	-0.131 **

Table A-8 Summary statistics for the hourly FP. from the Mexican export market at the interconnection node 'Xul-Ha' for each of the 24 h from 2018 to 2022

Hour	Average	Skew	Std. Deviation
0	0.07	2.17	0.47
1	0.10	4.80	0.47
2	0.14	3.46	0.41
3	0.18	2.04	0.37
4	0.25	3.59	0.38
5	0.34	5.52	0.41
6	0.39	2.68	0.46
7	0.42	6.86	0.71
8	0.44	5.85	0.79
9	0.43	5.13	0.82
10	0.41	5.01	0.87
11	0.40	4.66	0.88
12	0.37	6.37	0.85
13	0.34	4.07	0.74
14	0.32	3.88	0.73
15	0.34	3.89	0.73
16	0.28	3.12	0.61
17	0.27	2.71	0.57
18	0.38	4.45	0.67
19	0.48	3.76	0.75
20	0.51	6.85	0.93
21	0.45	5.52	0.92
22	0.28	3.86	0.73
23	0.15	4.40	0.63

Hour 0	FP0_x	σ_F^2 0_x	σ_s^2 0_x	IP0_x	D0_x
FP0_y	1.000	0.001	0.000	0.054	0.503
σ_F^2 0_y	0.514	1.000	0.003	0.049	0.035
σ_s^2 0_y	0.018	0.000	1.000	0.005	0.161
IP0_y	0.540	0.310	0.029	1.000	0.000
D0_y	0.000	0.448	0.044	0.003	1.000
Hour 1	FP1_x	σ_F^2 1_x	σ_s^2 1_x	IP1_x	D1_x
FP1_y	1.000	0.000	0.000	0.001	0.483
σ_F^2 1_y	0.000	1.000	0.000	0.714	0.079
σ_s^2 1_y	0.113	0.023	1.000	0.000	0.020
IP1_y	0.004	0.024	0.000	1.000	0.013
D1_y	0.000	0.355	0.035	0.460	1.000
Hour 2	FP2_x	σ_F^2 2_x	σ_s^2 2_x	IP2_x	D2_x
FP2_y	1.000	0.000	0.000	0.242	0.398
σ_F^2 2_y	0.000	1.000	0.000	0.013	0.265
σ_s^2 2_y	0.063	0.001	1.000	0.000	0.368
IP2_y	0.056	0.000	0.004	1.000	0.000
D2_y	0.010	0.155	0.012	0.767	1.000
Hour 3	FP3_x	σ_F^2 3_x	σ_s^2 3_x	IP3_x	D3_x
FP3_y	1.000	0.000	0.000	0.070	0.451
σ_F^2 3_y	0.000	1.000	0.000	0.350	0.064
σ_s^2 3_y	0.050	0.000	1.000	0.276	0.335
IP3_y	0.094	0.001	0.000	1.000	0.000
D3_y	0.082	0.027	0.000	0.653	1.000
Hour 4	FP4_x	σ_F^2 4_x	σ_s^2 4_x	IP4_x	D4_x
FP4_y	1.000	0.000	0.000	0.403	0.271
σ_F^2 4_y	0.000	1.000	0.000	0.322	0.087
σ_s^2 4_y	0.002	0.318	1.000	0.000	0.053
IP4_y	0.168	0.007	0.158	1.000	0.000
D4_y	0.039	0.002	0.253	0.348	1.000
Hour 12	FP12_x	σ_F^2 12_x	σ_s^2 12_x	IP12_x	D12_x
FP12_y	1.000	0.001	0.000	0.001	0.048
σ_F^2 12_y	0.000	1.000	0.000	0.000	0.155
σ_s^2 12_y	0.009	0.000	1.000	0.041	0.025
IP12_y	0.013	0.000	0.003	1.000	0.003
D12_y	0.000	0.015	0.226	0.000	1.000
Hour 13	FP13_x	σ_F^2 13_x	σ_s^2 13_x	IP13_x	D13_x
FP13_y	1.000	0.001	0.000	0.026	0.151
σ_F^2 13_y	0.000	1.000	0.000	0.056	0.644
σ_s^2 13_y	0.009	0.000	1.000	0.190	0.188
IP13_y	0.128	0.000	0.014	1.000	0.000
D13_y	0.001	0.038	0.173	0.000	1.000
Hour 14	FP14_x	σ_F^2 14_x	σ_s^2 14_x	IP14_x	D14_x
FP14_y	1.000	0.000	0.000	0.009	0.002
σ_F^2 14_y	0.000	1.000	0.000	0.059	0.608
σ_s^2 14_y	0.067	0.000	1.000	0.346	0.550
IP14_y	0.098	0.000	0.020	1.000	0.000
D14_y	0.001	0.006	0.035	0.000	1.000
Hour 15	FP15_x	σ_F^2 15_x	σ_s^2 15_x	IP15_x	D15_x
FP15_y	1.000	0.000	0.000	0.001	0.005
σ_F^2 15_y	0.000	1.000	0.000	0.279	0.237
σ_s^2 15_y	0.062	0.111	1.000	0.144	0.134
IP15_y	0.051	0.057	0.025	1.000	0.005
D15_y	0.000	0.041	0.001	0.000	1.000
Hour 16	FP16_x	σ_F^2 16_x	σ_s^2 16_x	IP16_x	D16_x
FP16_y	1.000	0.000	0.000	0.005	0.140
σ_F^2 16_y	0.000	1.000	0.000	0.014	0.723
σ_s^2 16_y	0.051	0.000	1.000	0.053	0.192
IP16_y	0.033	0.023	0.010	1.000	0.005
D16_y	0.001	0.188	0.010	0.000	1.000

Hour 5	FP5_x	σ_F^2 5_x	σ_s^2 5_x	IP5_x	D5_x	Hour 17	FP17_x	σ_F^2 17_x	σ_s^2 17_x	IP17_x	D17_x
FP5_y	1.000	0.000	0.000	0.093	0.544	FP17_y	1.000	0.000	0.000	0.150	0.219
σ_F^2 5_y	0.000	1.000	0.000	0.042	0.077	σ_F^2 17_y	0.456	1.000	0.004	0.284	0.181
σ_s^2 5_y	0.011	0.014	1.000	0.000	0.067	σ_s^2 17_y	0.035	0.005	1.000	0.000	0.026
IP5_y	0.005	0.025	0.020	1.000	0.000	IP17_y	0.026	0.091	0.030	1.000	0.094
D5_y	0.000	0.238	0.237	0.674	1.000	D17_y	0.212	0.045	0.257	0.000	1.000
Hour 6	FP6_x	σ_F^2 6_x	σ_s^2 6_x	IP6_x	D6_x	Hour 18	FP18_x	σ_F^2 18_x	σ_s^2 18_x	IP18_x	D18_x
FP6_y	1.000	0.000	0.000	0.010	0.000	FP18_y	1.000	0.004	0.001	0.141	0.332
σ_F^2 6_y	0.000	1.000	0.000	0.003	0.136	σ_F^2 18_y	0.723	1.000	0.000	0.335	0.327
σ_s^2 6_y	0.001	0.388	1.000	0.000	0.420	σ_s^2 18_y	0.009	0.533	1.000	0.001	0.069
IP6_y	0.000	0.063	0.000	1.000	0.000	IP18_y	0.036	0.337	0.021	1.000	0.543
D6_y	0.000	0.488	0.000	0.370	1.000	D18_y	0.016	0.269	0.415	0.000	1.000
Hour 7	FP7_x	σ_F^2 7_x	σ_s^2 7_x	IP7_x	D7_x	Hour 19	FP19_x	σ_F^2 19_x	σ_s^2 19_x	IP19_x	D19_x
FP7_y	1.000	0.000	0.000	0.005	0.000	FP19_y	1.000	0.004	0.000	0.043	0.050
σ_F^2 7_y	0.000	1.000	0.000	0.024	0.234	σ_F^2 19_y	0.019	1.000	0.000	0.014	0.142
σ_s^2 7_y	0.000	0.195	1.000	0.008	0.014	σ_s^2 19_y	0.001	0.071	1.000	0.014	0.163
IP7_y	0.010	0.012	0.000	1.000	0.000	IP19_y	0.119	0.000	0.002	1.000	0.024
D7_y	0.000	0.541	0.001	0.000	1.000	D19_y	0.001	0.000	0.010	0.000	1.000
Hour 8	FP8_x	σ_F^2 8_x	σ_s^2 8_x	IP8_x	D8_x	Hour 20	FP20_x	σ_F^2 20_x	σ_s^2 20_x	IP20_x	D20_x
FP8_y	1.000	0.014	0.017	0.000	0.000	FP20_y	1.000	0.006	0.000	0.007	0.000
σ_F^2 8_y	0.000	1.000	0.000	0.007	0.019	σ_F^2 20_y	0.000	1.000	0.000	0.005	0.067
σ_s^2 8_y	0.001	0.176	1.000	0.000	0.000	σ_s^2 20_y	0.307	0.021	1.000	0.002	0.049
IP8_y	0.024	0.012	0.001	1.000	0.000	IP20_y	0.079	0.000	0.003	1.000	0.016
D8_y	0.000	0.577	0.001	0.000	1.000	D20_y	0.000	0.000	0.023	0.000	1.000
Hour 9	FP9_x	σ_F^2 9_x	σ_s^2 9_x	IP9_x	D9_x	Hour 21	FP21_x	σ_F^2 21_x	σ_s^2 21_x	IP21_x	D21_x
FP9_y	1.000	0.059	0.000	0.000	0.000	FP21_y	1.000	0.014	0.000	0.389	0.019
σ_F^2 9_y	0.000	1.000	0.000	0.000	0.001	σ_F^2 21_y	0.000	1.000	0.000	0.002	0.040
σ_s^2 9_y	0.059	0.000	1.000	0.110	0.086	σ_s^2 21_y	0.039	0.000	1.000	0.008	0.087
IP9_y	0.043	0.070	0.048	1.000	0.000	IP21_y	0.262	0.000	0.001	1.000	0.001
D9_y	0.002	0.105	0.064	0.000	1.000	D21_y	0.001	0.000	0.003	0.000	1.000

Hour 10	FP10_x	σ_F^2 10_x	σ_S^2 10_x	IP10_x	D10_x	Hour 22	FP22_x	σ_F^2 22_x	σ_S^2 22_x	IP22_x	D22_x
FP10_y	1.000	0.014	0.009	0.001	0.001	FP22_y	1.000	0.000	0.000	0.088	0.072
σ_F^2 10_y	0.000	1.000	0.000	0.001	0.002	σ_F^2 22_y	0.000	1.000	0.000	0.011	0.281
σ_S^2 10_y	0.000	0.000	1.000	0.027	0.013	σ_S^2 22_y	0.532	0.058	1.000	0.002	0.084
IP10_y	0.054	0.203	0.081	1.000	0.000	IP22_y	0.238	0.003	0.000	1.000	0.001
D10_y	0.000	0.048	0.173	0.000	1.000	D22_y	0.064	0.006	0.000	0.000	1.000
Hour 11	FP11_x	σ_F^2 11_x	σ_S^2 11_x	IP11_x	D11_x	Hour 23	FP23_x	σ_F^2 23_x	σ_S^2 23_x	IP23_x	D23_x
FP11_y	1.000	0.012	0.000	0.002	0.017	FP23_y	1.000	0.000	0.000	0.747	0.107
σ_F^2 11_y	0.000	1.000	0.000	0.005	0.022	σ_F^2 23_y	0.003	1.000	0.000	0.032	0.924
σ_S^2 11_y	0.002	0.098	1.000	0.024	0.012	σ_S^2 23_y	0.221	0.000	1.000	0.001	0.036
IP11_y	0.039	0.058	0.018	1.000	0.000	IP23_y	0.297	0.001	0.015	1.000	0.000
D11_y	0.000	0.047	0.222	0.000	1.000	D23_y	0.023	0.004	0.049	0.000	1.000

Figure A-5 Granger causality test results- a p-value less than 0.05 indicating a confident rejection of the null hypothesis and that a possible link exists (highlighted cells)

Variable	Test Stat.	C(95%)	Signif.	Variable	Test Stat.	C(95%)	Signif.	Variable	Test Stat.	C(95%)	Signif.
Hour 0				Hour 8				Hour 16			
FP0	432.02	60.1	TRUE	FP8	424.68	60.1	TRUE	FP16	457.89	60.1	TRUE
σ_F^2 0	265.85	40.2	TRUE	σ_F^2 8	244.34	40.2	TRUE	σ_F^2 16	279.72	40.2	TRUE
σ_S^2 0	130.52	24.3	TRUE	σ_S^2 8	125.44	24.3	TRUE	σ_S^2 16	135.13	24.3	TRUE
IP0	50.3	12.3	TRUE	IP8	58.55	12.3	TRUE	IP16	59.44	12.3	TRUE
D0	4.04	4.1	FALSE	D8	4.65	4.1	TRUE	D16	4.63	4.1	TRUE
Hour 1				Hour 9				Hour 17			
FP1	471.49	60.1	TRUE	FP9	418.89	60.1	TRUE	FP17	411.75	60.1	TRUE
σ_F^2 1	298.94	40.2	TRUE	σ_F^2 9	247.66	40.2	TRUE	σ_F^2 17	251.33	40.2	TRUE
σ_S^2 1	136.46	24.3	TRUE	σ_S^2 9	132.04	24.3	TRUE	σ_S^2 17	130.48	24.3	TRUE
IP1	50.29	12.3	TRUE	IP9	58.09	12.3	TRUE	IP17	52.93	12.3	TRUE
D1	3.68	4.1	FALSE	D9	4.25	4.1	TRUE	D17	4.76	4.1	TRUE
Hour 2				Hour 10				Hour 18			
FP2	464.36	60.1	TRUE	FP10	464.83	60.1	TRUE	FP18	441.2	60.1	TRUE
σ_F^2 2	239.91	40.2	TRUE	σ_F^2 10	294.37	40.2	TRUE	σ_F^2 18	260.37	40.2	TRUE
σ_S^2 2	87.46	24.3	TRUE	σ_S^2 10	134.1	24.3	TRUE	σ_S^2 18	149.58	24.3	TRUE
IP2	40.78	12.3	TRUE	IP10	60.31	12.3	TRUE	IP18	59.39	12.3	TRUE
D2	3.46	4.1	FALSE	D10	4.27	4.1	TRUE	D18	3.73	4.1	FALSE
Hour 3				Hour 11				Hour 19			
FP3	FP7	390.12	60.1	FP11	459.94	60.1	TRUE	FP19	469.09	60.1	TRUE

σ_F^2 3	σ_F^2 7	223.86	40.2	σ_F^2 11	264.58	40.2	TRUE	σ_F^2 19	283.77	40.2	TRUE
σ_S^2 3	σ_S^2 7	87.84	24.3	σ_S^2 11	138.38	24.3	TRUE	σ_S^2 19	114.03	24.3	TRUE
IP3	IP7	42.56	12.3	IP11	63.49	12.3	TRUE	IP19	57.35	12.3	TRUE
D3	D7	4.06	4.1	D11	4.43	4.1	TRUE	D19	3.9	4.1	FALSE
Hour 4				Hour 12				Hour 20			
FP4	383.27	60.1	TRUE	FP12	518.75	60.1	TRUE	FP20	482.82	60.1	TRUE
σ_F^2 4	244.23	40.2	TRUE	σ_F^2 12	291.9	40.2	TRUE	σ_F^2 20	268.21	40.2	TRUE
σ_S^2 4	124.26	24.3	TRUE	σ_S^2 12	128.82	24.3	TRUE	σ_S^2 20	116.99	24.3	TRUE
IP4	49	12.3	TRUE	IP12	59.64	12.3	TRUE	IP20	54.97	12.3	TRUE
D4	3.59	4.1	FALSE	D12	4.74	4.1	TRUE	D20	4.04	4.1	FALSE
Hour 5				Hour 13				Hour 21			
FP5	383.37	60.1	TRUE	FP13	474.68	60.1	TRUE	FP21	415.48	60.1	TRUE
σ_F^2 5	246.26	40.2	TRUE	σ_F^2 13	259.62	40.2	TRUE	σ_F^2 21	259.97	40.2	TRUE
σ_S^2 5	125.85	24.3	TRUE	σ_S^2 13	124.4	24.3	TRUE	σ_S^2 21	112.59	24.3	TRUE
IP5	61.09	12.3	TRUE	IP13	59.31	12.3	TRUE	IP21	55.68	12.3	TRUE
D5	3.64	4.1	FALSE	D13	4.57	4.1	TRUE	D21	4.7	4.1	TRUE
Hour 6				Hour 14				Hour 22			
FP6	347.49	60.1	TRUE	FP14	472.28	60.1	TRUE	FP22	491.26	60.1	TRUE
σ_F^2 6	228.36	40.2	TRUE	σ_F^2 14	263.92	40.2	TRUE	σ_F^2 22	282.26	40.2	TRUE
σ_S^2 6	118.73	24.3	TRUE	σ_S^2 14	134.75	24.3	TRUE	σ_S^2 22	125.05	24.3	TRUE
IP6	52.05	12.3	TRUE	IP14	65.35	12.3	TRUE	IP22	56.87	12.3	TRUE
D6	4.02	4.1	FALSE	D14	5.05	4.1	TRUE	D22	5.38	4.1	TRUE
Hour 7				Hour 15				Hour 23			
FP7	390.12	60.1	TRUE	FP15	474.42	60.1	TRUE	FP23	545.18	60.1	TRUE
σ_F^2 7	223.86	40.2	TRUE	σ_F^2 15	277.81	40.2	TRUE	σ_F^2 23	337.76	40.2	TRUE
σ_S^2 7	87.84	24.3	TRUE	σ_S^2 15	157.71	24.3	TRUE	σ_S^2 23	149.8	24.3	TRUE
IP7	42.56	12.3	TRUE	IP15	67.11	12.3	TRUE	IP23	53.35	12.3	TRUE
D7	4.06	4.1	FALSE	D15	5.03	4.1	TRUE	D23	4.86	4.1	TRUE

Figure A-6 Results of the cointegration test, which identifies a significant link between two or more time series, marked as 'TRUE', and non-significant as 'FALSE'

Hour 0							Hour 12						
FP0	FP0	σ_F^2 0	σ_S^2 0	IP0	D0	DW	FP12	FP12	σ_F^2 12	σ_S^2 12	IP12	D12	DW
FP0	1.000	-0.087	0.316	-0.103	-0.038	2.01	FP12	1.000	-0.077	0.382	-0.135	-0.042	2.00
σ_F^2 0	-0.087	1.000	-0.005	-0.039	-0.019	2.00	σ_F^2 12	-0.077	1.000	0.130	-0.014	-0.021	1.99
σ_S^2 0	0.316	-0.005	1.000	-0.128	-0.064	1.99	σ_S^2 12	0.382	0.130	1.000	-0.111	-0.102	2.01
IP0	-0.103	-0.039	-0.128	1.000	0.561	2.06	IP12	-0.135	-0.014	-0.111	1.000	0.676	2.00
D0	-0.038	-0.019	-0.064	0.561	1.000	2.03	D12	-0.042	-0.021	-0.102	0.676	1.000	2.03
Hour 1							Hour 13						
FP1	FP1	σ_F^2 1	σ_S^2 1	IP1	D1		FP13	FP13	σ_F^2 13	σ_S^2 13	IP13	D13	

FP1	1.000	-0.114	0.523	-0.107	0.002	2.01	FP13	1.000	-0.090	0.396	-0.118	-0.001	2.00
σ_F^2 1	-0.114	1.000	0.009	-0.072	-0.024	2.00	σ_F^2 13	-0.090	1.000	0.085	-0.017	-0.025	1.99
σ_S^2 1	0.523	0.009	1.000	-0.108	-0.051	2.00	σ_S^2 13	0.396	0.085	1.000	-0.058	-0.021	2.02
IP1	-0.107	-0.072	-0.108	1.000	0.463	2.11	IP13	-0.118	-0.017	-0.058	1.000	0.689	2.00
D1	0.002	-0.024	-0.051	0.463	1.000	2.02	D13	-0.001	-0.025	-0.021	0.689	1.000	2.04
Hour 2	FP2	σ_F^2 2	σ_S^2 2	IP2	D2		Hour 14	FP14	σ_F^2 14	σ_S^2 14	IP14	D14	
FP2	1.000	-0.085	0.320	-0.055	0.036	2.02	FP14	1.000	-0.095	0.397	-0.125	-0.015	1.99
σ_F^2 2	-0.085	1.000	0.441	-0.040	-0.021	2.00	σ_F^2 14	-0.095	1.000	0.177	-0.021	-0.023	1.98
σ_S^2 2	0.320	0.441	1.000	-0.053	-0.017	2.00	σ_S^2 14	0.397	0.177	1.000	-0.094	-0.047	2.01
IP2	-0.055	-0.040	-0.053	1.000	0.398	2.12	IP14	-0.125	-0.021	-0.094	1.000	0.694	2.00
D2	0.036	-0.021	-0.017	0.398	1.000	2.00	D14	-0.015	-0.023	-0.047	0.694	1.000	2.04
Hour 3	FP3	σ_F^2 3	σ_S^2 3	IP3	D3		Hour 15	FP15	σ_F^2 15	σ_S^2 15	IP15	D15	
FP3	1.000	-0.105	0.377	-0.020	0.044	2.01	FP15	1.000	-0.075	0.408	-0.134	0.018	2.01
σ_F^2 3	-0.105	1.000	-0.014	-0.027	0.018	1.93	σ_F^2 15	-0.075	1.000	0.093	-0.035	-0.029	1.99
σ_S^2 3	0.377	-0.014	1.000	-0.015	-0.006	2.00	σ_S^2 15	0.408	0.093	1.000	-0.152	-0.061	2.00
IP3	-0.020	-0.027	-0.015	1.000	0.370	2.10	IP15	-0.134	-0.035	-0.152	1.000	0.664	2.05
D3	0.044	0.018	-0.006	0.370	1.000	2.00	D15	0.018	-0.029	-0.061	0.664	1.000	2.02
Hour 4	FP4	σ_F^2 4	σ_S^2 4	IP4	D4		Hour 16	FP16	σ_F^2 16	σ_S^2 16	IP16	D16	
FP4	1.000	-0.100	0.444	-0.042	0.045	2.01	FP16	1.000	-0.108	0.348	-0.139	-0.011	2.01
σ_F^2 4	-0.100	1.000	-0.025	-0.003	0.025	1.98	σ_F^2 16	-0.108	1.000	0.051	-0.026	-0.026	2.06
σ_S^2 4	0.444	-0.025	1.000	-0.047	-0.011	1.99	σ_S^2 16	0.348	0.051	1.000	-0.111	-0.045	2.01
IP4	-0.042	-0.003	-0.047	1.000	0.337	2.09	IP16	-0.139	-0.026	-0.111	1.000	0.641	2.09
D4	0.045	0.025	-0.011	0.337	1.000	1.99	D16	-0.011	-0.026	-0.045	0.641	1.000	1.99
Hour 5	FP5	σ_F^2 5	σ_S^2 5	IP5	D5		Hour 17	FP17	σ_F^2 17	σ_S^2 17	IP17	D17	
FP5	1.000	-0.157	0.537	-0.029	0.074	2.01	FP17	1.000	-0.101	0.350	-0.059	0.024	2.02
σ_F^2 5	-0.157	1.000	0.022	-0.050	0.000	1.97	σ_F^2 17	-0.101	1.000	0.000	-0.067	-0.047	2.00
σ_S^2 5	0.537	0.022	1.000	-0.059	0.007	2.00	σ_S^2 17	0.350	0.000	1.000	-0.066	-0.049	2.00
IP5	-0.029	-0.050	-0.059	1.000	0.320	2.11	IP17	-0.059	-0.067	-0.066	1.000	0.636	2.14
D5	0.074	0.000	0.007	0.320	1.000	1.99	D17	0.024	-0.047	-0.049	0.636	1.000	2.03
Hour 6	FP6	σ_F^2 6	σ_S^2 6	IP6	D6		Hour 18	FP18	σ_F^2 18	σ_S^2 18	IP18	D18	

FP6	1.000	-0.178	0.381	0.003	0.128	2.02	FP18	1.000	-0.088	0.409	-0.089	-0.044	2.01
σ_F^2 6	-0.178	1.000	0.010	-0.042	0.001	2.00	σ_F^2 18	-0.088	1.000	0.004	-0.033	-0.027	2.00
σ_S^2 6	0.381	0.010	1.000	-0.117	-0.026	1.99	σ_S^2 18	0.409	0.004	1.000	-0.088	-0.065	1.98
IP6	0.003	-0.042	-0.117	1.000	0.282	2.08	IP18	-0.089	-0.033	-0.088	1.000	0.799	2.09
D6	0.128	0.001	-0.026	0.282	1.000	2.03	D18	-0.044	-0.027	-0.065	0.799	1.000	2.04
Hour 7	FP7	σ_F^2 7	σ_S^2 7	IP7	D7		Hour 19	FP19	σ_F^2 19	σ_S^2 19	IP19	D19	
FP7	1.000	-0.094	0.631	-0.055	0.076	2.01	FP19	1.000	-0.068	0.423	-0.106	-0.064	2.01
σ_F^2 7	-0.094	1.000	0.008	-0.047	0.007	2.01	σ_F^2 19	-0.068	1.000	0.062	0.000	-0.012	1.98
σ_S^2 7	0.631	0.008	1.000	-0.117	-0.053	2.00	σ_S^2 19	0.423	0.062	1.000	-0.089	-0.062	1.97
IP7	-0.055	-0.047	-0.117	1.000	0.471	2.06	IP19	-0.106	0.000	-0.089	1.000	0.846	2.08
D7	0.076	0.007	-0.053	0.471	1.000	2.03	D19	-0.064	-0.012	-0.062	0.846	1.000	2.04
Hour 8	FP8	σ_F^2 8	σ_S^2 8	IP8	D8		Hour 20	FP20	σ_F^2 20	σ_S^2 20	IP20	D20	
FP8	1.000	-0.081	0.530	-0.077	0.068	2.00	FP20	1.000	-0.089	0.388	-0.092	-0.042	2.01
σ_F^2 8	-0.081	1.000	0.167	-0.001	-0.002	1.98	σ_F^2 20	-0.089	1.000	0.026	0.003	-0.020	1.99
σ_S^2 8	0.530	0.167	1.000	-0.164	-0.105	2.00	σ_S^2 20	0.388	0.026	1.000	-0.079	-0.059	2.00
IP8	-0.077	-0.001	-0.164	1.000	0.586	2.12	IP20	-0.092	0.003	-0.079	1.000	0.845	2.09
D8	0.068	-0.002	-0.105	0.586	1.000	1.99	D20	-0.042	-0.020	-0.059	0.845	1.000	2.03
Hour 9	FP9	σ_F^2 9	σ_S^2 9	IP9	D9		Hour 21	FP21	σ_F^2 21	σ_S^2 21	IP21	D21	
FP9	1.000	-0.103	0.460	-0.067	0.095	2.01	FP21	1.000	-0.083	0.417	-0.115	-0.070	2.00
σ_F^2 9	-0.103	1.000	0.015	-0.012	-0.019	1.96	σ_F^2 21	-0.083	1.000	0.028	0.009	-0.002	2.01
σ_S^2 9	0.460	0.015	1.000	-0.102	-0.044	2.00	σ_S^2 21	0.417	0.028	1.000	-0.120	-0.094	2.01
IP9	-0.067	-0.012	-0.102	1.000	0.618	2.12	IP21	-0.115	0.009	-0.120	1.000	0.814	2.07
D9	0.095	-0.019	-0.044	0.618	1.000	2.00	D21	-0.070	-0.002	-0.094	0.814	1.000	2.02
Hour 10	FP10	σ_F^2 10	σ_S^2 10	IP10	D10		Hour 22	FP22	σ_F^2 22	σ_S^2 22	IP22	D22	
FP10	1.000	-0.104	0.459	-0.093	0.012	2.00	FP22	1.000	-0.165	0.322	-0.066	-0.019	2.00
σ_F^2 10	-0.104	1.000	-0.024	0.026	-0.008	2.00	σ_F^2 22	-0.165	1.000	0.048	0.004	0.015	2.06
σ_S^2 10	0.459	-0.024	1.000	-0.083	-0.063	2.00	σ_S^2 22	0.322	0.048	1.000	-0.023	0.002	2.01
IP10	-0.093	0.026	-0.083	1.000	0.658	2.00	IP22	-0.066	0.004	-0.023	1.000	0.748	2.07
D10	0.012	-0.008	-0.063	0.658	1.000	2.03	D22	-0.019	0.015	0.002	0.748	1.000	2.02
Hour 11	FP11	σ_F^2 11	σ_S^2 11	IP11	D11		Hour 23	FP23	σ_F^2 23	σ_S^2 23	IP23	D23	

FP11	1.000	-0.038	0.442	-0.125	-0.022	2.00	FP23	1.000	-0.104	0.292	-0.090	-0.038	2.00
σ_F^2 11	-0.038	1.000	0.026	-0.016	-0.022	2.00	σ_F^2 23	-0.104	1.000	0.076	0.034	0.036	2.00
σ_s^2 11	0.442	0.026	1.000	-0.094	-0.087	2.00	σ_s^2 23	0.292	0.076	1.000	-0.098	-0.059	1.99
IP11	-0.125	-0.016	-0.094	1.000	0.685	2.00	IP23	-0.090	0.034	-0.098	1.000	0.674	2.07
D11	-0.022	-0.022	-0.087	0.685	1.000	2.03	D23	-0.038	0.036	-0.059	0.674	1.000	2.02

Figure A-7 Correlation matrices of the VAR analyses, where stronger correlation is indicated by weaker highlights (and vice versa), and the calculated Durbin–Watson (DW) statistic of each variable, statistic ranges from 0 to 4, with values closer to 2 indicating no significant correlation

Table A-9 List of distribution PDF's used in this study

Distribution	Probability density function	Parameter
normal	$\frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$	μ – mean σ – standard deviation
exponential	$\begin{cases} \lambda e^{-\lambda x} & x \geq 0, \\ 0 & x < 0 \end{cases}$	λ – rate parameter
pareto	$\begin{cases} \frac{\alpha x_m^\alpha}{x^{\alpha+1}} & x \geq x_m, \\ 0 & x < x_m \end{cases}$	x_m – minimum possible value of x α – shape parameter/tail index
weibull	$\begin{cases} \frac{k}{\lambda} \left(\frac{x}{\lambda}\right)^{k-1} e^{-\left(\frac{x}{\lambda}\right)^k} & x \geq 0, \\ 0 & x < 0 \end{cases}$	k – shape parameter λ – scale of distribution
t	$\frac{\Gamma\left(\frac{\nu+1}{2}\right)}{\sqrt{\pi\nu}\Gamma\left(\frac{\nu}{2}\right)} \left(1 + \frac{t^2}{\nu}\right)^{-(\nu+1)/2}$	ν – degrees of freedom Γ – gamma function
GEV	$\begin{cases} e^{-s} \exp(-e^{-s}) & \text{for } \xi = 0 \\ (1 + \xi s)^{-\left(1+\frac{1}{\xi}\right)} \exp\left(-\left(1 + \xi s\right)^{\frac{-1}{\xi}}\right) & \text{for } \xi \neq 0, \xi s > -1 \\ 0 & \text{otherwise} \end{cases}$	ξ – shape parameter s – location parameter
gamma	$\frac{x^{\alpha-1} e^{-\beta x} \beta^\alpha}{\Gamma(\alpha)} \quad x > 0 \quad \alpha, \beta > 0$	α, β – shape parameters Γ – gamma function

log normal	$\frac{1}{x\sigma\sqrt{2\pi}} \exp\left(-\frac{(\ln x - \mu)^2}{2\sigma^2}\right)$	μ - natural log mean σ - natural log standard deviation
beta	$\frac{1}{B(\alpha, \beta)} x^{\alpha-1} (1-x)^{\beta-1}$	α, β - shape parameters B- normalization constant
uniform	$\begin{cases} \frac{1}{b-a} & a \leq x \leq b, \\ 0 & x < a \text{ or } x > b \end{cases}$	a,b – minimum and maximum bounds
log gamma	$\frac{\lambda^\alpha}{\Gamma(\alpha)} \frac{(\log x)^{\alpha-1}}{x^{\lambda+1}}$	α - shape parameters λ - scale of distribution Γ - gamma function

Table A-10 Results of parameter estimation of the distribution fitting process and scoring of fits using RSS in order to rank the fits, whereby the highest ranking fit is highlighted in 'red'

(a) PE

Season	Distribution	RSS	Rank
Early Dry	normal	174.135	9
	exponential	24.234	3
	pareto	24.234	3
	weibull	125.247	8
	t	119.414	7
	GEV	38.240	6
	gamma	3.475	2
	log normal	25.570	5
	beta	2.831	1
	uniform	664.120	11
	log gamma	178.426	10
Late Dry	normal	299.378	9
	exponential	71.087	3
	pareto	71.087	3
	weibull	213.689	7
	t	203.947	6
	GEV	81.456	5
	gamma	697.393	10
	log normal	61.608	2
	beta	16.399	1
	uniform	1447.070	11
	log gamma	296.963	8
Early Wet	normal	492.381	9
	exponential	29.889	3
	pareto	29.889	3
	weibull	347.407	8
	t	323.893	7
	GEV	108.585	6
	gamma	6.221	2
	log normal	66.800	5
	beta	6.095	1
	uniform	1681.720	11
	log gamma	503.463	10
Late Wet	normal	327.835	8
	exponential	40.318	2
	pareto	42.010	3
	weibull	215.910	7
	t	190.403	6
	GEV	68.808	5
	gamma	531.113	10

	log normal	47.286	4
	beta	11.206	1
	uniform	1227.130	11
	log gamma	354.224	9

(b) PU

Season	Distribution	RSS	Rank
Early Dry	normal	9.467	6
	exponential	23.191	10
	pareto	23.191	10
	weibull	8.410	5
	t	9.467	7
	GEV	4.385	2
	gamma	10.011	9
	log normal	9.467	8
	beta	2.485	1
	uniform	6.220	4
	log gamma	5.590	3
Late Dry	normal	26.650	6
	exponential	96.983	10
	pareto	96.983	10
	weibull	24.676	3
	t	25.688	4
	GEV	21.623	2
	gamma	29.540	7
	log normal	26.471	5
	beta	37.028	8
	uniform	67.458	9
	log gamma	9.888	1
Early Wet	normal	13.158	6
	exponential	32.313	10
	pareto	32.313	10
	weibull	5.434	1
	t	13.158	8
	GEV	11.274	3
	gamma	13.139	4
	log normal	13.158	6
	beta	9.351	2
	uniform	17.440	9
	log gamma	13.145	5
Late Wet	normal	14.676	8
	exponential	21.628	10
	pareto	21.628	10
	weibull	7.861	1
	t	14.676	8

	GEV	13.691	5
	gamma	14.610	7
	log normal	13.383	4
	beta	9.031	2
	uniform	10.495	3
	log gamma	14.589	6

(c) PK

Season	Distribution	RSS	Rank
Early Dry	normal	3.429	6
	exponential	144.361	10
	pareto	144.361	10
	weibull	10.965	8
	t	3.429	7
	GEV	2.040	1
	gamma	2.586	4
	log normal	2.581	3
	beta	2.331	2
	uniform	92.019	9
	log gamma	3.389	5
Late Dry	normal	3.384	5
	exponential	138.269	10
	pareto	138.269	10
	weibull	5.557	8
	t	3.384	6
	GEV	2.100	1
	gamma	3.019	3
	log normal	2.997	2
	beta	4.235	7
	uniform	94.236	9
	log gamma	3.321	4
Early Wet	normal	5.373	4
	exponential	161.130	10
	pareto	161.130	10
	weibull	7.091	7
	t	5.373	5
	GEV	125.856	9
	gamma	5.299	2
	log normal	5.373	3
	beta	4.894	1
	uniform	111.461	8
	log gamma	5.509	6
Late Wet	normal	4.556	5
	exponential	145.056	10

	pareto	145.056	10
	weibull	6.535	8
	t	4.556	4
	GEV	3.657	1
	gamma	4.315	2
	log normal	4.449	3
	beta	4.705	6
	uniform	100.576	9
	log gamma	4.866	7

(d) FP

Season	Distribution	RSS	Rank
Early Dry	normal	4275.100	7
	exponential	563.132	1
	pareto	775.352	3
	weibull	2180.030	6
	t	1583.700	5
	GEV	965.400	4
	gamma	5923.220	9
	log normal	11555.600	11
	beta	593.196	2
	uniform	11349.300	10
	log gamma	4491.330	8
Late Dry	normal	5035.380	7
	exponential	555.753	1
	pareto	855.044	3
	weibull	3050.850	6
	t	1488.620	5
	GEV	836.784	2
	gamma	6770.940	9
	log normal	11551.600	10
	beta	1259.270	4
	uniform	11904.600	11
	log gamma	5636.840	8
Early Wet	normal	4648.500	7
	exponential	1331.130	4
	pareto	1781.760	5
	weibull	3169.760	6
	t	857.826	3
	GEV	452.987	1
	gamma	8813.020	9
	log normal	12178.800	11
	beta	736.449	2

	uniform	11979.900	10
	log gamma	5163.200	8
Late Wet	normal	5262.680	7
	exponential	713.711	2
	pareto	1065.730	4
	weibull	1895.200	6
	t	1192.070	5
	GEV	687.460	1
	gamma	7716.980	9
	log normal	11686.800	10
	beta	762.518	3
	uniform	12064.100	11
	log gamma	5648.630	8

Table A-11 Evaluation results of the joint distributions using the theoretical Gaussian and *t* copulas based on LL for each case

Case	Variables	Season	LL	
			Gaussian	t
1	[PE , FP]	Early dry	0.4012	-0.3928
		Late dry	0.7780	0.8374
		Early wet	0.3306	1.5575
		Late wet	2.4448	3.0894
2	[PU , PK]	Early dry	0.0489	-0.8444
		Late dry	0.0616	-0.7765
		Early wet	0.1490	1.4114
		Late wet	-0.0050	-0.1373
3	[PK ,PU , FP]	Early dry	5.7091	5.1105
		Late dry	1.1653	-0.6835
		Early wet	0.8230	1.2862
		Late wet	0.2672	-2.4446
4	All	Early dry	6.8772	3.4665
		Late dry	3.6390	-1.3443
		Early wet	1.5505	2.7388
		Late wet	3.5941	1.9977

List of publications

1. 'Managing power supply in small nations: A case on Belize's Idiosyncratic system', *Energy for Sustainable Development*, **2024**, DOI: 10.1016/J.ESD.2024.101548
2. 'A Price Risk Analysis on the Exposure of Cross-Border Electricity Trade in Liberalized Power Markets: Case Study of the Belize-Mexico Interconnection', *Energies*, **2024**, DOI: 10.3390/en17143464
3. 'Inherent Risk Analysis of Power Supply Management: Case of Belize's System Operator and Third-Party Actors', *Energies*, **2025**, DOI:10.3390/en18010049