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Chair for Management Sciences
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EWL Working Paper No. 06/2011

**FUEL MIX CHARACTERISTICS AND EXPECTED STOCK RETURNS
OF EUROPEAN POWER COMPANIES**

by

Malte Sunderkötter

October 2011

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Abstract

This article investigates the impact of the fuel mix structure in power generation portfolios on expected stock returns for major European power companies. The 22 biggest publicly listed European power producers are examined between January 2005 and December 2010. Based on the capital asset pricing model (CAPM) and multi-factor market models, the systematic risk of the power companies relative to the overall market performance and other typical energy and macroeconomic risk factors is analyzed. The full-information approach is used to determine technology-specific betas and risk factor sensitivities from the sample. Although most companies are not exclusively in the power producing business, it is shown that the generation fuel mix has a significant impact on the historical stock returns of the investigated companies. In particular, the sample companies exhibit significant differences in the systematic risk of gas and nuclear generation technologies compared with renewable technologies measured by technology-specific, delevered beta factors.

This study extends existing literature and contributes new insights in two ways: Firstly, this is to our knowledge the first empirical analysis comparing the financial risk of different electricity generation technologies. Secondly, the results provide practical benefit to determine adequate risk-adjusted capital costs for typical generation technologies. Therewith, this study is relevant for evaluating all kinds of power plant investments.

Keywords: power plant investments, asset pricing, fuel mix diversification

JEL-Classification : G11, G12, L94

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1. Introduction

Valuation of power generation assets under uncertainty represents one of the core issues for individuals and companies investing in power plants on liberalized electricity markets. Thereby, a thorough analysis of risk and return is particularly important due to three reasons: Firstly, newbuild plants are capital intensive and require—depending on size and selected technology—up to billions of euros. Secondly, plants typically have long life cycles of 30 to 50 years resulting in long periods of tied-up capital. Thirdly, investors face cost-, price-, and volume-risks which directly impact the return on investment on liberalized markets.

Following [Leahy and Whited \(1996\)](#), one fundamental dimension to classify investment theories under uncertainty is the scope of considered assets. Thereby, it can be distinguished between theories that look at a firm or investor in isolation and capture the risk of some aspect of the firm’s environment in total and theories that look at the firm or investor in relation to other market participants and emphasize the covariance in the returns of different investments. While in the first case the absolute value of a risk measure matters, uncertainty is only relevant in the second case as far it affects covariances with respect to some market measures. As the most prominent representative of the first class of models, mean-variance portfolio optimization based on the work of [Markowitz \(1952\)](#) applies variance of return as the relevant risk measure to derive an efficient frontier of asset combinations. Thereby, it is not distinguished between systematic and unsystematic asset fluctuations. In contrast, the CAPM ([Sharpe, 1964](#), [Lintner, 1965](#), [Mossin, 1966](#)) and other market models rely on the assumption that capital market investors will only value the systematic risk component of assets since firm-specific (i.e. unsystematic) risks can be eliminated through diversification and are thus irrelevant. Despite some ongoing controversy on the empirical validity of the CAPM, both approaches are widely used in academia and practice for asset pricing application and managerial decision support, although the models differ fundamentally in the treatment of unsystematic risk.

Investment decisions in the electricity industry bear the complexity that electricity can hardly be stored on a large-scale and thus needs to be instantly generated to serve demand. Taking into account this particularity, different authors have proposed optimization models for decision support tailored to long-term investment and portfolio management decisions on competitive electricity markets.

Different concepts to adapt mean-variance portfolio optimization to power plant investments under uncertainty from an investor perspective have been proposed in recent literature: Applying Monte-Carlo simulation, [Roques et al. \(2008\)](#) come to the result that portfolios with a high share of gas plants are most attractive in view of risk and return due to a high correlation of gas and electricity prices observable on many liberalized markets. Another set of publications uses partial equilibrium models to value the trade-off between risk and return in investment decision on liberalized electricity markets: [Chuang et al. \(2001\)](#) present a model for generation expansion planning based on an equilibrium formulation in a Cournot oligopoly. In a setting with separate energy and capacity markets, the authors find greater reserve capacities and thus

system reliability in Cournot competition than in centralized planning. [Zöttl \(2008\)](#) theoretically compares resulting equilibrium fuel mixes and electricity prices in markets with centralized planning, perfect and imperfect competition. [Botterud et al. \(2003\)](#) use stochastic dynamic programming to identify an optimal generation investment strategy from a profit-oriented investor perspective. Different from equilibrium models, the spot price is empirically estimated as a function of load level and installed generation capacity. More complex market interactions with several market constraints can be simulated with agent-based models (e.g. [Gnansounou et al., 2004](#)).

Although these studies indicate that power generation technologies differ fundamentally in terms of risk as measured e.g. by the absolute variance of generation costs, there is so far no empirical evidence to support the same hypothesis for the systematic risk with respect to the overall market and/or other risk factors. In other words, the proposed models may be adequate to manage all kinds of risks inherent in generation asset portfolios, but it is questionable whether these risks are relevant at all for decisions of capital market investors.

Empirical studies on asset pricing and costs of equity in the utility industry and for power producers are very rare: [Bower et al. \(1984\)](#) and investigate U.S. utility stocks over the period 1971-1979. The authors come to the conclusion that multi-factor models can better approximate expected returns of utility companies and should therefore be preferred to model risk compared to the CAPM. Extending this study, [Bubnys \(2005\)](#) cannot confirm the superiority of multi-factor models compared to the CAPM based on an analysis of 128 public utility companies over a longer period of time. [Sadorsky \(2001\)](#), [Boyer and Fillion \(2007\)](#) present a multi-factor market model to estimate the expected returns of Canadian oil and gas industry stock prices. In recent years, alternative energy companies have become another focus of research in the field of empirical works related to asset pricing in the energy industry (see e.g. [Henriques and Sadorsky, 2007](#)). However, all those articles are neither focusing on power generation companies nor on liberalized markets. Furthermore, the systematic risk characteristics of different power generation technologies and their implications on the cost of equity of power generation companies have not been investigated before to our best knowledge. Due to the lack of empirical evidence on technology-specific risk factors of power plants, utilities and power producers typically still rely on valuation approaches based on weighted average costs of capital (WACC). These, however, may massively bias an investment decision as the average company risk is assumed also for a specific investment project.

In this paper, the systematic risk characteristics of different power generation technologies (i.e. hard coal, lignite, nuclear, natural gas, and renewables) and their impact on (individual) stock returns of the power generation companies are investigated using an approach based on the capital asset pricing model (CAPM) and multi-factor market models. The analysis involves 22 major power generation companies that are publicly listed at European stock exchanges, representing together the biggest European listed

power generation firms. Thereby, one core question is whether different power generation technologies face significant differences in the systematic risk. Furthermore, this study aims to analyze the overall explanatory power of a technology-beta oriented market model.

The remainder of this paper is structured as follows: Section 2 provides an overview of the considered models and data. Empirical results for the estimated models focusing on the explanatory power of the models are discussed in section 3. The article concludes with section 4.

2. Models and data

2.1. Considered models

Following the well-known CAPM (Sharpe, 1964, Lintner, 1965, Mossin, 1966), the expected return of any asset i can be explained by the company-specific (market-)beta factor β_i and the expected excess return of the overall market performance by

$$\mathbf{E}[r_i] = r_f + \beta_i(\mathbf{E}[r_m] - r_f), \quad (1)$$

where r_i denotes the return of stock i and r_m the return of the market portfolio, and r_f the risk-free rate of return. OLS regression can be used to estimate from each asset return time series the average abnormal return over the expected return $\beta_i(r_{m,t} - r_{f,t})$, $\hat{\alpha}_i$, and $\hat{\beta}_i$ for each asset i from the equation

$$r_{i,t}^* = \hat{\alpha}_i + \hat{\beta}_i r_{m,t}^* + \epsilon_{i,t}. \quad (2)$$

Here, $r_{i,t}^* := r_{i,t} - r_{f,t}$ denotes the excess return over the risk-free rate for stock i and $\epsilon_{i,t}$ the error term. This yields the beta estimator $\hat{\beta}_i = \text{Cov}(r_m, r_i) / \text{Var}(r_i)$. The form of the model is identical with a standard one-factor model

$$r_{i,t}^* = \hat{\lambda}_{0,i} + \hat{\lambda}_{1,i} F_t + \epsilon_{i,t} \quad (3)$$

with the excess return of the market portfolio, $F_t \equiv r_m^* := r_{m,t} - r_{f,t}$ assumed as the only risk factor.

If the fuel mix of a power generation company has an impact on its systematic risk, then there will exist technology-specific beta factors β_u representing the systematic risk sensitivity of technology u in the market. Assuming the same capital structure for all companies, the technology betas are constant across the industry. Typically, the generation asset portfolio of a power producing company i consists of a mix of different generation technologies $u \in U$. Since in an arbitrage-free market a portfolio's beta must equal the weighted average of the constituent asset betas, the company-specific beta-factor β_i from Eqn. (1) can be decomposed into a weighted sum of technology-specific betas β_u yielding

$$\mathbf{E}[r_i] = \sum_{u \in U} w_{u,i} \cdot \mathbf{E}[r_{u,i}] = r_f + \sum_{u \in U} w_{u,i} \beta_u (\mathbf{E}[r_m] - r_f), \quad (4)$$

where $w_{u,i}$ denotes the value-based weighting factor of technology u in portfolio i with $\sum_{u \in U} w_{u,i} = 1$. Note that the technology beta β_u equals the company-specific beta in case of a “pure-play” power generator who operates only generation assets of technology u .

In fact, Eqn. (4) ignores differences in the companies’ capital structure. However, “borrowing from whatever source, while maintaining a fixed amount of equity, increases the risk of the investor” (Hamada, 1972) and companies with higher debt-to-equity ratio (leverage) face a higher systematic risk in the equity since debt is not subject to market risk. To realistically compare the systematic risk across the sample and identify the technology-specific impact, the impact on estimated betas induced by differences in the capital structure of the analyzed firms needs thus to be removed. To correct for differences in the sample companies’ leverage, delevered betas β_i^d are calculated from equity betas following Hamada (1972). Specifically, it is

$$\beta_i^d = \frac{\beta_i}{1 + D_i/E_i(1 - \tau_i)} \quad (5)$$

where τ_i is the corporate tax rate, and D_i and E_i denote the market value of debt and equity, respectively.

Assuming that portfolio weights $w_{u,i}$ are constant over time, unlevered technology betas can be obtained from a cross-sectional multiple least square regression of the form

$$\beta_i^d = \sum_{u \in U} w_{u,i} \hat{\beta}_u^d + \varepsilon_i \quad (6)$$

The selection of an adequate measure to determine weighting factors is crucial. Financial theory suggests to use weighting factors based on the actual market value of the respective asset in the portfolio with respect to the total portfolio market value. Since market values of power plants cannot be observed directly, one possibility would be to derive technology weights from actual installed capacities (in GW) times the average specific investment costs of the respective technologies (€/GW). Despite the difficulty of estimating time-constant specific investment costs for power plants of varying age, this methodology would ignore the technology characteristics of specific operational cost such as fuel costs and the resulting dispatch.

Following the peak-load pricing concept (see e.g. Oren et al., 1985), the electricity markets will reflect both fixed and variable costs in the (long-term) equilibrium. Operating hours of each technology can thus be determined from the full-cost characteristics of the different technologies. Therefore, actual electricity generation data (in TWh) should be a fairly good proxy for the relative market value of different technology classes. Actual production data from annual company reports is used to calculate the portfolio weights by dividing the electricity produced from one of six fuel types (hard coal and lignite, natural gas, nuclear, renewables and miscellaneous² technologies) by the total production of the respective year. Thereby, electricity purchases are not included. Since fuel type specific energy production data is not publicly reported

²The “miscellaneous” technology category includes reported generation from oil-fired plants, waste, combined heat and power, as well as generation from unreported sources and rounding differences.

by all companies for each year, time-constant average weighting factors are used for the periods 2005–2007 and 2008–2010 derived from the reported data.³

Estimation of technology-specific beta factors from the actual fuel mix of the considered companies proceeds along the lines proposed by [Boquist and Moore \(1983\)](#), [Ehrhardt and Bhagwat \(1991\)](#), [Kaplan and Peterson \(1998\)](#) for deriving full-information industry betas. Thereby, estimation of technology betas is performed in two steps: First, firm-specific beta factors β_i are estimated from an OLS time-series regression on historical returns 2005–2010 using Eqn. (2). In a second step, technology-specific betas β_u can be estimated from a multiple, cross-sectional regression based on Eqn. (6).

In addition to the one-factor models, the explanatory power of different multi-factor models (see e.g. [Ross, 1976](#)) of the form

$$r_{i,t}^* = \hat{\lambda}_{0,i} + \sum_{j=1}^k \hat{\lambda}_{i,j} F_{j,t} + \epsilon_{i,t}. \quad (7)$$

is investigated. Thereby, different energy-related risk factors are discussed and tested (cf. section 3.3). The full-information approach can be applied straightforwardly to derive technology-specific sensitivities for each risk factor.

2.2. Model tests

One classical approach for CAPM tests is based on cross-sectional analysis. The principle of these tests relies on the fact that given validity of the CAPM, average abnormal returns α_i must jointly equal zero. Adopting the well-known test of [Fama and MacBeth \(1973\)](#) with the regression equation

$$r_{i,t}^* = \gamma_{0,t} + \gamma_{1,t} \beta_i + \xi_{i,t}, \quad (8)$$

the hypothesis $\bar{\gamma}_0 = 0, \bar{\gamma}_1 > 0$ can be tested using the t -statistic $\gamma_j / \sigma_{\gamma_j}$. Thereby, the time-series averages are used as estimates of expected coefficient values, i.e. $\bar{\gamma}_j = \sum_{t=1}^T \hat{\gamma}_{j,t}, j = 1, 2$. However, this test requires the β_i to be known, whereas these coefficients need to be estimated in practice. Since the limited sample size in our application prevents from building sufficiently diversified asset portfolios to circumvent this problem, time-series tests are used instead. Thereby, the finite sample GRS test proposed by [Gibbons et al. \(1989\)](#) is applied to test the hypothesis whether the estimated α_i are jointly zero. Under the assumption of normal, homoskedastic, and independent disturbances over time, the test statistic is given by

$$W = \hat{\alpha}' \hat{\Sigma}^{-1} \hat{\alpha} \cdot \frac{T - N - 1}{N} \cdot \left(1 + \left(\frac{\hat{\mu}_m^*}{\hat{\sigma}_m} \right)^2 \right)^{-1} \sim F_{N, T-N-1}, \quad (9)$$

³Since investments and divestments affect the fuel mix of the sample companies over time, just taking the average fuel mix over the total period could bias the results. Since, however, the annual changes remain marginal and are subject to reporting inaccuracies, distinguishing two sub-periods seems most suitable.

where $\hat{\alpha}$ denotes the N -dimensional vector of estimated intercepts, $\hat{\Sigma}$ the residual covariance matrix computed from the vector of residuals ϵ_t by $\hat{\Sigma} := \mathbf{E}[\epsilon_t \epsilon_t']$, and $\hat{\mu}_m^*$ and $\hat{\sigma}_m$ sample mean and standard deviation of the excess return $r_{m,t}^* := r_{m,t} - r_{f,t}$. An overview of this test is e.g. provided in [Cochrane \(2001\)](#).

To ensure time-consistent results and exclude potential biasing effects from a specific selection of the analysis period, the [Chow \(1960\)](#) test is used to test for equality of coefficients over time versus structural breaks within the time series. For that, the time series is split up in sub-periods a and b . The CAPM regressions are then performed both for the combined period and for each sub-period separately. Let S be the sum of squared residuals from the combined data, S^a be the sum of squared residuals from the first sub-period, and S^b be the sum of squared residuals from the second sub-period. Furthermore, T^a and T^b denote the number of observations in each group and k the total number of parameters. Then the Chow test statistic is

$$\frac{(S - S^a - S^b)/(k + 1)}{(S^a + S^b)/(T^a + T^b - 2(k + 1))} \sim F_{k+1, T-2(k+1)}, \quad (10)$$

Having determined technology-specific beta-factors from the multiple regression according to Eqn. (6), the question arises whether the obtained β_u , $u \in U$ are significantly different from each other. To provide evidence on this question, we can pairwise test for the following hypothesis:

$$H_0 : \beta_u = \beta_{u'}, \quad u, u' \in U, u \neq u' \quad \text{versus} \quad H_1 : \beta_u \neq \beta_{u'}, \quad u, u' \in U, u \neq u'$$

If the null hypothesis is correct, a reduced regression model with five (or less) independent variables should explain as much variance in the delevered company beta factor β^d as the initial regression model with six independent variables. Testing for instance the null hypothesis that coal and gas technologies have equal beta coefficients, the initial regression model from Eqn. (6) would be restricted to

$$\beta_i^d = (w_{coal,i} + w_{gas,i})\hat{\beta}_{coal,gas}^d + \dots + w_{renew,i}\hat{\beta}_{renew}^d + \varepsilon_i$$

The pairwise hypotheses can be tested by comparing the unrestricted model with six independent variables with a restricted model with a reduced number of variables in an F-test with the following test statistic (cf. [Greene and Zhang, 2003](#)):

$$\frac{(R_u^2 - R_r^2)}{(1 - R_u^2)/(N - 1 - 1)} \sim F_{1, N-2}, \quad (11)$$

where R_u^2 and R_r^2 denote the coefficient of determination of the unrestricted and the restricted model, respectively.

2.3. The data

The following analyses are based on monthly returns of the 22 biggest power generation companies listed at different European stock exchanges in the period 2005–2010.⁴ Although most empirical stock return studies are based on longer analysis periods, we abstained from a longer time frame for two reasons: Firstly, electricity market liberalization started in most European countries in the late 1990s, triggered by the EU Directive 96/92/EC. While continental European countries had opened their electricity markets on average to less than 25% in 1999, the value increased to more than 75% in 2005 (Haas et al., 2006). Although the intensity of electricity market competition across European countries still varies, European electricity wholesale markets have reached sufficient comparability in the fundamental competitive structures since the mid-decade. Secondly, it has to be ensured that markets had fully absorbed all consequences of the Enron bankruptcy from 2001/2002 which were likely to disturb asset pricing in the whole energy sector for years.

In total, the considered time period yields $T = 72$ observations of monthly returns for each of the considered firms.⁵ The considered firms exhibit an annual average production from owned assets ranging from 18 to 621 TWh at an installed capacity between 4 and 131 GW. Annual electricity production data of the sample companies was then systematically categorized into the technology classes gas, coal/lignite, nuclear, renewable, and miscellaneous as illustrated in Figure 1. The companies' generation portfolios differ widely in the technology mix: Only two companies (Drax Group and Iberdrola Renewables) show “pure-play” generation portfolios consisting solely of hard coal respectively renewable generation technologies. A detailed description of the sample companies and corresponding operational and financial key data can be found in Appendix A.

For the classical CAPM specification, historical one-week Euribor rates provided by DB (2011) are used for the risk-free rate r_f of return and the Dow Jones Euro Stoxx Utility index (ECB, 2011) to represent the return of the relevant market portfolio r_m . Following and extending the work of Sadorsky (2001), the impact of potential risk factors such as commodity prices and economic sentiment indicators are investigated in one-factor and multi-factor models in addition to the classical CAPM specification. Where available, futures prices are used rather than spot prices since spot prices are more affected by short-run price fluctuations due to temporary market imbalances. All considered risk factors in this study are measured by excess returns r^* in monthly granularity as shown in Table 1. The relative development of all risk factor returns is depicted in Figure 2.

⁴Note that only companies with stock price data available in at least four years within the period 2005–2010 are included in the analysis. Companies that were de-listed during the period due to takeovers or mergers are also excluded.

⁵Shortened time series were accepted for Edf (listed since November 2005), Drax Power (listed since December 2005), and Iberdrola Renewables (listed since January 2008).

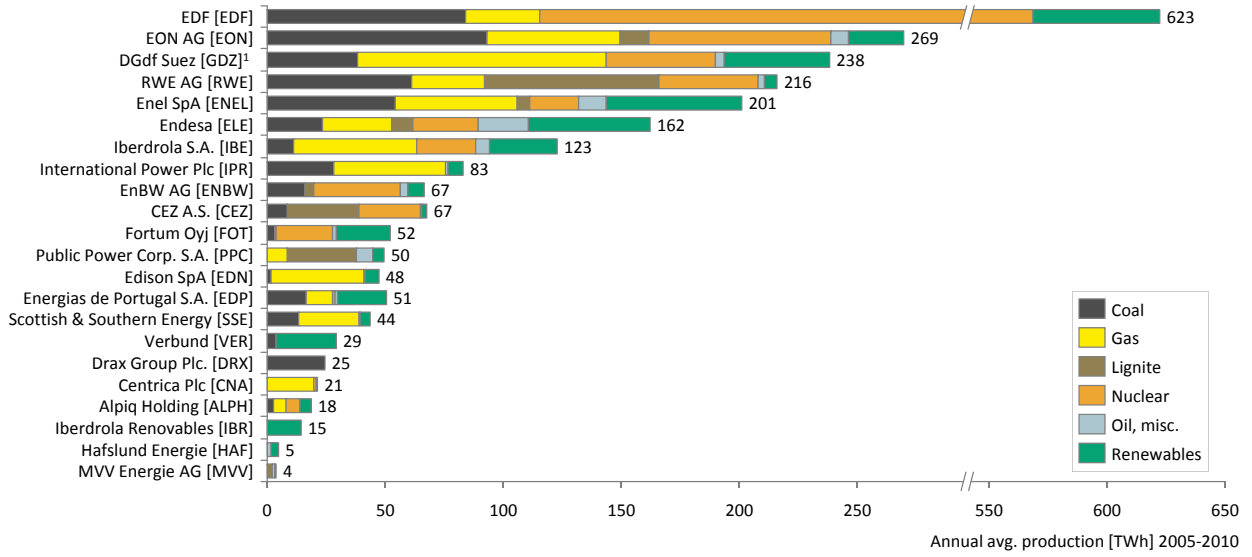


Figure 1: Annual average power production and generation fuel mix of the sample companies 2005–2010

Table 1: Captured risk factors and corresponding data sources in this study.

Symbol	Description	Source
r_m^*	Market portfolio return	Dow Jones Euro Stoxx Utility index (ECB, 2011)
r_{eua}^*	Carbon price return	EUA front year futures (EEX, 2011)
r_{el}^*	Electricity price return	EEX Phelix year-ahead base electricity futures (EEX, 2011)
r_{es}^*	Economic sentiment index	ifo German Business Climate index (IFO, 2011)
r_{oil}^*	Oil price return	WTI crude oil futures, four months to delivery (EIA, 2011)
r_{gas}^*	Gas price return	German cross-border gas import prices (BAFA, 2010)

3. Empirical results

This section provides the estimation results and corresponding tests on the explanatory power of the described models. Since the estimation of technology betas is performed in two steps, results for the standard CAPM with estimation of firm-specific beta factors β_i are presented first in section 3.1. Subsequently, estimation for technology-specific betas β_u in the CAPM framework are provided in section 3.2. Similarly, firm-specific results of different multi-factor market model specifications are analyzed in section 3.3, before the implied technology characteristics are discussed in section 3.4.

3.1. Firm characteristics in the one-factor models

Table 2 provides sample means of the estimated regression coefficients and coefficients of determination R^2 for the CAPM and other one-factor models.⁶The standard CAPM provides the best model fit measured

⁶Detailed regression results and coefficient estimates are provided in Appendix B.

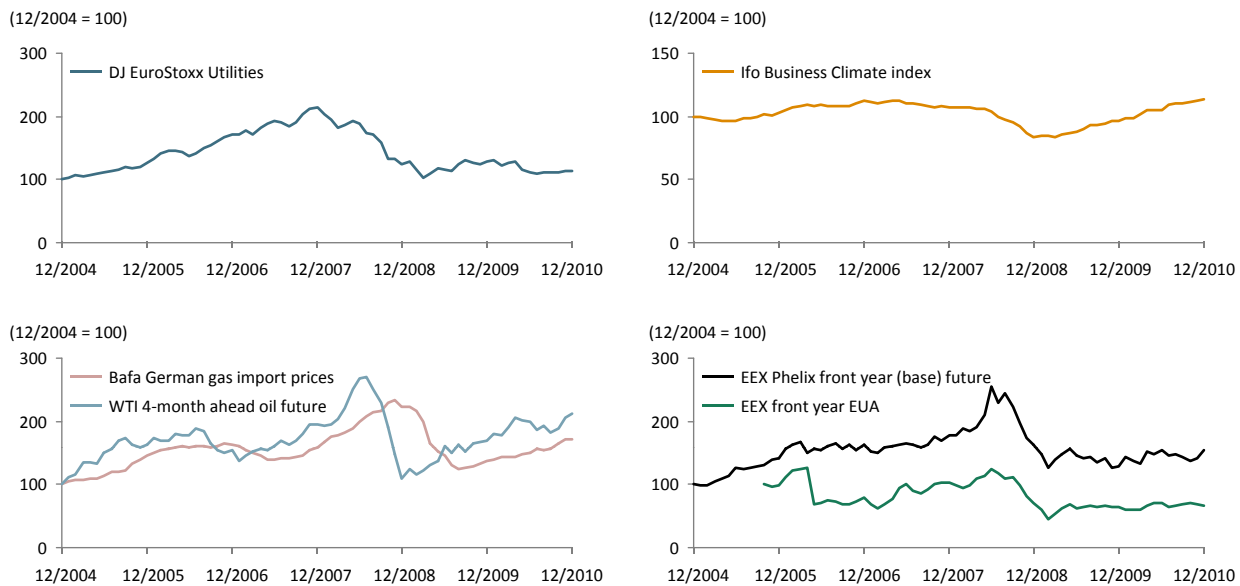


Figure 2: Relative development of DJ Euro Stoxx Utility index (ECB, 2011), IFO Business climate index for Germany (IFO, 2011), WTI oil futures four months to delivery (EIA, 2011), German gas import prices BAFA (2010), EEX Phelix year-ahead base and EUA year futures (EEX, 2011).

by the coefficient of determination at an average R^2 of 0.22, indicating that about 22% of the variation in returns of the considered energy companies may be explained through variations of the market portfolio represented through the DJ Euro Stoxx Utility index. The characteristics of the estimated coefficients from single time series support this hypothesis: For the standard CAPM, all estimated coefficients β_i are significantly greater than zero even beyond a 5% level of significance. In contrast, in all other one-factor models a non-zero number of stocks has β_i estimates which are not significantly different from zero. In particular, applying gas import price returns and the economic sentiment indicator as regressors yields 6 respectively 7 insignificant coefficients (cf. Tab. B.16 and Tab. B.14).

Table 2: Summary results for 2005–2010 univariate OLS regressions with varying risk factors. For each considered risk factor, the table provides sample averages of coefficient estimates α_i , β_i , standard errors are provided in parenthesis.

	$\bar{\alpha}_i$	$\bar{\beta}_i$	\bar{R}_i^2
r_m^*	0.002 (0.008)	0.780 (0.183)	0.22
r_{eua}^*	0.001 (0.010)	0.205 (0.090)	0.11
r_{el}^*	0.002 (0.009)	0.238 (0.134)	0.07
r_{es}^*	0.003 (0.009)	0.910 (0.501)	0.05
r_{oil}^*	0.002 (0.009)	0.132 (0.116)	0.04
r_{gas}^*	0.005 (0.009)	-0.335 (0.227)	0.04

The standard CAPM specification is tested for structural breaks within the analysis period. For that,

two additional OLS regressions are performed covering the sub-periods 2005–2007 and 2008–2010. The coefficient estimates are tested for significant cross-periodic differences applying the test procedure proposed by Chow (1960).⁷ The test results indicate only for 2 of 22 companies a structural break at a significance level of 10% as shown in Appendix B, Table B.11. Thus, we continue the majority of the following analyses for the combined period 2005–2010.

As described in the previous section, the specified CAPM is tested on abnormal returns using the GRS methodology. In consistency with the CAPM assumptions, the null hypothesis of jointly zero abnormal returns, i.e. $\alpha_i = 0$ ($i = 1, \dots, N$), cannot be rejected given a test statistic of $W = 1.06$ (p -value 0.418) for the full analysis period 2005–2010. For the sub-periods, the GRS tests confirm this result with $W = 0.525$ (p -value 0.911) for the sub-period 2005–2007 and $W = 0.281$ (p -value 0.996) for the sub-period 2008–2010.

3.2. Technology characteristics in the CAPM

Before the technology-specific beta factors are derived from the multiple regression, the data set is assessed for multicollinearity by computing the correlation matrix of the technology weighting factors $w_{u,i}$. This is important as neglecting multicollinearity in the multiple regression could yield misleading and erratical results. As shown in Table 3, the absolute coefficients of correlation of the pairwise analysis of weighting factors are consistently less than 0.5 and thus do not indicate multicollinearity.

Table 3: Pairwise coefficients of correlation of the technology weighting factors $w_{u,i}$ during the period 2005–2010.

R	w_{gas}	w_{coal}	w_{nuc}	w_{misc}	w_{renew}
w_{gas}	1.00	-0.45	-0.48	-0.17	-0.28
w_{coal}		1.00	-0.19	0.07	-0.41
w_{nuc}			1.00	-0.10	-0.13
w_{misc}				1.00	0.04
w_{renew}					1.00

Having estimated the firm-specific beta factors β_i from the historical returns, corporate tax rates 2008 from KPMG (2008) and 2008 debt and equity data from Bloomberg are used to calculate delevered company betas β_i^d . Next, a second pass cross-sectional OLS regression without constant according to Eqn. (6) is applied to estimate delevered technology-specific betas β_u^d . Coefficient estimates and standard errors are provided in Table 4. For the total analysis period 2005–2010 all coefficient estimates except for the miscellaneous technology class are greater than zero at a 5% level of significance at minimum. This is generally confirmed when considering the two sub-periods separately.

⁷Application of the Chow test requires knowledge about the timing of a structural break. Although there is no evidence on a structural break end of 2007, we abstain from testing for other potential timing of structural breaks due to the limited length of the considered analysis period.

Table 4: Delevered technology-specific coefficient estimates $\hat{\beta}_u^d$, standard errors, and adjusted coefficient of determination R_{adj}^2 from multiple OLS regression. Dependent variable is β_i . Thereby, *** denotes significance of the coefficient at the 1% level, ** at the 5% level and * at the 10% level.

	Period (2005–2010)		Period I (2005–2007)		Period II (2008–2010)	
$\hat{\beta}_{gas}^d$	0.262**	(0.204)	0.094	(0.129)	0.301**	(0.109)
$\hat{\beta}_{coal}^d$	0.367***	(0.230)	0.337**	(0.136)	0.337**	(0.123)
$\hat{\beta}_{nuc}^d$	0.431**	(0.299)	0.555***	(0.186)	0.28**	(0.158)
$\hat{\beta}_{misc}^d$	0.112	(1.049)	0.248	(0.538)	-0.27**	(0.436)
$\hat{\beta}_{renew}^d$	0.645***	(0.227)	0.897***	(0.194)	0.587***	(0.112)
R_{adj}^2	0.860	(0.166)	0.825	(0.204)	0.810	(0.171)

Note that the firm-specific β_i^d which are used as the left hand-side of the second pass regression (see Eqn. (6)) are subject to estimation errors. Given that beta factors are constant over time, this measurement error in beta declines as the time-series sample size, T , increases. Since the measurement errors occur only in the dependent variable while weighting factors $w_{u,i}$ as independent variables are without errors, the standard OLS regression model accounts sufficiently for errors in β_i .

The coefficient of determination of $R_{adj}^2 = 0.86$ indicates a very high explanatory power for the second pass regression. This is particularly remarkable taking into account that most of the considered companies are not pure power generators but companies with other utility-related business activities such as sales, trading, transmission, and distribution. Over the total period 2005–2010, all coefficients except β_{misc} are significantly greater than zero, with the beta factors of coal and nuclear technologies showing significance even at the 1% level. Renewables (i.e. predominantly hydro) exhibit absolutely the highest beta factors while gas technologies show the lowest β -sensitivity to the market portfolio. Hypothetically, this might be due to the fact that hydro technologies face only little volatility in generation costs. Consequently, the operational margin of these technologies highly depends on the electricity price which is expected to be cointegrated or even correlated with the overall market performance. The lower gas technology betas might be explained following the argumentation of [Roques et al. \(2008\)](#): Caused by a high correlation of earnings from electricity sales and costs from gas purchases, the resulting operational margin of gas technologies may be expected to be less volatile compared to nuclear or hydro generation, justifying a lower beta factor. These first hypotheses and potential explanations will be further investigated and tested in the following sections using different multi-factor market models.

As discussed before, we test for equality of technology-specific beta coefficients by applying the pairwise F -test as discussed in Section 2.2. As shown in Table 5, the null hypothesis of equal beta coefficient can be rejected at a confidence level of at least 5% for gas and renewables as well as for coal and renewable

technologies based on the analysis of the combined period and period I. In period II, the null hypothesis can only be rejected at a confidence level of 10% for gas and renewables technologies. This supports the hypothesis that the unlevered market beta factor of renewable technologies is significantly higher compared to the betas of gas and coal technology classes.

Table 5: Pairwise test on equality of technology-specific beta coefficients. The table provides the F -distributed test statistics applied on unlevered betas according to Eqn. (11). Thereby, *** denotes significance of the coefficient at the 1% level, ** at the 5% level and * at the 10% level.

		$\hat{\beta}_{coal}^d$	$\hat{\beta}_{nuc}^d$	$\hat{\beta}_{misc}^d$	$\hat{\beta}_{renew}^d$
Combined period (2005–2010)	$\hat{\beta}_{gas}^d$	0.414	0.976	0.168	4.812**
	$\hat{\beta}_{coal}^d$		0.140	0.439	3.216*
	$\hat{\beta}_{nuc}^d$			0.611	1.531
	$\hat{\beta}_{misc}^d$				4.959**
Period I (2005–2007)	$\hat{\beta}_{gas}^d$	1.529	4.057*	0.111	7.718**
	$\hat{\beta}_{coal}^d$		0.751	0.000	5.194**
	$\hat{\beta}_{nuc}^d$			0.387	1.574
	$\hat{\beta}_{misc}^d$				1.173
Period II (2008–2010)	$\hat{\beta}_{gas}^d$	0.099	0.026	1.747	3.046*
	$\hat{\beta}_{coal}^d$		0.101	1.637	2.621
	$\hat{\beta}_{nuc}^d$			1.636	2.321
	$\hat{\beta}_{misc}^d$				3.061*

3.3. Firm characteristics in the multi-factor models

Based on the insights gained from the analysis of the one-factor models, the explanatory power of a combination of risk factors with respect to stock returns and technology characteristics of power generation companies is investigated in multi-factor models. Thereby, we consider the same risk factors as in the univariate analysis. Multi-factor models, however, bear the risk that risk factors are not significantly different from zero or exhibit linear interdependencies among each other. To assess this risk of multicollinearity, the coefficient of correlation for each pair of risk factors is analyzed as shown in Table 6. With a maximum coefficient of correlation of $R = 0.45$ for the cross-correlation in returns between returns of EEX electricity futures and EEX EUA future prices, a risk for multicollinearity among the risk factors can be neglected.

The selection of risk factors for an optimal multi-factor specification is performed consistently for all sample companies $i = 1, \dots, N$ by backward selection starting with the complete 6-factor market model. The risk factor with the lowest F-stat over the sample average is removed for the next regression unless it is significantly different from zero at the 10%-level at minimum. Following this rule, all multi-factor models have to be rejected since only the market return shows significant difference from zero over the sample

Table 6: Pairwise coefficients of correlation in returns of the market portfolio r_m^* , electricity price r_{el} , oil price, r_{oil} , economic sentiment r_{es} , EUA price r_{eua} , and clean spark spread r_{sp} .

R	r_m^*	r_{eua}^*	r_{el}^*	r_{es}^*	r_{oil}^*	r_{gas}^*
r_m^*	1.00	0.29	0.29	0.42	0.31	-0.11
r_{eua}^*		1.00	0.45	0.21	0.35	-0.21
r_{el}^*			1.00	0.18	0.43	-0.02
r_{es}^*				1.00	0.41	-0.12
r_{oil}^*					1.00	-0.02
r_{gas}^*						1.00

Table 7: Comparison of sample averages of adjusted coefficients of determinations for the considered one-factor and multi-factor model specifications.

$\bar{R}_{adj,i}^2$	r_m^*	r_{eua}^*	r_{el}^*	r_{es}^*	r_{oil}^*	r_{gas}^*
1-factor models	0.21	0.10	0.19	0.04	0.03	0.03
2-factor model	- - - 0.27 - - -					
3-factor model	- - - - - 0.3 - - - - -					
4-factor model	- - - - - - - 0.31 - - - - -					
5-factor model	- - - - - - - - - 0.25 - - - - -					
6-factor model	- - - - - - - - - - - 0.36 - - - - -					

average. Even in the 2-factor model, only the sensitivity factors for 10 out of 22 companies are significantly different from zero with respect to the emission certificate price return (see Table C.17).

All multi-factor model specifications show an improved explanatory power compared to the CAPM measured by the adjusted coefficient of determination⁸ \bar{R}_{adj}^2 as shown in Table 7.

3.4. Technology characteristics in the multi-factor models

Again, multiple, cross-sectional OLS regressions according to Eqn. (6) are performed to determine technology-specific sensitivity factors. Thereby, the analysis is limited to the 2-factor model specification with market return and emission certificate price return representing the regressors, since the other risk factors yield non-significant coefficients for even more companies.

In this two-factor analysis, renewable (i.e. mostly hydro), gas, and coal technology classes exhibit in the second pass regression sensitivities significantly greater than zero with respect to the market portfolio (cf. Table 8). As in the one-factor model specification, we can again observe significant differences between

⁸The adjusted coefficient of determination is computed by $R_{adj,i}^2 = 1 - (1 - R_i^2) \frac{T-1}{T-K-1}$, with K denoting the number of applied risk factors (without constant).

Table 8: Unlevered technology-specific coefficient estimates $\hat{\lambda}_m^d$, $\hat{\lambda}_{eua}^d$ and standard errors from multiple OLS regressions corresponding to the two-factor model using market return and EUA future price return as relevant regressors. Thereby, *** denotes significance of the coefficient at the 1% level, ** at the 5% level and * at the 10% level.

	$\hat{\lambda}_{m,i}^d$		$\hat{\lambda}_{eua,i}^d$	
$\hat{\lambda}_{gas}^d$	0.274***	(0.094)	0.004	(0.046)
$\hat{\lambda}_{coal}^d$	0.267**	(0.104)	0.075	(0.051)
$\hat{\lambda}_{nuc}^d$	0.216	(0.136)	0.14*	(0.067)
$\hat{\lambda}_{misc}^d$	0.033	(0.375)	-0.06	(0.184)
$\hat{\lambda}_{renew}^d$	0.516***	(0.100)	0.068	(0.049)

the market risk factor coefficients for gas-renewable and nuclear-renewable technology combinations. In contrast, most technology classes do not show significant sensitivities with respect to the EUA price returns: Only the nuclear technology shows a sensitivity coefficient which satisfies a weak confidence level of 10%. This could be the fact that high certificate prices lead to high electricity prices and therewith to higher profits of the nuclear technology while the EUA price represents for all other thermal technologies also a cost factor.

4. Concluding remarks

This article investigates the systematic risk of European power generation companies relative to the overall market using an approach based on the CAPM and multi-factor market models. The analysis of historical stock returns of 22 European power companies over the period 2005–2010 supports the validity of the CAPM with respect to the sample. However, the explanatory power of the standard CAPM can be improved by including other energy-related and macroeconomic measures such as EUA prices, power prices, oil prices, gas prices, or an economic sentiment indicator as additional risk factors in multivariate model specifications.

A simple but powerful estimation approach is examined to derive technology-specific beta factors for the standard CAPM. The results indicate that gas and coal technologies face significantly lower beta factors with respect to the market portfolio as renewable (dominated by hydro) technologies, which show the highest market portfolio sensitivity across the sample. While the proposed model specification can be transferred to various markets, one should note that the estimated technology betas refer only to the European liberalized electricity markets. For companies with operational focus in non-liberalized electricity systems or in markets that differ in basic regulatory setting, technology betas may vary substantially. Therewith, this paper contributes an easy-applicable valuation approach which may be used in practice both for single power plant valuations as well as portfolio considerations.

References

- BAFA, 2010. Bafa energy statistics. Bundesamt für Wirtschaft und Ausfuhrkontrolle (German Federal Office of Economics and Export Control).
URL <http://www.bafa.de/>
- Boquist, J., Moore, W., 1983. Estimating the systematic risk of an industry segment: A mathematical programming approach. *Financial Management* 12 (4), 11–18.
- Botterud, A., Ilic, M., Wangensteen, I., 2003. Optimization of Generation Investments Under Uncertainty in Restructured Power Markets. In: *Proceedings of Intelligent System Application to Power System*. Lemnos, Greece.
- Bower, D., Bower, R., Logue, D., 1984. Arbitrage Pricing Theory and utility stock returns. *Journal of Finance*, 1041–1054.
- Boyer, M., Filion, D., 2007. Common and fundamental factors in stock returns of Canadian oil and gas companies. *Energy Economics* 29 (3), 428–453.
- Bubnys, E., 2005. Simulating and forecasting utility stock returns: Arbitrage pricing theory vs. capital asset pricing model. *Financial Review* 25 (1), 1–23.
- Chow, G., 1960. Tests of equality between sets of coefficients in two linear regressions. *Econometrica: Journal of the Econometric Society*, 591–605.
- Chuang, A., Wu, F., Varaiya, P., Nov. 2001. A game-theoretic model for generation expansion planning: problem formulation and numerical comparisons. *IEEE Journal on Power Systems* 16 (4), 885–891.
- Cochrane, J., 2001. *Asset Pricing*. Princeton University Press.
- DB, 2011. Money market rates. Deutsche Bundesbank statistics.
URL <http://www.bundesbank.de/statistik/statistik.php>
- ECB, 2011. ECB data warehouse. European Central Bank.
URL <http://sdw.ecb.europa.eu/>
- EEX, 2011. EEX historical data. European Energy Exchange.
URL <http://www.eex.com/>
- Ehrhardt, M., Bhagwat, Y., 1991. A full-information approach for estimating divisional betas. *Financial Management* 20 (2), 60–69.
- EIA, 2011. Petroleum data. Energy Information Administration.
URL http://www.eia.doe.gov/oil_gas/petroleum/info_glance/petroleum.html
- Fama, E., MacBeth, J., 1973. Risk, return, and equilibrium: Empirical tests. *Journal of political economy* 81 (3), 607.
- Gibbons, M., Ross, S., Shanken, J., 1989. A test of the efficiency of a given portfolio. *Econometrica: Journal of the Econometric Society* 57 (5), 1121–1152.
- Gnansounou, E., Dong, J., Pierre, S., Quintero, A., 2004. Market oriented planning of power generation expansion using agent-based model. In: *Proc. IEEE PES Power Systems Conference and Exposition*. pp. 1306–1311 vol.3.
- Greene, W., Zhang, C., 2003. *Econometric analysis*, 5th Edition. Prentice hall New Jersey.
- Haas, R., Glachant, J., Auer, H., Keseric, N., Perez, Y., 2006. Electricity market reform – an international perspective. Elsevier, Ch. Competition in the continental European electricity market: despair or work in progress?, pp. 265–316.
- Hamada, R., 1972. The effect of the firm’s capital structure on the systematic risk of common stocks. *Journal of Finance* 27 (2), 435–452.
- Henriques, I., Sadorsky, P., 2007. Oil prices and the stock prices of alternative energy companies. *Energy Economics* 30, 998–1010.
- IFO, 2011. The ifo business climate for germany.
URL http://www.cesifo-group.de/portal/page/portal/ifoHome/a-winfo/d6zeitreihen/15reihen/_reihenkt
- Kaplan, P., Peterson, J., 1998. Full-information industry betas. *Financial Management* 27 (2), 85–93.

- KPMG, 2008. Kpmg's corporate and indirect tax rate survey 2008. Tech. rep., KPMG.
URL <http://www.kpmg.com/om/PDF/Corporate%20and%20Indirect%20Tax%20Rate%20Survey%202008.pdf>
- Leahy, J., Whited, T., 1996. The effect of uncertainty on investment: Some stylized facts. *Journal of Money, Credit and Banking*, 64–83.
- Lintner, J., 1965. The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets. *Review of Economics and Statistics* 47 (1), 13–37.
- Markowitz, H., 1952. Portfolio selection. *The Journal of Finance* 7 (1), 77–91.
- Mossin, J., 1966. Equilibrium in a capital asset market. *Econometrica* 34 (4), 768–783.
- Oren, S., Smith, S., Wilson, R., 1985. Capacity pricing. *Econometrica* 53, 545–566.
- Roques, F., Newbery, D., Nuttall, W., 2008. Fuel mix diversification incentives in liberalized electricity markets: A mean-variance portfolio theory approach. *Energy Economics* 30 (4), 1831–1849.
- Ross, S., 1976. The arbitrage theory of capital asset pricing. *Journal of Economic Theory* 13 (3), 341–60.
- Sadorsky, P., 2001. Risk factors in stock returns of Canadian oil and gas companies. *Energy Economics* 23 (1), 17–28.
- Sharpe, W., 1964. Capital asset prices: A theory of market equilibrium under conditions of risk. *Journal of Finance* 19 (3), 425–442.
- Zöttl, G., June 2008. On investment decisions in liberalized electricity markets: the impact of price caps at the spot market. CORE Discussion Paper 2008/37, Université catholique de Louvain,.
URL http://www.ires.ucl.ac.be/DP/IRES_DP/2008-28.pdf

Appendix A. Sample company overview

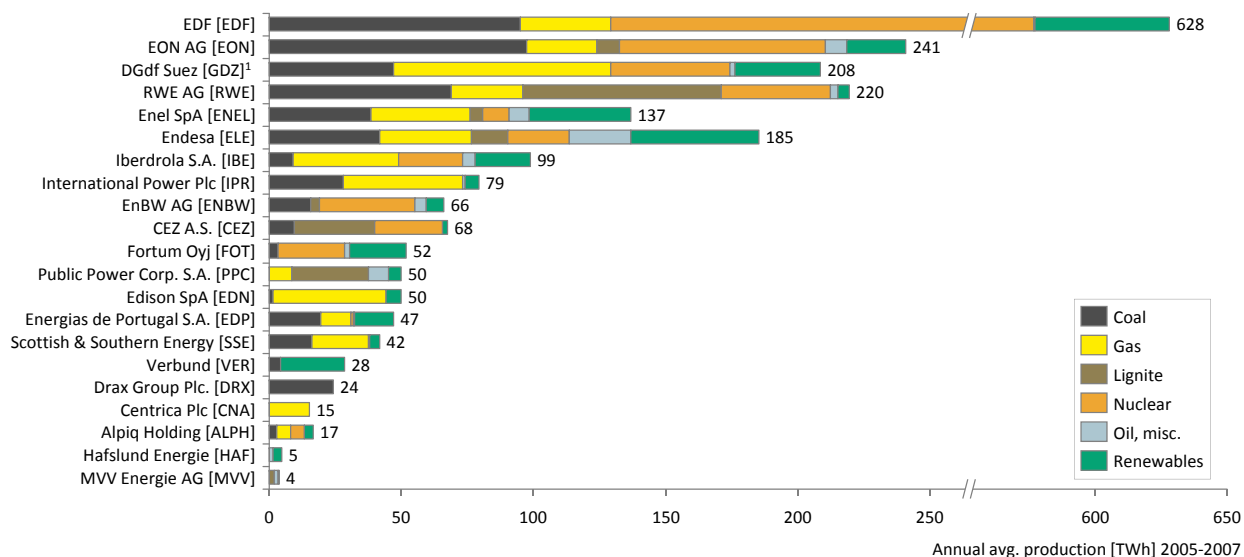


Figure A.3: Annual average power production and generation fuel mix of the sample companies 2005–2007

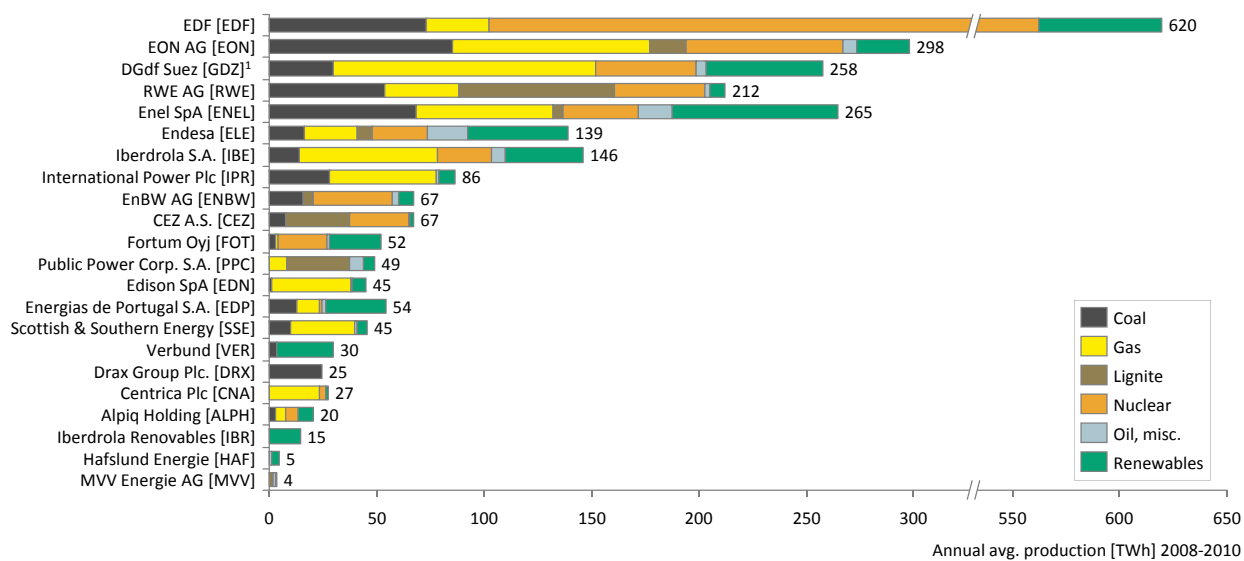


Figure A.4: Annual average power production and generation fuel mix of the sample companies 2008–2010

Table A.9: This table provides company names, respective stock exchange, summary statistics for the share price return r_i , and debt to equity ratios (D/E) for the sample companies in the relevant analysis periods.

Name	Symbol	Market	Combined period (2005-2010)			Period I (2005-2007)			Period II (2008-2010)		
			\bar{r}_i	σ_i	D/E	\bar{r}_i	σ_i	D/E	\bar{r}_i	σ_i	D/E
EDF	EDF	Paris	0.004	0.091	2.30	0.042	0.076	1.73	-0.023	0.092	2.86
EON AG	EON	Xetra	0.003	0.071	1.66	0.023	0.044	1.12	-0.017	0.086	2.20
Gdf Suez	GDZ	Paris	0.003	0.067	1.23	0.019	0.052	0.83	-0.008	0.075	1.62
RWE AG	RWE	Xetra	0.005	0.061	2.17	0.025	0.048	1.91	-0.016	0.066	2.43
Enel SpA	ENEL	Milan	-0.006	0.053	2.68	0.004	0.028	1.57	-0.015	0.069	3.78
Endesa	ELE	Madrid	0.006	0.096	1.39	0.023	0.071	1.23	-0.011	0.114	1.54
Iberdrola S.A.	IBE	Madrid	0.007	0.076	1.44	0.024	0.062	0.93	-0.011	0.086	1.95
International Power Plc	IPR	London	0.019	0.090	1.74	0.032	0.056	1.35	0.006	0.114	2.13
EnBW AG	ENBW	Xetra	0.007	0.062	2.34	0.022	0.066	1.81	-0.009	0.054	2.87
CEZ A.S.	CEZ	Prague	0.015	0.083	0.50	0.042	0.080	0.28	-0.012	0.076	0.72
Fortum Oyj	FOT	Helsinki	0.010	0.079	0.59	0.025	0.070	0.45	-0.005	0.086	0.74
DEI (Public Power Corporation)	DEI	Athens	-0.004	0.095	2.45	0.018	0.071	1.49	-0.027	0.110	3.41
Edison SpA	EDN	Milan	-0.005	0.080	1.27	0.010	0.045	0.95	-0.020	0.102	1.59
Energias de Portugal S.A.	EDP	Lisbon	0.003	0.059	2.25	0.020	0.043	1.58	-0.014	0.067	2.91
Scottish & Southern Energy	SSE	London	0.006	0.048	1.06	0.018	0.040	0.68	-0.007	0.052	1.43
Verbund	VER	Vienna	0.011	0.089	0.51	0.033	0.075	0.36	-0.010	0.097	0.66
Drax Group Plc	DRX	London	-0.002	0.093	0.63	0.009	0.100	0.49	-0.010	0.088	0.77
Centrica Plc	CNA	London	0.008	0.057	1.01	0.013	0.044	1.07	0.003	0.068	0.96
Alpiq Holding	ALPH	Zurich	0.012	0.084	1.09	0.035	0.083	1.26	-0.011	0.080	0.91
MVV Energie AG	MVV	Xetra	0.010	0.051	1.62	0.022	0.063	1.96	-0.003	0.030	1.28
Hafslund Energie	HNA	Oslo	0.013	0.101	1.04	0.044	0.095	0.72	-0.017	0.098	1.36
Iberdrola Renovables S.A.	IBR	Madrid	-0.014	0.104	0.89	NA	NA	NA	-0.014	0.104	0.89

Appendix B. Univariate regression results

Table B.10: 2005–2010 regression results with estimates for firm-specific equity coefficients α_i and $\beta_{m,i}$ for the standard CAPM model with DJ Euro Stoxx Utilities index as the relevant market portfolio. Standard errors are provided in parentheses. Thereby, *** denotes significance of the coefficient at the 1% level, ** at the 5% level and * at the 10% level.

Company	$\hat{\alpha}_i$		$\hat{\beta}_{m,i}$		R^2
EDF	0.002	(0.009)	1.195***	(0.199)	0.38
EON	-0.001	(0.007)	0.8***	(0.162)	0.26
GDZ	0.002	(0.008)	0.522***	(0.174)	0.13
RWE	0.001	(0.006)	0.633***	(0.142)	0.22
ENEL	-0.01*	(0.005)	0.696***	(0.114)	0.35
ELE	0.002	(0.011)	0.752***	(0.238)	0.12
IBE	0.002	(0.008)	0.762***	(0.180)	0.20
IPR	0.013	(0.008)	1.378***	(0.174)	0.47
ENBW	0.003	(0.007)	0.415**	(0.158)	0.09
CEZ	0.01	(0.009)	0.909***	(0.190)	0.25
FOT	0.006	(0.008)	0.929***	(0.179)	0.28
DEI	-0.009	(0.010)	0.795***	(0.232)	0.14
EDN	-0.009	(0.009)	0.784***	(0.190)	0.20
EDP	0	(0.006)	0.619***	(0.137)	0.23
SSE	0.003	(0.005)	0.457***	(0.114)	0.19
VER	0.006	(0.009)	0.962***	(0.206)	0.24
DRX	-0.004	(0.011)	0.733***	(0.236)	0.14
CNA	0.005	(0.007)	0.36**	(0.146)	0.08
ALPH	0.007	(0.009)	0.92***	(0.194)	0.24
MVV	0.016**	(0.007)	0.444***	(0.115)	0.21
HNA	0.008	(0.010)	1.267***	(0.220)	0.32
IBR	-0.006	(0.017)	0.827**	(0.319)	0.17
Mean	0.002	(0.008)	0.780	(0.183)	0.22

Table B.11: 2005–2007 and 2008–2010 regression results with estimates for firm-specific equity coefficients α_i and $\beta_{m,i}$ for the standard CAPM model with DJ Euro Stoxx Utilities index as the relevant market portfolio. Standard errors are provided in parentheses. Thereby, *** denotes significance of the coefficient at the 1% level, ** at the 5% level and * at the 10% level.

Company	Period I (2005-2007)					Period II (2008-2010)					Chow test	
	$\hat{\alpha}_i$		$\hat{\beta}_{m,i}$		R^2	$\hat{\alpha}_i$		$\hat{\beta}_{m,i}$		R^2	t-stat	(p-value)
EDF	0.015	(0.017)	1.242**	(0.443)	0.26	-0.01	(0.013)	0.369***	(0.247)	0.33	0.14	(0.868)
EON	0.012	(0.009)	0.435*	(0.243)	0.09	-0.007	(0.013)	0.331***	(0.248)	0.23	0.97	(0.385)
GDZ	0.004	(0.011)	0.738**	(0.303)	0.21	-0.004	(0.013)	0.199*	(0.239)	0.05	0.23	(0.799)
RWE	0.011	(0.009)	0.601**	(0.256)	0.14	-0.01	(0.011)	0.193**	(0.199)	0.14	1.44	(0.245)
ENEL	-0.006	(0.005)	0.363**	(0.148)	0.15	-0.005	(0.009)	0.234***	(0.179)	0.38	1.70	(0.190)
ELE	0.015	(0.014)	0.311	(0.408)	0.02	-0.001	(0.018)	0.408**	(0.349)	0.12	0.51	(0.603)
IBE	0.009	(0.012)	0.644*	(0.338)	0.10	-0.002	(0.013)	0.315***	(0.255)	0.18	0.20	(0.817)
IPR	0.011	(0.010)	0.934***	(0.285)	0.24	0.027**	(0.013)	0.653***	(0.250)	0.55	2.66	(0.077)
ENBW	0.006	(0.013)	0.716*	(0.363)	0.10	-0.008	(0.009)	0.069	(0.179)	0.01	1.79	(0.174)
CEZ	0.018	(0.015)	1.129**	(0.422)	0.17	-0.004	(0.012)	0.439***	(0.226)	0.19	1.65	(0.199)
FOT	0.006	(0.013)	0.848**	(0.376)	0.13	0.007	(0.012)	0.624***	(0.235)	0.31	0.04	(0.961)
DEI	0.007	(0.014)	0.446	(0.404)	0.03	-0.017	(0.018)	0.225**	(0.339)	0.12	0.62	(0.543)
EDN	0	(0.009)	0.356	(0.253)	0.06	-0.009	(0.016)	0.433***	(0.301)	0.19	0.73	(0.487)
EDP	0.005	(0.008)	0.658***	(0.225)	0.20	-0.008	(0.011)	0.167**	(0.204)	0.14	0.73	(0.484)
SSE	0.01	(0.008)	0.308	(0.228)	0.05	-0.002	(0.008)	0.221***	(0.154)	0.18	0.60	(0.552)
VER	0.009	(0.014)	1.082***	(0.395)	0.18	0	(0.015)	0.572***	(0.285)	0.19	0.29	(0.746)
DRX	-0.006	(0.024)	0.589	(0.652)	0.04	0	(0.014)	0.52***	(0.257)	0.20	0.32	(0.729)
CNA	0.005	(0.009)	0.246	(0.254)	0.03	0.008	(0.011)	0.249*	(0.215)	0.07	0.16	(0.848)
ALPH	0.014	(0.016)	0.98**	(0.451)	0.12	-0.002	(0.012)	0.465***	(0.226)	0.25	0.51	(0.601)
MVV	0	(0.011)	1.031***	(0.320)	0.23	-0.003	(0.005)	0.04	(0.097)	-0.01	6.32	(0.003)
HNA	0.013	(0.017)	1.446***	(0.493)	0.20	-0.004	(0.014)	0.553***	(0.266)	0.31	0.73	(0.484)
IBR	NA	NA	NA	NA	NA	-0.006	(0.017)	0.523**	(0.319)	0.14	NA	NA
Mean	0.007	(0.012)	0.719	(0.346)	0.13	-0.003	(0.013)	0.355	(0.240)	0.19		

Table B.12: 2005–2010 regression results with estimates for firm-specific equity coefficients α_i and $\beta_{el,i}$ with returns of EEX Phelix base front year futures (EEX, 2011) as considered risk factor. Standard errors are provided in parentheses. Thereby, *** denotes significance of the coefficient at the 1% level, ** at the 5% level and * at the 10% level.

Company	$\hat{\alpha}_i$	$\hat{\beta}_{el,i}$	R^2
EDF	0.001*** (0.012)	0.309* (0.165)	0.06
EON	-0.001*** (0.008)	0.299** (0.121)	0.08
GDZ	0.001*** (0.009)	0.173 (0.123)	0.03
RWE	0.001*** (0.007)	0.242** (0.104)	0.07
ENEL	-0.008*** (0.006)	0.036 (0.095)	0.00
ELE	0.004*** (0.011)	0.07 (0.171)	0.00
IBE	0.004*** (0.009)	0.069 (0.136)	0.00
IPR	0.015*** (0.011)	0.287* (0.157)	0.05
ENBW	0.004*** (0.007)	0.101 (0.111)	0.01
CEZ	0.009*** (0.009)	0.575*** (0.130)	0.22
FOT	0.004*** (0.008)	0.593*** (0.123)	0.25
DEI	-0.006*** (0.011)	-0.021 (0.169)	0.00
EDN	-0.008*** (0.009)	0.204 (0.140)	0.03
EDP	0.002*** (0.007)	-0.089 (0.104)	0.01
SSE	0.003*** (0.006)	0.167** (0.083)	0.05
VER	0.005*** (0.009)	0.698*** (0.135)	0.28
DRX	-0.005*** (0.011)	0.535*** (0.156)	0.17
CNA	0.006*** (0.007)	0.01 (0.102)	0.00
ALPH	0.008*** (0.010)	0.303** (0.146)	0.06
MVV	0.007*** (0.006)	0.081 (0.089)	0.01
HNA	0.009*** (0.012)	0.419** (0.173)	0.08
IBR	-0.016*** (0.018)	0.167 (0.213)	0.02
Mean	0.002 (0.009)	0.238 (0.134)	0.07

Table B.13: 2005–2010 regression results with estimates for firm-specific equity coefficients α_i and $\beta_{oil,i}$ with returns of WTI crude oil futures with four months to delivery (EIA, 2011) as considered risk factor. Standard errors are provided in parentheses. Thereby, *** denotes significance of the coefficient at the 1% level, ** at the 5% level and * at the 10% level.

Company	$\hat{\alpha}_i$	$\hat{\beta}_{oil,i}$	R^2
EDF	0 (0.012)	0.225 (0.148)	0.04
EON	-0.002 (0.008)	0.218** (0.104)	0.06
GDZ	0.002 (0.009)	-0.049 (0.111)	0.00
RWE	0.001 (0.007)	0.122 (0.090)	0.03
ENEL	-0.008 (0.006)	0.066 (0.080)	0.01
ELE	0.007 (0.011)	-0.247* (0.142)	0.04
IBE	0.005 (0.009)	-0.045 (0.115)	0.00
IPR	0.014 (0.011)	0.265** (0.133)	0.05
ENBW	0.003 (0.007)	0.106 (0.094)	0.02
CEZ	0.009 (0.009)	0.304** (0.119)	0.08
FOT	0.003 (0.009)	0.43*** (0.109)	0.18
DEI	-0.007 (0.011)	0.064 (0.143)	0.00
EDN	-0.01 (0.009)	0.257** (0.117)	0.06
EDP	0.001 (0.007)	0.059 (0.089)	0.01
SSE	0.003 (0.006)	0.045 (0.072)	0.01
VER	0.005 (0.010)	0.349*** (0.128)	0.10
DRX	-0.006 (0.012)	0.353** (0.144)	0.09
CNA	0.007 (0.007)	-0.072 (0.086)	0.01
ALPH	0.008 (0.010)	0.138 (0.126)	0.02
MVV	0.007 (0.006)	0.043 (0.076)	0.00
HNA	0.008 (0.012)	0.307** (0.148)	0.06
IBR	-0.016 (0.018)	-0.033 (0.189)	0.00
Mean	0.002 (0.009)	0.132 (0.116)	0.04

Table B.14: 2005–2010 regression results with estimates for firm-specific equity coefficients α_i and $\beta_{es,i}$ with monthly returns of the IFO Business Climate Index for Germany (IFO, 2011) as considered risk factor. Standard errors are provided in parentheses. Thereby, *** denotes significance of the coefficient at the 1% level, ** at the 5% level and * at the 10% level.

Company	$\hat{\alpha}_i$		$\hat{\beta}_{es,i}$		R^2
EDF	0.002	(0.012)	1.205*	(0.615)	0.06
EON	0.001	(0.008)	1.124**	(0.449)	0.08
GDZ	0.002	(0.009)	0.4	(0.464)	0.01
RWE	0.003	(0.007)	0.611	(0.393)	0.03
ENEL	-0.008	(0.006)	1.028***	(0.329)	0.12
ELE	0.004	(0.011)	0.96	(0.622)	0.03
IBE	0.005	(0.009)	0.862*	(0.492)	0.04
IPR	0.017*	(0.010)	1.644***	(0.563)	0.11
ENBW	0.005	(0.007)	0.796*	(0.401)	0.05
CEZ	0.013	(0.009)	1.26**	(0.524)	0.08
FOT	0.008	(0.009)	1.812***	(0.479)	0.17
DEI	-0.006	(0.011)	0.753	(0.619)	0.02
EDN	-0.007	(0.009)	1.194**	(0.507)	0.07
EDP	0.001	(0.007)	0.788**	(0.376)	0.06
SSE	0.004	(0.006)	0.517*	(0.309)	0.04
VER	0.009	(0.010)	1.13*	(0.571)	0.05
DRX	-0.004	(0.012)	0.555	(0.635)	0.01
CNA	0.006	(0.007)	0.649*	(0.372)	0.04
ALPH	0.01	(0.010)	0.558	(0.552)	0.01
MVV	0.008	(0.006)	0.489	(0.328)	0.03
HNA	0.012	(0.012)	1.043	(0.654)	0.04
IBR	-0.016	(0.018)	0.648	(0.769)	0.02
Mean	0.003	(0.009)	0.910	(0.501)	0.05

Table B.15: 2005–2010 regression results with estimates for firm-specific equity coefficients α_i and $\beta_{eua,i}$ with returns of EUA front year futures (EEX, 2011) as considered risk factor. Standard errors are provided in parentheses. Thereby, *** denotes significance of the coefficient at the 1% level, ** at the 5% level and * at the 10% level.

Company	$\hat{\alpha}_i$	$\hat{\beta}_{eua,i}$	R^2
EDF	0.002 (0.011)	0.392*** (0.098)	0.22
EON	0 (0.008)	0.349*** (0.078)	0.25
GDZ	0.002 (0.008)	0.257*** (0.074)	0.17
RWE	-0.001 (0.007)	0.223*** (0.069)	0.15
ENEL	-0.007 (0.007)	0.105 (0.067)	0.04
ELE	0.002 (0.013)	0.011 (0.118)	0.00
IBE	0.003 (0.010)	0.181* (0.093)	0.06
IPR	0.014 (0.012)	0.234** (0.110)	0.07
ENBW	-0.002 (0.006)	0.161*** (0.060)	0.11
CEZ	0.005 (0.008)	0.375*** (0.074)	0.30
FOT	0.008 (0.008)	0.351*** (0.079)	0.25
DEI	-0.004 (0.013)	0.122 (0.119)	0.02
EDN	-0.009 (0.010)	0.216** (0.096)	0.08
EDP	0.001 (0.008)	0.136* (0.073)	0.06
SSE	0.003 (0.006)	0.092 (0.058)	0.04
VER	0.004 (0.010)	0.446*** (0.093)	0.28
DRX	-0.004 (0.012)	0.185* (0.108)	0.05
CNA	0.007 (0.008)	0.055 (0.072)	0.01
ALPH	0.009 (0.010)	0.245*** (0.090)	0.11
MVV	0.007 (0.006)	0.169*** (0.053)	0.15
HNA	0.007 (0.012)	0.247** (0.113)	0.07
IBR	-0.016 (0.018)	-0.034 (0.187)	0.00
Mean	0.001 (0.010)	0.205 (0.090)	0.11

Table B.16: 2005–2010 regression results with estimates for firm-specific equity coefficients α_i and $\beta_{gas,i}$ with German gas import prices (BAFA, 2010) as considered risk factor. Standard errors are provided in parentheses. Thereby, *** denotes significance of the coefficient at the 1% level, ** at the 5% level and * at the 10% level.

Company	$\hat{\alpha}_i$		$\hat{\beta}_{gas,i}$		R^2
EDF	0.002	(0.012)	-0.476	(0.288)	0.04
EON	0.004	(0.008)	-0.522**	(0.200)	0.09
GDZ	0.002	(0.009)	-0.229	(0.215)	0.02
RWE	0.003	(0.007)	-0.091	(0.178)	0.00
ENEL	-0.005	(0.006)	-0.438***	(0.148)	0.11
ELE	0.007	(0.011)	-0.421	(0.278)	0.03
IBE	0.009	(0.009)	-0.591***	(0.213)	0.10
IPR	0.02*	(0.011)	-0.478*	(0.260)	0.05
ENBW	0.007	(0.007)	-0.369**	(0.179)	0.06
CEZ	0.017*	(0.010)	-0.544**	(0.234)	0.07
FOT	0.01	(0.009)	-0.307	(0.232)	0.02
DEI	-0.003	(0.011)	-0.481*	(0.273)	0.04
EDN	-0.003	(0.009)	-0.611***	(0.223)	0.10
EDP	0.003	(0.007)	-0.236	(0.171)	0.03
SSE	0.005	(0.006)	-0.123	(0.140)	0.01
VER	0.011	(0.011)	-0.263	(0.260)	0.01
DRX	-0.005	(0.012)	0.152	(0.296)	0.00
CNA	0.007	(0.007)	-0.127	(0.169)	0.01
ALPH	0.011	(0.010)	-0.174	(0.247)	0.01
MVV	0.008	(0.006)	0.015	(0.149)	0.00
HNA	0.015	(0.012)	-0.519*	(0.290)	0.04
IBR	-0.016	(0.017)	-0.527	(0.357)	0.06
Mean	0.005	(0.009)	-0.335	(0.227)	0.04

Appendix C. Multivariate regression results

Table C.17: Two-factor model: 2005–2010 regression results with estimates for firm-specific equity coefficients $\lambda_{0,i}$, $\lambda_{m,i}$ and $\lambda_{eua,i}$ with excess returns of the DJ Euro Stoxx Utilities index (ECB, 2011) and EUA front year futures (EEX, 2011) as considered risk factors. Standard errors are provided in parentheses. Thereby, *** denotes significance of the coefficient at the 1% level, ** at the 5% level and * at the 10% level.

Company	$\hat{\lambda}_{0,i}$	$\hat{\lambda}_{m,i}^*$	$\hat{\lambda}_{eua,i}^*$	R_{adj}^2
EDF	0.002 (0.009)	1.007*** (0.191)	0.263*** (0.084)	0.47
EON	-0.001 (0.008)	0.642*** (0.168)	0.267*** (0.074)	0.40
GDZ	0.001 (0.008)	0.357** (0.168)	0.21*** (0.074)	0.23
RWE	-0.001 (0.007)	0.508*** (0.152)	0.158** (0.067)	0.28
ENEL	-0.008 (0.006)	0.712*** (0.130)	0.014 (0.057)	0.36
ELE	0.001 (0.012)	0.775*** (0.263)	-0.087 (0.116)	0.13
IBE	0.002 (0.009)	0.684*** (0.205)	0.094 (0.090)	0.21
IPR	0.012 (0.009)	1.32*** (0.199)	0.067 (0.088)	0.47
ENBW	-0.003 (0.006)	0.212 (0.142)	0.134** (0.062)	0.14
CEZ	0.004 (0.007)	0.541*** (0.162)	0.306*** (0.071)	0.41
FOT	0.008 (0.007)	0.751*** (0.163)	0.256*** (0.072)	0.45
DEI	-0.005 (0.012)	0.801*** (0.265)	0.02 (0.117)	0.15
EDN	-0.01 (0.010)	0.699*** (0.211)	0.127 (0.093)	0.22
EDP	0 (0.007)	0.607*** (0.155)	0.059 (0.068)	0.25
SSE	0.002 (0.006)	0.427*** (0.128)	0.038 (0.056)	0.19
VER	0.003 (0.009)	0.654*** (0.205)	0.362*** (0.090)	0.39
DRX	-0.004 (0.011)	0.665*** (0.248)	0.1 (0.108)	0.15
CNA	0.007 (0.008)	0.361** (0.167)	0.009 (0.073)	0.08
ALPH	0.008 (0.009)	0.774*** (0.191)	0.146* (0.084)	0.30
MVV	0.006 (0.006)	0.204 (0.124)	0.143** (0.054)	0.18
HNA	0.005 (0.010)	1.12*** (0.227)	0.104 (0.100)	0.34
IBR	-0.006 (0.017)	0.892** (0.329)	-0.147 (0.176)	0.19
Mean	0.001 (0.009)	0.669 (0.191)	0.120 (0.085)	0.27

Table C.18: Three-factor model: 2005–2010 regression results with estimates for firm-specific equity coefficients $\lambda_{0,i}$, $\lambda_{m,i}$, $\lambda_{eua,i}$, and $\lambda_{el,i}$ with excess returns of the DJ Euro Stoxx Utilities index (ECB, 2011), EUA front year futures (EEX, 2011), and Phelix base front year futures (EEX, 2011) as considered risk factors. Standard errors are provided in parentheses. Thereby, *** denotes significance of the coefficient at the 1% level, ** at the 5% level and * at the 10% level.

Company	$\hat{\lambda}_{0,i}$	$\hat{\lambda}_{m,i}^*$	$\hat{\lambda}_{eua,i}^*$	$\hat{\lambda}_{el,i}^*$	R_{adj}^2
EDF	0.002 (0.009)	1.033*** (0.195)	0.289*** (0.092)	-0.099 (0.142)	0.48
EON	-0.001 (0.008)	0.644*** (0.173)	0.269*** (0.081)	-0.007 (0.124)	0.40
GDZ	0.001 (0.008)	0.374** (0.173)	0.226*** (0.081)	-0.062 (0.124)	0.23
RWE	-0.001 (0.007)	0.498*** (0.156)	0.149** (0.073)	0.034 (0.112)	0.28
ENEL	-0.008 (0.006)	0.754*** (0.131)	0.054 (0.061)	-0.154 (0.094)	0.39
ELE	0.001 (0.012)	0.796*** (0.270)	-0.068 (0.127)	-0.076 (0.194)	0.13
IBE	0.003 (0.009)	0.738*** (0.208)	0.145 (0.097)	-0.196 (0.149)	0.23
IPR	0.012 (0.009)	1.328*** (0.205)	0.075 (0.096)	-0.031 (0.148)	0.47
ENBW	-0.003 (0.006)	0.224 (0.146)	0.145** (0.068)	-0.041 (0.105)	0.14
CEZ	0.003 (0.007)	0.45*** (0.156)	0.222*** (0.073)	0.329*** (0.112)	0.49
FOT	0.006 (0.007)	0.641*** (0.151)	0.152** (0.071)	0.401*** (0.109)	0.55
DEI	-0.005 (0.012)	0.864*** (0.270)	0.079 (0.127)	-0.229 (0.194)	0.17
EDN	-0.01 (0.010)	0.711*** (0.217)	0.138 (0.102)	-0.044 (0.156)	0.22
EDP	0.002 (0.007)	0.695*** (0.149)	0.141** (0.070)	-0.318*** (0.107)	0.35
SSE	0.002 (0.006)	0.411*** (0.131)	0.023 (0.062)	0.057 (0.094)	0.20
VER	0.001 (0.009)	0.54*** (0.197)	0.256*** (0.092)	0.413*** (0.141)	0.46
DRX	-0.005 (0.011)	0.55** (0.241)	-0.014 (0.113)	0.437** (0.173)	0.24
CNA	0.007 (0.008)	0.384** (0.171)	0.03 (0.080)	-0.081 (0.123)	0.09
ALPH	0.007 (0.009)	0.748*** (0.196)	0.122 (0.092)	0.096 (0.141)	0.31
MVV	0.007 (0.006)	0.216* (0.127)	0.154** (0.060)	-0.042 (0.091)	0.19
HNA	0.005 (0.010)	1.087*** (0.233)	0.073 (0.109)	0.119 (0.167)	0.35
IBR	-0.007 (0.017)	0.847** (0.336)	-0.255 (0.222)	0.209 (0.258)	0.20
Mean	0.001 (0.009)	0.661 (0.192)	0.109 (0.093)	0.033 (0.139)	0.30

Table C.19: Four-factor model: 2005–2010 regression results with estimates for firm-specific equity coefficients $\lambda_{0,i}$, $\lambda_{m,i}$, $\lambda_{eua,i}$, $\lambda_{el,i}$, $\lambda_{es,i}$ with excess returns of the DJ Euro Stoxx Utilities index (ECB, 2011), EUA front year futures (EEX, 2011), Phelix base front year futures (EEX, 2011), and ifo Business Climate Index (IFO, 2011) as considered risk factors. Standard errors are provided in parentheses. Thereby, *** denotes significance of the coefficient at the 1% level, ** at the 5% level and * at the 10% level.

Company	$\hat{\lambda}_{0,i}$	$\hat{\lambda}_{m,i}^*$	$\hat{\lambda}_{eua,i}^*$	$\hat{\lambda}_{el,i}^*$	$\hat{\lambda}_{es,i}^*$	R_{adj}^2
EDF	0.002 (0.009)	1.081*** (0.216)	0.292*** (0.094)	-0.094 (0.150)	-0.289 (0.570)	0.48
EON	-0.001 (0.008)	0.616*** (0.192)	0.267*** (0.084)	-0.009 (0.132)	0.171 (0.506)	0.40
GDZ	0.001 (0.008)	0.435** (0.182)	0.231*** (0.079)	-0.057 (0.125)	-0.368 (0.480)	0.24
RWE	-0.001 (0.007)	0.514*** (0.171)	0.15** (0.075)	0.036 (0.118)	-0.096 (0.452)	0.28
ENEL	-0.007 (0.006)	0.675*** (0.140)	0.048 (0.061)	-0.16 (0.096)	0.48* (0.369)	0.41
ELE	0.001 (0.012)	0.754*** (0.263)	-0.071 (0.114)	-0.08 (0.181)	0.259** (0.693)	0.13
IBE	0.003 (0.009)	0.719*** (0.219)	0.143 (0.095)	-0.198 (0.151)	0.112 (0.578)	0.23
IPR	0.012 (0.009)	1.275*** (0.227)	0.071 (0.099)	-0.035 (0.156)	0.322 (0.598)	0.47
ENBW	-0.002 (0.006)	0.127 (0.155)	0.138** (0.068)	-0.049 (0.107)	0.58** (0.410)	0.18
CEZ	0.003 (0.007)	0.39** (0.169)	0.217*** (0.074)	0.324*** (0.117)	0.366 (0.447)	0.49
FOT	0.006 (0.006)	0.51*** (0.162)	0.143** (0.070)	0.391*** (0.112)	0.786* (0.427)	0.58
DEI	-0.005 (0.012)	0.877*** (0.299)	0.08 (0.130)	-0.228 (0.206)	-0.073 (0.790)	0.17
EDN	-0.009 (0.010)	0.615** (0.239)	0.131 (0.104)	-0.052 (0.164)	0.581 (0.630)	0.24
EDP	0.002 (0.007)	0.691*** (0.166)	0.14* (0.072)	-0.318*** (0.114)	0.022 (0.437)	0.35
SSE	0.002 (0.006)	0.392*** (0.143)	0.022 (0.062)	0.055 (0.099)	0.118 (0.378)	0.20
VER	0.001 (0.009)	0.533** (0.218)	0.256*** (0.095)	0.412*** (0.150)	0.041 (0.576)	0.46
DRX	-0.005 (0.011)	0.627** (0.263)	-0.009 (0.114)	0.445** (0.182)	-0.478 (0.695)	0.25
CNA	0.007 (0.008)	0.321* (0.182)	0.026 (0.079)	-0.086 (0.125)	0.379 (0.479)	0.10
ALPH	0.007 (0.009)	0.839*** (0.212)	0.128 (0.092)	0.104 (0.146)	-0.553 (0.559)	0.32
MVV	0.007 (0.006)	0.215 (0.141)	0.154** (0.061)	-0.042 (0.097)	0.007 (0.371)	0.19
HNA	0.005 (0.010)	1.151*** (0.258)	0.078 (0.112)	0.125 (0.178)	-0.388 (0.680)	0.35
IBR	-0.005 (0.018)	0.963** (0.395)	-0.247 (0.226)	0.215 (0.268)	-0.493 (0.976)	0.21
Mean	0.001 (0.009)	0.651 (0.209)	0.109 (0.094)	0.032 (0.144)	0.068 (0.550)	0.31

Table C.20: Five-factor model: 2005–2010 regression results with estimates for firm-specific equity coefficients $\lambda_{0,i}$, $\lambda_{m,i}$, $\lambda_{eua,i}$, $\lambda_{el,i}$, $\lambda_{es,i}$, and $\lambda_{oil,i}$ with excess returns of the DJ Euro Stoxx Utilities index (ECB, 2011), EUA front year futures (EEX, 2011), Phelix base front year futures (EEX, 2011), ifo Business Climate Index (IFO, 2011), and WTI oil futures (EIA, 2011) as considered risk factors. Standard errors are provided in parentheses. Thereby, *** denotes significance of the coefficient at the 1% level, ** at the 5% level and * at the 10% level.

Company	$\hat{\lambda}_{0,i}$		$\hat{\lambda}_{m,i}^*$		$\hat{\lambda}_{eua,i}^*$		$\hat{\lambda}_{el,i}^*$		$\hat{\lambda}_{es,i}^*$		$\hat{\lambda}_{oil,i}^*$		R_{adj}^2
EDF	0.002	(0.009)	1.085***	(0.216)	0.3***	(0.094)	-0.067	(0.150)	-0.152	(0.570)	-0.085	(0.140)	0.48
EON	-0.001	(0.008)	0.617***	(0.192)	0.27***	(0.084)	0	(0.132)	0.218	(0.506)	-0.029	(0.124)	0.40
GDZ	0.003	(0.007)	0.445**	(0.182)	0.259***	(0.079)	0.031	(0.125)	0.096	(0.480)	-0.283**	(0.118)	0.31
RWE	-0.001	(0.007)	0.519***	(0.171)	0.164**	(0.075)	0.078	(0.118)	0.127	(0.452)	-0.136	(0.111)	0.30
ENEL	-0.007	(0.006)	0.68***	(0.140)	0.063	(0.061)	-0.115	(0.096)	0.719*	(0.369)	-0.146	(0.090)	0.44
ELE	0.005	(0.011)	0.779***	(0.263)	0.001	(0.114)	0.138	(0.181)	1.414**	(0.693)	-0.704***	(0.170)	0.34
IBE	0.005	(0.009)	0.732***	(0.219)	0.179*	(0.095)	-0.088	(0.151)	0.693	(0.578)	-0.354**	(0.142)	0.31
IPR	0.013	(0.009)	1.278***	(0.227)	0.079	(0.099)	-0.009	(0.156)	0.462	(0.598)	-0.085	(0.147)	0.47
ENBW	-0.002	(0.006)	0.133	(0.155)	0.153**	(0.068)	-0.002	(0.107)	0.827**	(0.410)	-0.15	(0.101)	0.21
CEZ	0.004	(0.007)	0.395**	(0.169)	0.232***	(0.074)	0.369***	(0.117)	0.609	(0.447)	-0.148	(0.110)	0.51
FOT	0.006	(0.007)	0.509***	(0.162)	0.14*	(0.070)	0.38***	(0.112)	0.731*	(0.427)	0.034	(0.105)	0.58
DEI	-0.004	(0.012)	0.88***	(0.299)	0.089	(0.130)	-0.2	(0.206)	0.074	(0.790)	-0.09	(0.194)	0.17
EDN	-0.01	(0.010)	0.611**	(0.239)	0.121	(0.104)	-0.081	(0.164)	0.424	(0.630)	0.096	(0.154)	0.24
EDP	0.002	(0.007)	0.692***	(0.166)	0.143*	(0.072)	-0.31***	(0.114)	0.063	(0.437)	-0.025	(0.107)	0.35
SSE	0.003	(0.006)	0.397***	(0.143)	0.036	(0.062)	0.096	(0.099)	0.337	(0.378)	-0.134	(0.093)	0.23
VER	0.002	(0.009)	0.535**	(0.218)	0.261***	(0.095)	0.43***	(0.150)	0.132	(0.576)	-0.056	(0.141)	0.47
DRX	-0.006	(0.011)	0.617**	(0.263)	-0.028	(0.114)	0.384**	(0.182)	-0.791	(0.695)	0.191	(0.170)	0.27
CNA	0.008	(0.007)	0.33*	(0.182)	0.052	(0.079)	-0.007	(0.125)	0.798	(0.479)	-0.255**	(0.117)	0.17
ALPH	0.008	(0.009)	0.847***	(0.212)	0.149	(0.092)	0.167	(0.146)	-0.216	(0.559)	-0.205	(0.137)	0.35
MVV	0.007	(0.006)	0.217	(0.141)	0.16**	(0.061)	-0.024	(0.097)	0.103	(0.371)	-0.058	(0.091)	0.19
HNA	0.005	(0.010)	1.152***	(0.258)	0.081	(0.112)	0.133	(0.178)	-0.341	(0.680)	-0.029	(0.167)	0.35
IBR	-0.003	(0.017)	0.983**	(0.395)	-0.204	(0.226)	0.297	(0.268)	0.04	(0.976)	-0.284	(0.237)	0.25
Mean	0.002	(0.009)	0.656	(0.209)	0.123	(0.094)	0.073	(0.144)	0.289	(0.550)	-0.133	(0.135)	0.34

Table C.21: Six-factor model: 2005–2010 regression results with estimates for firm-specific equity coefficients $\lambda_{0,i}$, $\lambda_{m,i}$, $\lambda_{eua,i}$, $\lambda_{el,i}$, $\lambda_{es,i}$, $\lambda_{oil,i}$, and $\lambda_{gas,i}$ with excess returns of the DJ Euro Stoxx Utilities index (ECB, 2011), EUA front year futures (EEX, 2011), Phelix base front year futures (EEX, 2011), ifo Business Climate Index (IFO, 2011), WTI oil futures (EIA, 2011), and German gas import prices (BAFA, 2010) as considered risk factors. Standard errors are provided in parentheses. Thereby, *** denotes significance of the coefficient at the 1% level, ** at the 5% level and * at the 10% level.

Company	$\hat{\lambda}_{0,i}$	$\hat{\lambda}_{m,i}^*$	$\hat{\lambda}_{eua,i}^*$	$\hat{\lambda}_{el,i}^*$	$\hat{\lambda}_{es,i}^*$	$\hat{\lambda}_{oil,i}^*$	$\hat{\lambda}_{gas,i}^*$	R_{adj}^2
EDF	0.003 (0.009)	1.08*** (0.217)	0.286*** (0.097)	-0.061 (0.151)	-0.222 (0.580)	-0.074 (0.141)	0.286*** (0.097)	0.49
EON	0 (0.008)	0.608*** (0.187)	0.235*** (0.083)	0.018 (0.129)	0.05 (0.499)	-0.005 (0.121)	0.235*** (0.083)	0.44
GDZ	0.003 (0.007)	0.444** (0.184)	0.255*** (0.082)	0.033 (0.127)	0.075 (0.491)	-0.28** (0.119)	0.255*** (0.082)	0.31
RWE	-0.001 (0.007)	0.52*** (0.173)	0.166** (0.077)	0.077 (0.119)	0.135 (0.463)	-0.137 (0.112)	0.166** (0.077)	0.30
ENEL	-0.006 (0.006)	0.673*** (0.136)	0.037 (0.060)	-0.102 (0.094)	0.596 (0.363)	-0.129 (0.088)	0.037 (0.060)	0.48
ELE	0.005 (0.011)	0.773*** (0.263)	-0.024 (0.117)	0.151 (0.181)	1.296* (0.703)	-0.687*** (0.171)	-0.024 (0.117)	0.35
IBE	0.006 (0.009)	0.722*** (0.213)	0.139 (0.095)	-0.067 (0.147)	0.498 (0.569)	-0.327** (0.138)	0.139 (0.095)	0.36
IPR	0.013 (0.009)	1.271*** (0.226)	0.054 (0.100)	0.004 (0.156)	0.34 (0.604)	-0.068 (0.147)	0.054 (0.100)	0.49
ENBW	-0.001 (0.006)	0.127 (0.154)	0.132* (0.068)	0.009 (0.106)	0.723* (0.411)	-0.136 (0.100)	0.132* (0.068)	0.24
CEZ	0.004 (0.007)	0.386** (0.163)	0.198*** (0.073)	0.387*** (0.113)	0.442 (0.436)	-0.125 (0.106)	0.198*** (0.073)	0.55
FOT	0.006 (0.007)	0.508*** (0.163)	0.134* (0.073)	0.383*** (0.113)	0.705 (0.436)	0.037 (0.106)	0.134* (0.073)	0.58
DEI	-0.003 (0.012)	0.87*** (0.296)	0.051 (0.132)	-0.181 (0.205)	-0.113 (0.793)	-0.064 (0.193)	0.051 (0.132)	0.20
EDN	-0.009 (0.009)	0.6** (0.233)	0.079 (0.104)	-0.06 (0.161)	0.221 (0.623)	0.124 (0.151)	0.079 (0.104)	0.29
EDP	0.002 (0.007)	0.688*** (0.166)	0.129* (0.074)	-0.303** (0.115)	-0.003 (0.444)	-0.016 (0.108)	0.129* (0.074)	0.36
SSE	0.003 (0.006)	0.397*** (0.144)	0.036 (0.064)	0.096 (0.100)	0.338 (0.387)	-0.134 (0.094)	0.036 (0.064)	0.23
VER	0.002 (0.009)	0.535** (0.220)	0.258** (0.098)	0.431*** (0.152)	0.117 (0.589)	-0.054 (0.143)	0.258** (0.098)	0.47
DRX	-0.007 (0.011)	0.627** (0.264)	-0.008 (0.117)	0.377** (0.183)	-0.687 (0.708)	0.175 (0.171)	-0.008 (0.117)	0.28
CNA	0.008 (0.007)	0.331* (0.183)	0.056 (0.081)	-0.009 (0.127)	0.817 (0.490)	-0.258** (0.119)	0.056 (0.081)	0.17
ALPH	0.009 (0.009)	0.844*** (0.213)	0.138 (0.095)	0.173 (0.147)	-0.267 (0.570)	-0.198 (0.138)	0.138 (0.095)	0.35
MVV	0.007 (0.006)	0.219 (0.141)	0.17*** (0.063)	-0.029 (0.098)	0.151 (0.378)	-0.065 (0.092)	0.17*** (0.063)	0.20
HNA	0.006 (0.010)	1.145*** (0.257)	0.052 (0.114)	0.148 (0.177)	-0.479 (0.687)	-0.009 (0.167)	0.052 (0.114)	0.37
IBR	-0.004 (0.017)	0.943** (0.389)	-0.319 (0.236)	0.354 (0.266)	-0.302 (0.988)	-0.219 (0.237)	-0.319 (0.236)	0.30
Mean	0.002 (0.009)	0.651 (0.208)	0.102 (0.095)	0.083 (0.143)	0.201 (0.554)	-0.120 (0.134)	0.102 (0.095)	0.36