Stockholm School of Economics
MSc in Finance
Corporate Finance Specialization

Master's Degree Thesis (30 ECTS)
Spring Semester 2026

Is There a Nuclear Energy Premium?

Evidence from Electricity Generation Markets

Gian Luca Hedenström (50690)

Abstract:
Electricity generation is a capital-intensive sector where financing conditions influence investment decisions and the trajectory of the energy transition. Among generation technologies, nuclear power features exceptionally high upfront costs and long investment horizons. It is also a low-carbon and reliable energy source, central to many decarbonization models. Yet, nuclear has a contested risk profile: investors often avoid it due to concerns related to accident risk and waste management, while climate finance taxonomies are ambiguous about its classification. These features may limit its investor base and increase its perceived risk. However, it remains unclear how such factors are reflected in capital markets, and whether they suggest a risk profile closer to the expanding yet policy-dependent renewables, or to the declining yet system-critical fossil technologies. This study aims to answer this question by testing how nuclear exposure is priced in required returns relative to renewable and fossil exposure, and whether this relationship is moderated by generators' revenue model. For this purpose, a panel of 92 publicly listed electricity generators in OECD countries with nuclear on the power grid across 2010-2024 is collected and analyzed using two measures of required returns: Implied Cost of Equity and CAPM-adjusted Risk Premia. The results reveal no evidence of a distinct, unconditional pricing of nuclear exposure relative to fossil and renewable technologies. However, when revenue model is considered, a different pattern emerges. Under low merchant exposure, nuclear generation is associated with higher required returns than both fossil and renewable technologies; this premium disappears as merchant exposure increases. These findings suggest that the pricing of electricity generators is influenced by the interaction between technology and revenue model, indicating that their cost of equity depends more on how risks are allocated rather than on technology alone. These results have implications for asset pricing in electricity markets, policy design, and project development.

Supervisor: Tobias Sichert, Assistant Professor, Department of Finance, Stockholm School of Economics

Keywords: Nuclear Energy, Electricity Markets, Cost of Equity, Risk Premia, Merchant Exposure

Table of Contents

1. Introduction

1.1 Background

Investment decisions in electricity generation are fundamentally determined by the net present value of expected future cash flows, discounted at a required rate of return. This discount rate reflects investors' required compensation for risk and therefore plays a central role in determining which generation technologies attract capital (Steffen, 2020). In capital-intensive energy systems, where a large share of total costs is incurred upfront, small differences in required returns can translate into large differences in project viability (OECD NEA, 2019). Consequently, understanding how risk premia differ across generation technologies is critical for explaining investment patterns and the evolution of the energy transition.

The electricity system is undergoing a rapid transformation driven by technological change, decarbonization policies, and energy security concerns. Advances in modular and flexible generation technologies, together with climate targets, have accelerated the expansion of renewable energy, which has increasingly displaced carbon-intensive fossil fuel generation in several markets (IEA, 2023; Schneider et al., 2025). At the same time, continued dependence on fossil fuels and the 2021-2022 energy crisis have highlighted vulnerabilities in energy security and price stability, renewing interest in stable, dispatchable generation sources. Within this context, nuclear generation has re-emerged as a potential alternative to both fossil and renewable technologies, as it combines low-carbon production with stable output (IEA, 2022; IEA, 2023). However, nuclear power is also characterized by long construction periods, high capital intensity, and significant execution risk. Recent nuclear projects in developed economies have experienced cost overruns that are multiples of initial estimates and delays exceeding a decade (Schneider et al., 2025). Moreover, the past nuclear disasters of Chernobyl and Fukushima triggered abrupt policy reversals and long-term changes in public acceptance towards nuclear in several countries, such as Italy and Germany (Kim et al., 2013; Hayashi & Hughes, 2013). These factors contributed to a decline in the global share of nuclear generation, from 17.5% in the mid-1990s to around 9% in 2025, and to its contested position among investors, reflected in its exclusion from many green financing frameworks (Bowen & Guanio, 2023; Schneider et al., 2025).

These global developments alter both the risk profile of future cash flows and the discount rates applied to different technologies, thereby affecting their relative attractiveness to investors (Steffen, 2020). In this context, nuclear generation presents a particularly ambiguous case, combining characteristics that may either increase or decrease required returns through distinct and potentially offsetting risk channels. This raises a central question: how do investors price exposure to nuclear generation relative to other electricity generation technologies? Although extensive literature examines the cost of various energy technologies (OECD NEA, 2019; IEA, 2022), relatively little empirical research directly investigates whether nuclear exposure is systematically or conditionally associated with a premium or discount in required returns.

1.2 Research Problem

From a policy perspective, nuclear power is either regarded as a reliable, low-carbon, and critical component of the energy transition (IEA, 2022) or associated with safety concerns, accident risks, and waste management challenges, leading to its exclusion from energy and investment taxonomies (MIT Energy Initiative, 2018; Bowen & Guanio, 2023). Technologically and economically, nuclear power involves long development timelines, high capital exposure, and limited flexibility within increasingly decentralized systems (Finon & Roques, 2008; Schneider et al., 2025). From a financial perspective, these opposing factors generate conflicting predictions for required returns. Nuclear generation may be perceived as a stable, low-carbon infrastructure asset, suggesting lower required returns. Alternatively, it may be viewed as a technology subject to significant long-term risks, construction delays, regulatory uncertainty, and structural displacement, implying higher required returns.

Despite these strong arguments on both sides, capital markets do not demonstrate clear or consistent pricing of nuclear generation. Empirical evidence indicates that nuclear required returns vary widely depending on policy frameworks and risk allocation (Green & Staffell, 2013). Furthermore, nuclear projects are generally not bankable without substantial government involvement, indicating private investors' reluctance to finance them under standard market conditions (Weibezahn & Steigerwald, 2024). This situation is further reflected in the absence of a viable project finance model for nuclear investments, with financing instead relying on various project-specific arrangements that redistribute risks between public and private actors (EY, 2024).

This evidence suggests that nuclear's pricing ambiguity may need to be analyzed in light of the revenue model under which electricity generators operate, ranging from contract-based frameworks that stabilize cash flows to full exposure to market electricity prices (Roques et al., 2008; Gross et al., 2010). Revenue model may affect how technology-specific risks are incorporated into required returns by modifying exposure to key risk channels (Green & Staffell, 2013).

1.3 Purpose

Therefore, this study aims to examine how nuclear generation exposure is priced in capital markets relative to other generation technologies and how revenue model may shape this pricing. Specifically, it addresses the following research questions:

RQ1: How is nuclear generation exposure priced in capital markets relative to other technologies?
RQ2: Does the pricing of nuclear generation exposure depend on revenue model?

To address these questions, a conceptual framework is developed to derive hypotheses on how generation technology exposure affects required returns through distinct risk channels. Its predictions are empirically tested using a panel dataset of 92 publicly listed electricity generators in OECD countries with nuclear power in their national electricity systems from 2010 to 2024. The analysis uses pooled panel regression models relating required returns to firms' generation portfolios, measured by generation capacity shares for nuclear, renewables, and fossil. The empirical strategy examines both unconditional pricing and conditional effects via interactions with revenue structure. Results indicate that revenue model significantly affects relative required returns, whereas no systematic unconditional risk premium is observed for nuclear generation. These findings contribute to asset pricing in electricity markets by providing empirical evidence that generators' required returns are jointly determined by the interaction between technology characteristics and revenue structures, rather than by either dimension in isolation. They also have implications for policy design and project developers by suggesting that revenue stabilization does not eliminate risk but instead reallocates it from market-based price risk toward policy credibility and perception-based risks.

2. Theory Development

2.1 Asset Pricing Framework

Investment decisions in electricity generation can be understood through the net present value framework, in which expected future cash flows are discounted at a required rate of return.

$$NPV = \sum_{t=0}^{T} \frac{CF_t}{(1+r)^t}$$

Within this framework, the risk characteristics of electricity generation technologies are relevant only as far as they affect either (i) the level and volatility of expected cash flows or (ii) the discount rate applied by investors, reflecting compensation for risk (Cochrane, 2011). Therefore, differences in investment attractiveness across technologies arise from differences in how they shape cash flow dynamics and how they are perceived by investors in terms of risk. This study focuses on required returns as a measure of how risks associated with generation technologies are priced in financial markets, consistent with empirical approaches that infer risk premia from asset prices and forward-looking expectations (e.g., Pastor et al., 2021).

However, not all sources of risk are reflected in required returns. The asset pricing literature highlights three main channels through which risk may affect required returns. First, in equilibrium, investors demand additional compensation for assets that covary strongly with the market when the market declines (Ang et al., 2006). Long-run macro risks such as climate risk (Bansal et al., 2016) and political uncertainty (Pástor & Veronesi, 2013) can therefore carry a risk premium and affect required returns when they affect aggregate economic conditions. Second, assets exposed to downside states earn higher expected returns (Ang et al., 2006; Lettau et al., 2014), as illustrated by the higher cost of downside protection for carbon-intensive firms against climate tail risk (Ilhan et al., 2021). Third, required returns may also arise from investor segmentation and preferences. When assets are held by fewer investors, expected returns increase (Merton, 1987), as shown for stocks excluded due to social norms (Hong & Kacperczyk, 2009). Moreover, Pástor et al. (2021) find that green assets have lower expected returns because they hedge climate risk, and investors enjoy holding them. In summary, required returns are affected by exposure to systematic risk, downside tail risk, or capital supply constraints.

In electricity markets, two structural dimensions are particularly relevant for shaping risk exposure: the generation technology mix employed and the revenue model under which electricity is sold. These dimensions may determine exposure to different risk channels, which affect discount rates depending on their connection to the systematic repricing channels.

2.2 Technology Exposure

This study considers three main groups of generation technologies: (i) fossil, including coal, gas, and oil; (ii) renewable, including wind and solar; and (iii) nuclear. To examine how differences in generation technologies are reflected in required returns, the underlying sources of these differences must first be identified. Technologies vary along key dimensions such as fuel dependence, capital intensity, operational flexibility, and policy exposure. These characteristics give rise to distinct risk channels, which may be associated with differences in required returns across technologies. Based on a review of the electricity generation literature in liberalized markets, four structural risk dimensions, subdivided into nine risk channels, are identified below. The key question is whether these risk channels covary with aggregate conditions, magnify losses in bad states, or reduce the investor base willing to hold them.

Structural Risk Category	**Risk Channel**
A. Operating Margin Structure Risk	1. Variable Input Cost Exposure 2. Market Price Exposure 3. Output Variability Risk
B. Capital Structure Risk	4. Capital Duration Risk 5. Construction & Pre-Revenue Risk
C. Policy & Regulatory Risk	6. Regulatory Cost Uncertainty 7. Political Discontinuity Risk
D. Systematic Capital Reallocation Risk	8. Market-Driven Transition Risk 9. Investors Segmentation Risk

Table 1: Overview of technology-specific risk channels identified in the electricity generation literature.

Both (1) variable input cost exposure and (2) market price exposure may influence required returns when fuel prices or wholesale electricity prices move with economy-wide shocks rather than firm-specific factors (Kang et al., 2016; Demirer et al., 2020). Fuel cost shocks are often associated with geopolitical events affecting global energy markets, but may also reflect regional supply disruptions or market-specific constraints, such as storage limitations (Kilian, 2009). Electricity price shocks can arise from fuel cost shocks, macroeconomic demand fluctuations, or idiosyncratic events such as weather or outages (Joskow, 2008; Gross et al., 2010). However, these exposures are not consistently tied to aggregate risk, as they are driven by a mix of macroeconomic and idiosyncratic factors. Their impact on profitability is also indirect, depending on how such shocks are transmitted into firms' revenues and costs. In contrast, (3) output variability risk is mostly idiosyncratic, as generation shocks are generally unrelated to market downturns (Hirth, 2013; Borenstein, 2012). This suggests that higher volatility alone does not automatically translate into higher required returns.

(4) Capital duration risk may affect required returns indirectly through changes in discount rates, which often reflect systematic macro shocks (Fama & French, 1996; Giglio et al., 2018). This is especially relevant for generators, which are long-lived assets and are highly sensitive to discount rates (Finon & Roques, 2008). In addition, (5) construction and pre-revenue risk is typically idiosyncratic but can become priced if cost overruns or delays are connected to inflation or interest rate shocks (Lovering et al., 2016; Giglio et al., 2018).

Similarly, (6) regulatory cost uncertainty and (7) political discontinuity risk may create a premium when regulatory or policy changes translate into wider economic downsides (Pástor & Veronesi, 2013; Ilhan et al., 2021). While regulatory changes often occur incrementally, political discontinuity arises from elections or major accidents that trigger sudden policy reversals (Julio & Yook, 2012; Joskow & Parsons, 2012; Pástor & Veronesi, 2013) and expose generators to tail risk.

In the context of (8) market-driven transition, climate risk is particularly relevant as carbon exposure has been associated with higher returns (Bolton & Kacperczyk, 2021) and tail protection is more expensive for carbon-intensive firms (Ilhan et al., 2021). Therefore, transition risk may operate through both systematic and downside tail risk. Finally, (9) investor segmentation risk largely affects required returns through capital supply constraints (Merton, 1987; Hong & Kacperczyk, 2009; Pástor et al., 2021).

Taken together, this mapping suggests that some risk channels may be more likely to generate persistent differences in required returns because they operate through systematic risk, downside tail risk, or capital supply constraints. These are (7) political discontinuity, (8) market-driven transition, and (9) investor segmentation risk. Some other exposures may be systematic in certain contexts but are less consistently reflected in required returns, as their effects are often indirect and depend on how macroeconomic shocks are transmitted into cash flows or discount rates. These are (1) variable input cost, (2) market price exposure, (4) capital duration, and (6) regulatory cost uncertainty. Finally, (3) output variability and (5) construction and pre-revenue risk are mostly idiosyncratic and therefore less likely to create persistent differences in expected returns for generators, while still affecting cash flow volatility. This classification provides a useful framework for comparing how different technologies are exposed to priced risk channels.

2.2.1 Fossil Exposure

Fossil generators are primarily exposed to systematic capital reallocation and policy/regulatory risks. High-emission firms exhibit (8) higher downside tail risk and higher expected returns associated with a carbon risk premium (Bolton & Kacperczyk, 2021; Ilhan et al., 2021), as energy transition dynamics may also lead to asset impairments or stranded capital risk if fossil reserves cannot be burned in line with climate targets (SEI, 2016; van der Ploeg & Rezai, 2020). Relatedly, (9) assets perceived as controversial may be avoided by norm-constrained investors, reducing ownership and analyst coverage and potentially increasing required returns. ESG investment strategies frequently exclude carbon-intensive sectors, potentially exacerbating this effect (Hong & Kacperczyk, 2009; Bolton & Kacperczyk, 2021). In addition, (7) fossil generation is a politically charged topic at the center of discussions around climate transition. As a result, uncertainty about decarbonization policies can raise systematic climate risk for carbon-intensive generation investments (Blyth et al., 2007; Bolton & Kacperczyk, 2021; Ilhan et al., 2021). Finally, (6) fossil generators are sensitive to carbon pricing mechanisms such as emissions trading systems and carbon taxes that increase their operating costs (Blyth et al., 2007). However, the impact of carbon pricing on profitability might be mitigated by the plant's degree of price pass-through and its marginal cost position (i.e., merit order) in the wholesale market (explanation below).

In constrast, fossil generators are less exposed to operating margin risk channels due to (3) relatively predictable production volumes as they are typically dispatchable (i.e., can adjust output to meet demand) (MIT Energy Initiative, 2018) and (1-2) their price pass-through ability. Wholesale electricity markets operate according to merit-order dispatch, in which generators are dispatched from lowest to highest marginal cost until demand is met, and the last plant required to meet demand sets the market price (Kirschen & Strbac, 2004; Cramton, 2017). Fossil fuel plants are often the marginal generation technology required to meet demand and set electricity prices. This creates a partial natural hedge: when fossil fuel prices increase, electricity prices rise accordingly, allowing them to adjust their revenues and pass the cost increase to customers (Roques et al., 2008; Gross et al., 2010). In addition, from a capital structure perspective, fossil plants require relatively (4) lower upfront capital and (5) relatively short construction times than nuclear or renewable projects, thereby reducing capital duration and construction risk significantly (MIT Energy Initiative, 2018; OECD NEA, 2019).

2.2.2 Renewable Exposure

Renewable generators are primarily exposed to operating margin and capital structure risk channels. While wind and solar plants are (1) not exposed to fuel price volatility, (2) their revenues fluctuate with the market price of electricity, over which they have no control, leaving profitability strongly dependent on wholesale prices. When electricity prices are low, they cannot adjust costs and might earn very low returns (Roques et al., 2008; Gross et al., 2010). In addition, because renewable generation depends on weather conditions, (3) production is concentrated in specific hours, which affects the market price received and increases revenue volatility (Hirth, 2013). Renewables may also face balancing costs when production deviates from forecasts and grid congestion costs when generation occurs far from demand centers (Hirth, 2013). Revenue volatility is therefore tied to both market prices and volume fluctuations. When it comes to capital structure, renewable energy projects are characterized by (4) high upfront capital and close-to-zero marginal costs, making them capital-intensive and long-lived, requiring extensive financing (Gross et al., 2010; Hirth, 2013; Steffen, 2018). Renewable projects also involve (5) development risk, as installations must secure permits, financing, and grid connections before electricity generation begins, exposing investors to delays and regulatory uncertainty during the pre-revenue phase (Gross et al., 2010; Polzin et al., 2019).

In contrast, renewables are less exposed to policy/regulatory risks and systematic capital reallocation, which largely benefit them. From a regulatory perspective, (6) renewables may benefit from market rules such as carbon pricing that increase the relative competitiveness of low-carbon generation (Blyth et al., 2007; Ellerman et al., 2010; Fabra & Reguant, 2014). However, the effectiveness of these frameworks ultimately depends on (7) political commitment, as green policy rollbacks can increase investment uncertainty and alter project profitability (Polzin et al., 2019). Finally, renewable assets generally (8) benefit from the structural reallocation of capital toward low-carbon technologies during the energy transition (Bolton & Kacperczyk, 2021; Moen et al., 2025) and (9) are frequently favored by ESG-oriented investors and sustainable finance frameworks (Pástor et al., 2021). This can increase investor demand and improve financing conditions relative to carbon-intensive technologies.

2.2.3 The Ambiguous Case of Nuclear Exposure

Nuclear combines low-carbon, stable output characteristics with high political and institutional uncertainty, resulting in a hybrid and ambiguous risk profile.

Just like renewables, (1) nuclear plants have low, relatively stable marginal costs due to limited exposure to uranium fuel costs and are (2) highly sensitive to electricity market prices, increasing investment uncertainty and plant closures when prices fall (OECD NEA, 2019; Davis & Hausman, 2016). Similar to fossil, nuclear plants provide (3) stable baseload generation and are dispatchable, producing electricity independently of weather conditions and contributing to system reliability (MIT Energy Initiative, 2018; OECD NEA, 2019).

Nuclear generation requires (4) very large upfront investments recovered over decade-long time horizons, making projects highly sensitive to financing conditions and discount rates. The capital intensity of nuclear projects also translates into (5) significant construction risk. Historically, nuclear projects have experienced construction delays and cost overruns, increasing financing requirements and total project cost up to twice the original estimate (Koomey & Hultman, 2007; Stewart & Shirvan, 2022). However, these construction cost trends vary across countries, meaning that project management experience and institutional factors affect this risk (Lovering et al., 2016).

Nuclear also faces significant regulatory and political risks. Because of its exposure to wholesale market prices, (6) nuclear power can benefit from policies that increase the relative competitiveness of low-carbon technologies (Blyth et al., 2007). However, nuclear projects involve long planning and construction horizons, during which regulatory conditions may change significantly. An additional risk driver for nuclear is (7) political discontinuity. Phase-out policies, such as the accelerated shutdowns implemented in Germany after the Fukushima disaster, demonstrate how relatively stable regulatory frameworks can be reversed, leading to stranded asset risk (Schneider et al., 2017). Nuclear projects also depend on licensing approvals and subsequent extensions, which are subject to evolving safety standards and political scrutiny, especially after major accidents. Post-accident regulatory tightening can further increase compliance costs or suspend operations, even for technically safe plants (Joskow & Parsons, 2012).

In terms of carbon transition exposure, nuclear would be expected to be well-positioned as a low-carbon technology. However, in practice, this position is less clear. (8) Energy system modelling studies reach mixed conclusions about the costs and system benefits of nuclear power in a low-carbon transition, suggesting an uncertain role in the repricing of energy assets (Moen et al., 2025). Similarly, (9) public perceptions remain divided, with nuclear often associated with safety concerns and waste management challenges. Such perceptions can influence investor preferences through ESG-related considerations (Pástor et al., 2021). In practice, climate finance taxonomies frequently exclude nuclear power or remain ambiguous about its classification, despite its central role in many decarbonization models (Bowen & Guanio, 2023). Consistent with this treatment, nuclear energy is among the most frequently excluded industries from socially responsible funds in Europe, excluded in 33.9% of cases (Eurosif, 2018; Meunier & Ohadi, 2023), and 57% of global systemically important banks explicitly exclude nuclear from their green financing frameworks while 40% remain silent on the topic (Bowen & Guanio, 2023). As a result, nuclear may be excluded or underweighted by investors in a manner similar to other controversial sectors, potentially increasing the expected returns required to hold nuclear assets (Pástor et al., 2021; Hong & Kacperczyk, 2009).

2.2.4 Technology Risks Channels Summary

Structural Risk Category	Risk Channel	Fossil	Renewable	Nuclear	Required Returns Pricing Strength
A. Operating Margin Structure Risk	**1. Variable Input Cost Exposure**	High fuel and carbon cost volatility; partial pass-through to electricity prices *(Roques et al., 2008; Gross et al., 2010)*	No fuel input cost exposure *(Roques et al., 2008; Gross et al., 2010)*	Low fuel cost share; limited commodity price exposure *(OECD NEA, 2019; Davis & Hausman, 2016)*	Moderate: through partially hedged fuel and carbon price shocks *(Kilian, 2009; Kang et al., 2016; Demirer et al., 2020)*
	2. Market Price Exposure	Wholesale price dependent; partial hedge with fuel cost pass-through *(Roques et al., 2008; Gross et al., 2010)*	Fully dependent on wholesale electricity prices *(Roques et al., 2008; Gross et al., 2010)*	Fully dependent on wholesale electricity prices *(OECD NEA, 2019; Davis & Hausman, 2016)*	Moderate: through exposure to wholesale electricity price shocks *(Joskow, 2008; Kilian, 2009; Gross et al., 2010;Kang et al., 2016; Demirer et al., 2020)*
	3. Output Variability Risk	Dispatchable generation; stable production volumes *(MIT Energy Initiative, 2018)*	Weather-driven output; price cannibalization and balancing costs *(Hirth, 2013; Borenstein, 2012)*	Stable baseload generation; high capacity factors *(MIT Energy Initiative, 2018; OECD NEA, 2019)*	Weak: through mostly idiosyncratic weather-driven production shocks *(Borenstein, 2012; Hirth, 2013)*
B. Capital Structure Risk	**4. Capital Duration Risk**	Moderate capital duration; lower upfront investment *(MIT Energy Initiative, 2018; OECD NEA, 2019)*	High upfront capital; long-lived assets *(Gross et al., 2010; Hirth, 2013; Steffen, 2018)*	Extremely capital intensive; very long asset duration *(Finon & Roques, 2008; OECD NEA, 2019)*	Moderate: through discount-rate sensitivity of long-lived assets *(Fama & French, 1996; Finon & Roques, 2008; Giglio et al., 2018)*
	5.Construction & Pre-Revenue Risk	Short construction time; relatively low overrun risk *(MIT Energy Initiative, 2018; OECD NEA, 2019)*	Short construction period; moderate development risk *(Gross et al., 2010; Polzin et al., 2019)*	Long construction period, high cost overrun risk *(Koomey & Hultman, 2007; Lovering et al., 2016; Stewart & Shirvan, 2022)*	Weak: through mostly project-specific construction shocks *(Lovering et al., 2016; Giglio et al., 2018)*
C. Policy & Regulatory Risk	**6. Regulatory Cost Uncertainty**	Exposure to uncertainty in environmental and carbon policy *(Blyth et al., 2007; Ellerman et al., 2010; Fabra & Reguant, 2014)*	Dependence on subsidies and policy support *(Blyth et al., 2007; Ellerman et al., 2010; Kitzing et al., 2012; Fabra & Reguant, 2014)*	Safety regulation and evolving licensing requirements *(Blyth et al., 2007; Finon & Roques, 2008; MIT Energy Initiative, 2018)*	Moderate: through policy uncertainty affecting expected cash flows *(Pástor & Veronesi, 2013; Ilhan et al., 2021)*
	7. Political Discontinuity Risk	Gradual tightening of climate policy *(Blyth et al., 2007; Bolton & Kacperczyk, 2021; Ilhan et al., 2021)*	Low shutdown risk once installed *(Polzin et al., 2019)*	Phase-outs, licensing changes, post-accident policy reversals *(Schneider et al., 2017; Joskow & Parsons, 2012)*	Strong: through systemic policy shocks and regulatory reversals *(Julio & Yook, 2012; Joskow & Parsons, 2012; Pástor & Veronesi, 2013)*
D. Systematic Capital Reallocation Risk	**8. Market-Driven Transition Risk**	High stranded-asset and transition risk *(SEI, 2016; van der Ploeg & Rezai, 2020; Bolton & Kacperczyk, 2021; Ilhan et al., 2021)*	Aligned with decarbonization transition *(Bolton & Kacperczyk, 2021; Moen et al., 2025)*	Low-carbon but uncertain position in transition *(Schneider et al., 2017; MIT Energy Initiative, 2018; OECD NEA, 2019; Moen et al., 2025)*	Strong: through climate transition repricing and carbon risk premia *(Bolton & Kacperczyk, 2021; Ilhan et al., 2021)*
	9. Investors Segmentation Risk	Frequently excluded from ESG portfolios *(Hong & Kacperczyk, 2009; Bolton & Kacperczyk, 2021)*	Favored by ESG mandates and green finance *(Pástor et al., 2021)*	Contested ESG taxonomy status, investor exclusion in some mandates *(Hong & Kacperczyk, 2009; Bowen & Guanio, 2023; Meunier & Ohadi, 2023)*	Strong: through capital supply constraints from investor exclusion *(Merton, 1987; Hong & Kacperczyk, 2009; Pástor et al., 2021)*

Table 2: Summary of technology-specific risk channels and impact on required returns.

2.3 Hypothesis 1a-b: Pricing of Nuclear Generation Exposure

Fossil generation exposure is associated with several risk channels strongly linked to required returns. Fossil plants face high downside tail risk due to the transition-driven repricing of fossil assets (van der Ploeg & Rezai, 2020) and are frequently excluded from ESG investment strategies as carbon-intensive firms (Bolton & Kacperczyk, 2021). Moreover, they are the primary target of decarbonization policies, although this process is expected to occur gradually rather than through sudden disruptions (Blyth et al., 2007). In contrast, renewable generation is largely favored by these high-impact pricing factors, as renewable energy is often aligned with policy direction (Polzin et al., 2019), transition-driven repricing (Hirth, 2013; Gross et al., 2010), and investor demand for sustainable assets (Pástor et al., 2021; Hong & Kacperczyk, 2009). The main risks for renewables are tied to electricity price volatility, output variability, regulatory dependency, and sensitivity to discount rate due to long asset duration. However, these factors only imply weak to moderate effects on required returns.

Nuclear generation occupies an ambiguous positioning across these risk channels. Its operating margin structure resembles that of renewable generators, with low variable fuel costs and high electricity price exposure (MIT Energy Initiative, 2018), combined with an output stability profile similar to that of fossil plants (OECD NEA, 2019). Its capital structure risk is among the highest due to extremely long investment horizons (Finon & Roques, 2008) and high construction risk (Koomey & Hultman, 2007), while its regulatory cost uncertainty is aligned with that of renewables but with increasingly stricter safety and licensing requirements (Joskow & Parsons, 2012). However, its position remains ambiguous along the key pricing dimensions. On paper, nuclear could be positioned alongside renewables as a low-carbon technology, aligned with policy goals, climate transition targets, and investor demand. However, nuclear generation is a politically charged topic and has been historically subject to aggressive phase-outs (Schneider et al., 2017; Joskow & Parsons, 2012), its economic role in decarbonized electricity systems remains contested (OECD NEA, 2019; Moen et al., 2025), and institutional investors exclude it from certain investment taxonomies as controversial (Bowen & Guanio, 2023; Eurosif, 2018).

Altogether, the literature suggests that fossil generation exposure is associated with higher required returns, renewable generation exposure with relatively lower required returns, while nuclear exposure occupies an intermediate position. This leads to the following hypotheses:

H1a: Generators with greater nuclear generation exposure face lower required returns than generators with greater fossil generation exposure.

H1b: Generators with greater nuclear generation exposure face higher required returns than generators with greater renewable generation exposure.

2.4 Revenue Model Exposure

Electricity generators differ in their revenue models. Some operate under non-merchant frameworks, stabilizing revenues through regulation, long-term contracts with buyers, or policy support instruments. Others operate under merchant models, where revenues depend on wholesale electricity market prices. Many firms combine both structures within the same organization (Joskow, 2008; Borenstein & Bushnell, 2015; Newbery, 2016). The extent to which the technology risk channels affect firms may vary based on the combination of merchant and non-merchant revenue streams adopted, as non-merchant exposure can partially mitigate some risk channels.

Under non-merchant revenue frameworks, revenues are largely stabilized through regulatory mechanisms or long-term contracts, reducing direct exposure to wholesale electricity price volatility. Cost recovery mechanisms or contractual revenue guarantees can also improve the ability of firms to finance their projects, thereby mitigating capital duration and construction risk. Instead, risk arises mainly from regulatory and contractual factors (Joskow, 2008; Finon & Roques, 2008; Steffen, 2018). For example, under the cost-of-service model, electricity retail prices are set by regulators to recover operating, fuel, and capital costs, leaving investors with limited exposure to market price volatility but greater exposure to policy instability risk (Joskow, 2008). Policy support mechanisms, such as Contracts for Difference (CfD), also introduce regulatory risk, as revenues are stabilized around a strike price set by regulators (Newbery, 2016). Instead, under long-term agreements such as Power Purchase Agreements (PPAs), revenues depend on the financial stability and contractual commitment of the electricity buyer, meaning generators face the risk that the counterparty will default or seek to renegotiate the contract when market prices diverge from the agreed terms (Yescombe, 2014; Finon & Roques, 2008).

2.5 Hypothesis 2a-b: Merchant Exposure Moderation

The pricing of generation technologies may depend on revenue model. Empirical evidence shows that required returns for capital-intensive generation technologies vary significantly depending on the degree of revenue stabilization and policy support, with lower financing costs observed under non-merchant arrangements (Green & Staffell, 2013). However, it is unclear how that would influence relative differences in required returns among technologies.

A higher share of merchant revenues increases exposure to electricity price risk (Gross et al., 2010), while non-merchant frameworks partially insulate revenues from market fluctuations and mitigate capital structure risks (Steffen, 2018). Non-merchant arrangements also introduce contractual risks (Yescombe, 2014), which, however, do not vary meaningfully across technologies. Importantly, not all risk channels are equally relevant for required returns. Section 2.2 shows that operating margin and capital structure risks are only weakly to moderately priced, whereas political discontinuity risk, transition risk, and segmentation risk are more strongly linked to required returns. These high-impact channels are largely independent of revenue model.

As a result, non-merchant revenue structures may reduce exposure to those risks that are weakly or moderately priced, thereby increasing the relative importance of the core pricing channels. Because these channels imply a consistent ranking across technologies as outlined in H1a-H1b, non-merchant exposure is expected to make differences in required returns more pronounced. In contrast, higher merchant exposure introduces additional, more heterogeneous risks, which are expected to weaken these differences. This leads to the following hypotheses:

H2a: Higher merchant exposure is expected to weaken the difference in required returns between nuclear and fossil generation exposure.

H2b: Higher merchant exposure is expected to weaken the difference in required returns between nuclear and renewable generation exposure

3. Methodology

3.1 Research Design Overview

This study aims to answer two research questions:

RQ1: How is nuclear generation exposure priced in capital markets relative to other technologies?
RQ2: Does the pricing of nuclear generation exposure depend on revenue model?

To investigate how generation technology exposure is priced in capital markets, this study uses a panel dataset of 92 publicly listed electricity generation companies in OECD countries where nuclear power is on the national grid, observed annually from 2010 to 2024. Research Question 1 examines whether firms with greater nuclear generation exposure face different required returns relative to firms with greater fossil or renewable exposure. This comparison exploits cross-sectional variation in firms' generation technology portfolios. Research Question 2 examines whether the pricing of nuclear generation exposure relative to fossil and renewable technologies varies with firms' revenue model, exploiting variation in the share of generation capacity exposed to electricity market prices. These relationships are tested using panel regression models that relate firms' required returns to their technology exposures, firm characteristics, and fixed effects.

3.2 Identification and Estimation Strategy

3.2.1 Key Variable Definitions

Because reliance on a single indicator may provide an incomplete representation of financial constructs (Boyd et al., 2005), this study uses two complementary measures of firms' required returns. The first is the implied cost of equity (ICoE), derived from equity prices and analyst earnings forecasts. Estimates of expected returns derived from analyst forecasts and market prices are widely used in the literature on implied cost of capital (Claus & Thomas, 2001; Gebhardt et al., 2001; Hail & Leuz, 2003; Easton, 2004). The second is a CAPM-adjusted risk premium (Risk-Adjusted Gap), defined as the difference between implied cost of equity and a benchmark cost of equity predicted by the Capital Asset Pricing Model. This measure isolates the portion of required returns not explained by systematic market risk. All model specifications are estimated separately for both dependent variables, allowing the analysis to compare whether technology exposure affects overall required returns (ICoE) or only the residual premium not explained by systematic market risk (Risk-Adjusted Gap).

Generation exposure is measured as the share of electricity generation capacity attributable to each technology. The technology groups are Fossil, Renewables (incl. solar and wind power), Nuclear, Hydroelectric, and Other. Hydroelectric generation is treated separately from wind and solar, despite being a renewable technology, because it often represents legacy dispatchable infrastructure and can store energy in reservoirs, resulting in a distinct revenue and risk profile (IEA, 2021). Because hydro also dominates renewable capacity in many utilities, grouping it with wind and solar would obscure these differences. The 'Other' category is included to ensure that generation shares sum to one and to capture technologies such as biomass, geothermal, waste-to-energy, and other minor generation sources. Since generation shares sum to one, one technology category must be omitted to avoid perfect multicollinearity (Wooldridge, 2010). Fossil generation is therefore used as the baseline category, providing a conventional reference technology against which other generation exposures can be interpreted.

3.2.2 Cross-Sectional Identification and Interpretation

Generation capacity exposure is structural because firms' technology portfolios evolve slowly over time, given the capital-intensive nature of generation assets (Gross et al., 2010). In contrast, generation output fluctuates with short-term operational conditions such as fuel availability, weather conditions, and electricity demand (Hirth, 2013; MIT Energy Initiative, 2018). Investors are therefore more likely to price the long-term risk characteristics associated with capacity rather than short-term fluctuations in output. Accordingly, this study uses generation capacity exposure as the main explanatory variable.

Because generation capacity portfolios change gradually, most variation in technology exposure occurs across firms (between-firm) rather than within firms (within-firm variation) over time. Therefore, in this study, identification primarily relies on cross-sectional differences in generation technology exposure across firms. Accordingly, the results should be interpreted as reflecting differences in pricing across generators with different portfolios, rather than changes in required returns associated with increasing nuclear exposure within a given firm (Wooldridge, 2010).

Consistent with this identification logic, the empirical models are estimated using pooled panel regressions that exploit cross-sectional variation across firms while controlling for observable firm characteristics and fixed effects. Pooled panel regressions are appropriate because they utilize both the cross-sectional variation across firms and the limited within-firm variation available over time (Wooldridge, 2010). In Section 5.2, the pooled specifications are compared with models that include firm fixed effects. Firm fixed effects absorb time-invariant firm characteristics, meaning that identification relies only on within-firm variation in generation exposure over time

(Wooldridge, 2010). Since such variation is limited in the electricity generation sector, firm fixed effects are likely to substantially reduce the variation available to estimate the coefficients.

3.2.3 Fixed Effects Structure

The empirical models are estimated using pooled panel regressions that include year, country, and industry fixed effects. Fixed effects are commonly used in panel data models to control for unobserved heterogeneity that may influence both explanatory variables and outcomes (Hsiao, 2007; Wooldridge, 2010), helping to isolate the relationship between generation technology exposure and firms' required returns. Year fixed effects absorb shocks common to all generators in a given year, such as energy crises or other aggregate market downturns. Country fixed effects control for cross-country differences in regulatory regimes, capital market structures, and political environments. Industry fixed effects account for structural differences across segments of the electricity generation sector (i.e., renewable energy, electric utilities, independent power producers, and multi-utilities) not captured by the control variables. However, industry fixed effects may capture some structural differences in generation portfolios and revenue models across firms. To ensure that the estimated relationships are not driven by this specification choice, Section 5.3 reports robustness tests that re-estimate the models without industry fixed effects.

An alternative estimation approach in panel data models is the random effects model. However, random effects assume that explanatory variables are uncorrelated with unobserved firm-specific characteristics (Baltagi, 2008). In the context of electricity generation firms, this assumption is unlikely to hold. For example, generators' technology portfolios are closely linked to the regulatory environment in which they operate, which is likely correlated with both generation exposure and firms' required returns. For this reason, the empirical analysis relies on pooled OLS with multiple FE dummies, which allow unobserved firm characteristics to be correlated with the explanatory variables and therefore provide more reliable coefficient estimates in this setting.

3.2.4 Inference and Standard Errors

Another concern in regression analysis is heteroskedasticity, which arises when the error variance differs across observations (Wooldridge, 2010). When heteroskedasticity is present, conventional standard errors may underestimate the true variability of coefficient estimates, leading to overstated statistical significance (White, 1980). In panel datasets with repeated observations for the same firms, serial correlation may also occur if regression residuals are correlated within firms over time (Drukker, 2003). Serial correlation similarly affects the reliability of statistical inference by biasing standard errors (Drukker, 2003). To address both heteroskedasticity and potential within-firm serial correlation, all regression models in this study are estimated using standard errors clustered at the firm level. Firm-level clustering allows residuals to be arbitrarily correlated within firms over time while maintaining independence across firms (Wooldridge, 2010).

3.2.5 Identification Limitations and Endogeneity

A potential econometric concern is endogeneity, which arises when explanatory variables are correlated with unobserved determinants of the dependent variable (Angrist & Pischke, 2009; Wooldridge, 2010). In the context of electricity generation, firms' technology portfolios may be associated with characteristics that also influence their cost of capital. Several aspects of the empirical design mitigate these concerns. First, the inclusion of year, country, and industry fixed effects helps control for differences in macroeconomic conditions, regulatory standards, and business models. Second, the capital-intensive nature of generation assets implies that technology portfolios evolve slowly, reducing the likelihood that short-term movements in required returns directly influence generation mixes, rather than the other way around. Nevertheless, because identification primarily relies on cross-sectional variation in technology portfolios, the estimated relationships should be interpreted as associations rather than causal effects (Wooldridge, 2010). Therefore, the results provide evidence on how capital markets price different generation technologies, rather than establishing a causal effect of technology choices on required returns.

3.3 Model Specification

3.3.1 Technology Exposure Pricing Model (RQ1)

The baseline regression model is:

$$RR_{i,t} = \alpha + \beta_1 Nuclear_{i,t} + \beta_2 Renewable_{i,t} + \beta_3 Hydro_{i,t} + \beta_4 Other_{i,t} + \gamma X_{i,t} + FE + \varepsilon_{i,t}$$

Where:

- $RR_{i,t}$ denotes the required return for firm i in year t, measured as ICoE or Risk-Adjusted Gap
- $Nuclear$, $Renewable$, $Hydro$ and $Other$ represent the share of electricity generation attributable to each technology. $Fossil$ is omitted as the baseline category
- $X_{i,t}$ denotes a vector of firm-level controls: merchant generation share (%), firm size (Ln of Assets), leverage (Debt/Assets), operating profitability (EBIT/Assets), valuation (Book Equity/Market Value of Equity) and asset tangibility (NPPE/Assets)
- FE denotes fixed effects included to absorb systematic differences across firms and time, specifically year, country, and industry fixed effects

A statistically significant negative nuclear coefficient ($\beta_1 < 0$) would indicate that generators with greater nuclear exposure are associated with lower required returns relative to generators with greater fossil exposure, consistent with H1a. A statistically significant positive difference between the nuclear and renewable coefficients (β_1 - β_2 > 0), tested using a linear hypothesis test of coefficient equality (Wooldridge, 2010), would indicate that generators with greater nuclear exposure face higher required returns relative to ones with greater renewable exposure, consistent with H1b.

3.3.2 Merchant Interaction Model (RQ2)

Merchant generation share captures the extent to which revenues depend on market electricity prices rather than non-merchant revenue arrangements. Merchant exposure is already included as a control in the baseline model, only capturing general differences in revenue models. However, the effect of nuclear exposure may depend on whether revenues are earned in non-merchant or wholesale markets. To examine this possibility, the baseline model is extended by interacting nuclear and renewable exposure with merchant exposure. The interaction specification is:

$$RR_{i,t} = \alpha + \beta_1 Nuclear_{i,t} + \beta_2 Renewable_{i,t} + \beta_3 Hydro_{i,t} + \beta_4 Other_{i,t}$$
$$+ \beta_5 (Nuclear_{i,t} \times Merchant_{i,t}) + \beta_6 (Renewable_{i,t} \times Merchant_{i,t}) + \gamma X_{i,t} + FE + \varepsilon_{i,t}$$

Where:

- $Nuclear_{i,t} \times Merchant_{i,t}$ captures the interaction between nuclear exposure and merchant exposure and $Renewable_{i,t} \times Merchant_{i,t}$ the interaction between renewable and merchant
- $Merchant_{i,t}$ is included as a standalone control variable ensuring that the interaction effects capture deviations from the average effect of merchant exposure

A statistically significant negative coefficient on the nuclear interaction term with merchant (β_5 < 0) would indicate that, as merchant exposure increases, the difference in required returns between nuclear and fossil generation exposure decreases, consistent with H2a. A statistically significant negative difference between the nuclear and renewable interaction effects ($\beta_5 - \beta_6 < 0$), evaluated using a linear hypothesis test of equality of interaction slopes, would indicate that the difference in required returns between nuclear and renewable generation exposure decreases as merchant exposure increases, consistent with H2b.

In addition, to examine how the relative ranking between nuclear, renewable, and fossil generation varies with merchant exposure, conditional effects are computed for Merchant = 1 (i.e., full merchant exposure) by combining the main coefficients with their corresponding interaction terms. Specifically, the effect of nuclear generation relative to fossil at high levels of merchant exposure is given by ($\beta_1 + \beta_5$), and the effect of renewable generation relative to fossil is given by ($\beta_2 + \beta_6$). The difference between nuclear and renewable generation at high levels of merchant exposure is therefore given by ($\beta_1 - \beta_2$) + ($\beta_5 - \beta_6$).

4. Data

4.1 Sample Construction

4.1.1 Industry-Country Filters

The initial sample universe consisted of the 72,942 publicly listed companies available for screening on the S&P Capital IQ Pro database. The sample was first restricted to firms classified in the following Capital IQ Primary Industries within the Utilities sector: Electric Utilities, Multi-Utilities, Renewable Electricity, and Independent Power Producers (IPP). These categories capture firms most likely to own and operate electricity generation assets and disclose generation technology portfolios. Gas Utilities and Water Utilities were excluded because their primary activities involve natural gas or water distribution rather than electricity generation. After applying these industry restrictions, the sample consisted of 938 firms. The sample was then restricted to firms headquartered in OECD countries where nuclear power is part of the national electricity system, defined as countries that operated commercial nuclear reactors during the sample period, according to the International Atomic Energy Agency's Power Reactor Information System (IAEA PRIS) database. This resulted in 273 firms across 16 countries (see Appendix 1). This restriction ensures that all firms operate in electricity systems where nuclear generation is a feasible technology option, allowing differences in financing conditions to be interpreted as market pricing of nuclear exposure rather than technological infeasibility.

4.1.2 Manual Firm Screening

The remaining 273 firms underwent a manual screening procedure assisted by AI-based document screening tools. The procedure consisted of four sequential filters: (1) Data availability; (2) Business descriptions; (3) Corporate structure; (4) Annual report disclosures.

In step 1, firms without usable financial or market observations were excluded, as the analysis relies on market-based measures of cost of equity. 31 firms with no market data were removed.

In step 2, the detailed business descriptions available for each firm on Capital IQ were systematically examined using AI-assisted text screening. Firms were excluded if no references to generation activities were identified, such as ownership or operation of power plants, installed capacity, or generation portfolios. This filter ensures that technology exposure reflects actual generation activities rather than other segments such as retail supply, transmission networks, engineering services, project development, or financial holding structures. 124 firms without identifiable generation activities were removed.

In step 3, the dataset was reviewed to identify potential parent-subsidiary relationships or duplicate listings that could lead to double-counting of generation assets. Where subsidiaries or related entities were identified, only the listed entity owning generation assets was retained. 10 firms with duplicate listings were removed.

In step 4, firms' installed electricity generation capacity portfolios were verified using company annual reports for 2010, 2015, 2020, and 2024, screened with AI-assisted document analysis. To exclude cases where generation might represent only a marginal activity, firms were screened to ensure that installed generation portfolios were non-trivial, typically several hundred megawatts (500 MW or more). This benchmark reflects the scale of utility-level generation assets. For example, pumped-storage hydropower plants typically range from roughly 450 to 880 MW (IEA, 2021), and nuclear reactors typically exceed several hundred megawatts (MIT Energy Initiative, 2018). In principle, generation dominance could be verified using segment-level revenue or earnings shares. However, utility segment reporting is inconsistent across jurisdictions and often combines generation with retail supply or regulated network operations. Therefore, verification relied on the observable installed generation capacity reported in annual reports. 16 firms whose disclosures either indicated minimal electricity generation or did not feature enough capacity information were removed.

Overall, the manual screening procedure removed 181 firms from the initial sample of 273, leaving a final sample of 92 electricity generators (see Appendix 2 for categories of exclusion).

4.1.3 Firm-Year Verification and Final Sample

For the firms remaining in the sample, the presence of generation assets and listing status may vary over time due to corporate restructurings, asset divestitures, market entries, or acquisitions. Accordingly, firm-year observations were excluded when firms had not yet begun electricity generation operations, had ceased generation activities, or had exited public markets through delisting, privatization, or acquisition. When a firm was acquired by another company already present in the sample, observations were retained only up to the acquisition year, so that subsequent generation exposure and financial outcomes are reflected solely through the acquiring firm. This treatment prevents the double-counting of generation assets.

To verify the identification of nuclear-exposed firms and ensure enough nuclear representation in the sample, the IAEA PRIS database was used to identify all operators of commercial reactors worldwide. Reactor operators were consolidated and mapped to their ultimate parent. Only publicly listed parent companies with direct operational exposure to commercial nuclear reactors during the sample period were retained. All 44 identified listed nuclear operators in OECD countries were present in the final sample of 92 firms.

The final dataset consists of 92 publicly listed electricity generation companies observed between 2010 and 2024, forming an unbalanced panel of 1,170 firm-year observations. The unbalanced structure reflects firm entry, exit, and restructuring events during the sample period.

4.2 Variable Construction

4.2.1 Dependent Variables: ICoE and Risk-Adjusted Gap

This study uses two complementary measures of firms' required returns as dependent variables, implied cost of equity (ICoE) and CAPM-adjusted risk premium (Risk-Adjusted Gap, RGAP), which were constructed using financial data from the databases Compustat and LSEG IBES Academic, accessed through Wharton Research Data Services, and were computed for each firm annually in the period 2010-2024.

ICoE is the market-implied required return derived from current stock prices and analysts' earnings expectations. It captures forward-looking investor perceptions and embedded risk premia rather than accounting-based financing costs. This measure is widely used in the literature to examine how firm characteristics and risk exposures are priced in cost of equity (Claus & Thomas, 2001; Gebhardt et al., 2001; Hail & Leuz, 2003; Easton, 2004). ICoE was estimated using a residual-income valuation model that equates current share prices to the present value of expected residual incomes (Claus and Thomas, 2001). In practice, the model solves for the discount rate r such that:

$$P_t = BV_t + \sum_{k=1}^{2} \frac{RI_{t+k}}{(1+r)^k} + \frac{TV_{t+2}}{(1+r)^2} \;;\; \begin{aligned} RI_{t+1} &= EPS_{t+1} - r \cdot BV_t \\ RI_{t+2} &= EPS_{t+2} - r \cdot BV_{t+1} \\ BV_{t+1} &= BV_t + EPS_{t+1} - DPS_{t+1} \end{aligned} \;;\; TV_{t+2} = \frac{RI_{t+2}(1+g)}{r-g}$$

Where:

- P_t is the observed share price at time t.
- r is the ICoE that equates share price to the present value of expected residual income.
- BV_t and BV_{t+1} denote book value of equity per share at time t and $t+1$, respectively. BV_{t+1} is constructed using clean-surplus accounting.
- EPS_{t+1} and EPS_{t+2} are analyst consensus forecasts of EPS for fiscal years $t+1$ and $t+2$
- DPS_{t+1} denotes forecast dividends per share in year $t+1$.
- RI_{t+1} and RI_{t+2} represent residual income in periods $t+1$ and $t+2$, defined as earnings in excess of the required return on beginning book value.

- TV_{t+2} is the terminal value capturing residual income beyond year two.
- g denotes the constant long-run growth rate used in the terminal value calculation, set at 2% to approximate long-run inflation, consistent with steady-state growth assumptions commonly used in residual income valuation models (Claus & Thomas, 2001).

All inputs are measured on a per-share basis and observed on the same date. The implied cost of equity r was obtained in Excel by numerically solving the valuation identity above using Goal Seek, setting the model-implied price equal to the observed share price P_t, and solving for r. A VBA loop was used to automate this procedure across the 1,170 firm-year observations. Residual income models can generate extreme implied discount rates when residual income is negative, when the discount rate approaches the terminal growth rate, or when forecast inputs are inconsistent (Claus & Thomas, 2001; Easton, 2004). Therefore, ICoE was winsorized at the 1st and 99th percentiles of the sample distribution, reducing the range from 2.09% – 492.16% to 2.71% – 17.63%. This standard treatment limits the influence of extreme observations while preserving the cross-sectional variation in expected returns.

The second dependent variable is CAPM-adjusted risk premium (Risk-Adjusted Gap). This measure captures the difference between the previously estimated ICoE and a CAPM-based cost of equity to assess whether nuclear exposure is priced beyond systematic market risk. A positive value indicates that the market-implied required return exceeds the return justified by market beta risk alone. The CAPM cost of equity was computed as:

$$CAPM\ CoE_{i,t} = R_{f,t} + \beta_{i,t} \times MRP$$

where $R_{f,t}$ denotes the global risk-free rate, $\beta_{i,t}$ the firm's global equity beta, and MRP the global market risk premium. For each firm-year, global equity betas were estimated using rolling 36-month regressions of firm excess returns on market excess returns. Firm-level monthly stock prices were converted to USD prior to return calculation to ensure consistency with the global market returns, proxied using the MSCI World Index. Estimated betas were winsorized at the 1st and 99th percentiles to limit the influence of extreme values. The global risk-free rate was proxied as the U.S. 10-year Treasury yield, obtained from Federal Reserve Economic Data. The global market risk premium was set at 5.5%, consistent with estimates reported in the literature (Damodaran, 2024). Finally, CAPM cost of equity was constrained to be no lower than the contemporaneous risk-free rate to avoid implausible negative values (Fama & French, 1992; Elton et al., 2014).

4.2.2 Technology Exposure Variables

Firm-level electricity generation technology exposure was constructed using installed generation capacity data collected from company annual reports. Capacity portfolios were observed at four anchor years: 2010, 2015, 2020, and 2024. For each anchor year, installed electricity generation capacity was classified into the following categories: Nuclear, Hydro, Renewable (wind and solar), Fossil (coal, oil, natural gas), and Other (biomass, geothermal, waste-to-energy, and other minor generation sources). Capacity shares were expressed as percentages of total installed generation capacity, summing to 100% for each firm-year. The data was extracted from annual reports using AI-assisted document screening, based on a structured prompt designed to identify installed capacity disclosures. Where technologies were reported in aggregated categories (e.g., thermal, low-carbon, or other), classifications were disaggregated only when the mapping to specific technologies was explicitly stated. If disaggregation was not possible, residual capacity was assigned to Other. The extraction prompt and classification rules are provided in Appendix 3.

To avoid look-ahead bias, technology exposure variables were constructed using anchor values that remain fixed across observation years and are updated only at the next observed anchor. Formally, for each year t:

- If $2010 \leq t < 2015$, exposure equals the 2010 anchor
- If $2015 \leq t < 2020$, exposure equals the 2015 anchor
- If $2020 \leq t < 2024$, exposure equals the 2020 anchor
- If $t = 2024$, exposure equals the 2024 anchor

This approach reflects that generation portfolios evolve through discrete investment decisions rather than continuous operational changes. Constructing every annual exposure from document-based extraction would instead increase the scope for classification error and make systematic verification more difficult, given the scale and complexity of the underlying data.

4.2.3 Control Variables

To isolate the relationship between generation technology exposure and firms' required returns, the regressions include several control variables that capture key firm characteristics. These are merchant generation share (%), firm size (Ln of Assets), leverage (Debt/Assets), operating profitability (EBIT/Assets), valuation (Book Equity/Market Value of Equity), and asset tangibility (NPPE/Assets). All control variables are measured annually at the firm level, except for Merchant Generation Share, which was constructed using four anchor years, as for technology exposure. Control variables were selected based on established determinants of expected returns identified in asset pricing and corporate finance research.

Merchant Generation Share is measured using the same procedure described in section 4.2.2 for technology exposure (see Appendix 3 for AI prompt). Merchant exposure refers to generation capacity whose revenues are directly linked to wholesale electricity markets. In contrast, non-merchant exposure captures generation capacity whose revenues are earned under the cost-of-service model, Contracts for Difference (CfD), or Power Purchase Agreements (PPAs), where revenues are largely predetermined and therefore less sensitive to spot electricity prices. Generators' revenue models influence exposure to wholesale electricity prices and capital structure risks, which may affect the risk profile of generation assets and, in turn, their required returns.

Firm size is measured as the natural logarithm of total assets. The logarithmic transformation compresses large values, limiting the influence of extremely large firms in regression analysis (Gujarati & Porter, 2009). Larger firms are typically associated with lower expected returns and financing costs in asset pricing studies (Fama & French, 1993).

Leverage is measured as total debt divided by total assets. Higher leverage increases financial risk and may therefore raise investors' required return on equity (Modigliani & Miller, 1958).

Operating profitability is measured as earnings before interest and taxes divided by total assets. More profitable firms generally exhibit stronger operating performance and are associated with systematic differences in expected returns in asset pricing models (Fama & French, 2015).

Valuation is controlled for using the book-to-market ratio, defined as the book value of equity divided by the market value of equity. Firms with higher book-to-market ratios are often associated with higher expected returns in the asset pricing literature (Fama & French, 1992). Since the book-to-market ratio can take extreme values when market equity is very small, the variable is winsorized at the 1st and 99th percentiles, reducing its range from -0.77 to 6.87, to 0.11 to 3.45.

Finally, asset tangibility is measured as net property, plant, and equipment divided by total assets. In electricity generation firms, tangible assets primarily consist of large-scale generation infrastructure, which is highly capital-intensive and long-lived (IEA, 2021; IEA, 2022). Therefore, controlling for asset tangibility captures variation in the capital intensity of generation portfolios, which may influence firms' risk profiles and financing conditions.

4.2.4 Variables Summary Table

Variable	Definition	Source
Implied Cost of Equity (ICoE)	Expected return implied from stock price and analyst forecasts	WRDS
Risk-Adjusted Gap	Difference between implied return and CAPM benchmark	WRDS
Nuclear Generation Share	Installed capacity in % from nuclear plants	Annual Reports
Renewable Generation Share	Installed capacity in % from wind and solar	Annual Reports
Hydroelectric Generation Share	Installed capacity in % from hydro plants	Annual Reports
Fossil Generation Share	Installed capacity in % from coal, gas and oil plants	Annual Reports
Other Generation Share	Installed capacity in % from remaining technologies	Annual Reports
Merchant Generation Share	Capacity exposed to wholesale electricity markets in %	Annual Reports
Size (Ln Total Assets)	Natural log of total firm assets	S&P Capital IQ

Leverage (Debt/Assets)	Total debt divided by total assets	S&P Capital IQ
Operating Profitability (EBIT/A)	EBIT scaled by total assets	S&P Capital IQ
Valuation (B/M Ratio)	Book equity divided by market equity	S&P Capital IQ
Asset Tangibility (PPE/Assets)	Property, plant and equipment divided by total assets	S&P Capital IQ

Table 3: Variable definitions and sources.

4.3 Data Exploration

4.3.1 Summary Statistics

Table 4 reports summary statistics for the main variables used in the analysis. ICoE averages 8.13%, while Risk-Adjusted Gap averages 3.94%, indicating that market-implied returns typically exceed the CAPM benchmark. Fossil generation represents the largest share of installed capacity (55.90% on average), followed by renewables (17.15%), hydro (12.69%), and nuclear (9.62%). Merchant exposure also varies widely, averaging 36.95% but with a large dispersion across firms. The median nuclear exposure is zero, as only 48% of the sample's firms operate nuclear reactors.

Variable	Mean	Median	Std.Dev.	Min	Max
Implied Cost of Equity (ICoE)	8.13%	6.91%	3.80%	2.71%	17.63%
Risk-Adjusted Gap (ICoE − CAPM)	3.94%	3.46%	4.11%	-7.39%	15.80%
Nuclear Generation Share (%)	9.62%	0.00%	12.76%	0.00%	100.00%
Renewable Generation Share (%)	17.15%	6.00%	25.99%	0.00%	100.00%
Hydroelectric Generation Share (%)	12.69%	6.40%	16.79%	0.00%	86.30%
Fossil Generation Share (%)	55.90%	63.00%	30.41%	0.00%	100.00%
Other Generation Share (%)	4.64%	0.00%	18.47%	0.00%	100.00%
Merchant Generation Share (%)	36.95%	25.00%	37.23%	0.00%	100.00%
Size (Ln Total Assets)	23.53	23.92	1.59	17.89	26.35
Leverage (Debt / Assets)	0.41	0.40	0.15	0.00	1.02
Operating Profitability (EBIT / Assets)	4.12%	4.24%	3.22%	-16.02%	21.72%
Valuation (Book-to-Market Ratio)	0.91	0.70	0.64	0.11	3.45
Asset Tangibility (PPE / Assets)	64.61%	68.70%	15.87%	0.00%	94.04%

Table 4: Summary statistics

4.3.2 Correlation Matrix

Table 5 presents the correlation matrix among variables. The two dependent variables, ICoE and Risk-Adjusted Gap, are strongly correlated (0.860), as expected. Several moderate correlations appear among the explanatory variables. Nuclear exposure is positively correlated with firm size (0.465), reflecting that nuclear assets are typically operated by large utilities. Book-to-market also shows moderate positive correlations with both ICoE (0.442) and the Risk-Adjusted Gap (0.464), consistent with higher required returns for firms with higher valuation ratios. Leverage is positively correlated with asset tangibility (0.417), which is consistent with the use of tangible assets as collateral. Merchant exposure is negatively correlated with asset tangibility (-0.497), suggesting that firms with larger regulated network assets tend to have lower merchant exposure. Generation shares are negatively correlated due to the mechanical constraint that shares sum to one. Overall, correlations remain moderate and do not suggest severe multicollinearity concerns.

Variable	ICoE	RGAP	Size	Lev	Profit	B/M	Tang	Merch	Nuclear	Renew	Hydro	Fossil	Other
ICoE	1.000	0.860	-0.069	0.126	-0.153	0.442	-0.032	0.188	0.055	0.012	0.073	-0.067	-0.012
RGAP	0.860	1.000	-0.022	0.081	-0.162	0.464	0.018	0.112	0.110	-0.115	0.106	0.019	-0.042
Size	-0.069	-0.022	1.000	-0.146	-0.018	0.111	-0.141	-0.074	0.465	-0.263	0.088	0.194	-0.348
Leverage	0.126	0.081	-0.146	1.000	-0.218	0.122	0.417	-0.149	-0.065	0.324	0.029	-0.212	-0.091
Profit	-0.153	-0.162	-0.018	-0.218	1.000	-0.376	-0.046	0.123	-0.127	-0.074	-0.148	0.158	0.066
B/M	0.442	0.464	0.111	0.122	-0.376	1.000	0.090	-0.031	0.139	-0.141	0.219	-0.064	0.009
Tangibility	-0.032	0.018	-0.141	0.417	-0.046	0.090	1.000	-0.497	-0.012	-0.054	0.042	0.051	-0.037
Merchant	0.188	0.112	-0.074	-0.149	0.123	-0.031	-0.497	1.000	-0.119	0.271	0.033	-0.175	-0.042
Nuclear	0.055	0.110	0.465	-0.065	-0.127	0.139	-0.012	-0.119	1.000	-0.359	0.066	-0.053	-0.157
Renewables	0.012	-0.115	-0.263	0.324	-0.074	-0.141	-0.054	0.271	-0.359	1.000	-0.093	-0.573	-0.132
Hydro	0.073	0.106	0.088	0.029	-0.148	0.219	0.042	0.033	0.066	-0.093	1.000	-0.455	-0.073
Fossil	-0.067	0.019	0.194	-0.212	0.158	-0.064	0.051	-0.175	-0.053	-0.573	-0.455	1.000	-0.389
Other	-0.012	-0.042	-0.348	-0.091	0.066	0.009	-0.037	-0.042	-0.157	-0.132	-0.073	-0.389	1.000

Table 5: Correlation matrix between study variables

4.3.3 Generation Mix Across Industry and Country

Table 6 reports the average generation mix across firms by industry classification, while Table 7 presents the mix by country. Industry groups display distinct portfolio structures. Electric utilities operate relatively diversified generation portfolios, whereas independent power producers rely more heavily on fossil generation (72% on average). Renewable electricity firms are, as expected, dominated by renewable capacity (45%). Cross-country differences largely reflect differences in the portfolios of sampled firms rather than national electricity systems. In several cases, country averages are based on a single firm in the sample, so reported generation mixes correspond to that individual firm's portfolio.

Industry	Nuclear	Renewables	Hydro	Fossil	Other	Total	N. of firms
Electric Utilities	14%	11%	14%	60%	1%	100%	45
Renewable Electricity	0%	45%	13%	19%	23%	100%	22
Multi-Utilities	9%	11%	11%	68%	1%	100%	16
IPP	4%	13%	11%	72%	0%	100%	9

Table 6: Average electricity generation mix by industry in the sample (% of total generation)

Country	Nuclear	Renewables	Hydro	Fossil	Other	Total	N. of firms
USA	10%	12%	8%	67%	3%	100%	39
Japan	18%	2%	19%	56%	5%	100%	13
Canada	0%	31%	19%	43%	7%	100%	12
Spain	4%	54%	14%	27%	1%	100%	8
United Kingdom	0%	22%	8%	56%	14%	100%	4
Germany	17%	10%	9%	63%	1%	100%	4

France	5%	40%	10%	43%	2%	100%	2
Switzerland	9%	23%	41%	12%	15%	100%	2
Hungary	0%	19%	0%	23%	58%	100%	2
South Korea	15%	1%	5%	75%	4%	100%	2
Czechia	33%	1%	15%	51%	0%	100%	1
Finland	23%	1%	34%	42%	0%	100%	1
Netherlands	0%	99%	0%	1%	0%	100%	1
Portugal	0%	38%	26%	33%	3%	100%	1

Table 7: Average electricity generation mix by country in the sample (% of total generation)

4.3.4 Firm Characteristics by Nuclear Exposure

Table 8 compares firms with and without nuclear generation assets. Approximately 48% of firms operate nuclear reactors. Nuclear firms are, on average, significantly larger and exhibit slightly lower leverage. Merchant exposure is also lower among nuclear operators (36.6% vs. 48.6%), consistent with the more regulated revenue structures often associated with nuclear generation (Finon & Roques, 2008). Other firm characteristics are broadly similar across the two groups, including average required returns, which differ only modestly between nuclear and non-nuclear.

Variable	Nuclear Firms N firms = 44 (48%)	Non-Nuclear Firms N firms = 48 (52%)	Difference and Significance (T-test)
Implied Cost of Equity	8.0%	9.0%	−1.0%
Risk-Adjusted Gap (ICoE − CAPM)	3.8%	4.2%	−0.4%
Size (Ln Total Assets)	24.50	22.11	2.39***
Leverage (D/A)	38.1%	44.3%	−6.2%**
Operating Profitability (EBIT/A)	3.7%	4.5%	−0.7%
Book-to-Market Ratio	0.94	0.86	0.08
Asset Tangibility (NPPE/A)	61.4%	65.0%	−3.6%
Merchant Generation Share	36.6%	48.6%	−12.0%

Table 8: Comparison between nuclear and non-nuclear firms across study variables. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

While nuclear firms exhibit lower average merchant exposure (Table 8), Table 9 shows consistent variation in merchant exposure across different levels of nuclear exposure, suggesting that revenue model exposure is not only determined by generation technology.

Nuclear Share	Mean Merchant Share (%)	Std. Dev.	N. of Obervations
0%	41.6%	40.8	589
0–20%	35.0%	31.8	368
20–50%	24.1%	32.1	194
>50%	62.4%	26.7	19

Table 9: Distribution of merchant exposure across different levels of nuclear share

4.4 Econometric Diagnostics and Data Validity

4.4.1 Multicollinearity

Multicollinearity arises when explanatory variables in a regression model are highly correlated, potentially inflating standard errors and reducing the precision of coefficient estimates (Gujarati

& Porter, 2009). Because the key explanatory variables in this study are generation capacity shares, some mechanical correlation across technologies may arise, as shares sum to one. To avoid perfect multicollinearity, fossil generation is omitted as the baseline category, so that the technology coefficients measure differences relative to fossil. To formally assess multicollinearity, variance inflation factors (VIFs) were computed for all explanatory variables. The computed VIF values range between 1.1 and 1.7 (see Appendix 4), well below the commonly used threshold of 10 indicating problematic multicollinearity (Gujarati & Porter, 2009).

4.4.2 Exposure Dispersion and Cross-Sectional Identification

A key requirement for identifying pricing differences across generation technologies is sufficient variation in exposure across firms. Table 10 reports the distribution of firm-level generation technology exposure across capacity brackets. Nuclear generation is absent for a large share of firms, with 48 firms exhibiting zero nuclear exposure. However, exposure is distributed across several brackets, including 18 firms with nuclear shares between 20% and 40% and a small number of firms exceeding 40%. Similar dispersion is observed across other technologies. Table 11 reports a variance decomposition of generation technology exposure. For all technologies, the majority of variation occurs across firms rather than within firms over time. Between-firm variation accounts for approximately 88-95% of the total variance, depending on the technology, while within-firm variation accounts for roughly 5-12%.

Technology	0%	0-5%	5-10%	10-20%	20-40%	40-60%	60-100%
Nuclear	48	2	9	13	18	1	1
Renewables	9	29	14	13	10	5	12
Hydro	31	14	14	14	11	7	1
Fossil	13	4	1	3	5	19	47
Other	57	27	1	2	0	1	4

Table 10: Distribution of firm-level generation exposure across capacity brackets

Technology	Between	Within
Nuclear	88.5%	12.5%
Renewables	91.0%	9.7%
Hydro	88.5%	12.4%
Fossil	89.9%	11.0%
Other	94.9%	5.5%

Table 11: Variance decomposition

4.4.3 Measurement Error

Measurement error may be present for technology and revenue exposure, potentially distorting estimated relationships. In this study, exposure is measured using installed capacity shares observed at discrete anchor years. While this approach avoids look-ahead bias and reflects the structural nature of generation assets, it may introduce measurement error if firms adjust their generation portfolios between anchor years. The same issue applies to merchant exposure. Such within-interval changes constitute classical measurement error, which biases estimated coefficients toward zero and therefore implies that estimated relationships should be interpreted as conservative estimates of the underlying effects (Wooldridge, 2010).

5. Results

5.1 Study Results

Table 12 reports regression results and tests of coefficient equality for RQ1 and RQ2.

Variables	RQ1 Baseline Model		RQ2 Merchant Model	
	ICoE	RGAP	ICoE	RGAP
Nuclear	0.019 (0.017)	0.025 (0.017)	0.062*** (0.022)	0.060*** (0.023)
Renewable	-0.009 (0.017)	-0.002 (0.017)	0.005 (0.020)	0.015 (0.021)
Hydro	-0.002 (0.015)	-0.004 (0.014)	-0.003 (0.014)	-0.004 (0.013)
Other	-0.023 (0.014)	-0.020 (0.012)	-0.017 (0.014)	-0.014 (0.012)
Merchant	0.018* (0.010)	0.014 (0.010)	0.034*** (0.011)	0.030** (0.012)
Firm size (Ln of Assets)	-0.001 (0.002)	-0.001 (0.002)	-0.002 (0.002)	-0.001 (0.002)
Leverage (Debt/Assets)	0.015 (0.024)	0.012 (0.023)	0.012 (0.023)	0.012 (0.022)
Operating profitability (EBIT/Assets)	-0.008 (0.070)	0.006 (0.076)	0.008 (0.067)	0.012 (0.073)
Valuation (BE/MVE)	0.020*** (0.005)	0.024*** (0.004)	0.020*** (0.005)	0.024*** (0.004)
Asset tangibility (NPPE/Assets)	-0.013 (0.020)	-0.010 (0.019)	-0.017 (0.018)	-0.013 (0.018)
Diff: Nuclear – Renewable	0.028 (0.020)	0.027 (0.021)	0.058** (0.027)	0.044* (0.028)
Nuclear × Merchant	/	/	-0.127*** (0.038)	-0.104*** (0.038)
Renewable × Merchant	/	/	-0.024 (0.028)	-0.031 (0.027)
Diff: Nuclear × M. – Renewable × M.	/	/	-0.103*** (0.040)	-0.073* (0.038)
Nuclear (At Merchant = 1)	/	/	-0.064 (0.028)	-0.044 (0.027)
Renewable (At Merchant = 1)	/	/	-0.019 (0.023)	-0.015 (0.022)
Diff: Nuclear – Renewable (At Merchant = 1)	/	/	-0.046 (0.030)	-0.029 (0.029)
Observations	1170	1170	1170	1170
R^2	0.327	0.400	0.341	0.410
Year + Country + Industry FE	Yes	Yes	Yes	Yes
Clustered SE	Firm	Firm	Firm	Firm

Table 12: Study Results. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Note: Coefficients represent differences relative to fossil exposure.

In the baseline model (RQ1), in either specification, nuclear exposure is not statistically different from fossil (0.019 & 0.025) or renewable (0.028 & 0.027), and renewable is not statistically different relative to fossil (-0.009 & -0.002). Overall, the results do not provide strong evidence of a systematic ranking in required returns across technologies (H1a-b not supported).

In the merchant interaction model (RQ2), the interaction term between nuclear exposure and merchant share is negative and statistically significant across both specifications (-0.127*** & -0.104***). The difference between nuclear and renewable interaction effects is also negative and statistically significant (-0.103*** & -0.073*). This indicates that as merchant exposure increases, the differences in required returns between nuclear and both fossil and renewable generation become smaller, supporting H2a–H2b. Moreover, the RQ2 results show that the ranking of required returns depends on merchant exposure. At low levels of merchant exposure (merchant = 0), nuclear has a positive and statistically significant coefficient (0.062*** & 0.060***), while renewable is small and not significant (0.005 & 0.015). The difference between nuclear and renewable is also positive and significant (0.058** & 0.044*). This implies that nuclear has higher required returns than both fossil and renewable, while renewable is not significantly different from fossil (Nuclear > Renewable ≈ Fossil). At high levels of merchant exposure (merchant = 1), the nuclear term (-0.064 & -0.044), the renewable term (-0.019 & -0.015), and the difference between nuclear and renewable (-0.046 & -0.029) all become negative and statistically insignificant. This indicates that the nuclear premium disappears, and no statistically significant differences in required returns can be established across technologies (Fossil ≈ Renewable ≈ Nuclear).

Among the control variables, only valuation (book-to-market ratio) is consistently positive and statistically significant across all specifications at the 1% level, while all other controls remain statistically insignificant. This suggests that cross-sectional differences in required returns are strongly associated with valuation effects. To ensure that the results are not driven by valuation effects, the models are re-estimated without the book-to-market ratio in Section 5.2.4.

5.2 Robustness Tests

This section evaluates whether the estimated relationships between generation technology exposure and required returns are robust to alternative model specifications, measurement choices, sample restrictions, and choice of control variables (See Appendix 5 for full results).

5.2.1 Specification Robustness

To assess whether the results depend on the chosen fixed effects structure, two alternative specifications are estimated on all models: (a) excluding industry fixed effects (only Year + Country FE) and (b) including firm fixed effects (Only Year + Firm FE). The results remain robust when industry fixed effects are removed, with all main coefficients remaining mostly unchanged. Introducing firm fixed effects reduces statistical significance due to limited within-firm variation in generation portfolios as expected, but coefficient signs and magnitudes remain broadly consistent. This indicates that the findings are not driven by the fixed effects specification and are primarily identified from cross-sectional differences across firms.

5.2.2 Measurement Robustness

To assess sensitivity to variable construction, a model (c) replacing nuclear capacity share with a nuclear dummy is tested. Using a nuclear dummy variable results in similar conclusions, suggesting that the absence of a nuclear effect is not sensitive to how nuclear exposure is measured.

5.2.3 Sample Robustness

To examine whether the results are driven by comparisons between nuclear and non-nuclear firms, the sample is (d) restricted to firms with non-zero nuclear exposure. Under this restriction, the merchant interaction effects weaken but remain statistically significant for ICoE, while becoming statistically insignificant for RGAP, although they retain the same negative sign in both specifications. Overall, this suggests that only part of the variation in the results may be due to differences between nuclear and non-nuclear firms. At the same time, the consistency in coefficient signs indicates that the underlying relationships remain directionally unchanged, and the reduced cross-sectional variation due to the sample restriction may also contribute to these results.

5.2.4 Control Specification Robustness

To assess whether results are sensitive to the inclusion of certain control variables, two alternative models are estimated: (e) removing the book-to-market ratio and (f) removing merchant exposure (only for baseline model). Removing the book-to-market ratio does not materially affect the estimated coefficients, indicating that the results are not driven by the inclusion of valuation effects. The exclusion of merchant exposure also does not materially affect the estimated coefficients, suggesting that merchant exposure does not proxy for the same underlying variation as industry fixed effects, and that the results are not driven by overlapping controls.

5.3 Results Summary

The results show no evidence of a systematic unconditional risk premium for nuclear generation relative to other technologies, as nuclear exposure is consistently statistically insignificant across baseline specifications. However, the pricing of nuclear exposure appears to be conditional: nuclear is associated with higher required returns compared to both fossil and renewables at low levels of merchant exposure, but this premium disappears as merchant exposure increases. This indicates that revenue model structure plays an important role in shaping relative required returns.

6. Discussion

6.1 Results Discussion

The results point to three key insights.

Insight 1: Nuclear exposure is not priced unconditionally as a distinct systematic risk factor. The baseline results show no consistent difference in required returns across nuclear, fossil, and renewable generation. Therefore, nuclear is not associated with a systematic difference in required returns unconditionally, despite its distinct positioning relative to fossil and renewable generation along perception-based risk channels (i.e., political discontinuity, transition risk, and investor segmentation), which reflect how nuclear is perceived by policymakers and investors.

Insight 2: Revenue model influences how nuclear exposure is priced in required returns. The interaction results help explain why no unconditional nuclear premium is observed. Under merchant exposure, revenues move directly with electricity prices, increasing exposure to electricity market price risk and capital-related risks. These risk channels imply a different ordering of required returns across technologies than perception-based risks. While perception-based risks suggest that fossil exposure should command higher required returns and renewable generation lower required returns, market price and capital-related risks tend to favor fossil relative to nuclear and renewable generation. As a result, these opposing pricing effects can offset each other, compressing differences in required returns across generation technologies. By contrast, under non-merchant frameworks, revenues are stabilized through contracts or regulation, limiting the influence of market price and capital-related risks. This may allow perception-based risk channels to prevail, making differences in required returns across technologies more visible and enabling nuclear to assume a distinct risk positioning.

Insight 3: Observed technology risk premia do not fully align with expected risk ordering. Even where a ranking of required returns can be identified, it does not align with theoretical expectations. At low merchant exposure, nuclear is associated with higher required returns than both fossil and renewable generation, while no significant difference is observed between fossil and renewables. A feasible explanation is grounded in asset pricing theory. Asset prices reflect expected cash flows discounted by required returns (Cochrane, 2005), but not all risks affect required returns. Expected returns are primarily driven by discount-rate risk, while other shocks affect cash flows or realized returns (Campbell & Vuolteenaho, 2004; Chen, 2013). Investor demand can also influence prices without reflecting compensation for risk (Pástor et al., 2021).

Thus, risk differences between fossil and renewables may be reflected in expected profitability or valuation rather than in required returns.

Although all technologies face political discontinuity risk, transition risk, and investor segmentation, these risks may manifest differently. For fossil and renewable generation, policy developments tend to be more gradual and widely discussed, and investor segmentation is relatively stable and broadly anticipated. For nuclear generation, similar risks tend to materialize in a more abrupt and less predictable manner, as evidenced by sudden phase-out decisions and regulatory reversals (Schneider et al., 2017; Joskow & Parsons, 2012), as well as recurring shifts in its classification within sustainable finance taxonomies (Bowen & Guanio, 2023; Meunier & Ohadi, 2023). Such uncertainty can affect required returns when it is non-diversifiable (Pástor & Veronesi, 2013), and may also lead to more variable investor demand (Dragomirescu-Gaina et al., 2021). This suggests that similar risks are more likely to be reflected in required returns for nuclear generation, while for fossil and renewable generation, they are more fully absorbed into expected cash flows or valuation levels.

6.2 Results Implications

6.2.1 Implications for Asset Pricing in Electricity Markets

The empirical results suggest that differences in required returns are more strongly associated with the interaction between technology and revenue structure, rather than with either dimension in isolation. However, revenue models are not set arbitrarily, but often emerge from a combination of technology-specific requirements and market design constraints. This implies that required returns may reflect an equilibrium-like interaction in which technology characteristics, revenue models, and market conditions jointly determine firms' exposure to systematic risk.

Technology and market design first define the set of feasible exposures for firms by shaping their revenue structure. For example, capital-intensive technologies such as nuclear often require stable revenues to be financially viable and therefore tend to rely on contractual arrangements that limit direct exposure to wholesale electricity price volatility (Finon & Roques, 2008). At the same time, electricity market design can impose wholesale price exposure regardless of technology, as in energy-only markets such as ERCOT in Texas, where limited stabilization mechanisms leave generators mostly merchant (Cramton, 2017). Revenue structure then acts as a filter, determining which risk channels are priced in required returns by shaping firms' exposure to different sources of risk. Importantly, capital structure risks can enter pricing both directly and indirectly. Indirectly, by constraining which revenue models are feasible and therefore shaping the level of exposure firms can sustain, and directly, by increasing sensitivity to systematic discount rate shocks and adverse macroeconomic financing conditions. Consistent with this interpretation, nuclear operators exhibit lower merchant exposure on average (Table 8), indicating that capital constraints are associated with reduced exposure to electricity price risk rather than higher required returns.

This interpretation is closely related to the electricity market literature, which emphasizes that market design shapes revenue models, risk allocation, and investment incentives, particularly where risk cannot be fully hedged through market instruments (Joskow, 2008; Newbery, 2016). It is well established that revenue structures influence the allocation of risk across generation technologies (Finon & Roques, 2008; Cramton, 2017), particularly through differences in exposure to electricity price volatility and the availability of contractual arrangements. However, these relationships have primarily been analysed through conceptual and project-level frameworks, with limited empirical evidence on how such differences translate into required returns at the firm level. The results contribute to this literature by showing that the interaction between technology and revenue exposure carries most of the explanatory power in the empirical results, while the corresponding main effects are comparatively limited. This suggests that observed risk exposures are not well captured by either dimension in isolation, but are more accurately understood as arising from their joint effect.

6.2.2 Implications for Policy Design and Project Developers

The results suggest that revenue stabilization does not eliminate risk for nuclear generation, but instead changes which risks are reflected in required returns. By reducing exposure to electricity price volatility, non-merchant revenue frameworks make perception-based risks more prominent in pricing. This implies that revenue stabilization does not unambiguously reduce required returns, but instead shifts the composition of priced risk. In particular, nuclear projects become increasingly sensitive to policy credibility and investor sentiment under non-merchant frameworks. Therefore, while instruments such as CfDs or PPAs are necessary to make projects financeable, they do not, by themselves, reduce required returns if investors assign a high probability to future policy reversals or shifts in investor requirements. If policy makers are serious about the inclusion or expansion of nuclear energy in the national grid to reach climate targets, an area of focus to make it more financially viable may be to shift public perceptions around the topic, highlighting the benefits of low-carbon, stable generation, while mitigating risks related to its safety.

For project developers, this implies that financing outcomes do not depend solely on contractual structure. Projects may face higher required returns in jurisdictions or periods where nuclear is politically contested, excluded from sustainable investment mandates, or subject to uncertain transition pathways. This shifts strategic focus toward jurisdictions with credible long-term commitment, active management of regulatory risk, and investor base alignment, rather than purely optimizing financial structure. This can be illustrated by the Sizewell C project in the UK, a planned two-reactor nuclear power plant in Suffolk, that reached final investment decision in 2025 and is being developed under a Regulated Asset Base (RAB) financing model designed to reduce financing risk and thereby lower required returns. Despite this, expected returns for private investors remain relatively high, with Centrica, an equity investor in the project, indicating target returns above 12%, while a substantial share of financing is provided by public sources, including a significant government equity stake (Reuters, 2022; Financial Times, 2025). This suggests that removing market price risk may not be sufficient to reduce required returns.

6.3 Limitations

This study has several limitations. First, generation capacity shares are only an approximation of firms' true exposures. Different technologies produce electricity in different ways and at different times, so a given share of capacity does not necessarily translate into the same share of revenues or risk. As a result, the estimated relationships may not fully capture how generation technologies affect firms' cash flows and risk, which can weaken the ability to detect differences in required returns across technologies.

Second, the study cannot directly observe the underlying risk channels discussed in the theory, such as political risk or investor preferences. Instead, these are inferred from technology exposure and revenue model. If these risks depend more on specific events, policy decisions, or investor restrictions than on exposure levels alone, they may not be captured by the empirical model. This means that the absence of significant effects in the results may reflect limitations in how these risks are measured, rather than evidence that they are not priced in capital markets.

Third, the analysis is based on firm-level data, while many of the economic mechanisms discussed are at the project level. Large utilities often combine different technologies and revenue structures within the same firm, which means that firm-level required returns may not fully reflect the risk profile of specific generation assets, particularly nuclear projects.

Fourth, the interpretation of the merchant interaction results relies on a linear specification, in which the effect of nuclear exposure on required returns varies proportionally with the level of merchant exposure. This implies that differences between technologies adjust smoothly as merchant exposure increases. However, if the effect of merchant exposure is instead non-linear, such as concentrated at low or high levels, this specification may not capture such patterns. As a result, the estimated interaction effects may reflect an average relationship, which limits how precisely the conditional nature of the results can be interpreted.

7. Conclusions

7.1 Final Remarks

This study examined how nuclear generation exposure is priced in capital markets relative to fossil and renewable technologies, and whether this relationship varies across revenue models. The findings suggest that nuclear exposure is not systematically priced differently on an unconditional basis (RQ1) and that any observable differences in required returns arise primarily in interaction with revenue model exposure (RQ2). Taken together, these results highlight that the pricing of electricity generation is shaped less by technology alone and more by the broader context in which it operates, providing a foundation for further research on how market structures influence required returns in electricity systems.

7.2 Opportunities for Further Research

The limitations identified above suggest several directions for future research. First, future studies could improve the measurement of technology exposure by using revenue or earnings-based metrics rather than installed capacity. This would allow a more direct link between generation technology and firms' economic risk, and help assess whether the absence of a nuclear premium persists with more precise exposure measures.

Second, further research could aim to measure the underlying risk channels more directly. For example, incorporating proxies for political risk, policy uncertainty, or ESG-related investor demand could help disentangle whether nuclear generation is priced differently through these mechanisms rather than through technology exposure alone.

Third, extending the analysis to the project level would provide a more accurate assessment of financing conditions for different generation technologies. Project-level data on contract structures, financing costs, and regulatory frameworks could help clarify whether the firm-level results mask important differences in the cost of capital across technologies, particularly for nuclear investments.

Fourth, future work could explore nonlinearities in the relationship between technology exposure, revenue models, and required returns. In particular, testing whether effects differ across low, medium, and high levels of merchant exposure could provide a more detailed understanding of the conditional pricing patterns identified in this study.

Finally, future research could examine how emerging nuclear technologies, such as small modular reactors (SMRs) or nuclear fusion, may be priced in capital markets. As discussed in recent policy and industry developments, fusion and next-generation nuclear technologies are expected to differ significantly from traditional nuclear in terms of cost structure, scalability, and perceived risk (Whiting & Torkington, 2026). Understanding whether these innovations alter investor perceptions and required returns represents an important avenue for future work.

References

Ang, A., Chen, J., & Xing, Y. (2006). Downside risk. *Review of Financial Studies, 19*(4), 1191–1239. https://doi.org/10.1093/rfs/hhj035

Angrist, J. D., & Pischke, J.-S. (2009). *Mostly harmless econometrics: An empiricist's companion*. Princeton University Press. https://www.researchgate.net/publication/51992844_Mostly_Harmless_Econometrics_An_Empiricist's_Companion

Baltagi, B. H. (2021). *Econometric analysis of panel data* (6th ed.). Springer. https://doi.org/10.1007/978-3-030-53953-5

Bansal, R., Ochoa, M., & Kiku, D. (2019). *Climate change risk* (Working paper). https://www.frbsf.org/wp-content/uploads/Paper-5-2019-11-8-Kiku-1PM-1st-paper.pdf

Blyth, W., Bradley, R., Bunn, D., Clarke, C., Wilson, T., & Yang, M. (2007). Investment risks under uncertain climate change policy. *Energy Policy, 35*(11), 5766–5773. https://doi.org/10.1016/j.enpol.2007.05.030

Bolton, P., & Kacperczyk, M. (2021). Do investors care about carbon risk? *Journal of Financial Economics, 142*(2), 517–549. https://doi.org/10.1016/j.jfineco.2021.05.008

Borenstein, S. (2012). The private and public economics of renewable electricity generation. *Journal of Economic Perspectives, 26*(1), 67–92. https://doi.org/10.1257/jep.26.1.67

Borenstein, S., & Bushnell, J. (2015). The U.S. electricity industry after 20 years of restructuring. *Annual Review of Economics, 7*, 437–463. https://doi.org/10.1146/annurev-economics-080614-115630

Bowen, M., & Guanio, K. (2023). *A critical disconnect: Relying on nuclear energy in decarbonization models while excluding it from climate finance taxonomies*. Center on Global Energy Policy, Columbia University. https://www.energypolicy.columbia.edu/publications/a-critical-disconnect-relying-on-nuclear-energy-in-decarbonization-models-while-excluding-it-from-climate-finance-taxonomies/

Campbell, J. Y., & Vuolteenaho, T. (2004). Bad beta, good beta. *American Economic Review, 94*(5), 1249–1275. https://doi.org/10.1257/0002828043052240

Chen, B. (2013). Cash-flow or discount-rate risk? Evidence from the cross section of present values. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2364771

Claus, J., & Thomas, J. (2001). Equity premia as low as three percent? Evidence from analysts' earnings forecasts for domestic and international stock markets. *Journal of Finance, 56*(5), 1629–1666. https://doi.org/10.1111/0022-1082.00384

Cochrane, J. H. (2005). *Asset pricing* (2nd. ed.). Princeton University Press.

Cochrane, J. H. (2011). Discount rates. *Journal of Finance*, 66(4), 1047–1108. https://doi.org/10.1111/j.1540-6261.2011.01671.x

Cramton, P. (2017). Electricity market design. *Oxford Review of Economic Policy, 33*(4), 589–612. https://doi.org/10.1093/oxrep/grx041

Damodaran, A. (2024). *Equity risk premiums (ERP): Determinants, estimation, and implications*. Stern School of Business, New York University. http://dx.doi.org/10.2139/ssrn.4751941

Davis, L. W., & Hausman, C. (2016). Market impacts of a nuclear power plant closure. *American Economic Journal: Applied Economics, 8*(2), 92–122. https://doi.org/10.1257/app.20140473

Demirer, R., Ferrer, R., & Shahzad, S. J. H. (2020). Oil price shocks, global financial markets and their connectedness. *Energy Economics, 88*, 104771. https://doi.org/10.1016/j.eneco.2020.104771

Drukker, D. M. (2003). Testing for serial correlation in linear panel-data models. *Stata Journal, 3*(2), 168–177. https://doi.org/10.1177/1536867X0300300206

Easton, P. D. (2004). PE ratios, PEG ratios, and estimating the implied expected rate of return on equity capital. *Accounting Review, 79*(1), 73–95. https://doi.org/10.2308/accr.2004.79.1.73

Ellerman, A. D., Convery, F. J., & de Perthuis, C. (2010). *Pricing carbon: The European Union emissions trading scheme*. Cambridge University Press. https://www.researchgate.net/publication/233996243_Pricing_Carbon_The_European_Union_Emissions_Trading_Scheme

Elton, E. J., Gruber, M. J., Brown, S. J., & Goetzmann, W. N. (2014). *Modern portfolio theory and investment analysis* (8th ed.). Wiley. https://scispace.com/pdf/modern-portfolio-theory-and-investment-analysis-3cglxl084r.pdf

Ernst & Young. (2024). *Financing new nuclear in Sweden*. https://www.ey.com/en_se/insights/energy-resources/financing-new-nuclear-in-sweden

Eurosif. (2018). *European SRI study 2018*. https://www.eurosif.org/wp-content/uploads/2021/10/European-SRI-2018-Study.pdf

Fabra, N., & Reguant, M. (2014). Pass-through of emissions costs in electricity markets. *American Economic Review, 104*(9), 2872–2899. https://doi.org/10.1257/aer.104.9.2872

Fama, E. F., & French, K. R. (1992). The cross-section of expected stock returns. *Journal of Finance, 47*(2), 427–465. https://doi.org/10.1111/j.1540-6261.1992.tb04398.x

Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics, 33*(1), 3–56. https://doi.org/10.1016/0304-405X(93)90023-5

Fama, E. F., & French, K. R. (1996). Multifactor explanations of asset pricing anomalies. *Journal of Finance, 51*(1), 55–84. https://doi.org/10.1111/j.1540-6261.1996.tb05202.x

Fama, E. F., & French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics, 116*(1), 1–22. https://doi.org/10.1016/j.jfineco.2014.10.010

Finon, D., & Roques, F. (2008). Financing arrangements and industrial organisation for new nuclear build in electricity markets. *Competition and Regulation in Network Industries, 9*(3), 247–272. https://doi.org/10.1177/178359170800900303

Financial Times. (2025, August 1). Sizewell C costs could hit £100bn including financing. *Financial Times*. https://www.ft.com

Gebhardt, W. R., Lee, C. M. C., & Swaminathan, B. (2001). Toward an implied cost of capital. *Journal of Accounting Research, 39*(1), 135–176. https://doi.org/10.1111/1475-679X.00007

Giglio, S., Maggiori, M., Rao, K., Stroebel, J., & Weber, A. (2018). *Climate change and long-run discount rates: Evidence from real estate* (Chicago Booth Research Paper No. 17-22). https://doi.org/10.2139/ssrn.2639748

Green, R., & Staffell, I. (2013). *The impact of government interventions on investment in the GB electricity market*. Imperial College Business School. https://competition-policy.ec.europa.eu/document/download

Gross, R., Blyth, W., & Heptonstall, P. (2010). Risks, revenues and investment in electricity generation: Why policy needs to look beyond costs. *Energy Economics, 32*(4), 796–804. https://doi.org/10.1016/j.eneco.2009.09.017

Gujarati, D. N., & Porter, D. C. (2009). *Basic econometrics* (5th ed.). McGraw-Hill/Irwin. https://cbpbu.ac.in.pdf

Hail, L., & Leuz, C. (2003). International differences in the cost of equity capital: Do legal institutions and securities regulation matter? *The Rodney L. White Center for Financial Research Working Paper, No. 17-04*. https://ssrn.com/abstract=875016

Hayashi, M., & Hughes, L. (2013). The policy responses to the Fukushima nuclear accident and their effect on Japanese energy security. *Energy Policy, 59*, 86–101. https://doi.org/10.1016/j.enpol.2012.11.046

Hirth, L. (2013). The market value of variable renewables: The effect of solar wind power variability on their relative price. *Energy Economics, 38*, 218–236. https://doi.org/10.1016/j.eneco.2013.02.004

Hong, H., & Kacperczyk, M. (2009). The price of sin: The effects of social norms on markets. *Journal of Financial Economics, 93*(1), 15–36. https://doi.org/10.1016/j.jfineco.2008.09.001

Hsiao, C. (2007). Panel data analysis—Advantages and challenges. *Test, 16*(1), 1–22. https://doi.org/10.1007/s11749-007-0046-x

IEA (International Energy Agency). (2021). *Hydropower special market report: Analysis and forecast to 2030*. https://www.iea.org/reports/hydropower-special-market-report

IEA (International Energy Agency). (2022). *Nuclear power and secure energy transitions: From today's challenges to tomorrow's clean energy systems*. https://www.iea.org/reports/nuclear-power-and-secure-energy-transitions

IEA (International Energy Agency). (2023). *World energy outlook 2023*. https://www.iea.org/reports/world-energy-outlook-2023

Ilhan, E., Sautner, Z., & Vilkov, G. (2021). Carbon tail risk. *Review of Financial Studies, 34*(3), 1540–1571. https://doi.org/10.1093/rfs/hhaa071

Joskow, P. L. (2008). Lessons learned from electricity market liberalization. *Energy Journal, 29*(Special Issue 2), 9–42. https://doi.org/10.5547/ISSN0195-6574-EJ-Vol29-NoSI2-3

Joskow, P. L., & Parsons, J. E. (2012). The future of nuclear power after Fukushima. *Economics of Energy & Environmental Policy, 1*(2), 99–113. https://doi.org/10.5547/2160-5890.1.2.7

Julio, B., & Yook, Y. (2012). Political uncertainty and corporate investment cycles. *Journal of Finance, 67*(1), 45–83. https://doi.org/10.1111/j.1540-6261.2011.01707.x

Kang, W., Ratti, R. A., & Vespignani, J. (2016). The impact of oil price shocks on the U.S. stock market: A note on the roles of U.S. and non-U.S. oil production. *Economics Letters, 145*, 176–181. https://doi.org/10.1016/j.econlet.2016.06.008

Kim, Y., Kim, M., & Kim, W. (2013). Effect of the Fukushima nuclear disaster on global public acceptance of nuclear energy. *Energy Policy, 61*, 822–828. https://doi.org/10.1016/j.enpol.2013.06.107

Kilian, L. (2009). Not all oil price shocks are alike: Disentangling demand and supply shocks in the crude oil market. *American Economic Review, 99*(3), 1053–1069. https://doi.org/10.1257/aer.99.3.1053

Kirschen, D. S., & Strbac, G. (2004). *Fundamentals of power system economics*. John Wiley & Sons. https://doi.org/10.1002/0470020598

Kitzing, L., Mitchell, C., & Morthorst, P. E. (2012). Renewable energy policies in Europe: Converging or diverging? *Energy Policy, 51*, 192–201. https://doi.org/10.1016/j.enpol.2012.08.064

Koomey, J., & Hultman, N. E. (2007). A reactor-level analysis of busbar costs for U.S. nuclear plants, 1970–2005. *Energy Policy, 35*(11), 5630–5642. https://doi.org/10.1016/j.enpol.2007.06.005

Lovering, J. R., Yip, A., & Nordhaus, T. (2016). Historical construction costs of global nuclear power reactors. *Energy Policy, 91*, 371–382. https://doi.org/10.1016/j.enpol.2016.01.011

Meunier, L., & Ohadi, S. (2023). Exclusion strategy in socially responsible investment: One size does not fit all. *Journal of Behavioral and Experimental Finance, 39*, 100829. https://doi.org/10.1016/j.jbef.2023.100829

Merton, R. C. (1987). A simple model of capital market equilibrium with incomplete information. *Journal of Finance, 42*(3), 483–510. https://doi.org/10.1111/j.1540-6261.1987.tb04565.x

MIT Energy Initiative. (2018). *The future of nuclear energy in a carbon-constrained world: An interdisciplinary MIT study*. Massachusetts Institute of Technology. https://energy.mit.edu/research/future-nuclear-energy-carbon-constrained-world/

Modigliani, F., & Miller, M. H. (1958). The cost of capital, corporation finance and the theory of investment. *American Economic Review, 48*(3), 261–297. https://www.jstor.org/stable/1809766

Newbery, D. (2016). Missing money and missing markets: Reliability, capacity auctions and interconnectors. *Energy Policy, 94*, 401–410. https://doi.org/10.1016/j.enpol.2015.10.028

OECD Nuclear Energy Agency. (2019). *The costs of decarbonisation: System costs with high shares of nuclear and renewables* (NEA No. 7299). OECD Publishing. https://doi.org/10.1787/9789264312180-en

Pástor, Ľ., Stambaugh, R. F., & Taylor, L. A. (2021). Sustainable investing in equilibrium. *Journal of Financial Economics, 142*(2), 550–571. https://doi.org/10.1016/j.jfineco.2020.12.011

Pástor, Ľ., & Veronesi, P. (2013). Political uncertainty and risk premia. *Journal of Financial Economics, 110*(3), 520–545. https://doi.org/10.1016/j.jfineco.2013.08.007

Polzin, F., Egli, F., Steffen, B., & Schmidt, T. S. (2019). How do policies mobilize private finance for renewable energy? A systematic review with an investor perspective. *Applied Energy, 236*, 1249–1268. https://doi.org/10.1016/j.apenergy.2018.11.098

Reuters. (2022, November 29). UK to take 50% stake in Sizewell C nuclear project. *Reuters*. https://www.reuters.com/business/energy/uk-take-50-stake-sizewell-c-nuclear-project-2022-11-29/

Roques, F. A., Newbery, D. M., & Nuttall, W. J. (2008). Fuel mix diversification incentives in liberalised electricity markets: A mean-variance portfolio theory approach. *Energy Economics, 30*(4), 1831–1849. https://doi.org/10.1016/j.eneco.2007.11.008

Schneider, M., Froggatt, A., Hazemann, J., Katsuta, T., Ramana, M. V., Rodriguez, J. C., Rüdinger, A., & Stienne, A. (2017). *The World Nuclear Industry Status Report 2017*. Mycle Schneider Consulting. https://www.worldnuclearreport.org/World-Nuclear-Industry-Status-Report-2017-29

Schneider, M., Kobayashi, Y., Ting, Y.-C., Hazemann, J., Dvorak, P., Godoy, E., Müller, N., Ramana, M. V., Wimmers, A., & Winkler, H. (2025). *The World Nuclear Industry Status Report 2025*. Mycle Schneider Consulting. https://www.worldnuclearreport.org/World-Nuclear-Industry-Status-Report-2025

SEI (Stockholm Environment Institute). (2016). *Fossil fuel production in a 2°C world: The equity implications of a diminishing carbon budget*. Stockholm Environment Institute. https://www.sei.org/mediamanager/documents/Publications/Climate/SEI-DB-2016-Equity-fossil-fuel-production-rents-LR.pdf

Steffen, B. (2018). The importance of project finance for renewable energy projects. *Energy Economics, 69*, 280–294. https://doi.org/10.1016/j.eneco.2017.11.006

Steffen, B. (2020). Estimating the cost of capital for renewable energy projects. *Energy Economics, 88*, 104783. https://doi.org/10.1016/j.eneco.2020.104783

Stewart, W. R., & Shirvan, K. (2022). Capital cost estimation for advanced nuclear power plants. *Renewable and Sustainable Energy Reviews, 155*, 111880. https://doi.org/10.1016/j.rser.2021.111880 van der Ploeg, F., & Rezai, A. (2020). Stranded assets in the transition to a carbon-free economy. *Annual Review of Resource Economics, 12*, 281–298. https://doi.org/10.1146/annurev-resource-110519-040938

Weibezahn, J., & Steigerwald, B. (2024). Fission for funds: The financing of nuclear power plants. *Energy Policy, 195*, 114382. https://doi.org/10.1016/j.enpol.2024.114382

White, H. (1980). A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. *Econometrica, 48*(4), 817–838. https://doi.org/10.2307/1912934

Whiting, K., & Torkington, S. (2026, February 12). Nuclear fusion: The science behind the energy technology, explained. *World Economic Forum*. https://www.weforum.org/stories/2026/02/nuclear-fusion-science-explained/

Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data*. MIT Press.

Yescombe, E. R. (2014). *Principles of project finance* (2nd ed.). Academic Press.

Appendix

1. Countries that are both OECD members and had active nuclear reactors in the period 2010-2024

- United States
- Canada
- France
- Spain
- Sweden
- United Kingdom
- Finland
- Czech Republic
- Slovakia
- Belgium
- Hungary
- Netherlands
- Switzerland
- Korea, Republic of (South Korea)
- Japan
- Mexico

2. Summary of Sample Construction & Categories of Exclusion

a. Summary of Sample Construction

Step	Screening Criterion	Firm count
1	Publicly listed companies available for screening in S&P Capital IQ Pro	72,942
2	Firms classified in Capital IQ Primary Industries as : Electric Utilities, Multi-Utilities, Renewable Electricity, and Independent Power Producers (IPP)	938
3	Firms headquartered in OECD countries where nuclear power is part of the national electricity system	273
4	Firms removed through manual screening (see table below)	−181
Final Sample	**Electricity-generating utility firms used in the empirical analysis**	**92**

b. Categories of Exclusion

Category of Removal	Firm count
No usable market data	31
Detailed description screening (no generation activities)	124
Retail / Commercialization activities only	*9*
Transmission / Network operators	*13*
Engineering / Energy service providers	*12*
Project developers without operating assets	*28*
Investment / Holding company structures	*15*
Fuel / Non-electric energy activities	*13*
Non-energy or miscellaneous activities	*10*
Nuclear technology or R&D firms	*3*
Legacy, obsolete, or non-comparable entities	*21*
Duplicate listings	10
No capacity details / Not enough capacity	16
Total Excluded	**181**

3. AI Prompt for Technology Exposure Data Extraction

"For this firm, based exclusively on the provided annual reports, calculate the installed electricity generation capacity exposure for the following years:

(1) 2010, (2) 2015, (3) 2020, and (4) 2024.

For each year, report capacity split into the following categories:

• "Nuclear"
• "Renewables (wind + solar only)"
• "Hydro"
• "Fossil (coal + oil + natural gas)"
• "Other (all remaining or unclassified technologies)"

Capacity should be measured as installed electricity generation capacity (MW) and expressed both in absolute MW and as percentage of total installed capacity. Percentages must sum to 100% for each year.

If technologies are reported in aggregated categories (e.g. "thermal", "low-carbon", "other"), reclassify only where the mapping is explicit. If disaggregation is not possible, allocate the residual to Other.

Additionally, report market exposure of generation capacity:

• "Merchant" (revenues linked to wholesale electricity markets)
• "Regulated / Contracted" (regulated tariffs, capacity payments, or long-term PPAs)

Report merchant and regulated exposure both in MW and percentage of total installed generation capacity. Report results only for consolidated entities as presented in the firm's annual reports.

Determine merchant vs regulated classification using segment descriptions, regulatory disclosures, or stated revenue models of generation assets. If classification cannot be determined from the annual report, flag explicitly.

If assumptions are required due to missing, aggregated, or ambiguous disclosures, state each assumption explicitly and concisely so it can be directly copied and documented.

Be brief and standardized: report only the MW split, corresponding percentages, merchant/regulation classification, assumptions, and flags.

If data quality is insufficient or classification is unclear, flag explicitly."

4. VIF Diagnostics for Multicollinearity

Variable	VIF
Constant	420.1486
NUCLEAR_EX	1.431551
RENEWABLE_EX	1.586397
HYDRO_EX	1.081491
OTHER_EX	1.255404
LN_TOTAL_ASSETS	1.572729
LEVERAGE	1.498204
OP_PROFITABILITY	1.297809
BOOK_TO_MARKET	1.283356
ASSETS_TANGIBILITY	1.702355
MERCHANT_PCP	1.541601

5. Robustness Tests

Specification Robustuness

a) Alternative Fixed Effects 1: Year + Country FE (No Industry) - Applied to both models

Variables	RQ1 Baseline Model		RQ2 Merchant Model	
	ICoE	RGAP	ICoE	RGAP
Nuclear	0.019 (0.017)	0.025 (0.017)	0.066*** (0.022)	0.061*** (0.022)
Renewable	-0.009 (0.017)	-0.002 (0.017)	0.014 (0.020)	0.013 (0.019)
Hydro	-0.002 (0.015)	-0.004 (0.014)	0.000 (0.015)	-0.003 (0.014)
Other	-0.023 (0.014)	-0.020 (0.012)	-0.007 (0.011)	-0.014 (0.010)
Merchant	0.018* (0.010)	0.014 (0.010)	0.037*** (0.011)	0.025** (0.012)
Firm size (Ln of Assets)	-0.001 (0.002)	-0.001 (0.002)	-0.002 (0.002)	-0.001 (0.002)
Leverage (Debt/Assets)	0.015 (0.024)	0.012 (0.023)	0.018 (0.023)	0.012 (0.022)
Op. profitability (EBIT/Assets)	-0.008 (0.070)	0.006 (0.076)	0.011 (0.067)	0.018 (0.070)
Valuation (BE/MVE)	0.020*** (0.005)	0.024*** (0.004)	0.020*** (0.005)	0.024*** (0.004)
Tangibility (NPPE/Assets)	-0.013 (0.020)	-0.010 (0.019)	-0.016 (0.019)	-0.013 (0.020)
Diff: Nuclear - Renewable	0.028 (0.020)	0.027 (0.021)	/	/
Nuclear × Merchant	/	/	-0.129*** (0.039)	-0.096** (0.037)
Renewable × Merchant	/	/	-0.028 (0.028)	-0.025 (0.026)
Diff: Nucl. × M. - Renew. × M.	/	/	-0.101** (0.039)	-0.071* (0.038)

b) Alternative Fixed Effects 2: Year + Firm FE - Applied to both models

Variables	RQ1 Baseline Model		RQ2 Merchant Model	
	ICoE	RGAP	ICoE	RGAP
Nuclear	-0.003 (0.015)	0.023 (0.019)	0.008 (0.019)	0.022 (0.018)
Renewable	-0.035 (0.039)	-0.021 (0.037)	-0.007 (0.019)	0.012 (0.019)
Hydro	-0.043 (0.027)	-0.067** (0.031)	-0.044 (0.028)	-0.074** (0.032)
Other	0.051 (0.036)	0.028 (0.040)	0.052 (0.036)	0.028 (0.039)
Merchant	-0.003 (0.012)	0.025 (0.015)	0.015 (0.021)	0.031 (0.021)
Firm size (Ln of Assets)	-0.002 (0.006)	-0.014** (0.006)	-0.001 (0.006)	-0.013** (0.006)
Leverage (Debt/Assets)	0.044* (0.026)	0.035 (0.029)	0.041 (0.025)	0.032 (0.029)
Op. profitability (EBIT/Assets)	0.077 (0.070)	0.062 (0.075)	0.085 (0.071)	0.072 (0.073)
Valuation (BE/MVE)	0.021*** (0.005)	0.025*** (0.004)	0.020*** (0.005)	0.024*** (0.004)
Tangibility (NPPE/Assets)	-0.073** (0.035)	-0.059** (0.029)	-0.070* (0.036)	-0.053 (0.030)
Diff: Nuclear - Renewable	0.032 (0.039)	0.043 (0.039)	/	/
Nuclear × Merchant	/	/	-0.055 (0.083)	0.043 (0.086)
Renewable × Merchant	/	/	-0.064 (0.072)	-0.081 (0.059)
Diff: Nucl. × M. - Renew. × M.	/	/	0.009 (0.078)	0.124 (0.079)

Measurement robustness

c) Nuclear Dummy - Applied to both models

Variables	RQ1 Baseline Model		RQ2 Merchant Model	
	ICoE	RGAP	ICoE	RGAP
Nuclear Dummy	0.006 (0.006)	0.009 (0.006)	0.014** (0.006)	0.016** (0.006)
Renewable	-0.008 (0.018)	-0.001 (0.017)	-0.001 (0.020)	0.011 (0.020)
Hydro	-0.000 (0.015)	-0.001 (0.014)	-0.001 (0.014)	-0.002 (0.013)
Other	-0.020 (0.014)	-0.020* (0.011)	-0.017 (0.014)	-0.013 (0.012)
Merchant	0.018* (0.010)	0.014 (0.010)	0.038*** (0.014)	0.035** (0.015)
Firm size (Ln of Assets)	-0.002 (0.003)	-0.002 (0.003)	-0.002 (0.003)	-0.001 (0.003)
Leverage (Debt/Assets)	0.014 (0.024)	0.011 (0.023)	0.021 (0.022)	0.020 (0.021)
Op. profitability (EBIT/Assets)	-0.008 (0.069)	0.007 (0.074)	0.008 (0.067)	0.022 (0.072)
Valuation (BE/MVE)	0.020*** (0.005)	0.025*** (0.004)	0.021*** (0.005)	0.025*** (0.004)
Tangibility (NPPE/Assets)	-0.013 (0.019)	-0.010 (0.019)	-0.025 (0.019)	-0.021 (0.018)
Nuclear × Merchant	/	/	-0.038** (0.016)	-0.035** (0.016)

Renewable × Merchant	/	/	-0.027 (0.030)	-0.034 (0.028)
Diff: Nucl. × M. - Renew. × M.	/	/	-0.011* (0.027)	-0.001* (0.026)

Sample robustness

d) Excluding Zero-Nuclear Firms - Applied to both models

Variables	RQ1 Baseline Model		RQ2 Merchant Model	
	ICoE	RGAP	ICoE	RGAP
Nuclear	0.005 (0.010)	0.003 (0.014)	0.030 (0.021)	0.019 (0.027)
Renewable	-0.025** (0.012)	-0.022 (0.015)	-0.009 (0.012)	-0.001 (0.015)
Hydro	0.016 (0.019)	0.008 (0.012)	0.014 (0.018)	0.007 (0.012)
Other	0.033 (0.062)	-0.002 (0.066)	0.029 (0.059)	-0.012 (0.066)
Merchant	-0.005 (0.013)	0.006 (0.011)	0.013 (0.018)	0.019 (0.020)
Firm size (Ln of Assets)	0.002 (0.002)	0.000 (0.002)	0.002 (0.002)	0.001 (0.002)
Leverage (Debt/Assets)	0.031 (0.022)	0.026 (0.025)	0.017 (0.023)	0.018 (0.027)
Op. profitability (EBIT/Assets)	0.038 (0.094)	0.097 (0.096)	0.038 (0.097)	0.100 (0.099)
Valuation (BE/MVE)	0.012** (0.006)	0.019*** (0.006)	0.012* (0.006)	0.019*** (0.006)
Tangibility (NPPE/Assets)	-0.040 (0.034)	-0.000 (0.025)	-0.036 (0.033)	0.002 (0.026)
Diff: Nuclear - Renewable	0.030** (0.015)	0.025 (0.017)	/	/
Nuclear × Merchant	/	/	-0.066* (0.041)	-0.040 (0.050)
Renewable × Merchant	/	/	-0.052 (0.039)	-0.065 (0.038)
Diff: Nucl. × M. - Renew. × M.	/	/	-0.014* (0.055)	-0.025 (0.053)

Control specification

e) Removing Book-to-Market - Applied to both models

Variables	RQ1 Baseline Model		RQ2 Merchant Model	
	ICoE	RGAP	ICoE	RGAP
Nuclear	0.011 (0.016)	0.014 (0.017)	0.055*** (0.021)	0.051** (0.022)
Renewable	-0.007 (0.018)	-0.000 (0.019)	0.007 (0.025)	0.018 (0.027)
Hydro	0.002 (0.016)	0.001 (0.015)	0.001 (0.015)	0.001 (0.015)
Other	-0.019 (0.018)	-0.015 (0.016)	-0.013 (0.017)	-0.009 (0.017)
Merchant	0.023** (0.010)	0.019* (0.010)	0.039*** (0.012)	0.036*** (0.013)
Firm size (Ln of Assets)	0.001 (0.002)	0.002 (0.003)	0.001 (0.002)	0.002 (0.003)
Leverage (Debt/Assets)	-0.006 (0.025)	-0.014 (0.024)	-0.009 (0.024)	-0.014 (0.023)
Op. profitability (EBIT/Assets)	-0.093 (0.070)	-0.097 (0.075)	-0.076 (0.066)	-0.082 (0.071)
Tangibility (NPPE/Assets)	0.003 (0.022)	0.010 (0.021)	-0.001 (0.020)	0.007 (0.020)
Diff: Nuclear - Renewable	0.018 (0.022)	0.015 (0.024)	/	/
Nuclear × Merchant	/	/	-0.130*** (0.037)	-0.108*** (0.038)
Renewable × Merchant	/	/	-0.025 (0.030)	-0.032 (0.030)
Diff: Nucl. × M. - Renew. × M.	/	/	-0.105*** (0.039)	-0.076* (0.039)

f) Removing Merchant Control Variable - Applied to baseline model

	ICoE	RGAP
Nuclear	0.025 (0.016)	0.029* (0.016)
Renewable	-0.007 (0.017)	-0.001 (0.016)
Hydro	-0.003 (0.017)	-0.004 (0.015)
Other	-0.031** (0.015)	-0.026** (0.011)
Firm size (Ln of Assets)	-0.001 (0.003)	-0.001 (0.003)
Leverage (Debt/Assets)	0.015 (0.027)	0.012 (0.024)
Op. profitability (EBIT/Assets)	0.007 (0.070)	0.018 (0.073)
Valuation (BE/MVE)	0.021*** (0.004)	0.025*** (0.004)
Tangibility (NPPE/Assets)	-0.028 (0.018)	-0.021 (0.017)
Diff: Nuclear - Renewable	0.032 (0.023)	0.030 (0.023)