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Financing the Nordic Energy Transition: An Empirical Analysis of Leverage, Pricing and Return Expectations in Renewable Energy Transactions

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ABSTRACT

This study examines whether leverage and pricing in transactions of renewable energy infrastructure assets are impacted by the same factors that have been found to determine financial structures in buyout transactions. It primarily draws on a proprietary data set of 261 wind and solar photovoltaic (PV) transactions in the Nordics between 2011 and 2023 and explores the effect of acquirer-, asset-, and industry-specific characteristics as well as time-varying variables on leverage, pricing and return expectations. Using a standard regression set-up, I show that the most consistent effect on financial structures in renewable energy transactions originates from the volatility of forecasted power prices, which negatively impacts leverage, valuation multiples and return expectations. Transactions of assets that include agreements to sell a proportion of their future production at a set price have higher odds of being levered and are associated with higher return expectations. In addition, experienced and Nordics-based acquirers tend to use less leverage. I conclude that contrary to buyouts, leverage and pricing in renewable energy deals are not determined by time-series variation related to debt market conditions, but rather by acquirer-, asset- and industry-related attributes. Thus, an understanding of the industry-specific context, particularly an awareness for the importance of price risk, is crucial for investors looking to enter this sector.

Keywords: *Buyouts, Leverage, Valuation, Renewable Energy, Infrastructure Investment*

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List of Abbreviations

AuM	Assets under Management
Capex	Capital Expenditures
D	Debt
EBITDA	Earnings before Interest, Tax, Depreciation and Amortization
EV	Enterprise Value
FiT	Feed-in Tariff
IPP	Independent Power Producer
IRR	Internal Rate of Return
LBO	Leveraged Buyout
LTV	Loan-to-Value
MW	Megawatt
OAS	Option-Adjusted Spread
OECD	Organization for Economic Co-operation and Development
Opex	Operational Expenditures
PCA	Principal Component Analysis
PE	Private Equity
PPA	Power Purchase Agreement
Solar PV	Solar Photovoltaic
SPV	Special Purpose Vehicle

1 Introduction

Worldwide, USD 495 billion have been invested in renewable energy in 2022, up 17% from 2021, making last year a record one for renewable energy investment (BloombergNEF, 2023). The energy crisis triggered by Russia's invasion of Ukraine has led to an increased focus on renewables as an alternative source of energy, creating strong tailwinds and accelerating new installations (IEA, 2022). Such strong build-out requires large amounts of private capital, causing the entry of new types of investors to the market. This, together with the increased political focus on renewable energy, energy prices at record highs, as well as rising interest rates and inflation, creates a dynamic environment for renewable energy investment. Against this backdrop, a better understanding of how renewable energy infrastructure assets are financed and priced is required. Considering the volatility of the current market environment, many aspects that may impact financial structures and pricing of renewable energy assets are in motion.

In this context, I aim to provide an understanding of the drivers that have historically impacted capital structures and valuations in transactions of renewable energy assets. Identifying the factors that have historically been priced by investors when evaluating renewable energy infrastructure investments allows market participants to make informed decisions and may thus align expectations regarding financial structures and pricing in renewable energy transactions. This enables developers to set up assets strategically to increase their attractiveness to investors and is equally important for investors to deploy capital efficiently.

In fact, the determinants of financing structures and pricing in transactions of renewable energy assets have received limited attention in academic research. Thus, parallels are drawn to financing terms in buyouts. Both types of deals are structured as M&A processes and involve the use of debt and equity by strategic and financial investors to gain controlling interest of an asset. Evidence from the academic literature on buyout financing shows that the use of debt and pricing are more strongly related to economy-wide factors, particularly the availability of "cheap" debt, than to asset-specific aspects. Considering these findings, my study intends to shed light on the extent to which results for buyout capital structure and pricing are applicable to renewable energy deals.

The majority of data (231 transactions) is drawn from a unique proprietary dataset provided by an M&A advisor specialized in renewable energy transactions in the Nordics (throughout this study defined as including the countries Denmark, Finland, Norway and Sweden). I extend this initial sample through my own data collection and use the resulting data set of 261 transactions of renewable energy assets signed between 2011 and 2023 in the Nordics to run regression analyses to determine the factors that impact leverage, pricing and return expectations. The return expectations examined in this study are approximated return expectations by the acquirer based on the purchase price as well as the buyer's operational and macroeconomic assumptions. My definition of renewable energy encompasses solely onshore wind and solar PV assets. These have been the most active technologies in terms of build-out and investment. In 2021, wind and solar accounted for more than half of the total electricity generated from renewable sources in the EU (Eurostat, 2023). Moreover, my study focuses on transactions in the Nordics, as this region has been at the forefront of renewable energy, in particular of wind power (Dahlström, 2022).

Studying the impact of time-series and cross-sectional variables on leverage, pricing and return expectations in these transactions, I find that in contrast to buyouts, leverage and pricing in renewable energy deals are not determined by time-series variation related to debt market conditions as proxied by the high-yield spread. Instead, my results suggest that acquirer-, asset- and industry-specific attributes impact debt financing, valuations and return expectations.

I show that the most consistent effect on financial structures in renewable energy transactions originates from industry-specific time-series effects related to the volatility of forecasted power prices. The latter negatively impacts all three financial aspects studied in these deals, i.e., leverage, valuation multiples and return expectations.

Moreover, I study the impact of cross-sectional aspects. Examining asset-specific characteristics, specifically of the asset's revenue strategy (power purchase agreement yes/no) and size (in megawatts), I find that the odds of a transaction being levered increase when the underlying asset has entered an agreement to sell a proportion of its future production at a set price. I relate this to results in the corporate finance literature that cash flow predictability is positively related to bank loan contracting. In addition, acquirers expect higher returns from an investment in an asset with such an agreement in place.

Finally, I investigate the effect of acquirer characteristics based on the acquirer's industry-specific experience, acquirer type (financial vs. industrial) and acquirer origin (Nordic vs. international). My results suggest that acquirers with more industry-specific experience in buying renewable energy assets and acquirers based in Nordic countries tend to use less leverage.

I contribute to the existing academic literature by showing that results from research on buyout leverage and pricing are not necessarily applicable to renewable energy transactions. The lack of an association between leveraged buyout (LBO) financial structures and financial structures in renewable energy transactions shows that different explanatory approaches from those for buyouts are needed to reconcile capital structures and prices paid in renewable energy deals. Besides financial knowledge, an understanding of the industry-specific context is required to explain leverage and pricing of renewable energy deals. Hence, my findings may be of interest for new investors considering to enter this market as they highlight the differences to regular buyout transactions and direct the focus to industry-specific factors that impact financial structures and valuations in renewable energy deals. By emphasizing the importance of price risk for the financing of renewable energy transactions, I simultaneously contribute to the literature on renewable energy investment risk.

The thesis proceeds as follows. Section 2 reviews related literature on buyout leverage and pricing. In Section 3, I provide background on the institutional setting and in Section 4, I develop my hypotheses. Section 5 presents the data collection process, sample statistics, as well as variables used and the regression models. While Section 6 presents and discusses the research findings, Section 7 concludes by discussing implications and limitations of results.

2 Related Literature

My study relates to two strands of literature: the determinants of leverage and of pricing in buyouts. Due to the lack of research on the drivers of leverage, valuations and return expectations in renewable energy M&A transactions, parallels are drawn to buyouts in general. The financing of buyout transactions is relevant for this study as both types of transactions involve the use of debt and equity by strategic and financial investors to gain controlling interest of an asset. In the following, I present an overview of the results of relevant papers, explain how they relate to this study and outline how my work differentiates itself from existing research.

First, with regards to leverage determinants, Jensen (1986) puts forth the view that private equity-backed firms have superior governance compared to public companies. Therefore, they more strongly adjust their targets' capital structures to take full advantage of tax and incentive benefits of leverage, in tradeoff against the costs of financial distress. This implies that leverage in buyouts should be strongly related to firm-specific debt capacity characteristics that explain capital structures in public firms. By contrast, a series of later studies shows that leverage in buyouts is cross-sectionally unrelated to and not explained by the same factors as public firm leverage (Axelson et al., 2007; Demiroglu & James, 2007; De Maeseneire & Brinkhuis, 2009; Achleitner et al., 2011; Axelson et al., 2013). While firm-specific characteristics are not related to buyout leverage, the economy-wide cost of borrowing drives both leverage and pricing. Research provides two theories to explain the relationship between debt market conditions and buyout leverage. First, based on Kaplan & Strömberg (2009), private equity (PE) firms may be uniquely positioned to time the market by arbitraging debt versus equity in times of cheap debt due to their superior access to debt financing. Alternatively, following Axelson et al. (2009), PE firms have an incentive to lever up their transactions and overpay for assets they are acquiring when credit market conditions are good because they hold an option-like stake in the acquiring fund. Axelson et al. (2013) find a strong negative relationship between the high-yield spread and pricing even after controlling for pricing in public markets, indicating that debt market conditions have an independent effect on pricing beyond variation in the economy-wide discount rate. While my study is similar to these papers in that it tests a potential link between debt market conditions and leverage as well as pricing, it differs from the above research due to the focus on M&A transactions of renewable energy assets in the Nordics instead of buyout deals.

In studies analyzing the effects of acquirer-, firm- and transaction-related aspects, i.e., of cross-sectional variables, on buyout leverage, reputation of the acquiring private equity (PE) firm is found to be positively related to the amount of leverage (Demiroglu & James, 2007; De Maeseneire & Brinkhuis, 2009; Achleitner et al., 2011; Achleitner et al., 2018). Furthermore, studies show that primary transactions and smaller deals have lower debt levels (De Maeseneire & Brinkhuis, 2009; Gao et al., 2021). Analogous to these papers, my study considers the effects of acquirer characteristics on leverage and pricing. However, instead of reputation, the relevant acquirer attributes in my paper are industry-specific experience as well as the distinction between Nordic and international as well as financial and strategic buyers. As these papers exclusively study PE-sponsored buyouts, the inclusion of strategic acquirers in the data sample further distinguishes my study from existing literature.

Studies examining determinants of pricing in buyouts also focus on the impact of acquirer characteristics. Bargeron et al. (2008) find that buyout premia are significantly higher when the acquirer is a public versus a private firm. Grouping acquirers by geographic origin, Hammer et al. (2020) show that cross-border buyouts are associated with higher multiples, whereby the spread between cross-border and domestic multiples decreases when information asymmetries are smaller. Finally, Hammer et al. (2022) distinguish between financial and strategic acquirers and find that transaction multiples in private equity buyouts are lower on average. Again, my study resembles these papers as it relates acquirer attributes to pricing in M&A transactions. In addition to this, however, I examine the effects of asset- and industry-specific characteristics on transaction prices.

To my knowledge, my study is the first one to investigate the factors that may impact the returns buyers expect from their transactions. It therefore fills a gap in the literature on the interaction between return expectations and pricing in M&A deals. I find that return expectations are impacted by the acquirer's experience and origin as well as by the premium paid. Moreover, industry-specific attributes, specifically the asset 's revenue strategy and forecasted price volatility appear to affect return expectations in renewable energy deals.

3 Institutional Background

In this section, I present an overview of the relevant institutional setting for this study. First, revenue strategies generally employed for renewable energy assets are introduced (Subsection 3.1). Subsequently, Subsection 3.2 considers renewable energy investment risks. This fosters the understanding of relevant industry-specific attributes for investors, so that research results can be interpreted in this context. Finally, the use of project finance for renewable energy assets is discussed (Subsection 3.3). A general understanding of this financial structure is required to comprehend how renewable energy transactions may be different from M&A transactions in general.

3.1 Revenue strategy

Power Purchase Agreement

As policy mechanisms to incentivize renewable energy production, feed-in tariffs (FiTs) offer a guaranteed (minimum) purchasing price for electricity produced from renewable energy sources for a fixed period (Painuly & Wohlgemuth, 2021)[1]. Initially, they provided high predictability of future revenues of renewable energy assets. In recent years, however, FiTs have gradually been phased out in many countries and certainty of future cash flows has more frequently been achieved through long-term power purchase agreements (PPAs) (Steffen, 2018). As part of a PPA, a (corporate) buyer ("offtaker") commits to buy future energy production of a renewable energy producer at an agreed fixed price (Ghiassi-Farrokhfal et al., 2021). For buyers, PPAs are an attractive way to meet sustainability targets. For sellers, these agreements can provide price certainty for future periods, shielding them from volatile market prices. This, in turn, enables sellers to secure the funding necessary to build and operate the project (Gabrielli et al., 2022). However, IRENA (2016) note that many local financial institutions lack the experience or information to assess the bankability of PPAs as this requires an understanding of both financial and technical aspects of renewables. Moreover, on the downside, a PPA exposes a renewable energy producer to counterparty risk, arising from the financial risk that a distressed offtaker is unable to meet payment obligations. To mitigate this risk, project developers typically seek investment grade rated buyers, such as utilities or large technology companies. Finally, recent developments with high power prices have made many existing PPAs financially unattractive for sellers as fixed PPA prices are significantly below current spot prices. However, PPAs were prevalent during the time period of my study, where 50% of projects in my dataset include PPAs.

[1] The exact policy design varies by country.

Nord Pool Power Market

The share of a project's power production that is not sold through a power purchase agreement is traded on the (merchant) spot market. As my study examines transactions in the Nordics, the relevant marketplace for the trading of electricity is the Nord Pool power market (Svenska Kraftnät, 2023). The Nord Pool market is divided into several bidding areas. Due to limitations in available transmission capacity between price zones, the flow of power between bidding areas may be restricted, causing different area prices (Nord Pool, 2023). Due to systematic imbalances of supply and demand between price areas, prices and thus price forecasts for the different bidding areas can vary substantially even within the same country. As an asset's non-contracted revenues are estimated by the forecasted price level at which an asset will be able to sell its output, these price differentials have likely impacted investor interest and competitiveness in transactions of assets located in different price zones in my study.

3.2 Renewable energy investment risk

The deals in my study comprise transactions of renewable energy assets, which are subject to specific risks. These risks can act as barriers to investment and significantly impact how investors value assets and structure transactions. Table 1 presents an overview of risk types identified in academic literature.

Initially, policy risk, which is the risk of lower-than-expected revenues due to retroactive changes in support policies or taxation, used to play an important role for solar PV and onshore wind investments in the EU (Blondiau et al., 2017; Leisen et al., 2019). However, the dynamics have changed with increasing renewable energy build-out. Business-related risks, such as financial risk regarding the access to capital and market risk concerning future power prices have become relatively more important as markets matured. Meanwhile, technology risk (risk of lower-than-expected revenues or higher-than-expected maintenance costs due to a technology's novelty) and policy risk have declined in relative importance over time. The decrease in technology risk resulted from increased technology deployment, which enhanced experience and data availability. The reduction in technology risk has led to a diversification of the investor base for renewable energy assets. This, in turn, has put pressure on equity returns as specialized (financial) investors exploit their relatively low cost of capital to pay higher prices than those affordable by traditional investors in these types of assets, i.e., utilities and independent power producers (IPPs) (Vázquez-Vázquez et al., 2021). At the same time, price risk (risk of volatility in power prices due to merchant price exposure) and curtailment risk (lower-than-expected revenues due to unexpected grid bottlenecks) have become more relevant (Egli, 2020). Thus, energy prices have strong effects on driving renewable energy investment and uncertainties in future energy prices create an important obstacle for investors (World Economic Forum, 2017; Azhgaliyeva et al., 2022).

Table 1. Overview of key renewable energy investment risks

The table below presents relevant risks in renewable energy investments identified in the academic literature.

Risk Type	Description	References
Resource risk	Risk associated with uncertainties around the availability and / or supply of the renewable energy resource.	Noothout et al. (2016) IRENA (2016)
Price risk	Risk of lower revenues due to volatility in merchant prices.	World Economic Forum (2017) Egli (2020) Azhgaliyeva et al. (2022)
Curtailment risk	Risk of lower revenues due to unexpected curtailment, e.g., due to grid bottlenecks.	Egli (2020)
Political and policy risk	Risk of lower revenues due to a change in renewable energy technology policies or taxation.	Noothout et al. (2016) IRENA (2016) World Economic Forum (2017) Mazzucato & Semieniuk (2018) Egli (2020)
Technology risk	Risk of lower revenues or higher maintenance costs due to a technology's nascency.	Noothout et al. (2016) IRENA (2016) Egli (2020) Azhgaliyeva et al. (2022)
Counterparty risk	Credit and default risk by an off-taker in a power purchase agreement.	IRENA (2016)
Refinancing risk	Risk that an outstanding loan cannot be refinanced during the project life due to inadequate loan terms.	Noothout et al. (2016) IRENA (2016)
Currency risk	Risk of adverse effects on investment returns due to changing foreign exchange rates.	IRENA (2016) World Economic Forum (2017)
Construction risk	Risk of cost overruns and delays in the scheduled commercial operation date (in case of greenfield assets).	Noothout et al. (2016) World Economic Forum (2017)

3.3 Project finance

Like other types of infrastructure assets, power plants can generally be set up using either corporate finance (i.e., "on balance sheet"), or project finance (i.e., "off balance sheet" as a new entity) structures. According to the Basel III framework, project finance is "a method of funding in which the lender looks primarily to the revenues generated by a single project, both as the source of repayment and as security for the exposure". The sponsor creates a separate legal entity, i.e., a special purpose vehicle (SPV) to own the asset. The asset is then financed at the SPV level using debt and equity capital. As project finance implies non-recourse financing, the setup of a distinct legal entity holding the asset has implications for investors. For repayment, equity and debt providers are entirely dependent on the future cash flows of the project and cannot resort to other assets of the sponsor (Steffen, 2020). Therefore, high certainty of future revenue streams may be more important for lenders in transactions of assets financed using project finance than in buyouts in general. My study focuses on transactions of renewable energy assets, primarily of wind farms. In contrast to fossil fuel power plants, these assets are generally financed through project finance structures (Steffen, 2020; Azhgaliyeva et al., 2022). For example, the World Economic Forum (2017) estimates that in 2015, more than half of all new investment in renewable energy projects globally was done through project finance, with even higher shares in OECD countries. The frequent use of project finance in renewable energy projects in investment-grade countries has been explained through the fact that project finance serves to address capital constraints of new power generation players. Using corporate finance, projects are financed through equity and debt on the sponsor's balance sheet. Thus, the ability to finance new projects is dependent on the strength of the sponsor's balance sheet. Opting for project finance instead, sponsors are able to realize projects that are otherwise unviable and to achieve a higher debt ratio for the project than feasible under corporate finance. Moreover, the higher debt ratio that may be achieved in project finance compared to corporate finance serves as a disciplining mechanism for managers as it may prevent value-destructing re-investments due to high debt service. This effect is particularly relevant for renewable energy power plants due to their high Capex and low Opex cost structures (Steffen, 2018).

It becomes clear that transactions of renewable energy assets differ from buyouts in general due to the use of project finance instead of corporate finance and the assets' specific revenue strategies. Moreover, while research on renewable energy technology financing has identified risks that prevent investment, the understanding of aspects that impact how investors finance and price renewable energy assets is narrow. Therefore, by testing the relationship between various acquirer-, asset- and industry-specific characteristics as well as economy-wide effects and leverage, pricing and return expectations in renewable energy transactions, my objective is to determine whether findings from research on buyouts are applicable to renewable energy transactions. Through this, I aim to promote the understanding of how investors evaluate renewable energy infrastructure investments.

4 Hypotheses Development

My study aims to examine the determinants of leverage, pricing and return expectations in renewable energy transactions in the Nordics. According to research, the determinants of leverage in buyouts differ from classical leverage determinants based on capital structure theories, such as firm-specific factors. Debt financing and pricing in buyouts are found to be primarily related to the availability of cheap debt, i.e., to time-series effects, rather than to target-specific attributes. Therefore, one objective of my study is to establish if the same pattern holds for leverage in renewable energy deals. Furthermore, I aim to map out industry-specific properties that determine how investors approach financing and valuation in renewable energy transactions. Building on the previous sections, I use the results from existing literature on leverage and pricing in buyouts as well as on renewable energy technology financing as starting point to develop my hypotheses. I do so by considering factors that have been found to be significant drivers of leverage or pricing in buyout transactions in the academic studies mentioned above. In a next step, I establish parallels as well as differences between the sample used in existing literature and my dataset of renewable energy transactions to determine whether a similar relationship may hold for the population I am studying, i.e., renewable energy M&A transactions in the Nordics. Moreover, building on the findings from literature on renewable energy investment risks, I come up with hypotheses about the impact of industry-specific attributes.

Following the above approach, I distinguish between hypotheses related to (i) factors that have been shown to impact leverage and pricing in buyouts (Subsection 4.1) and (ii) asset-specific attributes derived from the literature on renewable energy financing (Subsection 4.2).

In total, I form 9 hypotheses: 5 hypotheses to test whether findings on the determinants of leverage and pricing in buyouts are applicable to renewable energy transactions in the Nordics and 4 hypotheses to examine the impact of asset-specific factors in the energy industry on financing terms in M&A transactions. Using a different categorization, I build 5 hypotheses regarding cross-sectional analysis, i.e., acquirer-, asset- or transaction-specific factors, and 4 hypotheses relating to time-varying variables. Table 2 at the end of this section presents an overview of all hypotheses.

4.1 Determinants of leverage and pricing in buyouts

In this subsection, I develop hypotheses based on the results of academic studies about the determinants of leverage and pricing in buyout transactions in general.

Acquirer experience

Acquirer reputation and experience positively affect the use of debt in M&A transactions (Demiroglu & James, 2007; De Maeseneire & Brinkhuis, 2009; Achleitner et al., 2011; Achleitner et al., 2018). As acquirers build up reputation and relationships to banks, they are perceived to be less inclined to invest in risky projects, lowering agency costs for debt providers. In addition, reputation of a sponsor is regarded as an indicator of its superior selection and value creation skills, increasing the likelihood of financial outperformance of the transaction. Similarly, acquirer reputation in the context of renewable energy transactions may serve as an indicator of experience in renewable energy financing. More experienced acquirers may therefore be believed to have superior abilities to assess project risks and select projects. Consequently, lenders may view borrowing to more experienced acquirers as less risky (De Maeseneire & Brinkhuis, 2009). This lowers agency costs of debt providers, increasing the likelihood that they are willing to provide debt financing and the amount they are willing to lend. Based on this, I derive the first hypothesis as follows:

H1: More experienced acquirers use higher leverage.

Nordic acquirers

Foreign investors face several disadvantages compared to local players. First, they may lack important local connections and therefore have access to fewer deal opportunities. The importance of relationships with developers for access to renewable energy deals has been noted in the literature (World Economic Forum, 2017). In addition, cross-border investors face information asymmetries due to both geographical and cultural distance to the country they invest in. Both aspects reduce the likelihood that international players find attractively priced targets. Finally, cross-border acquirers lack country-specific expertise, reducing their negotiation power (Hammer et al., 2020). As a result of local relationships providing them with access to deal opportunities and improving their bargaining power, local buyers may be able to acquire assets at lower valuations. Therefore, I construct the following hypothesis:

H2: Nordic acquirers pay lower acquisition multiples.

Financial acquirers

Transaction multiples in buyouts in which the sponsor is a PE firm are lower on average than those in which the sponsor is a strategic acquirer (Hammer et al., 2022). Strategic acquirers may pay higher prices compared to financial investors as synergistic value with the target provides them with additional room for negotiation (Dittmar et al., 2008). For strategic acquirers of renewable energy assets, such as utilities or independent power producers, synergies may for example arise from streamlining the technical management or maintenance of assets, reducing operating expenses during the holding period. Thus, strategic may be willing to pay higher prices. On the other hand, the World Economic

Forum (2017) finds that investors who have been involved early on in the sector have fostered long-term relationships with project developers. As financial buyers have generally entered the market at a later time, they may lack these connections. Their relationships to project developers, i.e., sellers, may put strategic buyers in a better position to negotiate lower acquisition prices for a given asset. However, non-financial buyers may hesitate to exploit their potential negotiation power in transactions of assets with high synergetic or strategic value to their existing portfolios. Hence, my hypothesis is:

H3: Financial acquirers pay lower acquisition multiples.

Instead of cross-sectional characteristics, variation in leverage and pricing in M&A transactions is found to be primarily related to time-series effects.

<u>Debt market conditions</u>

Existing literature on determinants of leverage and pricing in buyout transactions unanimously points to the relevance of credit market conditions (Axelson et al., 2007; Demiroglu & James, 2007; De Maeseneire & Brinkhuis, 2009; Achleitner et al., 2011; Axelson et al., 2013). A similar association can be expected to hold for renewable energy transactions because acquirers, particularly financial sponsors, may be inclined to lever up more when the relative cost of debt is lower. As in M&A deals in general, the access to relatively cheap leverage may induce acquirers of renewable energy projects to bid higher prices. Proxying credit market conditions through credit spreads[2], I hypothesize:

H4.1: There is a negative relationship between credit spreads and leverage.

H4.2: There is a negative relationship between credit spreads and acquisition multiples.

4.2 Asset -specific factors in the energy industry

From Section 2, it becomes clear that asset-specific (i.e., firm-specific) characteristics, particularly classical leverage determinants according to corporate finance theories (such as firm size, excess cash, asset collateral value or growth potential), fail to explain cross-sectional variation in leverage in buyout transactions. However, as renewable energy projects are generally financed using project finance and the underlying assets in my population under study are power plants, asset-specific features may be related to the variation in leverage and pricing for these types of transactions.

<u>Transaction size</u>

Building on the pecking order theory, acquirers may become more reliant on external financing with increasing deal size as internal cash becomes insufficient to finance the

[2] This is in line with Axelson et al. (2013), Achleitner et al. (2016), Van der Hijden (2016) and Gille & Karlsson (2019).

transaction (Gao et al., 2021). IRENA (2016) note that insufficient investment deal size presents a barrier to renewable energy investment by large-scale financial investors, especially institutional investors. Institutional investors such as pension funds and insurance companies require a minimum deal size because they often lack the internal capacity or willingness to evaluate small renewable energy projects. Therefore, these investors are expected to be primarily involved in larger transactions. As these types of acquirers have been associated with using more debt capital, their disproportional participation in larger deals may impact leverage. Based on this, I create the following hypothesis:

H5: Larger transactions involve higher leverage.

<u>Asset revenue strategy</u>

As outlined in Section 3, PPAs provide better visibility of future revenues and therefore cash flows and shield the energy producer from the volatility in power price markets. This, in turn, facilitates securing debt financing for a project (Gabrielli et al., 2022). However, PPAs also introduce counterparty risk arising from the offtaker's credit risk, which is an important consideration for banks (IRENA, 2016). If the creditworthiness of the offtaker in a PPA is perceived as low, banks may be less inclined to lend to a project. Nevertheless, despite introducing counterparty risk, power purchase agreements address price risk in renewable energy projects, a risk that academic research has found to be of high importance (Blondiau et al., 2017; Egli et al., 2018; Leisen et al., 2019; Azhgaliyeva et al., 2022). Hence, my hypothesis is:

H6: Transactions of assets with a power purchase agreement involve higher leverage.

<u>Merchant price volatility</u>

Uncertainties in future energy prices are an important barrier for renewable energy investment (Blondiau et al., 2017; World Economic Forum, 2017; Egli et al., 2018; Leisen et al., 2019; Azhgaliyeva et al., 2022). As the renewable energy industry moved from support schemes to become predominantly market-based, the relevance of price risk has increased over time (Blondiau et al., 2017; Egli et al., 2018; Leisen et al., 2019). Based on the high relevance of the uncertainty in future energy prices, it seems reasonable to conclude that investors' financing decisions may be influenced by the volatility of expected power prices. However, this aspect has not been researched in previous academic studies on the determinants of buyout financing. Intuitively, higher fluctuations in predicted or expected future energy prices indicate higher uncertainty regarding future price developments. Higher uncertainty about future prices, in turn, implies that an asset is exposed to higher price risk. Risk-averse lenders might be less inclined to lend to more risky investments or reduce the amount of debt they are willing to provide, making it more difficult for sponsors to lever up a transaction. Likewise, depending on their mandate, certain investors may unable or unwilling to invest in assets with high exposure to price risk, resulting in lower competition and lower valuations in transactions of these assets. Therefore, I derive my last set of hypotheses as follows:

H7.1: There is a negative relationship between the volatility of power price forecasts and leverage.

H7.2: There is a negative relationship between the volatility of power price forecasts and acquisition multiples.

Table 2. Summary of hypotheses

The table below shows the hypotheses for the determinants of leverage and pricing in renewable energy transactions.

H1	More experienced acquirers use higher leverage.
H2	Nordic acquirers pay lower acquisition multiples.
H3	Financial acquirers pay lower acquisition multiples.
H4.1	There is a negative relationship between credit spreads and leverage.
H4.2	There is a negative relationship between credit spreads and acquisition multiples.
H5	Larger transactions involve higher leverage.
H6	Transactions of assets with a power purchase agreement involve higher leverage.
H7.1	There is a negative relationship between the volatility of power price forecasts and leverage.
H7.2	There is a negative relationship between the volatility of power price forecasts and acquisition multiples.

5 Data and Methodology

This chapter outlines the data sample as well as the research design used to test the hypotheses developed in the previous section. I start by explaining the data collection process to obtain the sample as well as its characteristics in Section 5.1. Subsequently, the representativeness of the sample is discussed (Section 5.2), followed by an introduction to the regression variables (Section 5.3). Finally, I present descriptive statistics (Section 5.4) and establish the regression models (Section 5.5).

5.1 Sample derivation and characteristics

One key obstacle for research on the financing structures of renewable energy transactions is the limited availability of holistic datasets. While some information on the location and technical details of wind farms and solar PV plants is publicly accessible[3], data on how these assets are traded and financed is scarce. Similar to transaction data in the PE industry, this type of information generally remains private. This study circumvents the data confidentiality issue by basing the analysis primarily on a propriety dataset collected from Newsec Infra. The dataset contains 231 renewable energy transactions in the Nordics over the period from 2011 to 2023. Almost all of the transacted assets (99%) are onshore wind farms, the remainder being solar PV parks. Owing to the M&A advisor's focus on the Nordic market, all assets in its dataset are located in either Denmark, Finland, Norway, or Sweden. Similar to Achleitner et al. (2018) who include leveraged recapitalizations in their study of PE sponsored leveraged buyouts, 21 stake sales were included as they are identical to the remaining observations except that not all of the asset's shares are acquired. The initial sample provided by the M&A advisor contains detailed deal information as well as technical and operational data of the underlying asset. Using this proprietary sample as a starting point, I expand the dataset by screening *Inframation* by Infralogic, a commercial database for infrastructure finance, for transactions in the "Renewables" sector. Specifically, I filter for "Onshore Wind" and "Solar PV" assets located in the Nordics, i.e., in Denmark, Finland, Norway, and Sweden or the time span from 2011 to 2023. In addition to the use of *Inframation*, whenever available, I check deal announcements from the acquirer, seller, or advisors as well as news articles for all entries with incomplete information. Following this procedure, I am able to increase the sample size from the initial 231 entries to a total of 278 entries. In a first step, I remove duplicated transactions from the supplemented data sample, decreasing the sample size to 276 transactions. Furthermore, I drop observations with missing values for transaction year, acquirer origin and asset location, which reduces my sample size to 261 deals. To use as much of the supplemented data sample as possible despite varying availability of data across observations, I create a separate subsample for

[3] For Sweden, this type of data is for example provided by Energimyndigheten and Svensk Vindenergi.

each of the four sets of regressions before sorting out observations with missing values. This approach results in sample sizes of 153 and 71 transactions for the regressions on the two different leverage measures, respectively. Moreover, the samples for the regressions on pricing and return expectations contain 103 and 70 observations, respectively.[4]

Table 3. Sample derivation

The table below shows the process of creating the data sample. The dataset covers wind onshore and solar PV assets in the Nordics over the timespan from 2011 to 2023. The table shows the remaining number of observations after eliminating duplicated entries, dropping observations with missing data, and creating subsets for each set of regressions.

		Number of observations
Proprietary database	**Sample derivation**	231
Inframation by Infralogic		45
Total transactions		**278**
Excluding duplicated transactions	**Filter 1**	-2
Excluding transactions with missing values for transaction year, acquirer origin and asset location		-15
Remaining transactions		**261**
Clean sub-sample for leverage 1	**Filter 2**	153
Clean sub-sample for leverage 2		71
Clean sub-sample for pricing		103
Clean sub-sample for returns		70

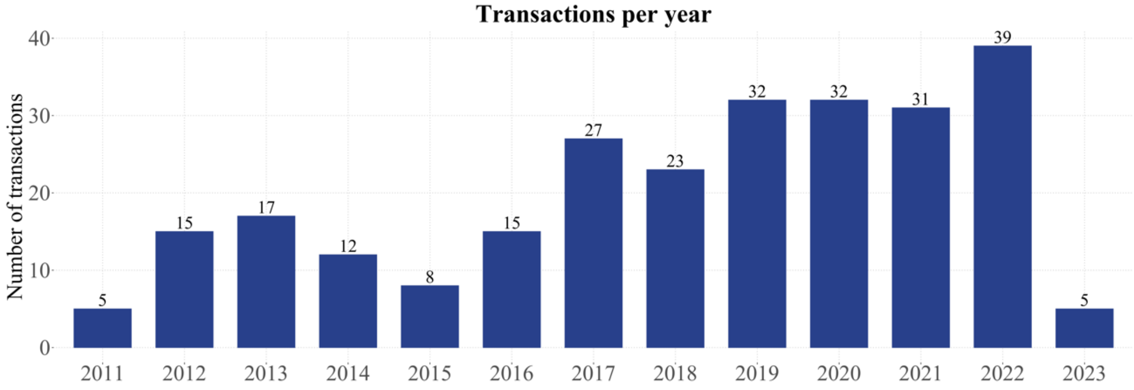
The final data sample of 261 transactions of renewable energy assets in the Nordics provides diverse insights into the development of the Nordic renewable energy transactions market. First, in terms of deal activity, Figure 1 shows the relative nascency of the industry. Deal activity started to increase from 2017 onwards. The last transaction in the sample was signed on February 2nd, 2023.

Second, as can be seen in Figure 2, this development pattern applies not only to the distribution of the number of transactions, but also to the transacted capacities in megawatts (MW) and financial sums (enterprise values in EURm) per year.

[4] Comparing my sample sizes to studies on financing conditions of private (buyout) transactions, such as Achleitner et al. (2018), it becomes apparent that sample sizes for these types of studies are generally not large. The authors analyze leverage of 130 German PE sponsored leveraged transactions between 2000 and 2008. My sample is naturally limited given its geographic focus and the small underlying market.

Figure 1. Distribution of transactions over the sample period

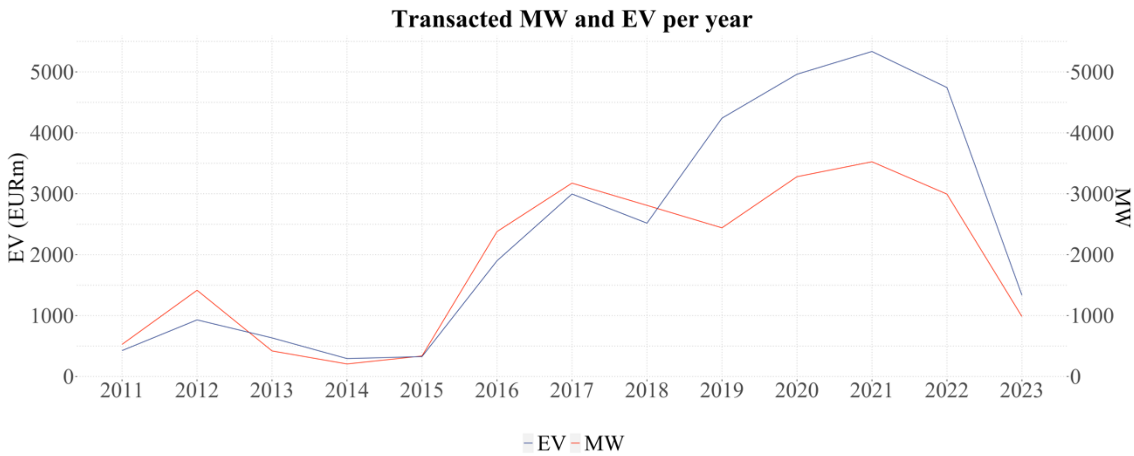
The figure displays how the transactions are distributed over the sample period from 2011 to 2023. Transaction years are based on the deal signing date.



The development of transacted capacities in MW and the acquisition prices paid for these capacities exhibits a similar shape as described above for the number of transactions. In addition, Figure 2 indicates that, starting in 2019, purchase prices paid for these assets started to decouple from their capacities in terms of MW. Prior to 2019, total enterprise values (EVs) in EURm were generally in line with total transacted capacities in MW per year, resulting in a total EV/MW multiple of approximately one. In the period thereafter, total EVs increased relative to total transacted capacities, which means that overall, acquirers paid higher prices per MW transacted. As can be seen in Appendix 1, this development does not appear to be directly related to the evolution of spot prices, which began to rise from 2021 onwards.

Figure 2. Transacted MW and EV per year

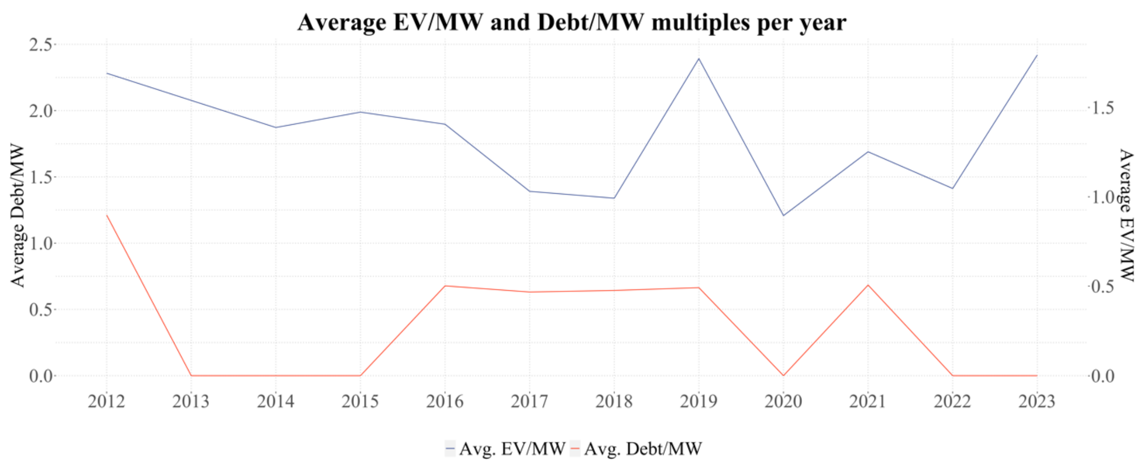
The figure summarizes the yearly total of transacted capacities in MW and enterprise values in EURm.



Finally, if findings on the determinants of leverage and pricing in buyouts apply to renewable energy transactions, both should predominantly be conditional on time-series variation in debt market conditions. To investigate whether there is an indication that leverage and pricing of renewable energy transactions vary together over time, Figure 3 plots average leverage (in debt per MW) and valuation (in enterprise value per MW) multiples per year. With the exception of the period from 2013 to 2015 and the year 2022, when none of the transactions in the data sample were levered, debt per MW multiples in the sample transactions remain around 0.5 to 0.7 and do not exhibit strong cyclicality. This is in contrast to Axelson et al. (2013), who find that buyout leverage is highly cyclical. Again, contradictory to their study, Figure 3 does not provide an indication for a relationship between leverage and transaction prices. Plotting the time series of debt per MW multiples together with the average high-yield spread per year confirms that leverage in the transactions in the data sample does not appear to be affected by debt market conditions (see Appendix 2).

Figure 3. Yearly time series of leverage and pricing multiples

The figure plots the average EV per MW and Debt per MW multiples for each year from 2012 to 2023. 2011 has been excluded as leverage information on the transactions in this year is not available.



Considering geographical distributions, the data sample includes buyers from 20 different countries, whereby approximately 50% of all transactions were signed with buyers from two countries, Germany and Sweden. It is interesting to note that the country with the highest count of acquirers is Germany and not a Nordic country. The assets in the transactions sample are from four Nordic countries. Almost two-thirds of all assets transacted in the data sample are located in Sweden, while another 20% are located in Finland and 10% in Norway. A small share of transactions is signed for assets located in Denmark and 3.8% of transactions are portfolio sales for assets in multiple countries. Finally, the data sample includes a total number of 134 distinct acquirers. Almost two-thirds of acquirers appear as buyers only once in the data sample, while the remaining 50 sponsors act on the buy-side at least twice (see Table 4).

Table 4. Overview of acquirers and assets in the sample

The table on the left-hand side shows the geographical distribution of acquirers (based on their headquarters), summarizing countries with only one acquirer per country as "Other". The table on the upper right-hand side lists the number of transactions per acquirer in the data sample, while the lower table displays the geographical distribution of the assets transacted.

Acquirer origin	**N**	**%**
Germany	66	25.3%
Sweden	65	24.9%
UK	38	14.6%
Finland	17	6.5%
Switzerland	16	6.1%
France	13	5.0%
Norway	10	3.8%
US	8	3.1%
Denmark	6	2.3%
Italy	4	1.5%
Luxembourg	4	1.5%
Japan	3	1.2%
Netherlands	3	1.2%
Other	8	3.8%

Number of transactions per acquirer	**N**	**%**
1 Transaction	84	62.9%
2 Transactions	20	15.0%
3 Transactions	10	7.5%
4 Transactions	9	6.6%
5 Transactions	5	3.6%
> 5 Transactions	6	4.5%

Asset location	**N**	**%**
Sweden	167	64.0%
Finland	52	19.9%
Norway	27	10.3%
Denmark	5	1.9%
Various	10	3.8%

5.2 Representativeness

While the proprietary data sample from the M&A advisor provides access to rich data to analyze financial structures of renewable energy transactions in the Nordics, it is important to consider potential biases of the data. One concern might be that the advisor only supplied information for a filtered subset of their data. The fact that a considerable share (73%) of transactions in the provided proprietary data sample were not advised by the M&A advisor indicates that the sample is not filtered. Moreover, the supplementation of the initial data sample with data retrieved from *Inframation*, deal announcements and news articles further increases the share of transactions that were not advised by the M&A advisor to 78%, reducing the bias of non-random selection by the sample provider. As an additional measure to address this concern, the cumulative installed capacities in MW per year in the data sample are checked against publicly available information on installed capacities in the four countries. While access was made to transaction information for the time span from 2011 to 2023, complete public data of capacities of newly built onshore wind farms and solar PV plants in all four Nordic countries could only be compiled for the period from 2017 to 2021. Table 5 compares the installed capacities in MW per year in the data sample used in this study to public data on onshore wind and solar PV build-out in the four Nordic countries. The development of newly built assets shows that my sample mirrors the overall market development but overweighs earlier periods. One reason for market coverages above 100% may be that capacities in my sample were recorded based on the financial closing date, i.e., before the asset had actually been built, whereas other data sources recognized capacities at commercial operations date, i.e., when the asset became operational. The comparison demonstrates that for the period from 2017 to 2021, the sample provides thorough coverage of the overall market, covering on average 96% of the overall market in terms of newly built assets according to public sources.

Table 5. Sample comparison

This table presents the megawatt (MW) volumes of newly installed onshore wind and solar PV assets in the sample in relation to the Nordic market for these assets. While the sample contains data from 2011 to 2023, complete comparison data from public sources could only be gathered for the period from 2017 to 2021. Capacities are based on primary transactions, i.e., of newly built assets in the sample. Comparison data on the Nordic market is retrieved from Energimyndigheten for Sweden and Statista for Denmark, Finland, and Norway.

Year	Newly installed capacity	
	Sample (MW)	Market coverage of Sample vs. the Nordic market as %
2017	2985.90	133.17%
2018	2645.25	153.40%
2019	2622.55	61.37%
2020	4126.70	65.56%
2021	4451.55	63.97%

Based on the above, I expect my data sample to capture the overall development of the Nordic renewable energy transactions market. The sample may be biased towards onshore wind assets considering the dominance of this technology in the data sample (96% of transactions in the extended sample). However, considering that solar PV still represents a small source (0.43%) of total energy consumption in the Nordics to date, this fact mirrors the overall market structure (Formolli et al., 2021). All transactions in this sample of onshore wind and solar PV assets are financed using project finance structures. This is in line with observations by Steffen (2018), who find that project finance is especially important for wind onshore and solar PV projects, implying that the data sample may be representative for how these transactions are financed.

5.3 Variables

In the following, I provide an overview of the dependent and independent variables as well as fixed effects used in my regression models. The dependent variables in the four sets of regressions represent different attributes of the financial structures of renewable energy transactions, namely leverage involved, their pricing and returns expected by investors at the time of the transaction. The independent variables, on the other hand, are derived from the hypotheses developed in Chapter 4. A full list of all variables, their calculation and data source can be found in Appendix 4. Table 6 in Subsection 5.4 presents definitions as well as descriptive statistics for all dependent and independent variables.

5.3.1 Dependent variables

This study analyzes three aspects regarding the financing of renewable energy transactions, namely leverage, pricing and expected returns. As my study aims to compare the determinants of financial structures of renewable energy transactions to those of private equity buyout transactions in general, I construct similar measures for these features to those generally used for the PE industry in academic literature and practice.

Leverage

Both practitioners and the academic literature generally rely on two different measures of leverage: total debt divided by earnings before interest, tax, depreciation and amortization (D/EBITDA) and total debt divided by enterprise value (D/EV) (Axelson, et al., 2013; Achleitner et al., 2018). Reflecting common practice in the industry, my main measure of leverage is debt divided by the asset's capacity in MW (*D/MW*). For robustness checks, *D/MW* is replaced by debt divided by EV (i.e., loan-to-value, *LTV*). A square root transformation is applied to reduce positive skewness. I supplement the analysis of leverage with a categorical measure of debt financing, *LEV*. This measure is a binary variable taking the values "*geared*" (*LEV* = 1) or "*all equity*" (*LEV* = 0), indicating whether or not debt financing was involved in the transaction.[5]

Pricing

In line with quantifying leverage as *D/MW*, I use EV divided by the asset's capacity in MW (*EV/MW*) as measure of transaction pricing. The use of this multiple is motivated by its widespread application by industry practitioners. Moreover, normalizing both leverage (debt) and pricing (EV) by the asset's capacity in MW ensures consistency across the regression analyses with these two dependent variables. Again, a square root transformation is applied to reduce positive skewness.

[5] A similar measure is employed by Gao et al. (2021), who use variables measuring firm and deal characteristics to estimate the probability of (private) loan financing in M&A transactions using a probit model.

Expected returns

Deal-level performance in private equity is generally measured through the internal rate of return (IRR) both in academic literature and by practitioners (Gompers et al., 2016, Harris et al., 2022. The IRR is calculated by equating the net present value of cash flows to and from the project to zero. As a result of general confidentiality about both expected and realized returns in private markets, returns data is often not directly available to researchers and alternative methods are used to approximate IRR measures. Due to access to proprietary deal documentation on the transactions advised by the M&A advisor, I am able to retrieve the expected IRR, IRR^e, by the buyer. The expected IRR is calculated by Newsec Infra for transactions it advises based on the asset fundamentals, operational and macroeconomic assumptions as reported by the acquirer, as well as the price at which the asset is sold. It is important to note that these values constitute *expected* IRRs, i.e., the return the buyer likely anticipates derived from the fundamentals of the transacted asset, the assumptions disclosed to Newsec Infra by the acquirer as well as the acquisition price. Data on realized IRRs is not available. Due to positive skewness, a logarithmic transformation is applied to IRR^e.

5.3.2 Independent variables

The variable *ACQUIRER_EXP* measures the buyer's reputation and experience within the industry as the number of Nordic wind and solar PV transactions in which the acquirer was involved prior to the transaction at hand[6]. Consequently, this acquirer characteristic is time-varying. In contrast to existing research on the effect of private equity firm reputation on leverage, which often measures reputation only for financial buyers and excludes strategic acquirers (Demiroglu et al., 2007; Axelson et al., 2013; Achleitner et al., 2018), I determine this variable for both types of buyers. This is motivated by the fact that both types of acquirers build up reputation and industry-specific knowledge over time through involvement in transactions. However, while this experience may help both types of buyers to negotiate lower acquisition prices, the effect of experience on the ability to raise debt may be concentrated on financial buyers if nonfinancial acquirers do not tend to raise debt for their acquisitions. Thus, I include an interaction term between *ACQUIRER_EXP* and the dummy variable *ACQUIRER_FIN* (see Table 6), *ACQUIRER_EXP*ACQUIRER_FIN* in the regressions on *D/MW* and *LEV*.

[6] As Demiroglu, et al. (2007) and Achleitner, et al. (2018) note, the number of previous assets an acquirer was able to purchase may be influenced by the general level of activity in the industry, resulting in higher numbers of transactions in economic upturns and lower numbers in downturns. In addition, the number transactions may be comparable across buyers of similar size or origin. Nevertheless, it can be reasoned that the number of previous transactions quantifies reputation and experience as it likely measures a bidder's success in winning a process. Gaining relevant experience is likely particularly important in the renewable energy sector as early investors have fostered long-term relationship with project developers, giving them access to deal pipeline (World Economic Forum, 2017).

ASSET_PPA is a binary variable capturing whether the underlying asset has a PPA in place or is supported through a FiT scheme at the time of the transaction (*ASSET_PPA* = 1). As outlined in Section 2, banks are generally more inclined to provide debt financing to an asset that has an off taking agreement (i.e., a PPA) in place. Based on this, a positive association between the variables *ASSET_PPA* and *LEV* may be expected. To investigate this potential interrelationship further, I include an interaction term these variables, *ASSET_PPA*LEV,* in the regressions on *EV/MW* and IRR^e.

TRANSACTION_SIZE measures the size of each transaction in terms of the asset's number of megawatts (MW). As the distribution of this variable is positively skewed, a logarithmic transformation is applied.

TRANSACTION_PRIMARY captures whether the asset is transacted for the first time or not. The initial data sample provided includes a variable containing information on the phase in which the asset is transacted. This variable assumes the values "*Operational*" and "*Pre-Operational*". As the financial close of an asset, which is the first time it is sold, generally takes place during the development process, i.e., before an asset becomes operational, all operational assets have been transacted at least once before. Thus, I use an analogous categorization and classify all "*Pre-Operational*" deals as primary transactions (*TRANSACTION_PRIMARY* = 1*)*.

In academic research, variations in economy-wide credit conditions and the cost of borrowing have commonly been proxied by credit spreads, i.e., the spread between high-yield bonds and an interbank rate (De Maeseneire & Brinkhuis, 2009; Van der Hijden, 2016; Gille & Karlsson, 2019). In line with Van der Hijden (2016) and Gille & Karlsson (2019), I use the Option-Adjusted Spread (OAS) of the ICE BofAML Euro High Yield Index[7] to create the variable *CREDIT_SPREAD*.[8] I retrieve the index data on a daily basis and then calculate average yearly spreads. In a next step, I match each transaction with the average yearly spread based on the year in which the transaction was signed. As the variable exhibits a positive skewness, a logarithmic transformation is applied.

Finally, the variable *POWER_PRICE_VOL* is constructed to capture market participants' expectations regarding the volatility of future electricity prices. High observations indicate higher expected variation and lower certainty in future power prices. To construct the variable *PRICE_FORECAST_VOL*, I calculate the standard deviation of price projections for electricity for each Nord Pool price zone and quarter from 2012 to 2022. As a next step, I compute the yearly average per Nord Pool price zone across forecast

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[7] The OAS of the ICE BofAML Euro High Yield Index tracks the performance of Euro denominated below investment grade corporate debt publicly issued in the euro domestic or eurobond markets. Due the lack of a Nordics-based comparable measure and the Euro's high relevance for the Nordic countries, I determine it as a suitable measurement of credit spreads. It is calculated as spread between the OAS index of all bonds below investment grade rating and a spot Treasury curve (FRED, 2023).

[8] Axelson et al. (2013) use the high-yield spread defined as the Merrill Lynch High-Yield Index to measure debt market conditions. However, this index tracks the performance of US dollar denominated debt.

providers and quarters and match this average with the transactions in the sample based on the transaction's signing year and the asset's Nord Pool price zone.[9] Taking the average across forecast providers serves an estimation of a general view on future electricity prices. Yearly averages of the forecasts, which are generally published on a quarterly basis, are computed because sales processes regularly extend over several quarters and thus investors often use forecasts from more than one quarter in their financial models of the underlying asset. While most forecast providers issue a low-, base- and high-case reflecting potential future price developments in different market conditions, this study relies on the base- or reference cases as these are most commonly used by equity investors. Transactions that occur in the first quarter of 2023 are matched with the corresponding variable value for 2022 due to unavailability of the 2023 forecasts until the end of the quarter. Due to positive skewness, a logarithmic transformation is applied.

In line with the existing literature on the determinants of buyout financing and the characteristics of my data sample, geography fixed effects are included in the regression analyses. The categorical variable *PRICE_ZONE* controls for the Nord Pool price zone in which an asset is located, as the asset's location can have an effect on leverage choices and pricing (Axelson et al., 2013). As explained in Section 3, the price zone in which an asset is located and therefore sells its output can impact wholesale electricity prices and thereby leverage and valuations. Hence, I control for the geographic location of the assets through *PRICE_ZONE* fixed effects. In accordance with the geographic location of the assets in the data sample in Denmark, Finland, Norway and Sweden, the variable *PRICE_ZONE* takes the values DK1, DK2, DK3, DK4, FI, NO1, NO2, NO3, NO4, NO5, SE1, SE2, SE3 and SE4.

5.4 Descriptive statistics

Table 6 presents definitions as well as descriptive statistics for all dependent and independent variables used in this study, based on the data sample of 261 renewable energy transactions between 2011 and 2023. The mean (median) *D/MW* and *EV/MW* multiples (in EURm/MW) as well as IRR^e are 0.23 (0.00), 1.23 (1.19) and 8.00% (8.00%), respectively.

[9] Price projections are taken from Markedskraft, Pöyry, Redpoint Energy, SKM Market Predictor, Baringa, Wattsight, AFRY and Volue. Appendix 3 provides a detailed overview of the forecast providers used per year and quarter.

Table 6. Summary statistics for regression variables

The table presents a definition and descriptive statistics for all dependent and independent variables used in the four sets of regressions. For the variables to which square root and logarithmic transformations are applied, the table reports summary statistics for the untransformed values for a more intuitive interpretation. Summary statistics for binary variables are reported in the form of frequency tables of the dependent variable LEV (where LEV = 1 means that a transaction involves leverage and LEV = 0 implies all-equity financing).

Numeric variables	Definition	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
D/MW	Quotient of debt in EURm and installed capacity in MW	88	0.23	0.35	0.00	0.00	0.47	1.21
EV/MW	Quotient of enterprise value (EV) in EURm and installed capacity in MW	145	1.23	0.68	0.01	1.01	1.47	7.11
IRR^e	Expected IRR based on the buyer's stated assumptions and the purchase price	127	0.08	0.02	0.04	0.07	0.09	0.13
ACQUIRER_EXP	Number of renewable energy transactions that the acquirer has been involved prior to the respective transaction	261	1.24	1.97	0	0	2	12
TRANSACTION_SIZE	Asset capacity in MW	259	118.30	153.60	2.40	30.00	155.20	1,000.00
CREDIT_SPREAD	Average credit spread in the transaction year	261	0.04	0.01	0.03	0.03	0.05	0.08
PRICE_FORECAST_VOL	Average volatility of the yearly price forecasts for the asset's Nord Pool price zone	224	8.80	5.54	3.64	5.70	9.70	41.62

Binary variables	Definition		*LEV* = 0	*LEV* = 1	Total
ACQUIRER_FIN	Dummy to capture if the acquirer(s) include(s) a financial institution	0	23 (46.00%)	27 (54.00%)	50
		1	42 (40.78%)	61 (59.22%)	103
ACQUIRER_NORDIC	Dummy to capture if the acquirer(s) is / are based in the Nordics	0	37 (39.36%)	57 (60.64%)	94
		1	28 (47.46%)	31 (52.54%)	59
TRANSACTION_PRIMARY	Dummy to capture if the asset(s) are transacted for the first time	0	9 (52.94%)	8 (47.06%)	17
		1	56 (41.18%)	80 (58.82%)	136
ASSET_PPA	Dummy to capture if the asset(s) involve(s) a power purchase agreement (PPA)	0	46 (55.42%)	37 (44.58%)	83
		1	19 (27.14%)	51 (72.86%)	70
Total			65	88	153

EV/MW shows high dispersion with an average of 1.23 as well as a minimum and maximum of 0.01 and 7.11, respectively. Considering the binary measure of leverage, *LEV*, the split of levered vs. all-equity-financed transactions is 88 vs. 65, respectively, and thus relatively even. The minimum and maximum of expected returns (IRR^es) of 4.00% and 13.00% in the data sample do not indicate high dispersion, despite this being a widely recognized issue in the academic literature. This is potentially due to the fact that contrary to most return measures studied in the literature, the IRR^es in my sample measure *expected* and not *realized* returns. Thus, investors may tend to underestimate the likelihood of extreme or unexpected events that cause negative or positive extreme return values.

Considering the independent variables, Table 6 shows that the mean realization of the variable *ACQUIRER_EXP* is 1.24, suggesting that on average, acquirers have been part of 1.24 previous renewable energy transactions. The fact that the 75^{th}-percentile value is 2, while the maximum is 12 indicates that in many transactions in the data sample, acquirers have limited prior industry-relevant experience. The average *TRANSACTION_SIZE* (MW), is 118.30, while the minimum and maximum variable values are 2.40 and 1,000.00, respectively. This indicates a high dispersion of transaction sizes. The average yearly *CREDIT_SPREAD* reaches its maximum in 2012 following the financial crisis and its minimum in 2017. *PRICE_FORECAST_VOL* varies between a minimum of 3.64 and a maximum of 41.62, indicating that for some periods and price zones, forecast providers expect future prices to remain much more stable than for others.

From the distribution of *ACQUIRER_FIN*, it becomes apparent that approximately two thirds of all acquirers are classified as financial acquirers. The split across levered vs. all-equity transactions is relatively even for both types of acquirers. The distribution of *ACQUIRER_NORDIC*, shows that a majority of buyers in the data sample are not based in a Nordic country. The distribution of the variable *TRANSACTION_PRIMARY* shows a large majority of observations in the data sample are primary transactions. Approximately half (70 of 153) of transacted assets have a PPA in place. In line with hypothesis 4, the share of levered transactions of assets for which a PPA is in place is 72.86%, considerably higher than the proportion of levered transactions of assets that have no offtaking agreement in place (44.58%).

Finally, pairwise associations between the variables are considered to verify no strong associations between independent variables. A matrix displaying pairwise associations is presented in Appendix 5. The analysis shows that the square-root of the one-way ANOVA R^2 is 0.96, indicating that the binary variable *LEV* is suitable as an alternative measure of leverage to *D/MW*.

5.5 Research methodology

The following subsection provides an overview of the research design, split into the two main methods used: multiple linear regressions for the numeric dependent variables *D/MW, EV/MW* and IRR^e and multiple logistic regression for the binary dependent variable *LEV*.

Multiple linear regressions

In line with existing research on the determinants of leverage and pricing in buyouts (Axelson et al., 2013; Achleitner et al., 2018) and the characteristics of my regression variables, multiple linear regression models are applied to estimate the dependent variables *D/MW, EV/MW* and IRR^e using ordinary least squares (OLS).

As outlined in Subsection 5.3.1, *D/MW, EV/MW* and IRR^e are all positively skewed. A Box-Cox test is applied to determine whether logarithmic transformations of these variables are more suitable. While Axelson et al. (2013) apply a logarithmic transformation to their dependent variables for leverage and pricing, the Box-Cox test does not support the use of a logarithmic transformation for *D/MW* and *EV/MW*. Thus, a square root transformation is applied to these two variables to reduce positive skewness. Positive skew of IRR^e is reduced through a logarithmic transformation.

Multiple logistic regression

To estimate the binary dependent variable LEV, I use a multiple logistic regression model. Logistic regression models the probabilities for a classification problem for a binary variable, i.e., one with two possible outcomes, and is thus suitable to model the binary dependent variable *LEV*.

Using the methods described above, the following regression models are set up to test the hypotheses from Section 4:

(1)

$$\begin{aligned}
Leverage_i &\\
= \alpha &+ \beta_1 ACQUIRER_EXP_i + \beta_2 ACQUIRER_FIN_i \\
&+ \beta_3\, ACQUIRER_NORDIC_i + \beta_4 ASSET_PPA_i \\
&+ \beta_5 TRANSACTION_PRIMARY_i + \beta_6 TRANSACTION_SIZE_i \\
&+ \beta_7 CREDIT_SPREAD_i + \beta_8 PRICE_FORECAST_VOL_i \\
&+ \beta_9 ACQUIRER_EXP_i * ACQUIRER_FIN_i + \varepsilon_i
\end{aligned}$$

where $Leverage_i$ can be both sqrt(*D/MW*)$_i$ and LEV_i.

(2)

$$\begin{aligned}
sqrt(EV/MW)_i &\\
= \alpha &+ \beta_1 ACQUIRER_EXP_i + \beta_2 ACQUIRER_FIN_i \\
&+ \beta_3\, ACQUIRER_NORDIC_i + \beta_4 ASSET_PPA_i + \beta_5 LEV_i \\
&+ \beta_6 TRANSACTION_PRIMARY_i + \beta_7 TRANSACTION_SIZE_i \\
&+ \beta_8 CREDIT_SPREAD_i + \beta_9 PRICE_FORECAST_VOL_i \\
&+ \beta_{10} ASSET_PPA * LEV_i + \varepsilon_i
\end{aligned}$$

(3)

$$
\begin{aligned}
log(IRR^e)_i \\
&= \alpha + \beta_1 ACQUIRER\_EXP_i + \beta_2 ACQUIRER\_FIN_i \\
&+ \beta_3\, ACQUIRER\_NORDIC_i + \beta_4 ASSET\_PPA_i + \beta_5 LEV_i \\
&+ \beta_6 TRANSACTION\_PRIMARY_i + \beta_7 TRANSACTION\_SIZE_i \\
&+ \beta_8 EV/MW_i + \beta_9 CREDIT\_SPREAD_i \\
&+ \beta_{10} PRICE\_FORECAST\_VOL_i + \beta_{11} ASSET\_PPA * LEV_i + \varepsilon_i
\end{aligned}
$$

In all four sets of regressions, i.e., in both the multiple linear regression and in the multiple logistic regression models, I apply Nord Pool price zone fixed effects and cluster standard errors at the Nord Pool price zone level.

Finally, multicollinearity tests are applied. As shown in Appendix 6, multicollinearity does not appear to be a concern.

6 Results

Regression results for the three financing aspects of interest (leverage, pricing and expected returns) are presented and analyzed in Subsections 6.1 to 6.3. Subsection 6.4 discusses the robustness of results. For each set of regressions, I first discuss the significant results, before summarizing insignificant ones.

6.1 Leverage

Table 7 shows the results for the multiple linear regression model with *D/MW* as dependent variable. The regression results for the multiple logistic regression model with *LEV* as explained variable are presented in Appendix 7.

I find that acquirer characteristics, specifically the acquirer's experience within the industry and the acquirer being based in the Nordics, are related to the amount of debt relative to the transacted capacity. However, the direction of impact of acquirer experience is opposite of hypothesis 1. Based on hypothesis 1, the acquirer's experience, as measured by the number of prior renewable energy assets purchased by that acquirer, is expected to have a positive impact on leverage. In Table 7, I observe a negative effect of acquirer experience on the leverage multiple *D/MW*, which is statistically significant at the 0.1% level in Specification (5). This implies that a buyer's prior involvement as purchasing entity in renewable energy transactions reduces the amount of leverage. These results contradict those of Demiroglu & James (2007) and Achleitner et al. (2018), who find a positive effect of acquirer reputation on leverage. This could potentially be related to sample characteristics, as Demiroglu & James (2007) analyze public-to-private buyouts and Achleitner et al. (2018) study leveraged buyouts in Germany, whereas this study focuses on renewable energy transactions in the Nordics, or to the definition of acquirer experience or reputation. Achleitner et al. (2018) run a principal component analysis (PCA) on three variables, namely firm age, assets under management (AuM) and the number of deals completed in the past three years, to create a latent variable measuring PE group reputation. In this study, I use the total number of prior renewable energy transactions in which the acquirer acted as buyer to measure industry-relevant experience. Finally, the type of buyers in this study differs from those in Demiroglu & James (2007) and Achleitner et al. (2018). Both of these papers exclusively study buyout transactions in which the buyer is a PE firm. In my study, on the contrary, buyers include both financial and industrial acquirers. The positive coefficient on the interaction term between acquirer experience and financial acquirer, statistically significant at the 1% in Model (5) supports the view that the divergence in results for this variable between my study and previous research may arise from studying different types of acquirers. It suggests that the negative impact of the acquirer's experience on the debt multiple is smaller when the acquirer is a financial institution. The positive effect of acquirer experience on the use of debt in

Table 7. Regression table: D/MW regression

*The table shows the regression output for multiple linear regressions on D/MW using OLS with standard errors clustered at the Nord Pool price zone level. To account for skewness, the dependent variable D/MW is square-root- and the independent variables credit spread and price forecast volatility are log-transformed. In Model (1), I model leverage as a function of acquirer characteristics. In Models (2) and (3), I add asset- and transaction-specific characteristics. Specifications (4) and (5) additionally include credit spread and price forecast volatility to account for time-varying factors. Finally, Model (6) shows D/MW as a function of time-varying variables only. Due to the potential association between acquirer experience and financial acquirer, I add an interaction term between these variables. I control for Nord Pool price zone fixed effects. Standard errors for each variable are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. A detailed overview of the regression variables is presented in Appendix 4 and robustness tests are shown in Appendices 8 to 10.*

	Dependent variable:					
	D/MW					
	(1)	(2)	(3)	(4)	(5)	(6)
Acquirer Experience	-0.036	-0.052	-0.096	-0.083	-0.126^{***}	
	(0.097)	(0.101)	(0.084)	(0.049)	(0.037)	
Financial Acquirer	-0.008	-0.076	-0.123	-0.122	-0.129	
	(0.136)	(0.102)	(0.101)	(0.102)	(0.123)	
Nordic Acquirer	-0.308^{**}	-0.298^{*}	-0.286^{**}	-0.281^{**}	-0.289^{**}	
	(0.114)	(0.138)	(0.125)	(0.109)	(0.104)	
PPA		0.191	0.154	0.151	0.134	
		(0.109)	(0.101)	(0.108)	(0.118)	
Primary Transaction			-0.200^{*}	-0.193	-0.205	
			(0.109)	(0.120)	(0.120)	
Transaction Size			0.101^{***}	0.103^{***}	0.080	
			(0.023)	(0.031)	(0.053)	
Credit Spread				-0.053	0.047	-0.165
				(0.201)	(0.158)	(0.126)
Price Forecast Volatility					-0.294^{**}	-0.350^{***}
					(0.129)	(0.089)
Interaction Acquirer Experience*Financial Acquirer	-0.003	0.008	0.053	0.042	0.091^{**}	
	(0.078)	(0.087)	(0.077)	(0.047)	(0.037)	
Price Area Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Stand. Error	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered
Observations	71	71	71	71	71	71
Adjusted R^2	0.120	0.160	0.198	0.183	0.255	0.138
Note:	.p<0.1;*p<0.05;**p<0.01;***p<0.001					

buyouts in earlier studies may be driven by financial acquirers. Strategic acquirers may differ from financial buyers in that they increasingly use their industry-specific knowledge for operational improvements and thus rely less on leverage for driving returns as they become more experienced.

The negative coefficient on Nordic acquirer is significant at the 1% level in Model (5). Thus, I find that Nordics-based acquirers use less leverage in their transactions. One way to explain this negative relationship of an acquirer being based in a Nordic country with the leverage multiple could be that Nordic and international acquirers take different perspectives on return creation. International acquirers may rely more heavily on leverage to reduce the cost of capital and thus increase returns. Nordic buyers, on the other hand, may focus more heavily on improving operations of the asset to improve returns from their investments. Thus, Nordic acquirers may be less inclined than international buyers to maximize leverage in their transactions, creating a negative association between Nordic acquirer and the leverage multiple.

Supporting hypothesis 5, transaction size positively impacts the leverage multiple. In Models (3) and (4) in Table 7, the coefficients on this variable are statistically significant at the 0.1% level. It follows that the size of the transaction in megawatts appears to have a positive impact on the amount of debt used. This finding is in line with results from previous literature on buyout financing determinants (Demiroglu et al., 2007; Axelson et al., 2013; Gao et al., 2021). Larger transactions may make it more difficult for acquirers to pay the purchase price using their own funds, thus increasing the proportion of debt financing used to pay the purchase price. Moreover, larger transactions may attract more institutional investors, with a preference to finance the deals using higher leverage. However, it should be noted that the coefficient on transaction size becomes insignificant when adding price forecast volatility in Model (5).

In line with hypothesis 7.1, I find a negative effect of the volatility of forecasted merchant prices on *D/MW* in Model (5) in Table 7, significant at the 1% level. Thus, the regression results suggest that the leverage multiple decreases as the standard deviation of forecasted power prices increases. In line with my hypothesis, it could be inferred that buyers apply less leverage to transactions when merchant prices are forecasted to be volatile. This finding provides support for the high relevance of the uncertainty in future energy prices for renewable energy investment emphasized in existing literature (World Economic Forum, 2017; Karneyeva et al., 2017; Egli et al., 2018; Leisen et al., 2019; Azhgaliyeva et al., 2022) and shows that capital structures may be affected by the level of uncertainty regarding future prices at which the asset can sell its output. In line with findings in the literature on renewable energy financing risks, this emphasizes that renewable energy investment appears to be impacted by power price uncertainty.

Contradictory to hypothesis 4.1, I do not find a significant effect of the high-yield spread on the leverage multiple. Thus, in contrast to Axelson et al. (2007), Demiroglu & James (2007), De Maeseneire & Brinkhuis (2009) and Axelson et al. (2013), I do not find support for the relevance of credit market conditions for leverage for the transactions in my data sample. This difference does not appear to be caused by the relatively shorter time horizon covered by my data sample. While Axelson et al. (2013) study transactions in the period from 1980 to 2008, De Maeseneire & Brinkhuis (2007) cover a shorter period from 2000 to 2007. Yet, both authors find indication that leverage levels in buyouts are related to debt market conditions. However, it might not just be the length of the horizon, but rather what happened during these periods (e.g., previous studies do not cover the post-financial crisis or the Covid-19 periods) that may cause this association to disappear in my study.

Furthermore, my results do not support hypothesis 6, expecting that transactions of assets with a power purchase agreement involve higher leverage. Considering the positive and statistically significant regression results for PPA on the binary leverage indicator *LEV* (Appendix 7), it appears that having a PPA in place facilitates obtaining debt capital for a transaction but does not allow sponsors to raise higher amounts of debt. A detailed discussion of the regression results on *LEV* follows at the end of the section.

Finally, I do not find that primary and secondary transactions differ in the amounts of leverage involved. De Maeseneire & Brinkhuis (2009), on the other hand, find a negative and significant effect of primary transaction on leverage in their study of European buyouts. The reason I do not find a significant effect could be that transactions of wind assets differ from conventional buyouts in that operational restructuring of the assets is generally more limited and thus less relevant for driving returns, particularly in primary transactions. Consequently, the difference in the importance of leverage for investment returns between primary and secondary transactions may be less pronounced for renewable energy transactions.

The results for the multiple logistic regression model on the binary measure *LEV* partially differ from those on *D/MW*. The most significant and largest effect is found for the variable PPA (Appendix 7). Significant at the 1% level in Model (5), the odds ratio for this variable indicates that the odds of a transaction being levered is three times higher when an asset has a PPA in place. The direction of this association is in line with hypothesis 6. As mentioned, though the coefficients on this variable in the regressions on *D/MW* are positive as well, they are not statistically significant, and their size is smaller than the odds ratios in the regressions on *LEV*. This suggests that without a PPA, sponsors may find it difficult to raise debt. On the other hand, having a PPA in place does not appear to enable acquirers to increase the amount of debt used to finance the transaction. Thus, entering into an offtaking agreement may be a requirement by lenders for providing debt to renewable energy projects but may not cause them to lend higher sums to a given project. Generally, the positive association between the asset having entered into a power purchase agreement and the transaction being levered provides support for the high relevance of price risk in renewable energy projects found in previous academic research (Karneyeva et al., 2017; Egli et al., 2018; Leisen et al., 2019; Azhgaliyeva et al., 2022). Despite not enabling sponsors to increase the *amount* of leverage, the existence of a PPA appears to enhance the *odds* of securing debt financing. Entering into such agreements may add counterparty risk and eliminate the upside of benefitting from potential price increases in the spot market for the share of the asset's output that is part of the PPA. Nevertheless, debt providers may be more willing to lend to an asset that has such an agreement in place as a PPA provides protection against downward movements in spot prices, thereby reducing risk. This implies that the mitigation of price risk seems to outweigh the potential increase in risk introduced by the counterparty in the PPA and the reduced upside from potential future price increases in the spot market. My results also support Gabrielli et al. (2022), who points to the high relevance of PPAs for renewable energy projects. More generally, the finding that transactions of assets with a PPA in place have higher odds of being levered can be related to insights from the corporate finance literature that cash flow or earnings predictability is positively related to bank loan contracting (Hasan et al., 2012). A PPA locks in a price at which at least part of the asset's future output will be sold and thereby increases predictability of revenues and cash flows. Higher certainty of future revenues may provide confidence to lenders that debt can be serviced, increasing their willingness to provide leverage for a given project.

Moreover, I find a positive effect of acquirer experience on *LEV*, statistically significant at the 1% level in Model (5). This implies that the odds of a transaction being levered increase with the acquirer's experience, but not the amount of debt used in the transaction. The coefficient on the interaction term between the acquirer's experience and its categorization as financial buyer is less than one, suggesting that the positive impact of acquirer experience on the odds of the transaction being levered decreases when the acquirer is a financial institution. Thus, the results for *LEV* suggest an opposite association between acquirer experience, financial acquirers and leverage than those for *D/MW*.

In contrast to the results in Table 7, I do not find an effect of Nordic acquirer or transaction size on the odds of a transaction being financed with debt.

In summary, I find that leverage in my sample is impacted by acquirer characteristics, specifically by the acquirer being based in the Nordics and its industry-specific experience. The latter seems to be primarily relevant for leverage in deals with financial acquirers. Furthermore, the volatility of forecasted merchant prices negatively impacts the amount of leverage. Finally, at the extensive margin, leverage appears to be determined largely by the asset having a PPA in place.

6.2 Pricing

In this subsection, I discuss the results obtained from the regression model on the dependent variable *EV/MW* presented in Table 8.

Table 8. Regression table: EV/MW regression

*The table shows the regression output for multiple linear regressions on EV/MW using OLS with standard errors clustered at the Nord Pool price zone level. To account for skewness, the dependent variable EV/MW is square-root- and the independent variables credit spread and price forecast volatility are log-transformed. In Model (1), I model pricing as a function of acquirer characteristics. In Models (2) and (3), I add asset- and transaction-specific characteristics. Specifications (4) and (5) additionally include credit spread and price forecast volatility to account for time-varying factors. Finally, Model (6) shows EV/MW as a function of time-varying variables only. Due to the potential association between PPA and LEV, I add an interaction term between these variables. I control for Nord Pool price zone fixed effects. Standard errors for each variable are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. A detailed overview of the regression variables is presented in Appendix 4 and robustness tests are shown in Appendices 9 and 10.*

	Dependent variable:					
	EV/MW					
	(1)	(2)	(3)	(4)	(5)	(6)
Acquirer Experience	-0.010	-0.013	-0.011	-0.017	-0.013	
	(0.018)	(0.022)	(0.024)	(0.023)	(0.019)	
Financial Acquirer	0.053	0.034	0.048	0.062	0.083	
	(0.108)	(0.078)	(0.104)	(0.096)	(0.105)	
Nordic Acquirer	0.054	0.054	0.063	0.045	0.057	
	(0.124)	(0.126)	(0.145)	(0.146)	(0.159)	
PPA		0.095	0.102	0.102	0.110	
		(0.170)	(0.168)	(0.174)	(0.158)	
Levered		-0.013	-0.018	-0.049	-0.071	
		(0.062)	(0.067)	(0.095)	(0.086)	
Primary Transaction			0.187	0.185	0.157	
			(0.110)	(0.112)	(0.088)	
Transaction Size			-0.024	-0.030	-0.035	
			(0.063)	(0.060)	(0.053)	
Credit Spread				0.211	0.241^{**}	0.183^{**}
				(0.148)	(0.106)	(0.071)
Price Forecast Volatility					-0.227^{**}	-0.218^{***}
					(0.077)	(0.064)
Interaction PPA*Levered		-0.064	-0.041	0.010	-0.011	
		(0.113)	(0.089)	(0.124)	(0.107)	
Price Area Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Stand. Error	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered
Observations	103	103	103	103	103	103
Adjusted R^2	-0.004	-0.029	-0.015	-0.00005	0.073	0.088
Note:				.p<0.1;*p<0.05;**p<0.01;***p<0.001		

In line with hypothesis 7.2, I find a negative effect of the volatility of forecasted merchant prices on pricing multiples. Significant at the 1% level in Model (5), the negative coefficients on price forecast volatility suggest that pricing multiples are negatively related to the expected volatility in future power prices. Again, this points to the aforementioned importance of price risk for renewable energy investors, which I find to impact both leverage and pricing.

Contrary to hypothesis 4.2, I find a positive impact of credit spread on pricing, statistically significant at the 1% level in Model (5). This implies that acquisition multiples in my sample of renewable energy transactions appear to be higher when debt is comparatively expensive, contradicting results from research on buyout pricing (Axelson et al., 2007; Axelson et al., 2013). Axelson et al. (2013) find indication that the high-yield spread proxies not only for debt market conditions, but also picks up changes in the economy-wide risk premium. Assuming that credit spread acts as a proxy for the economy-wide risk premium, a potential implication of this finding may be that demand for renewable energy infrastructure assets increases in times when the risk premium is high.

I do not find evidence for hypotheses 2 and 3, expecting that Nordic and financial acquirers pay lower acquisition multiples. This indicates that the asset's synergistic or strategic value may not be priced by investors and that local connections to developers may be of limited relevance for transaction prices of renewable energy assets.

Finally, the lack of relationship between an asset having a PPA in place and the multiple at which it is transacted emphasizes the role of power purchase agreements as a means to mitigate downside price risk rather than as a value driver. While the existence of a PPA is found to positively impact the odds of the transaction being levered, it does not affect the value investors assign to the asset. Among others, this could be due to the fact that that a power purchase agreement locks in a price at which (part or all of) the asset's output is sold over a specific period. Thus, entering into such an agreement reduces or completely eliminates the opportunity to benefit from future price increases in the spot market during that period.

In short, valuation multiples in renewable energy deals appear to be determined by two time-varying factors. First, the volatility of forecasted merchant prices negatively impacts transaction prices, highlighting the importance of price risk. Second, pricing multiples appear to be positively related to the credit spread.

6.3 Return expectations

The regression results for multiple linear regressions on return expectations, the third aspect of renewable energy financing of interest, are presented in Table 9.

Table 9. Regression table: IRR^e regression

*The table shows the regression output for multiple linear regressions on IRR^e using OLS with standard errors clustered at the Nord Pool price zone level. To account for skewness, the dependent variable IRR^e and the independent variables credit spread and price forecast volatility are log- transformed. In Model (1), I model expected returns as a function of acquirer characteristics. In Models (2) and (3), I add asset- and transaction-specific characteristics. Specifications (4) and (5) additionally include credit spread and price forecast volatility to account for time-varying factors. Finally, Model (6) shows IRR^e as a function of time-varying variables only. Due to the potential association between PPA and LEV, I add an interaction term between these variables. I control for Nord Pool price zone fixed effects. Standard errors for each variable are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. A detailed overview of the regression variables is presented in Appendix 4 and robustness tests are shown in Appendices 9 and 10.*

	Dependent variable: IRR^e					
	(1)	(2)	(3)	(4)	(5)	(6)
Acquirer Experience	-0.014***	-0.010	-0.011***	-0.017**	-0.012**	
	(0.003)	(0.007)	(0.002)	(0.005)	(0.005)	
Financial Acquirer	0.053	0.035	0.047	0.079	0.102	
	(0.050)	(0.066)	(0.084)	(0.083)	(0.067)	
Nordic Acquirer	0.092*	0.097*	0.121	0.092	0.092*	
	(0.048)	(0.053)	(0.069)	(0.053)	(0.049)	
PPA		0.005	0.053	0.088**	0.100**	-0.009
		(0.053)	(0.042)	(0.029)	(0.032)	(0.045)
Levered		0.185*	0.163*	0.091	0.051	0.197
		(0.101)	(0.078)	(0.151)	(0.144)	(0.110)
Primary Transaction			0.151*	0.211	0.211	
			(0.082)	(0.119)	(0.118)	
Transaction Size			-0.032	-0.043	-0.060	
			(0.030)	(0.037)	(0.040)	
EV/MW			-0.166**	-0.213*	-0.274**	
			(0.065)	(0.109)	(0.119)	
Credit Spread				0.276	0.306	
				(0.196)	(0.183)	
Price Forecast Volatility					-0.161**	
					(0.072)	
Interaction PPA*Levered		-0.043	-0.036	0.061	0.070	-0.051
		(0.140)	(0.131)	(0.219)	(0.201)	(0.147)
Price Area Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Stand. Error	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered
Observations	70	70	70	70	70	70
Adjusted R^2	-0.070	0.030	0.084	0.159	0.211	0.029
Note:				.p<0.1;*p<0.05;**p<0.01;***p<0.001		

The acquirer's experience in acting as a buyer in renewable energy transactions appears to be negatively related to return expectations. Though the coefficient is small, this suggests that investors lower their return expectations as they become more experienced in purchasing wind and solar PV assets in the Nordics, potentially based on realized returns from previous investments. Furthermore, I find indication that Nordic acquirers have higher return expectations than international investors. Statistically significant at the 5% level in Model (5), the positive coefficient on Nordic acquirer suggest that Nordic-based buyers expect higher returns on their investments, though the magnitude of the effect is again small. The reason for this could be that Nordic acquirers assume to be able to use their local connections to re-negotiate operational agreements with local contractors, allowing them to expect higher returns based on these operational restructurings.

Furthermore, the coefficients on PPA are positive and statistically significant at the 1% level in Model (5). Thus, even though assets with a power purchase agreement in place do not appear to be priced at higher multiples, acquirers seem to increase their return expectations for these assets. Considering that an offtaking agreement reduces the upside potential of an investment through locking in a future price for at least part of the asset's output, a potential explanation for this may be that for the transactions in my sample, acquirers' expectations of future merchant prices were below PPA prices. Consequently, buyers may have assumed higher returns from investments in assets with a PPA in place.

The valuation multiple at which an asset is acquired is negatively related to return expectations acquirers have for their investment. The coefficients on *EV/MW* are negative and statistically significant at the 1% level in Model (5). As buyers pay a higher premium per megawatt of capacity acquired, they expect lower returns from that transaction.

Finally, I find a negative effect of the volatility of forecasted merchant prices on expected IRR^es, significant at the 1% level. Combining results for the explanatory variable price forecast volatility in the regressions on *D/MW*, *EV/MW* and IRR^e, the consistent negative effect of this variable on financial structures in transactions of renewable energy assets provides support for the high relevance of price risk for renewable energy investment emphasized in the literature. It complements existing research on renewable energy financing by showing that price risk materializes in lower leverage, valuation multiples and return expectations in transactions of renewable energy assets.

In summary, return expectations appear to be impacted by acquirer-, asset- and industry-specific characteristics. Less experienced and Nordics-based buyers expect higher returns. Moreover, return expectations are higher in transactions of assets that have entered into a PPA and when the premium paid per MW is lower. Once more emphasizing price risk, volatility in forecasted merchant prices reduces expected returns.

6.4 Robustness

To ensure that the above results are robust, the sample needs to mirror a relevant proportion of the underlying population. As presented in Table 5, it can be shown that the data sample used in this study appears to reflect more than half of newly installed capacity from 2017 to 2021, alleviating concerns around sample representativeness.

The difference in results for the regressions on *D/MW* and *LEV*, both testing the impact of the independent variables on leverage in renewable energy transactions, gives rise to questions around the internal consistency of these measures. Thus, I create the variable *LTV*, which is calculated as the square root of debt per enterprise value (sqrt(Debt/EV)). Then, I re-run the regressions in Table 7. As can be seen in the regression table in Appendix 8, the negative effect of price forecast volatility remains robust using this alternative measure of leverage. The effects of acquirer experience and Nordic acquirer, however, do not appear to be robust.

Finally, I evaluate the robustness of my results in all four sets of regressions by changing fixed effects (Appendix 9). Specifically, I replace Nord Pool price zone fixed effects with country fixed effects (e.g., Axelson et al., 2013). In addition, in Appendix 10, I adjust the credit spread variable to reflect the monthly average high-yield spread at transaction signing instead of the yearly average high-yield spread (e.g., Achleitner et al., 2016). I note that all significant effects are robust when changing Nord Pool price zone fixed effects to country fixed effects, except for the effect of financial acquirer on IRR^e. The coefficient on credit spread becomes insignificant in the regression on *EV/MW* when using a monthly specification of the high-yield spread.

7 Conclusion

This study examines the impact of acquirer-, asset-, and industry-specific characteristics as well as time-series variables on leverage, pricing and return expectations in renewable energy transactions in Nordic countries. It is primarily based on a proprietary data sample of 231 transactions provided by an M&A advisor specialized on renewable energy transactions in the Nordic market. The final data sample of 261 Nordic wind and solar PV deals signed between 2011 and 2023 includes 30 additional hand-collected transactions. Throughout the study, I investigate whether research findings for leverage and valuations in buyout transactions are equally applicable to transactions in the increasingly important renewable energy sector.

I find that contrarily to buyout transactions in general, leverage in renewable energy transactions does not appear to be driven by time-series variation related to debt market conditions. The lack of an association between LBO financial structures and financial structures in renewable energy transactions implies that different factors impact how investors make capital structure and valuation decisions in acquisitions of renewable energy assets compared to regular buyouts. Thus, different explanations from those for buyouts are needed to reconcile capital structures and prices paid in renewable energy deals. My results indicate that leverage and pricing in renewable energy deals are primarily determined by variation in acquirer-, asset- and industry-specific attributes.

The most consistent effect on financial structures in renewable energy transactions originates from the forecasted volatility merchant prices, which negatively impacts leverage, valuation multiples and return expectations in these deals. In this context, my empirical results are consistent with academic research on renewable energy financing, which points to the high relevance of price risk. The importance of price risk is further emphasized through my finding that the odds of a transaction being levered increase when the underlying asset has entered an agreement to sell a proportion of its future production at a set price. In addition, acquirers expect higher returns from an investment in an asset with such an agreement in place.

Moreover, my study suggests that acquirers with more industry-specific experience in buying renewable energy assets and acquirers based in Nordic countries use less leverage. The impact of acquirer-related factors on leverage in renewable energy deals may stem from the investor base in these types of transactions being more diverse than in buyout transactions in general. In fact, an increasing diversification of the investor universe has been noted in academic studies.

Taken together, beyond financial structures in renewable energy transactions primarily being determined by cross-sectional variation instead of time-series variation related to debt market conditions, my results suggest that an understanding of the industry-specific context is required to explain leverage, pricing and return expectations in these deals. This has important implications considering the increased attention this sector has received in recent years and the entry of international capital in the market. Due to the aforementioned developments, new players may consider investing in the renewable energy market. My study shows, however, that the determinants of financial structures of transactions in this sector are different from those in buyouts. To participate in buyout transactions, which are primarily affected by debt market conditions, an understanding of economic and financial aspects may be sufficient. As renewable energy transactions appear to be determined primarily by industry-specific and cross-sectional characteristics, economic and financial knowledge may not suffice to invest in this sector. Investors considering participating in this market should be aware of these impacts and aim at building sector-specific knowledge.

A limitation of my analysis is that a large share of the data is provided by only one M&A advisor, which gives rise to concerns regarding sample representativeness. Due to general privacy around the financial details of these transactions (and buyouts overall), the hand-collected part of the data sample is small. Apart from the proven representativeness of the sample for the period from 2015 to 2021, my sample may under- or overweigh specific transactions. For example, the dataset may overweigh transactions involving certain sellers or acquirers that the M&A advisor has worked with in multiple transactions and omit others. Finally, my data sample covers a shorter time period (2011 to 2023) compared to Axelson et al. (2013), who analyze the period from 1980 to 2008, which may partially explain the apparent lack of time variation in leverage and pricing in my sample.

The renewable energy market is dynamic. Thus, this study calls for further research to promote a deeper understanding of how capital structure and valuation decisions are made in renewable energy deals. First, I suggest examining whether the same industry-specific aspects found to impact leverage and pricing in private deals of renewable energy assets also affect capital structures and valuations of public firms in the same industry. This could be achieved by adding controls for leverage and valuations of a set of matched public renewable energy companies to the regression analyses, conducting a similar analysis as Axelson et al. (2013), focused exclusively on the renewable energy sector. Second, the importance of long-term offtaking agreements to deal with price risk and obtain debt financing in renewable energy transactions emphasized by my results requires more attention. It would be interesting to shed light on the interplay between a PPA enabling higher returns by lowering the cost of capital through leverage and a PPA potentially reducing investment returns by eliminating or reducing the potential to benefit from future spot price increases.

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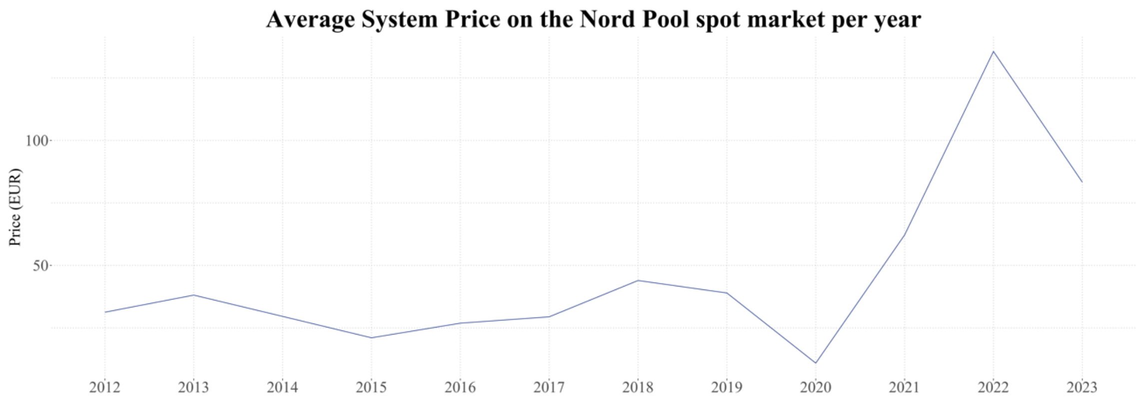
9 Appendices

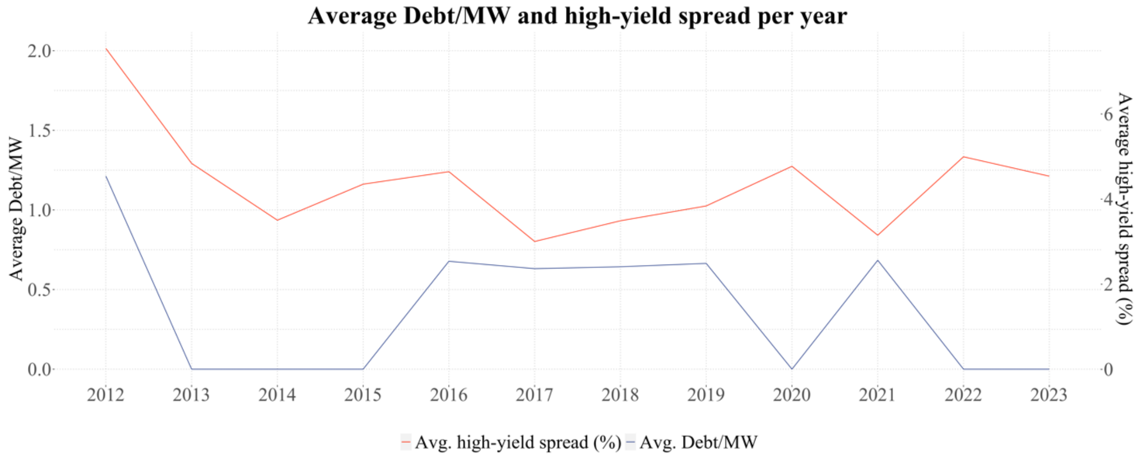
Appendix 1. Average Nord Pool System Price per year

The figure below displays the average yearly Nord Pool System Price from 2012 until April 2023. Data is retrieved from Nord Pool.



Appendix 2. Debt per MW multiple and high-yield spread over time

The figure below displays the average Debt per MW multiple (in EURm/MW) and high-yield spread (in %) for each year from 2012 to 2023. The average high-yield spread is calculated based on the daily Option-Adjusted Spread (OAS) of the ICE BofAML Euro High Yield Index.



Appendix 3. Overview of electricity price forecasts used

The table shows the electricity price forecasts used for the calculation of the variable PRICE_FORECAST_VOL by Nord Pool price zone and year.

Year	**Price Zones**	**Forecast providers**
2012	SE	Markedskraft
2013	SE	Pöyry, Markedskraft, Redpoint Energy
2014	SE	Pöyry, Markedskraft,
2015	SE	Pöyry, Markedskraft, SKM Market Predictor
2016	NO1, NO2, NO3, NO4, NO5, SE1, SE2, SE3, SE4, FI, DK1, DK2, SYS	Baringa, Volue
2017	NO1, NO2, NO3, NO4, NO5, SE1, SE2, SE3, SE4, FI, DK1, DK2, SYS	Pöyry, SKM Market Predictor, Baringa, Volue
2018	SE1, SE2, SE3, SE4, FI, SYS	Pöyry, Baringa, Wattsight,
2019	SE1, SE2, S3, SE4, DK, FI, NO	Baringa, Volue
2020	SE2, SE4	Baringa, Wattsight, AFRY
2021	SE, FI	Baringa
2022	NO1, NO2, NO3, NO4, NO5, SE1, SE2, SE3, SE4, FI, DK1, DK2, SYS	Baringa, Volue, Aurora

Appendix 4. Variable overview

The table below shows all variables used in the regression models.

Variable	Description	Calculation / Values	Source
Dependent Variables			
D/MW	Measures the square root of the quotient of debt in EURm and installed capacity in MW at transaction close. If several assets are transacted as part of a portfolio, their capacities are added.	$= \sqrt{\frac{(LTV * EV)}{Installed\ capacity}}$	Newsec Infra data base, Inframation, press, websites of buyers / sellers / developers
LEV	Binary variable that measures whether a transaction was financed using 100% equity or involved debt.	*1 = Levered* *0 = All equity*	Newsec Infra data base, Inframation, press, websites of buyers / sellers / developers
EV/MW	Measures the square root of the quotient of enterprise value (EV) in EURm and installed capacity in MW at transaction close. If several assets are transacted as part of a portfolio, their capacities are added.	$= \sqrt{\frac{EV}{Installed\ capacity}}$	Newsec Infra data base, Inframation, press, websites of buyers / sellers / developers
IRR^e	Measures the log transformed expected IRR based on the buyer's stated assumptions and the purchase price.	$= log\ (IRR^e)$	Newsec Infra data base
Independent Variables			
ACQUIRER _EXP	Measures the number of wind and solar transactions that the acquirer has been involved prior to the respective transaction.	*# Prior wind and solar PV transactions*	Newsec Infra data base, Inframation, press, websites buyers / sellers / developers
ACQUIRER _FIN	Dummy to capture if the acquirer(s) include(s) a financial institution.	*1 = Financial acquirer* *0 = No financial acquirer*	Newsec Infra data base, Inframation, press, websites of buyers
ACQUIRER _NORDIC	Dummy to capture if the acquirer(s) is / are based in the Nordics.	*1 = Nordics-based acquirer* *0 = No Nordics-based acquirer*	Newsec Infra data base, Inframation, press, websites of buyers
TRANSACTION _SIZE	Measures the natural logarithm of the asset's installed capacity in MW.	$= log\ (MW)$	Newsec Infra data base, Inframation, press, websites of buyers / sellers / developers
TRANSACTION _PRIMARY	Dummy to capture if the asset(s) are transacted for the first time.	*1 = Primary transaction* *0 = No primary transaction*	Newsec Infra data base, Inframation, press
ASSET_PPA	Dummy to capture if the asset(s) involve(s) a power purchase agreement (PPA).	*1 = PPA or feed-in tariff* *0 = No PPA or feed-in tariff*	Newsec Infra data base, Inframation, press
CREDIT _SPREAD	Measures the natural logarithm of the average credit spread in the year in which the respective transaction occurred.	$= log(\frac{\sum_t Daily\ High{-}Yield\ Spread_t}{n})$ *where n = # days and t = transaction year*	ICE BofA Euro High Yield Index Option-Adjusted Spread
PRICE_ FORECAST _VOL	Measures the natural logarithm of the average volatility of the yearly price forecasts (reference cases) for the Nord Pool price zone in which the asset(s) is / are located and the year in which the respective transaction occurred.	$= log(Mean_t^i(Std(Forecast_t^i))))$ *where i = Nord Pool price zone and t = transaction year*	Pöyry, Markedskraft, Redpoint, Baringa, Wattsight, AFRY, Volue

Variable	Description	Calculation / Values	Source
Control Variables			
ACQUIRER_EXP ACQUIRER_FIN*	Interaction term between *ACQUIRER_EXP* and *ACQUIRER_FIN*	*= ACQUIRER_EXP * ACQUIRER_FIN*	Newsec Infra data base, Inframation, press, websites of buyers
ASSET_PPA LEV*	Interaction term between *ASSET_PPA* and *LEV*	*= ASSET_PPA * LEV*	Newsec Infra data base, Inframation, press, websites of buyers
Geography Fixed Effects			
PRICE_ZONE	Categorical variable to capture the Nord Pool price zone in which the asset(s) is / are located.	*SE1, SE2, SE3, SE4, NO1, NO2, NO3, NO4, NO5, DK1, DK2, FI, Various*	Newsec Infra data base, Inframation, press, websites of buyers / sellers / developers

Appendix 5. Strength of association matrix

The table shows the pairwise association between all dependent and independent variables used in the regressions (n varying between 70 and 153). As the regression variables include several binary attributes, strength of association is calculated with Spearman correlation for numeric vs. numeric variable pairs, with a bias-corrected Cramer's V for binary vs. binary variable pairs and with ANOVA for binary vs. numeric variable pairs. Most interestingly, I find that the association between the dependent variables D/MW and LEV is high, indicating that the binary variable LEV is suitable for measuring leverage. The table verifies that there is no strong correlation between the independent regression variables, indicating that the variables measure different acquirer-, asset-, industry- and time-series related aspects.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) *D/MW*	1.00											
(2) *LEV*	0.96	0.59										
(3) *EV/MW*	-0.07	0.06	1.00									
(4) *IRR^e*	0.28	0.40	-0.06	1.00								
(5) *ACQUIRER_EXP*	-0.16	0.04	-0.06	-0.08	1.00							
(6) *ACQUIRER_FIN*	0.24	0.00	0.06	0.05	0.11	1.00						
(7) *ACQUIRER_NORDIC*	0.22	0.00	0.01	0.00	0.15	0.45	1.00					
(8) *TRANSACTION_SIZE*	0.34	0.15	-0.21	0.17	0.01	0.15	0.19	1.00				
(9) *TRANSACTION_PRIMARY*	0.01	0.00	0.13	0.12	0.03	0.09	0.00	0.22	0.69			
(10) *ASSET_PPA*	0.26	0.19	0.01	0.17	0.07	0.27	0.34	0.26	0.00	1.00		
(11) *CREDIT_SPREAD*	-0.06	0.02	0.16	0.13	-0.02	0.14	0.27	-0.08	0.01	0.26	1.00	
(12) *PRICE_FORECAST_VOL*	-0.13	0.17	-0.10	-0.24	0.01	0.08	0.02	-0.07	0.14	0.10	0.23	1.00

Appendix 6. Multicollinearity test

The table shows the Generalized Variance Inflation Factor (GVIF) for Specification (5) for each of the four sets of regressions. The GVIF provides an indication for the increase in the variation of a variable's coefficient due to multicollinearity. Generally, a GVIF of greater than 10 suggests strong multicollinearity. The analysis shows that all GVIFs are below 10, except for the GVIF of ACQUIRER_EXP and its interaction with ACQUIRER_FIN in Model (1) and the GVIF of the variable PRICE_ZONE in Model (4). Both are expected and do not present an issue.

Variables	(1) **D/MW**	(2) **LEV**	(3) **EV/MW**	(4) **IRR^e**
ACQUIRER_EXP	52.954	8.527	1.275	1.347
ACQUIRER_FIN	2.186	1.599	1.624	1.854
ACQUIRER_NORDIC	1.724	1.846	1.810	1.741
ASSET_PPA	1.446	1.542	3.400	3.307
LEV			2.545	3.732
TRANSACTION_PRIMARY	1.722	1.251	1.343	1.970
TRANSACTION_SIZE	1.805	1.485	1.675	2.249
EV/MW				1.614
CREDIT_SPREAD	1.692	1.190	1.313	1.905
PRICE_FORECAST_VOL	1.454	1.232	1.321	1.872
PRICE_ZONE	4.744	2.543	4.133	12.683
*ACQUIRER_EXP*ACQUIRER_FIN*	53.279	9.628		
*ASSET_PPA*LEV*			5.645	6.119

Appendix 7. Regression table: LEV regression

*The table shows the regression output for multiple logistic regressions on LEV with standard errors clustered at the Nord Pool price zone level. LEV is modeled using logistic regression; thus, the regression coefficients are not directly interpretable. To facilitate the analysis, coefficients are transformed to odds ratios. In logistic regression, a variable's odds ratio represents its effect on the likelihood that the outcome will occur, i.e., in this context that a transaction involves leverage. To account for skewness, the independent variables credit spread and price forecast volatility are log- transformed. In Model (1), I model leverage as a function of acquirer characteristics. In Models (2) and (3), I add asset- and transaction-specific characteristics. Specifications (4) and (5) additionally include credit spread and price forecast volatility to account for time-varying factors. Finally, Model (6) shows LEV as a function of time-varying variables only. Due to the potential association between acquirer experience and financial acquirer, I add an interaction term between these variables. I control for Nord Pool price zone fixed effects. Standard errors for each variable are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. A detailed overview of the regression variables is presented in Appendix 4 and robustness tests are shown in Appendices 9 and 10.*

	Dependent variable:					
	LEV					
	(1)	(2)	(3)	(4)	(5)	(6)
Acquirer Experience	1.761^{**}	1.704^{*}	1.771^{**}	1.747^{**}	1.865^{**}	
	(0.153)	(0.157)	(0.219)	(0.238)	(0.283)	
Financial Acquirer	1.977	1.469	1.478	1.570	1.663	
	(0.286)	(0.256)	(0.231)	(0.220)	(0.277)	
Nordic Acquirer	0.702	0.961	0.935	0.867	0.876	
	(0.402)	(0.484)	(0.421)	(0.384)	(0.496)	
PPA		3.375^{***}	3.171^{**}	3.474^{***}	3.302^{**}	
		(0.462)	(0.536)	(0.640)	(0.616)	
Primary Transaction			1.826	1.788	1.600	
			(0.561)	(0.589)	(0.567)	
Transaction Size			1.183	1.186	1.145	
			(0.246)	(0.267)	(0.346)	
Credit Spread				2.410	2.272	1.268
				(0.881)	(0.775)	(0.699)
Price Forecast Volatility					0.255^{***}	0.239^{***}
					(0.417)	(0.317)
Interaction Acquirer Experience*Financial Acquirer	0.482^{**}	0.481^{**}	0.463^{**}	0.460^{***}	0.449^{***}	
	(0.206)	(0.194)	(0.268)	(0.291)	(0.330)	
Price Area Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Stand. Error	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered
Observations	153	153	153	153	153	153
Akaike Inf. Crit.	220.500	214.200	215.900	216.500	211.200	214.700

Note: .p<0.1;*p<0.05;**p<0.01;***p<0.001

Coefficients are shown as odds ratios for easier interpretation.

Appendix 8. Robustness test: replacing D/MW with LTV

*The table shows the regression output for the robustness tests for the regressions on D/MW, replacing D/MW with LTV (D/EV). To account for skewness, the dependent variable LTV is square-root- and the independent variables credit spread and price forecast volatility are log- transformed. In Model (1), I model leverage as a function of acquirer characteristics. In Models (2) and (3), I add asset- and transaction-specific characteristics. Specifications (4) and (5) additionally include credit spread and price forecast volatility to account for time-varying factors. Finally, Model (6) shows D/MW as a function of time-varying variables only. I control for Nord Pool price zone fixed effects. Standard errors for each variable are clustered at the Nord Pool price zone level and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.*

	Dependent variable: LTV					
	(1)	(2)	(3)	(4)	(5)	(6)
Acquirer Experience	-0.015	-0.029	-0.048	-0.016	-0.029	
	(0.074)	(0.071)	(0.049)	(0.045)	(0.043)	
Financial Acquirer	0.016	-0.030	-0.043	-0.040	-0.019	
	(0.092)	(0.073)	(0.073)	(0.081)	(0.099)	
Nordic Acquirer	-0.217***	-0.191**	-0.155*	-0.136*	-0.119	
	(0.061)	(0.083)	(0.081)	(0.067)	(0.069)	
PPA		0.166	0.132	0.125	0.108	
		(0.095)	(0.090)	(0.088)	(0.092)	
Primary Transaction			-0.075	-0.066	-0.083	
			(0.164)	(0.157)	(0.143)	
Transaction Size			0.069**	0.076**	0.062	
			(0.024)	(0.028)	(0.045)	
Credit Spread				-0.179	-0.137	-0.202**
				(0.154)	(0.108)	(0.079)
Price Forecast Volatility					-0.218*	-0.288**
					(0.110)	(0.093)
Interaction Acquirer Experience*Financial Acquirer	-0.014	-0.005	0.017	-0.011	0.008	
	(0.059)	(0.062)	(0.043)	(0.041)	(0.038)	
Price Area Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Stand. Error	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered
Observations	88	88	88	88	88	88
Adjusted R^2	0.156	0.194	0.209	0.212	0.260	0.203
Note:				.p<0.1;*p<0.05;**p<0.01;***p<0.001		

Appendix 9. Robustness test: country fixed effects

*The table shows the regression output for the robustness tests for Model (5) for each of the four sets of regressions, replacing Nord Pool price zone by country fixed effects. To account for skewness, the variables D/MW and EV/MW are square-root- and the variables IRR^e, credit spread and price forecast volatility are log- transformed. Standard errors are clustered at the country level and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.*

	Dependent variable:			
	D/MW	LEV	EV/MW	IRR^e
	(1)	(2)	(3)	(4)
Acquirer Experience	-0.152^{***}	0.643^{**}	-0.015	-0.016^{***}
	(0.026)	(0.283)	(0.008)	(0.002)
Financial Acquirer	-0.081	0.384	0.130^{**}	0.078^{**}
	(0.091)	(0.528)	(0.044)	(0.016)
Nordic Acquirer	-0.217^{*}	-0.360	0.069	0.024
	(0.083)	(0.482)	(0.051)	(0.016)
PPA	0.180	1.447^{***}	0.098	0.082^{***}
	(0.135)	(0.476)	(0.108)	(0.014)
Levered			-0.068	0.008
			(0.114)	(0.040)
Primary Transaction	-0.125^{**}	0.334	0.153^{***}	0.193^{***}
	(0.040)	(0.616)	(0.007)	(0.001)
Transaction Size	0.070	-0.059	-0.034^{**}	-0.051^{**}
	(0.076)	(0.192)	(0.011)	(0.011)
EV/MW				-0.246^{***}
				(0.036)
Credit Spread	0.018	0.809	0.249^{*}	0.345^{**}
	(0.203)	(0.768)	(0.095)	(0.082)
Price Forecast Volatility	-0.327^{**}	-1.701^{***}	-0.203^{*}	-0.139^{*}
	(0.099)	(0.548)	(0.074)	(0.047)
Interaction Acquirer Experience*Financial Acquirer	0.121^{***}	-0.849^{***}		
	(0.018)	(0.307)		
Interaction PPA*Levered			-0.020	0.121^{**}
			(0.058)	(0.028)
Geography Fixed Effects	Country	Country	Country	Country
Stand. Error	Clustered	Clustered	Clustered	Clustered
Observations	71	153	103	70
Adjusted R^2	0.276		0.037	0.292
Log Likelihood		-81.640		
Akaike Inf. Crit.		191.300		
Note:				.p<0.1;*p<0.05;**p<0.01;***p<0.001

Appendix 10. Robustness test: monthly credit spread

*The table shows the regression output for the robustness tests for Model (5) for each of the four sets of regressions, changing the variable credit spread from the yearly average to the monthly average high-yield spread. To account for skewness, the variables D/MW and EV/MW are square-root- and the variables IRR^e, credit spread and price forecast volatility are log- transformed. I control for Nord Pool price zone fixed effects. Standard errors are clustered at the Nord Pool price zone level and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.*

	Dependent variable:			
	D/MW	LEV	EV/MW	IRR^e
	(1)	(2)	(3)	(4)
Acquirer Experience	-0.152***	0.634**	-0.009	-0.008*
	(0.028)	(0.278)	(0.021)	(0.004)
Financial Acquirer	-0.121	0.523	0.076	0.086
	(0.124)	(0.544)	(0.100)	(0.065)
Nordic Acquirer	-0.316**	-0.133	0.066	0.108**
	(0.115)	(0.490)	(0.160)	(0.043)
PPA	0.156	1.271***	0.133	0.079**
	(0.117)	(0.485)	(0.185)	(0.026)
Levered			-0.046	0.091
			(0.071)	(0.124)
Primary Transaction	-0.215*	0.579	0.164*	0.185
	(0.101)	(0.640)	(0.090)	(0.113)
Transaction Size	0.070	0.125	-0.032	-0.054
	(0.058)	(0.197)	(0.046)	(0.039)
EV/MW				-0.242**
				(0.105)
Credit Spread	0.166	0.331	0.141	0.162
	(0.098)	(0.694)	(0.108)	(0.114)
Price Forecast Volatility	-0.336**	-1.495***	-0.230**	-0.161*
	(0.122)	(0.535)	(0.087)	(0.075)
Interaction Acquirer Experience*Financial Acquirer	0.114***	-0.815***		
	(0.025)	(0.304)		
Interaction PPA*Levered			-0.066	0.022
			(0.130)	(0.180)
Price Area Fixed Effects	Yes	Yes	Yes	Yes
Stand. Error	Clustered	Clustered	Clustered	Clustered
Observations	70	152	102	70
Adjusted R^2	0.300		0.059	0.146
Log Likelihood		-82.820		
Akaike Inf. Crit.		207.600		
Note:		.p<0.1;*p<0.05;**p<0.01;***p<0.001		