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Regulated Correlations — Climate Policy and Investment Risks

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Abstract

Investments in energy technologies are substantially governed by climate policy. We demonstrate analytically that price-based instruments, such as carbon-taxes, and quantity-based regulations, like emission trading systems, have distinct effects on the (co-)variance of power plant profits. If investors are risk-averse, these differences lead to divergent investment portfolios, breaking the equivalence of price- and quantity-based policy instruments under risk-neutrality. Using the European power sector as a case study, we calibrate an electricity market model with stochastic demand and find that, compared to a carbon tax, emissions trading pushes up the share of fossil fuel assets in a representative investor's portfolio since counteracting effects of permit and electricity prices reduce the covariance with other technologies, thereby enhancing the diversification value of these assets. Uncertainty about the stringency of carbon taxes leads to lower shares of fossil fuel assets with increasing risk aversion.

Keywords: Climate policy, Investment under uncertainty, Modern Portfolio Theory, Risk aversion.

JEL Codes: D81, E22, G11, P48.

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1 Introduction

To transition to a low-carbon economy, enormous investments in clean technologies are necessary. Global power sector investment was USD 0.82 trillion in 2021, but to reach net zero emissions by 2050, clean energy investments must triple the current level by 2030 (International Energy Agency, 2021). In the EU, annual investments of more than EUR 300 billion are already required in the period 2026-30 in order to be able to reach climate neutrality by 2050 (Klaassen & Steffen, 2023). However, since most of these investments will stem from the private sector, they will take place only if their risk-return profile aligns with the preferences of investors.

The assets originating from these investments often have a lifetime of several decades. Thus, investment decisions are taken under substantial risk concerning future market conditions: Sudden demand changes, as observed during the pandemic, unexpected changes in input costs, as seen for natural gas in Europe after the Russian invasion of Ukraine, or unforeseen policy changes as during the European debt crisis, where several countries scrapped their renewable support policies, lead to ex-ante uncertain returns of investment projects.

Most analyses of climate policies' effectiveness in incentivising investments in low-carbon technologies either ignore these risks entirely, assuming that investors have perfect foresight in a deterministic environment, or assume that investors are risk-neutral and investment decisions are derived thus solely from the first moment—the expected returns—of the return probability distributions.

Finance theory, most prominently in the seminal Modern Portfolio Theory (Markowitz, 1952), demonstrates that second moments of assets' return distributions are a key determinant of the composition of investment portfolios. However, the role of assets' return variance, as well as the correlation between asset returns, has been largely ignored in the literature on the effectiveness of climate policy instruments.

In this paper we show—to the best of our knowledge for the first time in an explicit model—how climate policy instruments shape the variance and covariance of and between assets and subsequently the generation-technology portfolio risk-averse investors are going to hold. We demonstrate that, although equivalent under risk-neutrality, price-based climate policy instruments such as carbon taxes lead to different investment allocations compared to quantity-based instruments such as emission trading systems (ETS) if investors are risk-averse.

We develop a model where an investor with constant relative risk aversion (CRRA) faces uncertain future demand and allocates capital across technologies that vary in profitability and carbon intensity. We demonstrate analytically that climate policy instruments not only affect the expected returns of the investment opportunities but also impact the variance and covariance of the return distributions and thus alter the equilibrium electricity-generation portfolio held by risk-averse investors. Calibrating this model to the European power sector, we find that the counteracting effect of emission permit and electricity prices—permit prices rise when electricity demand is high, reducing the profits of regulated fossil fuel plants in states of high demand—depress the variance of fossil fuel assets. In an ETS regime, the equilibrium portfolio of a risk-averse investor consists of a higher share of fossil fuel assets compared to a carbon tax regime, since under an ETS these assets contribute less to the portfolio risk. However, overall, there is less investment in generation capacity and electricity prices are higher.

An overwhelming share of investments into power-generating assets is done by firms (utility companies in particular). Despite being impersonal organisations, there is clear evidence for risk-averse behaviour in managerial decisions, often also due to the personal risk aversion of decision-makers (Bodnar, Giambona, Graham, & Harvey, 2019). This risk aversion is manifested by financial hedging activities of firms, such as using derivatives, to mitigate exposure to volatile commodity prices or output market risks.[1]

Energy System Models or Integrated Assessments Models—the classes of models often used to ex-ante assess climate policies and decarbonisation options—normally neglect this dimension of investment behaviour. In most models used to study the cost-effectiveness of policy interventions, the composition of the energy system is the consequence of cost-minimising under policy constraints, ignoring risk aversion of investors. As we show in this paper, this could lead to misguided projections and conclusions, as different policy interventions affect these risk-return profiles of decarbonisation options differently.

We are, of course, not the first to point out these gaps in the literature: Battiston, Monasterolo, Riahi, and Ruijven (2021) argue that climate-economy models need a better representation of financial markets and investor behaviour. By providing a framework

[1] Pérez-González and Yun (2013) document that energy-sector firms using weather derivatives have a higher stock market valuation than their non-hedging counterparts. Géczy, Minton, and Schrand (2006) show that firms in the natural gas industry also use, in addition to financial hedging, diversification as a risk management practice both by investing in different geographies and lines of business.

that incorporates risk-return trade-offs as well as the willingness to diversify the risk of different investment opportunities, our paper helps to close this gap. Peng et al. (2021) note that behavioural mechanisms are also not sufficiently incorporated in these models. Modelling risk aversion and portfolio choices explicitly, as we do in this paper, provides a richer behavioural framework for assessing climate policy options.

We start with developing a two-stage analytical model that enables investigating the impact of policies on the risk-return profile of technologies and investment decisions. The first-stage model is a stylised representation of the power market where multiple technologies that differ in costs and carbon intensity serve electricity demand and are exposed to different policy regimes. Comparative static exercises reveal then how demand shocks, conditionally on the policy regime, affect the profits of technologies differently. These exercises also demonstrate that the correlation of profits of generation technologies decreases with increasing policy cost differences between technologies. If policy stringency depends on demand, as it is the case in an ETS, the profit elasticity of the regulated technology with respect to demand is lower than if the policy stringency is demand-invariant such as in case of a carbon tax.

The second-stage model then takes the perspective of a risk-averse firm which maximises its risk-preferences adjusted portfolio value given the covariance structure of profits of generation technologies informed by the first-stage equilibrium model. This analysis shows that even if the expected relative profits of renewable assets increase marginally, the share of fossil fuel assets in the portfolio can nevertheless rise, conditional on the covariances and risk preferences.

The two stages of the analytical model are then conjoined in a calibrated stochastic electricity market investment model, where the expected returns of different assets are correlated through the mediation of equilibrium mechanisms. The simulations show that an ETS regime that is calibrated such that under risk neutrality it leads to the same abatement decisions as the carbon tax induces less emission reduction under risk aversion than the carbon tax. A risk-averse investor is less keen to fully exploit the profit potential of infrequent states of high demand, leading to lower output but higher electricity prices. This reduces permit prices and thus abatement relative to a no-climate-policy scenario. Relative to risk neutrality, a risk-averse investor reduces investments in coal and natural gas less. Under a carbon tax regime, we do not find such strong effects of risk aversion.

Another source of risk is the risk of a sudden and unexpected change in the policy regime after the investment took place. Based on a survey among renewable energy investors, Egli (2020) diagnoses that policy risk—the risk of earning less than expected revenues due to retroactive policy changes—is one of the most important and most frequently mentioned risks by investors. This is not surprising as several governments have retroactively changed the policy environment in the past, deteriorating the returns of renewable energy investments in particular. For instance, austerity measures following the European debt crisis led to retroactive downward adjustments in renewable support measures in several countries, including Italy, Spain, Greece, and the Czech Republic (FS-UNEP Centre & BNEF, 2013). We thus analyse, in addition, how the perceived risk of policy changes affects the equilibrium portfolio of risk-averse investors. It shows that uncertainty about the establishment of carbon taxes is a drag on the investment in fossil fuel technologies as the higher profit risk of these technologies reduces the attractiveness for risk-averse investors.

Since the seminal contribution of Weitzman (1974), economists have been thinking about how uncertainty affects the optimal choice of environmental policy instruments. Weitzman compared the effectiveness of price and quantity regulations under uncertain environmental damages versus uncertain pollution abatement costs and showed that the two types of regulation are not equivalently efficient depending on the source of uncertainty. In this paper, we also reveal a break of the equivalence between price- and quantity-based instruments under uncertainty. However, we study an environment where regulations govern the (co-)variance of the returns of regulated and unregulated assets and show how risk-averse investors respond to divergent impacts of price and quantity-based regulations on the covariance structure of return by holding different portfolios in equilibrium.

Recently, a growing strand of literature has focused on optimal carbon pricing under risk aversion. In general, there are two ways for risk-averse investors to deal with risks. Investors aim to manage these risks over time using hedging strategies based on option pricing approaches (Dixit & Pindyck, 1994). Bretschger and Soretz (2022), for instance, introduce also CRRA in a stochastic growth model with environmental policy risk. There, policy uncertainty leads, inter alia, to precautionary savings as hedging against these risks. This is different from our paper, where investors optimise their investments in the cross-section by exploiting differences in expected returns, their variances and covariances.

Diversification as a risk management strategy has been modelled in Hambel, Kraft, and van der Ploeg (in press) where uncertainty about the economic damages of carbon emissions affects optimal climate policy by implying a diversification strategy where fossil fuel assets are not shut down completely, hedging against the possibility of low damages from fossil fuel emissions. Furthermore, van den Bremer and van der Ploeg (2021) demonstrate that the optimal social cost of carbon under uncertainty differs with regard to the degree of relative risk aversion and with regard to the correlation between climate damage uncertainty and uncertainty of future asset returns. Unlike these papers, we do not study optimal carbon prices but investigate the response of investors to different manifestations of policy instruments that are often seen as proxies for carbon prices by policymakers.

Also looking at uncertainty about future demand, Fischer and Springborn (2011) and Heutel (2012) use dynamic stochastic general equilibrium (DSGE) models to study the impact of climate policy instruments on aggregate output volatility. Similar to us, Fischer and Springborn (2011) find that an ETS dampens the output volatility compared to a carbon tax. Heutel (2012) shows that the optimal climate policy dampens the procyclicality of emissions slightly. These two papers discuss and compare the effects of policy instruments from a macroeconomic perspective, e.g., on welfare gains/losses and economic volatility, whereas our focus is on discovering the mechanisms of how instruments affect investments in energy systems.

Uncertainty does not only affect investors. Borenstein, Bushnell, Wolak, and Zaragoza-Watkins (2019) point out the difficulty for the regulator to correctly predict future "business-as-usual" emissions and subsequently set a reasonable cap when designing and implementing an ETS. In this paper, we look at the other side of the regulation and aim to understand how risk-averse firms respond to this uncertainty by investing in a portfolio of power plants that differ in their marginal costs and policy exposure.

There is also an increasing strand of literature that studies climate policy risk, in particular as a source of so-called "stranded assets"—non-depreciated assets that become unprofitable, in particular, due to changes in the climate policy regime. By juxtaposing instrument choice under policy uncertainty, Rozenberg, Vogt-Schilb, and Hallegatte (2018) and van der Ploeg and Rezai (2020) share the spirit of our paper. They demonstrate a trade-off between the higher efficiency of carbon pricing but less induced stranded assets with second-best policy instruments such as renewable mandates or subsidies. However, unlike our paper, their models assume that policy changes arise unexpectedly and investors are myopic concerning policy pathways. This contrasts with our model, where investors are aware of the policy risks but are risk-averse and optimise their technology portfolio accordingly.

In the remainder of the paper, we start by developing two linked analytical models that reflect each key puzzle pieces of our research question in Section 2. These models equip us with the framework to understand how policy instruments can shape correlations in the electricity market and how this affects the investment decisions of risk-averse investors in principle. We then blend in Section 3 the two models, calibrate them to match characteristics of the EU power sector and run policy experiments to understand how different regulatory regimes lead to different correlations and thus to differences in the equilibrium composition of the power sector. Finally, Section 4 concludes.

2 Analytical model

To structure the problem, we develop two simple analytical models that each capture a different stage of the investment decision-making process in the power sector. First, a stylised partial equilibrium model of the electricity sector allows to analyse how the interplay of varying demand and policy instruments shape the profit variance and covariance of different generation technologies. In the second stage, this policy-shaped covariance structure is used to rationalise portfolio investment decisions of a risk-averse investor. This reveals key mechanisms of how policy design and uncertainty govern the composition of the technology portfolio.

2.1 Electricity sector

Electricity is produced with two different technologies indexed by $j \in \{c, d\}$.[2] Either, electricity is generated with fossil fuel-burning and carbon-emitting power plants (called "dirty"), indexed by d. Alternatively, electricity can be produced with renewable and clean generation technologies (in short, "clean"), indexed by c.

Similar to many medium-term electricity sector models, for instance Fischer and Newell (2008), technologies are described by quadratic cost functions $C_j(q_j) = c_{1j}\, q_j + (c_{2j}/2)q_j{}^2$, where the parameter $c_{1j} > 0$ captures the constant part of the marginal costs (such as fuel or maintenance costs), $c_{2j} > 0$ describes the positive slope of the supply schedule (as, for instance, the quality of available sites is decreasing). The quantity of electricity generated by technology j is denoted q_j. Electricity demand is assumed to be linear in

[2] Later, in the numerical model, a broader and more specific set of technologies will be available.

price and can be described by the inverse demand function

$$p = \frac{a - \sum_j q_j}{b}, \tag{1}$$

where $a > 0$ and $b > 0$ are demand parameters and p is the price per unit of electricity.[3] Due to externalities causing climate change and air pollution but also because of other policy considerations such as energy security, the electricity market is ripe with policy interventions. Dirty, fossil fuel power plants may have to pay carbon taxes or are covered by cap and trade schemes and forced to purchase permits when releasing carbon emissions. The deployment of renewable technologies may be supported by tax credits, FiTs or other policies.

In order to hold the notation compact, we denote the net value of a regulatory technology-specific intervention per unit of electricity ϱ_j. If the policy intervention takes the form of a subsidy, $\varrho_j > 0$, but $\varrho_j < 0$ if the policy intervention is a tax or causes costs to purchase emission permits. Tax revenues or subsidy expenditures are absorbed by governmental budgets.

Electricity generators of technology j thus have profits $\pi_j = (p + \varrho_j)\, q_j - C_j(q_j)$. Being agnostic about the precise input factors, it is assumed that the investor provides some unspecified resources (which, for simplicity, we call capital in the following) to the power plants and is in exchange rewarded with the power plant's profits.

Power plants are price-takers, assuming a competitive electricity market. The first-order condition of profit-maximisation of a generator j with respect to the quantity q_j is thus

$$p + \varrho_j = c_{1j} + c_{2j}\, q_j. \tag{2}$$

For given price p and policy intervention ϱ_j, a profit maximising generator j sets the quantity of generated electricity such that marginal costs equate the electricity price plus policy costs or subsidies.

Plugging the inverse demand function (1) into the first-order condition (2) and solving the subsequent system of equations provides the equilibrium quantity q_j generated by

[3]Linear demand provides an analytical closed-form equilibrium solution. However, for calibration purposes, in the numerical model a demand function with constant elasticity is applied.

technology j:

$$q_j(\varrho_j, \varrho_i) = \frac{c_{1i} - c_{1j} + \varrho_j - \varrho_j + c_{2i}\ (a - b\,(c_{1j} - \varrho_j))}{c_{2d} + c_{2c} + b\ c_{2d}\ c_{2c}} \qquad \forall j \neq i. \tag{3}$$

We assume that parameters are such that in equilibrium $q_j > 0$ for both technologies. Then, $\frac{\partial q_j}{\partial \varrho_j} = \frac{1+b\,c_{2i}}{\omega} > 0$, where $\omega = c_{2d} + c_{2c} + b\ c_{2d}\ c_{2c}$, and $\frac{\partial q_j}{\partial \varrho_i} = \frac{-1}{\omega} < 0 \quad \forall j \neq i$.
In order to get equilibrium profits of technology j, plug in inverse demand and then equilibrium quantities q_j into the profit function:

$$\bar{\pi}_j = \frac{c_{2j}}{2}\ q_j(\varrho_j, \varrho_i)^2 \qquad \forall j \neq i. \tag{4}$$

Note that $\bar{\pi}_j$ describes the baseline profits prior to any stochastic shock. Profits vary by technology due to relative differences in input and policy costs and increase by the square of quantity. In the following, we conduct three comparative static exercises to understand if and how different policy instruments—a price-based and demand-invariant instrument such as constant carbon tax or a feed-in tariff on the one hand and a quantity-based, demand-responsive instrument like an emission trading system on the other hand—govern technologies' profits and the sensitivity of these profits to exogenous demand shocks as well as exogenous policy shocks.

2.1.1 Price-based instruments: Carbon taxes and feed-in tariffs

Electricity demand is highly correlated to economic activity, which is ex-ante often uncertain and prone to shocks. In the first comparative static exercise, we study the change in profits of generators j with respect to a shift of the demand curve through a change in the demand shifting parameter a. The change in profits of j with respect to a marginal change in a is:

$$\frac{\partial \pi_j}{\partial a} = \delta\ q_j(\varrho_j, \varrho_i) \qquad \forall j \neq i, \tag{5}$$

where, in order to simplify notation, $\delta = c_d^2 c_c^2/\omega > 0$.
Let us define the stochastic change in a as $\hat{a} \equiv \frac{a'-a}{a}$, where a' is the realisation of the demand parameter after a shock. Thus, after the shift of the demand curve to a', profits are $\pi'_j \approx \bar{\pi}_j + \hat{a}\frac{\partial \pi_j}{\partial a}$. We assume that $\hat{a}$ follows an IID process such that $\hat{a} \sim \mathcal{N}(0,1)$.[4]
The covariance matrix of the profit distribution can be described by $\begin{pmatrix} \sigma_c^2 & \sigma_{cd} \\ \sigma_{cd} & \sigma_d^2 \end{pmatrix}$, where σ_j^2

[4]Later, in the numerical simulations, we are going to calibrate a more nuanced demand distribution.

denotes the variance of profits of technology j and σ_{cd} is the covariance of the profits of clean and dirty technologies. Hence, from the distribution of $\hat{a}$, profits of technology j follow a normal distribution with mean $\mu_j = \bar{\pi}_j$ and variance $\sigma_j^2 = \delta^2 \ q_j(\varrho_j, \varrho_i)^2$: $\pi_j \sim \mathcal{N}(\bar{\pi}_j, \delta^2 q_j(\varrho_j, \varrho_i)^2)$. The covariance between profits of technology i and j is then $\sigma_{ij} = \delta^2 \ q_i \ q_j$.

Equipped with the structural characteristics of the profit distribution, we then are going to analyse the effect of demand-invariant, price-based intervention like a carbon tax on the profit distribution. Different to emission trading, where the permit price depends on supply and demand balancing and is thus state-dependent, the carbon tax level is exogenously fixed. Another example of such a price-based intervention is a constant renewable subsidy per unit of electricity output. As the mechanisms are similar, let us focus on the carbon tax. As only dirty generators emit carbon, $\varrho_d < 0$ and $\varrho_c = 0$. Inspecting equilibrium quantities (3) and profits (4) reveal that, since $\varrho_d < 0$, dirty quantities and profits are decreasing with an increasing carbon tax. Clean production and profits increase in case of higher carbon taxes.

Looking at the impact of a marginal carbon tax increase on the profit variance of the dirty technology σ_d^2 reveals

$$\frac{\partial \sigma_d^2}{\partial \varrho_d} = \frac{2\delta^2(1 + bc_c^2)q_d(\varrho_d)}{\omega},$$

which is negative for $\varrho_d < 0$. If the carbon tax rises (and ϱ_d becomes more negative), the quantity of dirty generations and, subsequently, the profit variance decreases. The derivative of the profit variance of clean generators with respect to a carbon tax rise shows

$$\frac{\partial \sigma_c^2}{\partial \varrho_d} = \frac{-2\delta^2 q_c(\varrho_d)}{\omega},$$

indicating an increase in the variance of the clean technology if ϱ_d becomes more negative. Finally, the derivative of the covariance reveals

$$\frac{\partial \sigma_{cd}}{\partial \varrho_d} = \frac{\delta^2 \left((1 + b\, c_c^2)q_c(\varrho_d) - q_d(\varrho_d)\right)}{\omega}.$$

The covariance between dirty and clean profits is decreasing when the carbon tax is rising (ϱ_d becomes more negative) if q_c, including the equilibrium response ($b\, c_c^2$), is greater than q_d.

Hence, a marginal rise in the carbon tax reduces the variance of dirty technologies but increases the variance of clean technologies with respect to a shift in the demand schedule. Consequentially, the covariance of profits is substantially governed by the difference in quantities and the carbon tax level.

Corollary 1. *A marginal carbon tax rise decreases (increases) the profit variance due to stochastic demand of dirty (clean) generators. The profit covariance decreases (increases) when the power sector is dominated by clean (dirty) generation.*

We know from Modern Portfolio Theory that variance and covariance are important determinants of investment decisions. This indicates that the stringency of a carbon tax affects not only the second moments of the profits distribution but also investment decisions.

2.1.2 Quantity-based instruments: Emission trading

Next we analyse how the profit variance induced by stochastic demand changes if the policy costs per unit of output are governed by an endogenous market-derived price mechanism that regulates quantities. The prime example are emission permit markets such as the EU ETS, which set a cap on carbon emissions and allow trading of the allowances to emit carbon.

Since in our simplified model the sole source of carbon emissions is the generation of electricity using the dirty technology and as we abstract from fuel substitution or other abatement options to reduce the dirty technologies' carbon intensity, setting a cap on emissions is similar to setting a cap on the production of fossil fuel-based electricity. Thus, $\bar{C} = q_d$, where $\bar{C}$ denotes the exogenously given cap. Assuming that the cap is binding, $\varrho_d > 0$, which describes now the shadow price of the cap, i.e. the permit price.

As $q_d = \bar{C}$ is now an exogenously given parameter but ϱ_d becomes a variable, we solve the system of equations that consists of equations (1) and (2) for q_c and ϱ_d. Plugging the resulting equilibrium quantity q_c as well as the equilibrium permit price ϱ_d, jointly with inverse demand (1) into the expression for profits provides baseline equilibrium profits: $\bar{\pi}_d = (c_{2d}\,\bar{C})^2/2$ and $\bar{\pi}_c = (c_{2c}(\bar{C} + bc_{1c} - a)^2/(2(1 + bc_{2c})^2$. Note the $\bar{\pi}_d$ depends in equilibrium only on the slope of the supply schedule and the cap. As the cap is always binding (and $\varrho_d < 0$), profits of the dirty technology are independent of demand. In our specification, the potentially higher profits from higher demand (and thus higher electricity prices) are exactly offset by the higher emission permit costs.

As in the carbon tax case above $\pi'_j \approx \bar{\pi}_j + \hat{a}\frac{\partial \pi_j}{\partial a}$, where $\hat{a} \sim \mathcal{N}(0,1)$ describes the stochastic IID process of demand variation. Hence, similar to the carbon tax case, profits are distributed $\pi'_j \sim \mathcal{N}(\bar{\pi}_j, \sigma_j^2)$, where σ_j^2 is the square of $\partial \pi_j / \partial a$, which is

$$\begin{aligned}\sigma_d^2 &= 0,\\ \sigma_c^2 &= \left(\frac{c_{2c}(a - b\, c_{1c} - \bar{C})}{(1 + b\, c_{2c})^2}\right)^2 > 0.\end{aligned}$$

In our simplified model with linear demand, a single source of carbon emissions, constant carbon intensity of this technology, and a binding cap, profits of the dirty technology are driven by cost parameters and the cap only but are invariant to changes in demand. Expected profits and profit variance of the clean technology increase with a tighter cap on dirty generators. Since profits of the dirty technology are invariant to changes in a, by definition the covariance between the two technologies $\sigma_{ij} = 0$.

Corollary 2. *In an emission trading regime with a binding cap and stochastic demand, the dirty generator's profit variance and covariance with clean generators is zero. The profit variance of the clean technology is increasing in the stringency of the cap on dirty generation.*

From the point of view of a risk-averse investor, assets covered by an ETS are attractive —at least in our simplified model— since the profits of these assets are invariant to demand shocks and uncorrelated to clean assets.

2.1.3 Policy uncertainty

Another source of risk for investors in the power market are changes in regulation. In our last comparative static exercise, we study how a change in the policy variable ϱ_d, expressed as $\hat{\varrho}_d \equiv \frac{\varrho'_d - \varrho_d}{\varrho_d}$, where ϱ'_d is the realisation of the policy stringency after the policy shock. Let us assume that $\hat{\varrho}_d \sim \mathcal{N}(0,1)$. Following from this $\pi'_j \approx \bar{\pi}_j + \hat{\varrho}_d \frac{\partial \pi_j}{\partial \varrho_d}$ and hence $\pi'_j \sim \mathcal{N}(\bar{\pi}_j, \sigma_j^2)$, where σ_j^2 is the square of $\partial \pi_j / \partial \varrho_d$, which is

$$\sigma_d^2 = \left(\frac{(1 + b\, c_{2c})c_{2d}}{\omega} q_d(\varrho_d)\right)^2, \tag{6}$$

$$\sigma_c^2 = \left(-\frac{c_{2c}}{\omega} q_c(\varrho_d)\right)^2, \tag{7}$$

respectively. Expressions (6) and (7) show the variance of equilibrium profits of both technologies with respect to a change in the stringency of the policy instrument addressing the carbon-emitting sectors ϱ_d. A carbon tax increase reduces the production of dirty electricity and hence the profit variance of the dirty technology. The profit variance of clean technologies increases with a higher carbon tax.

Corollary 3. *A marginal increase in the carbon tax* $\varrho_d < 0$ *reduces the profit variance of dirty generators but raises the profit variance of clean generators from a uncertain policy process. The covariance between the two technologies is negative if uncertainty is driven by an uncertain carbon tax policy process.*

The profits of the two technologies respond in opposite directions to an idiosyncratic policy shock. Therefore, a risk-averse investor, expecting a positive probability of change in the stringency of the carbon tax, may invest in both technologies to hedge her profits against the occurrence of policy shocks. This might lead to stranded assets in expectation (as the investor may hold assets of the in expectation less profitable technology), but holding these assets acts as insurance against those policy risks.

However, the extent to which such hedging takes place is not only driven by the structure of the electricity market. It is, of course, also governed by the degree of risk aversion of the investor. We will have a closer look at the investor perspective in the next section.

2.2 Investment portfolio composition

The electricity market model revealed how technology-specific profits, as well as their variance and covariance, change if demand or policy stringency changes. The second stage of the analysis examines how the revealed first and second moments of the profit distributions shape the optimal portfolio held by risk-averse investors. This separation of portfolio decisions and electricity market characteristics simplifies the theoretical analysis but ignores the feedback effects of portfolio decisions on the electricity market. The numerical model below will integrate both stages and include these feedback effects.

For reasons of tractability but different to the electricity market model above, we transform the profit distributions and assume that profits are log-normal distributed and hence $log\, \pi_j = \Pi_j \sim \mathcal{N}(\mu_j, \sigma_j^2)$.

The log-normal distributed portfolio profit $\bar{\pi}$ is the weighted average of both generators' profits with weight $0 \leq \alpha_j \leq 1$. With only two assets, we express everything in terms of the portfolio weight of the dirty asset and suppress the technology index in the weight of the asset allocation,

$$\bar{\pi} = \alpha\ \pi_d + (1-\alpha)\ \pi_c.$$

We assume that the investor values her portfolio under CRRA,

$$V = \bar{\pi}^{1-\gamma}/(1-\gamma), \tag{8}$$

where V is the risk-preference adjusted valuation of the portfolio of power plant profits and $\gamma \geq 0$ is the risk aversion parameter.

Campbell and Viceira (2002) point out that a good approximation of the log portfolio profits $\bar{\Pi}$ is

$$\bar{\Pi} = \Pi_c + \alpha(\Pi_d - \Pi_c) + \alpha(1-\alpha)\eta/2, \tag{9}$$

where $\eta = \sigma_c^2 + \sigma_d^2 - 2\sigma_{cd}$ denotes the unconditional sum of the variance of the dirty and clean profits net of the covariance. We derive this term in Appendix A.1.

Using the approximation of the portfolio profits in equation (9) and plugging this into (8), the expected risk-preferences adjusted portfolio value is

$$\mathbb{E}[V(\bar{\pi})] \approx (1-\gamma)^{-1}\mathbb{E}\left[exp\left(\Pi_c + \alpha(\Pi_d - \Pi_c) + \alpha(1-\alpha)\eta/2\right)^{1-\gamma}\right]. \tag{10}$$

Only the log profits Π_c and Π_d are stochastic. Thus, we take the third summand in the exponential function out of the expectation term. Hence,

$$\mathbb{E}[V(\bar{\Pi})] \approx (1-\gamma)^{-1}exp((1-\gamma)\alpha(1-\alpha)\eta/2)\mathbb{E}\left[(exp((\Pi_c + \alpha(\Pi_d - \Pi_c))(1-\gamma))\right]. \tag{11}$$

The investor maximises the risk-preferences adjusted expected valuation of the portfolio by choosing the asset allocation weight α:

$$\max_{\alpha} \mathbb{E}[V(\bar{\pi})].$$

Following Carroll (2021), we show the derivation of the log problem's first-order condition in the Appendix A.2 and obtain the valuation-maximising portfolio weight α for dirty generators:

$$\alpha = \frac{\mu_d - \mu_c + \eta/2 - (\gamma-1)(\sigma_{cd} - \sigma_c^2)}{\gamma\ \eta}. \tag{12}$$

Equation (12) shows that the portfolio share of dirty generators is governed by five parameters. The portfolio share of dirty generators is increasing in the expected excess profits of the dirty generators relative to the clean generators, $\mu_d - \mu_c$. A higher profit of dirty relative to clean generators increases the portfolio weight of dirty generators. Note that if $\gamma = 1$, the investor has log-utility $V = log(\bar{\pi})$ and seeks the portfolio with the highest possible portfolio log profits. If $\gamma > 1$, the investor chooses a less risky portfolio as more risk is penalised.

Based on equation (12), we study in the following how changes in variances and covariance affect the share of dirty generators in the portfolio.

Change in the profit variance of clean generators. Taking the derivative of equation (12) with respect to the clean profits variance is

$$\frac{\partial \alpha}{\partial \sigma_c^2} = \frac{\mu_c - \mu_d - (\gamma - 1)(\sigma_{cd} - \sigma_d^2)}{\gamma\, \eta^2}. \tag{13}$$

Assume for a moment that both assets lead to the same expected profits, $\mu_c = \mu_d$, and $\gamma > 1$. The unconditional portfolio variance net of the covariance must be positive and thus $\eta > 0$. Assuming $\sigma_d^2 > \sigma_{cd}$, hence $\partial\alpha/\partial\sigma_c^2 > 0$, i.e. if the dirty profit variance is greater than the covariance, then a marginal rise in the clean variance increases the share of dirty assets in the portfolio and vice versa.

Change in the profit variance of dirty generators. Now, taking the first derivative of equation (12) with respect to the variance of the dirty asset leads to

$$\frac{\partial \alpha}{\partial \sigma_d^2} = \frac{\mu_c - \mu_d - (\gamma - 1)(\sigma_c^2 - \sigma_{cd})}{\gamma\, \eta^2}. \tag{14}$$

Under the same assumptions $\mu_c = \mu_d$, $\gamma > 1$ and $\eta > 0$ and if the variance of the profits of the clean asset is greater than the covariance between the two assets $\sigma_c^2 > \sigma_{cd}$, $\partial\alpha/\partial\sigma_d^2 < 0$, i.e. a marginal increase in the variance of dirty profits reduces the share of dirty assets in the portfolio of an investor.

Change in the covariance of clean and dirty assets. Finally, we take the first derivative of equation (12) with respect to the covariance σ_{cd}:

$$\frac{\partial\alpha}{\partial\sigma_{cd}} = \frac{2(\mu_d - \mu_c) - (\gamma - 1)(\sigma_d^2 - \sigma_c^2)}{\gamma\eta^2}. \tag{15}$$

Again under the same assumptions as above and if the profit variance of clean generators is greater than the variance of the dirty generators, $\sigma_c^2 > \sigma_d^2$, then a marginal rise in the covariance σ_{cd} pushes up the share of dirty generators in the portfolio. On the contrary, if $\sigma_d^2 > \sigma_c^2$, a marginal rise in σ_{cd} leads to a decrease in α. This leads to the question if there are conditions that push up α even if the expected profits of clean assets are increasing.

Increasing portfolio share of dirty assets despite lower dirty profits. Let us assume a policy intervention aims at reducing the mean return of dirty power plants, for instance, via a carbon tax or an ETS. However, the policy has unintended side effects as it also affects the covariance structure of both available technologies. In the following, we examine if it is possible that the share of dirty generators in the portfolio increases despite its lower expected returns.

For this, we take the total differential of the portfolio composition expression (12) but assume for simplicity that the expected return of the clean asset remains constant. The total differential of the share of dirty assets is then

$$\mathrm{d}\alpha = \frac{\mathrm{d}\mu_d + (\gamma - 1)(\mathrm{d}\sigma_c^2 - \mathrm{d}\sigma_{cd}) + \mathrm{d}\eta/2}{\gamma\eta} - \alpha\frac{\mathrm{d}\eta}{\eta}. \tag{16}$$

We are interested in cases where $\mathrm{d}\alpha > 0$ and $\mathrm{d}\mu_d < 0$. After some rearranging, we can show that $\mathrm{d}\alpha > 0$ even if μ_d decreases if

$$\mathrm{d}\eta\left(\gamma\alpha - \frac{1}{2}\right) - (\gamma - 1)\left(\mathrm{d}\sigma_c^2 - \mathrm{d}\sigma_{cd}\right) < \mathrm{d}\mu_d. \tag{17}$$

As $\mathrm{d}\mu_d$ is negative in this scenario, the left-hand side must be negative too. The reduction in mean dirty profits must be smaller than the risk-preference adjusted change in the relative variance of clean generators. The first term on the left-hand side measures the change in the unconditional "raw" portfolio variance net of covariance relative to the risk-adjusted portfolio share of dirty generators. This term is negative if either $\mathrm{d}\eta < 0$ and $\gamma\alpha > 1/2$ or vice versa. The second term on the left-hand side measures the risk-adjusted change in the clean variance net of the change in covariance. If the increase in the clean variance is sufficiently large, taking into account the change in the variance of both available assets, the share of dirty assets in the portfolio might increase despite a reduction in the mean expected profits of the dirty asset.

Proposition 1 (Potential Stranded Assets)**.** *A policy instrument $\varrho_d < 0$ that marginally reduces the mean profits of dirty generators μ_d can cause a marginal increase of their portfolio weight α if the reduction in mean profits of dirty generators is smaller than the risk-preference adjusted change in the relative variance of clean generators.*

This shows the potential possibility that policy instruments that generally reduce the expected profitability of dirty generators induce additional investments in dirty generators if the policy also raises the relative variance of alternative investments sufficiently. An instrument that reduces profits of dirty generators can thus, at least at the margin, still lead to additional investments in dirty technologies if the investor is sufficiently risk-averse and clean (dirty) assets become sufficiently more (less) volatile. In this sense, these investments are potentially stranded assets driven by risk management considerations.

3 Numerical model

As learned from the analytical reflections above, the composition of the technology portfolio is governed by the expected profits and investment risks of the individual assets, the correlation of profits among them and the risk aversion of the investor. We now calibrate our electricity market model and blend it with our portfolio investment model to study the impact of climate policy instruments on investments. Different to the analytical model where the electricity market structure is exogenously given, we now model the equilibrium mechanisms that endogenously shape the investments under uncertainty and risk aversion. We then examine how those policy instruments govern the optimal investment portfolio. Finally, we study how the perceived risk of an abrupt change in policy stringency, manifested as the abolition risk of a carbon tax, affects investment decisions.

3.1 Model description

A risk-averse investor, who applies the same valuation function as above in equation (8), aims at maximising her risk-adjusted expected total profits by choosing the generation quantity of technology q_j in the face of stochastic electricity demand.

$$V = \mathbb{E}\left(\frac{\sum_j \pi_j(q_j)}{1-\gamma}\right)^{1-\gamma},$$

where profits of a generation technology j in electricity demand state s are

$$\pi_{js}(q_j) = (p_s + \varrho_{js})q_j - C_j(q_j).$$

Note that depending on the policy instrument choice, ϱ_{js} could be state-specific. In the case of a price-based instrument like a FiT or a carbon tax, ϱ_{js} is state-invariant. In the case of a quantity-based instrument like an ETS or renewable certificates, the level of ϱ_{js} is state-dependent. The profit-maximising investor's output choice is governed by the first-order condition in equation (18),

$$\mathbb{E}\left(p_s + \varrho_j - C'_{js}(q_j)\right)\mathbb{E}\left(\sum_i \left(p_s + \varrho_i\right) q_i - C_{is}(q_i)\right)^{-\gamma} = 0, \tag{18}$$

where $C'_j(q_j)$ denotes marginal costs of technology j.

Note that now—and different to the analytical portfolio choice model that assumes a log-normal profit distribution—if $\gamma = 0$, the investor is risk-neutral in the valuation of her assets and equation (18) collapses to a standard zero-profit condition. Electricity prices and policy compliance costs must equal the marginal costs so that the generation quantities increase until the marginal profits are zero.

The electricity market equilibrium in state s is described by the market clearing condition

$$\sum_j q_j = D_s(p_s), \tag{19}$$

such that the total electricity supply is equal to demand $D_s(p_s)$, where $D_s(p_s)$ describes a stochastic demand function. Different to the assumed linear demand in the analytical model above, we parameterise now $D(p_s) = \psi_s\left(\bar{D} + \varepsilon(p_s - \bar{p})\bar{D}/\bar{p}\right)$, where ψ_s is a normal distributed parameter with mean one and a standard deviation that we are going to calibrate below, exogenously shifting electricity demand for given prices. $\bar{p}$ and $\bar{D}$ are benchmark electricity prices and demand, respectively. ε is the demand elasticity.

As the carbon emissions of the European electricity market are regulated through an ETS, in general, the following market clearing condition on the emission permit market has to hold in policy scenarios that contain emission trading:

$$\bar{C} \leq \sum_{d} \phi_d q_d, \tag{20}$$

where $\bar{C}$ is again the exogenously defined emission cap, ϕ_d is the emission-intensity factor that translates quantities q_d in regulated carbon emissions.

However, we also study policy scenarios that target other variables than emission reductions. For instance, policymakers may aim at targeting a specific share of renewables in the electricity system instead of addressing emissions directly, using renewable certificates that ensure that generation from renewable sources complies with the renewable share requirements:

$$\bar{R} \leq \frac{\sum_c q_c}{\sum_i q_i}, \tag{21}$$

where $\bar{R}$ is the exogenously given renewable shares target, which is reached via an endogenously derived renewable certificates price.

Equations (18), (19), and depending on the policy scenario, (20) or (21) constitute the electricity market equilibrium.

3.2 Calibration

The model is calibrated to the EU Reference Scenario 2020 (De Vita et al., 2021) such that it replicates in the benchmark scenario the quantities produced by the respective generation technologies as projected for the year 2030. The EU Reference Scenario provides the baseline against which decision-makers in the European Union examine and assess policy proposals.

The calibrated model covers eight technologies: nuclear, biomass, hydro, onshore wind, offshore wind, solar, coal and natural gas. Out of these, we define four renewable technologies (biomass, onshore wind, offshore wind and solar) that are going to be subsidised by FiTs or supported through the renewable certificate market. Two carbon-based generation technologies—coal and natural gas—are, depending on the policy scenario, subject to tradeable carbon permits or carbon taxes.

As above, quadratic cost functions are used to model each of the generation technologies, hence marginal costs are increasing in quantity. We calibrate c_{1j} such that in benchmark, the unit costs replicate the Levelized Cost of Electricity (LCOE) estimates of Koste et al.

(2021). The remaining parts of the cost function are calibrated following the approach of Fischer, Hübler, and Schenker (2021). We compare supplied quantities at different electricity prices in two closely related official policy scenarios, MIX and MIX-CP, that are both derived from the EU Reference Scenario 2020 to compute the slope of the supply schedules c_{2j} of the generation technologies. These two scenarios were developed in July 2021 for the impact assessment of the European Green Deal policy package. Whereas scenario MIX assumes that the building and transport sectors are integrated in the EU ETS, scenario MIX-CP assumes that carbon prices differ between the sectors currently integrated in the EU ETS and the building and transport sectors (European Commission, 2021). This leads to different carbon prices across scenarios, leading to different electricity prices and supplies by the respective generation technologies. By comparing electricity and carbon prices with the supplied generation quantities of the respective technologies, we construct the slope of the supply schedules c_{2j}, assuming they are linear around the benchmark. However, for nuclear, biomass and hydro, we assume a fixed supply as these technologies have, at least in the short-run, only very limited capacities for extension.

Table A.1 in the Appendix shows the benchmark quantities as well as the computed slopes of the supply schedules. In 2030, the EU Reference Scenario projects an average electricity price of 161.3 EUR/MWh and a carbon price of 32 EUR/tCO_2.

Uncertainty stems from demand: Although the reference scenarios provide expectations about electricity demand in 2030, the finally realised demand is uncertain. In 2020, electricity demand in the EU decreased by 4.8% relative to the average of 2015-2019 as a consequence of the COVID-19 pandemic. Assuming that the pandemic was an extreme event, we define the normal distribution from which the demand parameter $\psi \sim \mathcal{N}(1, 0.027)$ are drawn such that a comparable demand shock is two standard deviations away from the mean projection as used in the EU Reference scenario 2020.

3.3 Policy scenarios

As a useful benchmark, we start first with a *No policy* scenario where the market equilibrium is solely defined by supply and demand without any policy inference.

Second, the ETS scenario assumes that a cap-and-trade system governs the carbon emissions of the electricity sector. In expectation, this scenario is also identical to our benchmark scenario that includes the EU ETS as the central EU climate policy instrument in the electricity sector and replicates the state of the EU electricity sector in 2030 as projected by the EU Reference Scenario 2020.

We then contrast the ETS scenario, where the permit price adjusts to changing demand, with the carbon tax scenario. Note that the carbon tax is calibrated such that its level is equal to the mean carbon permit price across demand states (or equal to the projected ETS permit price in 2030 in the Reference Scenario 2020) and thus should lead in expectation and under risk neutrality to the same emission reduction as the ETS scenario.

In the fourth policy scenario we focus on renewable policies. Related to the ETS scenario, we assume that policymakers implement a renewable share target that matches the renewable share in the ETS scenario by using tradable renewable certificates as the key characteristic of this scenario. No additional specific emission reduction policies are implemented in this scenario.

We then contrast this market-based renewable policy with a FiT regime, the fifth policy scenario. The FiT provides a fixed remuneration for each quantity provided by the renewable technologies biomass, solar, on- and offshore wind, independent of the demand state and electricity market price. The FiT is calibrated such that it leads with risk-neutral investors in expectation to the same remuneration for renewables as in the tradeable renewable certificates scenario. However, the eliminated price risk influences the investment decisions of risk-averse investors.

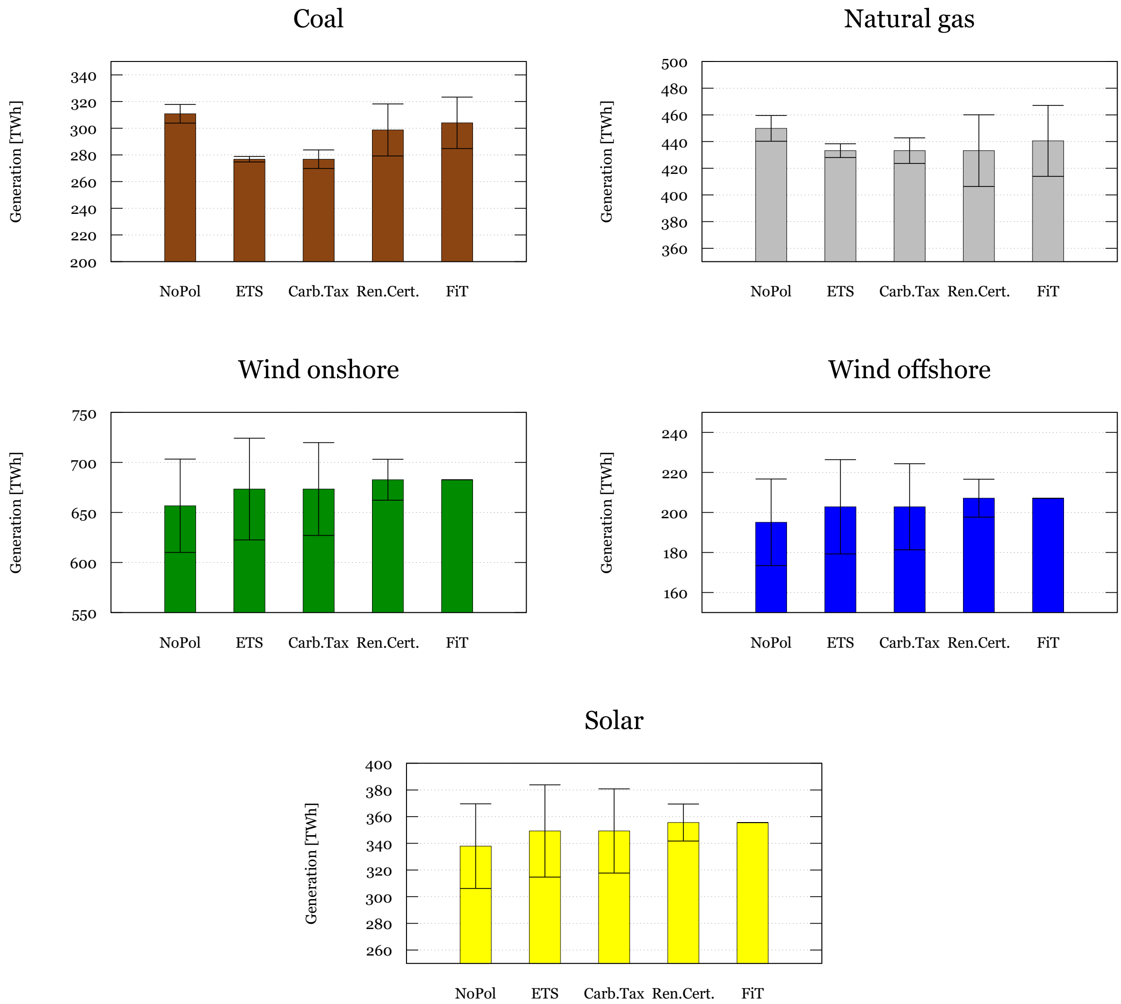
3.4 Results

3.4.1 Stochastic electricity market

In the first step, we study the general impact of stochastic demand on the electricity market and examine how policy instruments shape the variance and covariance of profits. For the moment and similar to our first-stage analytical model of the electricity market, we ignore decision-making under risk aversion and its consequences for the electricity market equilibrium.

We run a Monte Carlo simulation based on 10,000 draws of the normal distributed demand parameter ψ. We truncate extreme values and include only equilibria in the analysis where electricity demand is within three standard deviations as very extreme states cannot be well represented given the linearized supply schedules around the benchmark. Figure A.1 in the appendix shows the distribution of electricity and carbon prices in the benchmark policy scenario.

Figure 1: Mean generation per variable technology.



Mean generation in TWh of the the adjustable technologies based on Monte Carlo simulations with 10'000 draws. The error bars show the 95% confidence interval.

Stochastic electricity generation. Figure 1 shows the mean generation of the set of adjustable technologies: solar, wind onshore, wind offshore, natural gas, and coal. The generation using biomass, hydro and nuclear is fixed as we assume that these technologies have only a limited potential to adjust within the horizon of the model to demand shocks and policy changes.

Remember that the policy instruments have been calibrated such that in expectation the carbon price in the ETS scenario is identical to the carbon tax, and the expected value of the renewable certificates is similar to the FiT. Natural gas and coal mean generation is similar under the carbon tax and the ETS regime. However, as substantial differences in the width of the confidence intervals indicate, the variances differ significantly between scenarios and technologies.

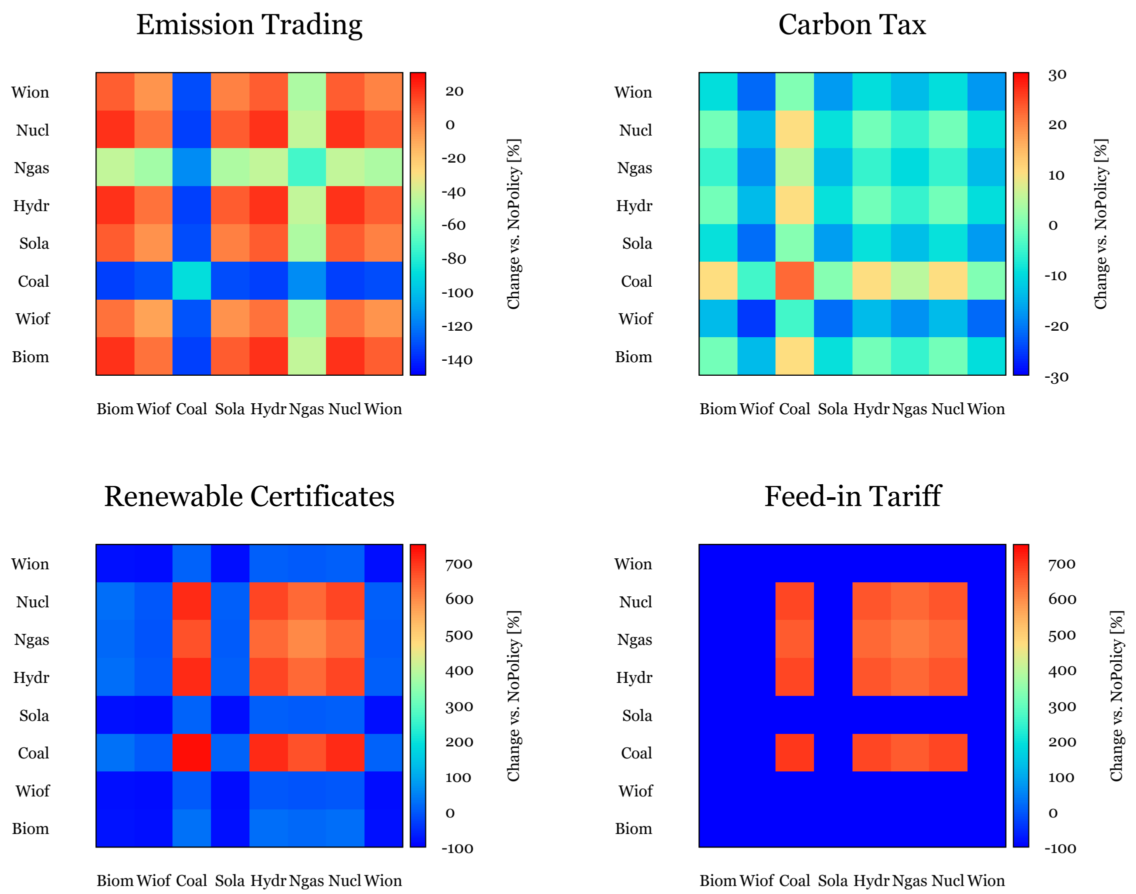
The two panels on top of Figure 1 show the generation with coal and natural gas. Under ETS with stochastic emission permit prices, these two fossil fuel technologies face lower output volatility relative to a policy regime with constant carbon taxes. As already discussed with respect to profits in the analytical first-stage comparative static exercises: Higher demand pushes electricity prices up, which in turn induce more production. But at the same time, higher permit prices reduce, ceteris paribus, the generation of fossil fuel technologies. With a fixed carbon tax, coal and gas generation is not exposed to this counteracting carbon price risk. Therefore, while coal in the ETS scenario has a spread of 4.2 TWh of the 95% quantity interval, this spread raises to 14 TWh, more than three times higher, in the carbon tax scenario.

Also in the absence of policies, renewable technologies respond more sensitive to demand shocks than fossil-fuel technologies, as can be seen in the bottom three panels of Figure 1. To match demand, renewable technologies face higher volatility in the ETS and carbon tax regimes. Renewable certificates, also a quantity-based policy instrument, have a similar volatility reducing effect on renewables as emission permit trading has on fossil-fuel generators, since states of high demand yield more renewables, which in turn reduces the value of renewable certificates and thus the profit incentives to expand output. This counteracting effect reduces the volatility of renewable generation. Finally, in the FiT scenario, renewable output remains constant since FiT provides remuneration independent of market prices.

Policy impact on the covariance structure. Corollaries 1 and 2 indicate that policy instruments shape the profit variance and the covariance of the profitability of technologies. Figure 2 shows the percentage changes of the covariance of profit margins of technologies under the different policy regimes relative to the *No policy* case. The *No policy* covariance is shown in the Appendix A.7. If the covariance increases relative to *No policy*, cells are marked red but coloured dark blue if the covariance decreases.

The top-left panel of Figure 2 shows the covariance change of an ETS implementation relative to *No policy*. The covariance of renewables faces a pairwise rise of up to 18% with other renewable technologies. On the contrary, and consistent with Corollary 2, the covariance of both fossil fuel technologies experience a reduction of up to -180%, leading to a change in the sign of coal's covariance with other technologies. Profit margins of coal are negatively correlated with the profits of on- and offshore wind and solar in *No policy*, but

Figure 2: Policy-induced changes in covariance structure.



Percentage changes in the covariance of profit margins of technologies under the different climate policy regimes relative to *No policy*.

turn positive in the ETS scenario. As positive demand shocks not only push up electricity prices but also emission permit prices, profit margins of carbon-based technologies rise less strongly, leading to a positive correlation with renewables profits. In comparison, the wedge of a demand-invariant carbon tax leads to smaller covariance changes of between -26% and 10% as can be seen in the top-right panel.

The bottom-left panel in Figure 2 shows substantial changes due to a renewable certificates regime. On the one hand, the covariance increases by more than 700% in coal, natural gas, hydro and nuclear technologies. On the other hand, covariance decreases between other renewable technologies. If a positive demand shock leads, ceteris paribus, to a higher share of renewables in the system under the *No Policy* scenario, the value of renewable certificates declines, leading to a dampened increase in profit margins of renewables. Hence, incentives to increase generation capacity in the event of shocks are weaker. Non-renewable technologies have to respond in order to clear markets. Therefore, electricity prices become more volatile as there is less supply response. The standard deviation of the electricity price increases from 2.3 EUR/MWh in *No policy* to 3.8 EUR/MWh in the regime with renewable certificates.

A FiT has the distinct feature that it provides constant remuneration to generators independent of market prices and demand shocks. The profits of covered technologies (on- and offshore wind, solar, biomass) are thus constant and uncorrelated to other technologies, as can be seen in the bottom-right panel in Figure 2. At the same time, the covariance among non-supported technologies coal, natural gas, hydro and nuclear rises sharply. With fixed remuneration from FiT replacing volatile market electricity prices, renewables do not respond to a demand shock. Hence, the remaining technologies have to balance volatile demand solely.

Minimum variance portfolio. To understand how the policy impact on covariance structures affects portfolio composition, we take for a brief exercise (and similar to the second-stage analytical model described in Section 2.2) profits, variances and covariances of technologies as given and assume that a highly risk-averse investor would invest in the minimum-variance portfolio. A standard benchmark in Portfolio Theory, the minimum-variance portfolio is a portfolio constructed with the objective of minimising the portfolio variance. In addition, we constrain the portfolio choice such that the expected portfolio return is not lower than the return from the mean technology mix in the baseline simulations.

Table 1 shows the portfolio shares in the different policy scenarios. Remember that portfolio construction puts the emphasis on reducing risk not maximising returns. As the ETS reduces the variance of coal and gas, the share of fossil fuel technologies increases sharply—from 38% to 70% in natural gas and 18% to 28% in coal. This increase is much smaller under a carbon tax. Renewable certificates and FiT result in a larger share of renewables. In particular, FiT yield a 100% renewable energy portfolio. These changes are driven by the reduction, and respective elimination of risk among renewable energy technologies.

Proposition 1 indicates that policies increasing only the relative profitability of renewable technologies do not guarantee policy success. This indication is reflected in the minimum variance portfolios. If the profits of the desired technologies are relatively more volatile (riskier), a highly risk-averse investor will find the fossil fuel technologies more attractive,

Table 1: Minimum variance portfolios under policy scenarios

	No Policy	ETS	Carb. Tax	Ren. Cert.	FiT
Nuclear	0	0	0	0	0
Biomass	0	0	0	0.10	0
Hydro	0	0	0	0	0
Wind onshore	0.44	0	0.45	0.74	0.85
Wind offshore	0	0	0	0	0.01
Solar	0	0.02	0	0	0.14
Coal	0.18	0.28	0.15	0	0
Natural gas	0.38	0.70	0.40	0.16	0
Portfolio variance	0.004	6×10^{-5}	0.003	0.001	0
Portfolio profits	100	98.54	98.53	96.21	97.53

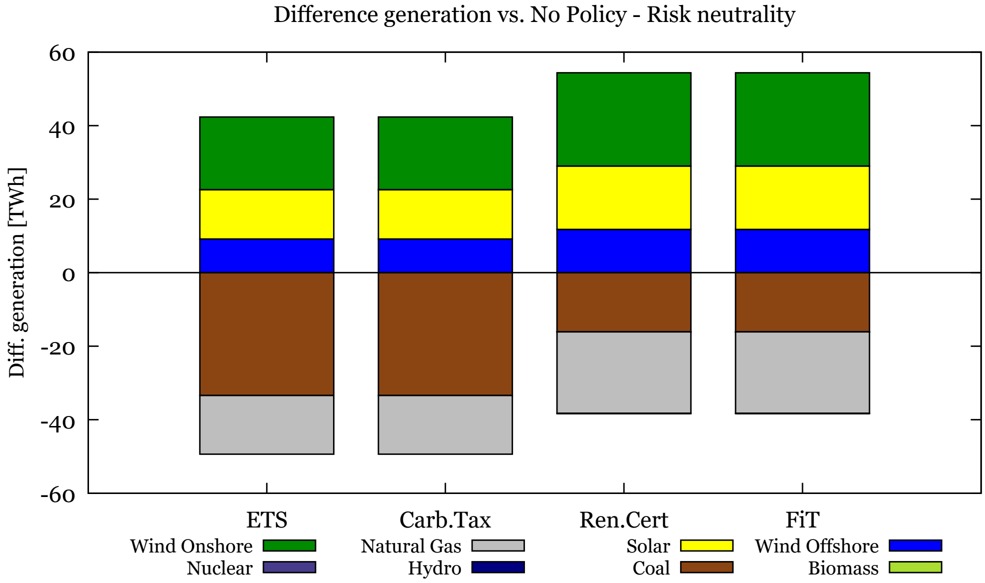
Technology shares in portfolio. Portfolio profits are relative to *No policy*.

investing 98% in coal and gas combined (see in the ETS scenario). In this case, FiT is a better instrument to incentive investments of highly risk-averse investors.

3.4.2 Equilibrium policy impacts with risk-averse investors

So far, we ignored how risk and risk preferences affect investments in equilibrium. Now in the next step, we incorporate risk aversion in the output decisions as governed by the first-order condition (18). Investors are aware that their investments face profitability risks from stochastic demand. As a consequence, investors incorporate their knowledge about the probability distribution of demand and adjust their investment portfolio accordingly. As decision making of investors depends now on all states known to the investor, the state space needs to be reduced for computational reasons. Thus, from the same demand distribution as above, 1,000 demand states are drawn. In light of expectations of the market equilibria, and additionally shaped by policies, as well as risk aversion, the investors choose the valuation-maximising generation portfolio. Figure 3 shows the difference in generation portfolios in the four policy regimes relative to the *No Policy* scenario assuming a risk-neutral investor (with $\gamma = 0$). For a risk-neutral investor, differences in the covariance structure of price- and quantity-based instruments do not affect allocation decisions. Since policy instruments have been calibrated such that the mean emission permit price equals the carbon tax and the mean renewable permit price equals the FiT, investment decisions under risk neutrality lead to identical market equilibria and thus differences relative to the *No policy* scenario of the two climate policy instruments (ETS

Figure 3: Difference between policy scenarios and *No policy* under risk neutrality.



Difference between policy scenario and *No policy* in TWh of electricity generation per technology under risk neutrality ($\gamma = 0$).

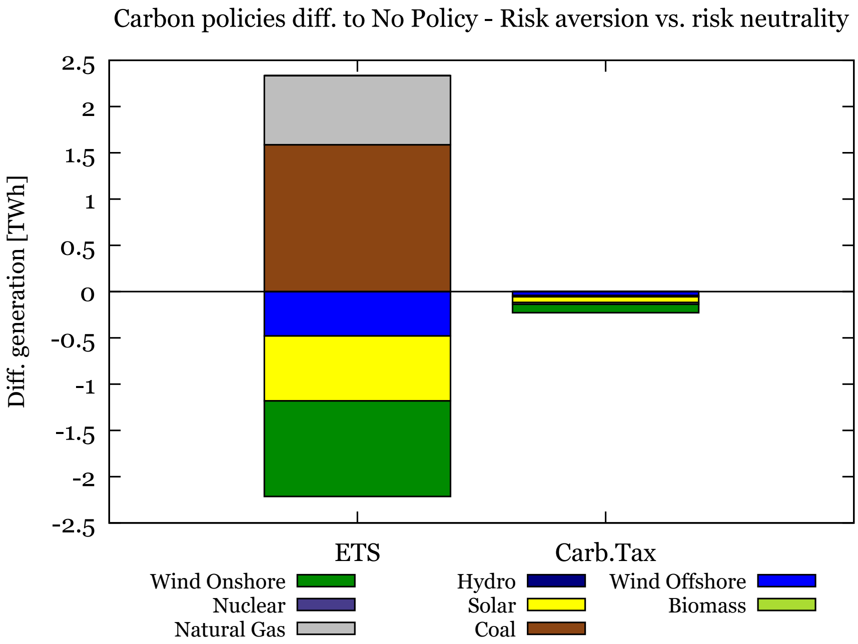
and carbon taxes) and the two renewables (renewable certificates and FiT), respectively (see Table A.3 in the Appendix).

However, this equivalence does not hold under risk aversion. Figure 4 compares the difference of risk neutrality ($\gamma = 0$) and risk aversion ($\gamma = 1.4$) in the output changes between *No policy* and one of the two carbon pricing instruments ETS or carbon tax, respectively, or more precisely $\Delta q^{sc}_{j,\gamma=1.4} = \left(q^{sc}_{j,\gamma=1.4} - q^{np}_{j,\gamma=1.4}\right) - \left(q^{sc}_{j,\gamma=0} - q^{np}_{j,\gamma=0}\right)$, where $sc \in \{\text{carbon tax, ETS, renewable certificates, FiT}\}$ indexes policy scenarios and np labels the *No Policy* scenario. In the carbon tax scenario, risk aversion does not lead to substantial differences since a constant carbon price does not alter the covariance structure substantially, as we saw already in the top-right panel of Figure 2.

Note that we lack a robust prior of the level of risk aversion of actual European utilities and other power market investors. Hence, our parameterisation of γ is rather ad-hoc and only able to show how risk aversion affects investment choices but not a projection based on robust empirical evidence about actual observed levels of risk aversion.

A first-order equilibrium effect of investors with risk aversion compared to a risk-neutral investor is an output reduction. A risk-averse investor is less willing to expand capacities to fully exploit profit opportunities from positive demand shocks. Therefore, average electricity prices are higher under risk aversion. As a result, the cap under the ETS is

Figure 4: Carbon pricing under risk aversion



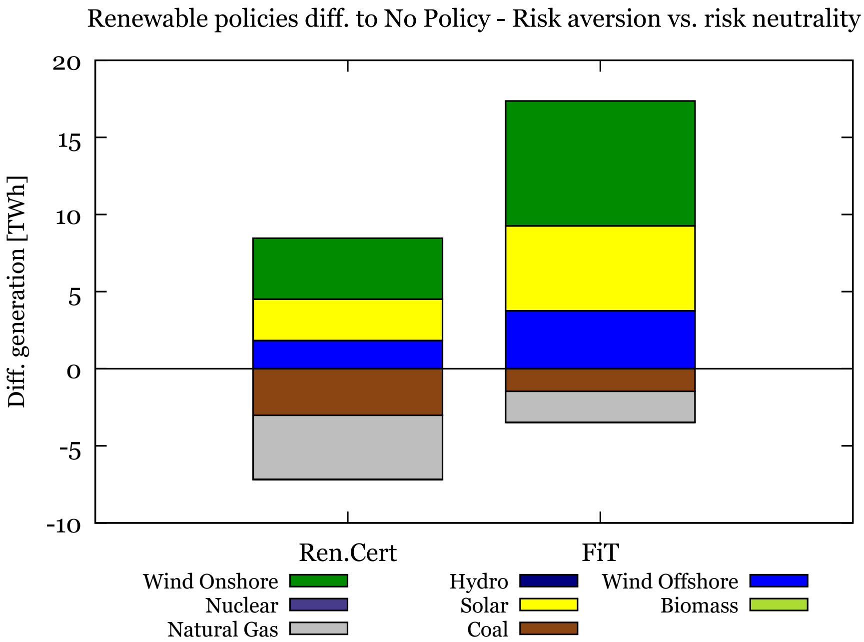
Difference-in-differences of output difference between carbon pricing scenarios and *No policy* under $\gamma = 1.4$ and output difference between carbon pricing scenarios and *No policy* under $\gamma = 0$.

less binding, and permit prices are lower compared to risk neutrality.

As under risk aversion carbon emissions are lower under *No policy*, the ETS reduces less emissions compared to the fixed carbon tax. Hence, there is less reduction of coal and gas, as can be seen in the left bar of Figure 4. In addition to the lower permit prices, we learned from Corollary 2 and from Figure 2 that the ETS reduces variances and covariance of coal and gas profits, which increases their attractiveness as an investment option under risk aversion.

This is different with renewable policies. Figure 5 shows that risk aversion leads in the case of renewable energy policies to more renewables and fewer fossil fuel generation. In the case of a FiT—where the variance and covariance of renewables is zero— this is even more pronounced. The story is similar under the renewable certificate scenario, but the aggregate output in this case is generally lower under risk aversion. Interestingly, as an investor benefits from a fixed reimbursement per sold unit of electricity independent of electricity market prices, the aggregate output in FIT increases under risk aversion.

Figure 5: Renewable policy under risk aversion



Difference-in-differences of output difference between renewable policy scenarios and *No policy* under $\gamma = 1.4$ and output difference between renewable policy scenarios and *No policy* under $\gamma = 0$.

3.4.3 Policy uncertainty.

Retroactive policy changes reduce the trust and confidence of investors. This distrust persists throughout the lifetime of the investment project (Egli, 2020). A risk-neutral investor responds to this risk straightforwardly by computing the expected profits of the technologies across the policy state space. However, the response of a risk-averse investor is more nuanced as we show below.

As the mechanisms of policy risk do not differ significantly across policy instruments, we focus on the risk of a possible scrapping of a carbon tax. We understand "policy scrapping" as states where policies are removed before their promised end date. The horizontal axis of Figure 6 depicts the increasing expected probability of carbon tax scrapping from $P = 0$ to $P = 1$. The vertical axis plots the difference in carbon emissions released in a generation portfolio governed by risk-neutral investors relative to a portfolio held by a risk-averse investor. This difference is U-shaped as in both ends of the probability distribution the policy risk is zero, and risk aversion plays no role. The risk (and thus the impact of risk aversion) is largest at policy scrap probability' $P = 0.5$ and also increases in CRRA γ.

Figure 6: Policy uncertainty carbon tax.

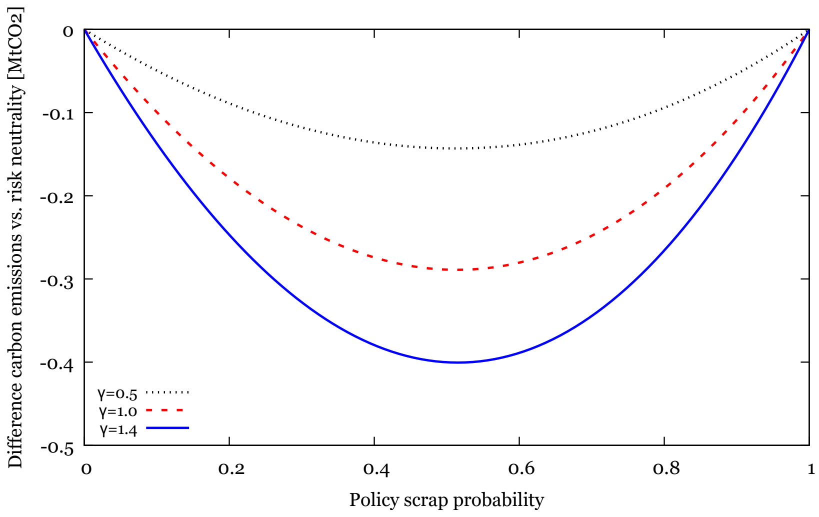
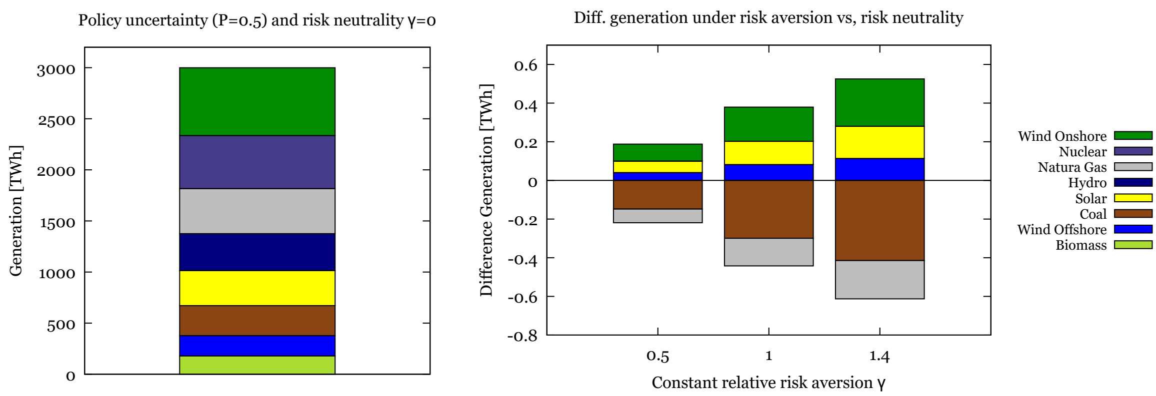


Figure 7: Difference: generation risk aversion vs. risk neutrality



The reason for the emission reduction with increasing risk aversion becomes clear when looking at Figure 7. The left panel shows the portfolio composition under risk neutrality at policy scrap probability $P = 0.5$ and its right panel shows its difference compared to different risk aversion levels.

The reduction in fossil fuel generation under policy uncertainty is increasing in γ. Faced with policy uncertainty, risk-averse investors reduce their exposure to carbon price risk by increasing the renewable share in their portfolio. The diversification is obviously shaped by the covariance structure: In a carbon tax regime, coal and gas are positively correlated and risk-averse investors invest in renewables to diversify and reduce their carbon tax risk.

4 Conclusion

Investments in energy technologies often have a lifespan of several decades—a time span in which profitability conditions may alter substantially, making such investments risky. Climate policies shape, depending on their design, the distribution of those profit risks. We show in this paper that if investors are risk-averse—an assumption that finds general support from robust empirical evidence—price-based instruments such as carbon taxes and quantity-based instruments like emission trading schemes do not lead to equivalent outcomes.

We show that carbon taxes and emission permit trading differ substantially in their ramifications for the variance and covariance of the returns of energy technologies. While a constant carbon tax has only a limited impact on the covariance structure of the returns, the endogenous emission permit price reduces the variance of fossil fuel-based generation technologies from stochastic demand. This has consequences for the investment decisions of risk-averse utilities. Although carbon tax and ETS lead to the same emission reduction under risk-neutrality, under risk aversion the carbon tax is more effective in reducing emissions than the ETS. Similar results can be found for renewable support policies. Comparing a FiT for renewables—which provide a fixed remuneration to renewable generators that is uncorrelated to the returns of other technologies—with a tradeable renewable certificate regime shows equivalency under risk-neutrality. However, if investors are risk-averse, the FiT induces more investment in renewables than tradeable renewable certificates.

Climate policies are often controversial which may cause abrupt changes in policy regimes. Investors may assume that once-established policies can be suddenly abolished, changing their investment calculus. Our analysis shows that uncertainty about the permanence of carbon taxes is a drag on the investment in fossil fuel technologies as the increased risk of these technologies reduces the attractiveness for risk-averse investors.

The impact of policies on the second moments of the return distribution and subsequently on investment incentives, which affect the efficacy of these policies has been largely overlooked. To the best of our knowledge, this is the first attempt to comprehensively model and analyse the interplay of policies in stochastic market equilibria with portfolio investment decisions that are driven by diversification motives.

The mechanisms uncovered in this paper are relevant not only for climate policy-making but also have implications for public policies in other domains where regulation alters the volatility and correlation between returns of different investment options.

Farmers, for example, usually grow a portfolio of crops that are subject to weather, market and policy risks. Evidence suggests that the risk preferences of farmers shape these portfolios (Bezabih & Sarr, 2012). Policies that aim at protecting crop revenues of farmers affect the farmers' cropping decisions and diversification strategies (Ramsey, Goodwin, & Ghosh, 2019). Hence, in order to comprehensively analyse such agricultural policies, we need to take into account the risk management response of farmers to changes in the (co-)variance of their crop portfolio.

Also tax policies can affect investment diversification strategies. Desai and Dharmapala (2011) show how changes in dividend tax policies induce portfolio reallocations towards investments in tax-favoured countries. As the impact of differentiated dividend taxes also affects the covariance structure of net returns of other assets, such policies can have consequences beyond the tax' impact on mean returns if investors are risk-averse.

We developed a generic framework where policies have differentiated impacts on the covariance structure of the profits of projects that compete in a common market. This comes at the price of neglecting many specifics of electricity markets that also drive technology decisions and capital allocation in these markets. For instance, the potential and intermittency of renewables, the availability of storage, network- and grid-dependencies, ramp-up times, and political constraints such as local resistance to specific projects or technologies. We focused on demand variability as the source of uncertainty and ignored other potential sources such as uncertain developments of generation costs, either because of uncertain fuel costs or uncertainty about technological progress. Nevertheless, we believe that we are able to shed light on an important mechanism that policymakers should consider when designing climate policy instruments.

However, in order to effectively analyse how investor's risk aversion shapes the effectiveness of public policies in general and of climate policies in particular, robust empirical evidence of the degree of actual risk aversion of specific types of investors is needed. We hope that our study may motivate such research endeavours.

References

Battiston, S., Monasterolo, I., Riahi, K., & Ruijven, B. J. V. (2021). Accounting for finance is key for climate mitigation pathways. *Science*, *372*, 918-920.

Bezabih, M., & Sarr, M. (2012). Risk preferences and environmental uncertainty: Implications for crop diversification decisions in Ethiopia. *Environmental and Resource Economics*, *53*, 483–505.

Bodnar, G. M., Giambona, E., Graham, J. R., & Harvey, C. R. (2019). A view inside corporate risk management. *Management Science*, *65*(11), 5001–5026.

Borenstein, S., Bushnell, J., Wolak, F. A., & Zaragoza-Watkins, M. (2019). Expecting the unexpected: Emissions uncertainty and environmental market design. *American Economic Review*, *109*(11), 3953–3977.

Bretschger, L., & Soretz, S. (2022). Stranded assets: How policy uncertainty affects capital, growth, and the environment. *Environmental and Resource Economics*, *83*(2), 261–288.

Campbell, J. Y., & Viceira, L. M. (2002). *Strategic asset allocation: Portfolio choice for long-term investors*. Clarendon Lectures in Economic.

Carroll, C. D. (2021). *Constant relative risk aversion portfolio choice with two risky assets* (Tech. Rep.). Johns Hopkins University. Retrieved from `https://www.econ2.jhu.edu/people/ccarroll/public/lecturenotes/AssetPricing/Portfolio-Multi-CRRA/`

Desai, M. A., & Dharmapala, D. (2011). Dividend taxes and international portfolio choice. *The Review of Economics and Statistics*, *93*(1), 266–284.

De Vita, A., Capros, P., Paroussos, L., Fragkiadakis, K., Karkatsoulis, P., Höglund-Isaksson, L., … Kalokyris, T. (2021). *EU reference scenario 2020: Energy, transport and GHG emissions - Trends to 2050* (Tech. Rep.). European Commission. Retrieved from `https://energy.ec.europa.eu/data-and-analysis/energy-modelling/eu-reference-scenario-2020_en`

Dixit, A. K., & Pindyck, R. S. (1994). *Investment under uncertainty*. Princeton University Press.

Egli, F. (2020). Renewable energy investment risk: An investigation of changes over time and the underlying drivers. *Energy Policy*, *140*, 111428.

European Commission. (2021). *Policy scenarios for delivering the Euro-*

pean Green Deal (Tech. Rep.). European Commission. Retrieved from https://energy.ec.europa.eu/data-and-analysis/energy-modelling/policy-scenarios-delivering-european-green-deal_en

Fischer, C., Hübler, M., & Schenker, O. (2021). More birds than stones–a framework for second-best energy and climate policy adjustments. *Journal of Public Economics*, *203*, 104515.

Fischer, C., & Newell, R. G. (2008). Environmental and technology policies for climate mitigation. *Journal of environmental economics and management*, *55*(2), 142–162.

Fischer, C., & Springborn, M. (2011). Emissions targets and the real business cycle: Intensity targets versus caps or taxes. *Journal of Environmental Economics and Management*, *62*, 352-366.

FS-UNEP Centre & BNEF. (2013). *Global trends in renewable energy 2013* (Tech. Rep.). Frankfurt School of Finance & Management and Bloomberg New Energy Finance. Retrieved from https://www.fs-unep-centre.org/wp-content/uploads/2019/11/Global_Trends_Report_2013.pdf

Géczy, C., Christopher, Minton, B. A., & Schrand, C. (2006). The use of multiple risk management strategies: Evidence from the natural gas industry. *The Journal of Risk*, *8*(3), 1-54.

Hambel, C., Kraft, H., & van der Ploeg, F. (in press). Asset diversification versus climate action. *International Economic Review*.

Heutel, G. (2012). How should environmental policy respond to business cycles? optimal policy under persistent productivity shocks. *Review of Economic Dynamics*, *15*, 244-264.

International Energy Agency. (2021). *World energy investment 2021* (Tech. Rep.). Retrieved from https://doi.org/10.1787/bfddacd3-en

Klaassen, L., & Steffen, B. (2023). Meta-analysis on necessary investment shifts to reach net zero pathways in europe. *Nature Climate Change*, *13*(1), 58–66.

Koste, C., Shammugam, S., Fluri, V., Peper, D., Memar, A. D., & Schlegel, T. (2021). *Levelized cost of electricity – renewable energy technologies* (Tech. Rep.). Fraunhofer Institute for Solar Energy Systems ISE. Retrieved from https://www.ise.fraunhofer.de/en/publications/studies/cost-of-electricity.html

Markowitz, H. (1952). Portfolio selection. *The Journal of Finance*, *7*, 77-91.

Peng, W., Iyer, G., Bosetti, V., Chaturvedi, V., Edmonds, J., Fawcett, A. A., . . . Weyant,

J. (2021). Climate policy models need to get real about people - here's how. *Nature*, *594*, 174-176.

Pérez-González, F., & Yun, H. (2013). Risk management and firm value: Evidence from weather derivatives. *The Journal of Finance*, *68*(5), 2143–2176.

Ramsey, A. F., Goodwin, B. K., & Ghosh, S. K. (2019). How high the hedge. *Journal of Agricultural and Resource Economics*, *44*(2), 227–245.

Rozenberg, J., Vogt-Schilb, A., & Hallegatte, S. (2018). Instrument choice and stranded assets in the transition to clean capital. *Journal of Environmental Economics and Management*, *100*, 102183.

van den Bremer, T. S., & van der Ploeg, F. (2021). The risk-adjusted carbon price. *American Economic Review*, *111*(9), 2782–2810.

van der Ploeg, F., & Rezai, A. (2020). The risk of policy tipping and stranded carbon assets. *Journal of Environmental Economics and Management*, *100*, 102258.

Weitzman, M. L. (1974). Prices vs. quantities. *Review of Economic Studies*, *41*, 477-491.

A Appendix

A.1 Approximation of portfolio profits

$\bar{\pi}$ is the log-normally distributed portfolio profit. The portfolio is a composite of clean and dirty assets: α is the portfolio weight of the dirty assets and $(1-\alpha)$ is the share of clean assets.

$$\bar{\pi} = \alpha\pi_d + (1-\alpha)\pi_c.$$

With some manipulation we get

$$\frac{1+\bar{\pi}}{1+\pi_c} = 1 + \alpha\left(\frac{1+\pi_d}{1+\pi_c} - 1\right).$$

Taking logs—and remember that we denote log variables in capital letters—leads to

$$\bar{\Pi} - \Pi_c = log\left[1 + \alpha(exp(\Pi_d - \Pi_c) - 1)\right]$$

Campbell and Viceira (2002) demonstrate that this relation can be approximated well using a second-order Taylor expansion evaluated at the point $\Pi_d - \Pi_c = 0$:

$$f(\Pi_d - \Pi_c) \approx f(0) + f'(0)(\Pi_d - \Pi_c) + \frac{1}{2}f''(0)(\Pi_d - \Pi_c)^2, \tag{A.1}$$

where $f'(0) = \alpha$ and $f''(0) = \alpha(1-\alpha)$. Then, we replace $(\Pi_d - \Pi_c)^2$ with its conditional expectations (see Campbell and Viceira (2002)) $\eta = (\sigma_d^2 + \sigma_c^2 - 2\sigma_{cd})$, which is the variance of the difference $\Pi_d - \Pi_c$.
Plugging this into (A.1) and some manipulations leads to

$$\bar{\Pi} = \Pi_c + \alpha\left(\Pi_d - \Pi_c\right) + \frac{1}{2}\alpha(1-\alpha)\,\eta. \tag{A.2}$$

A.2 Maximize expected portfolio profits

Take the logarithm of expected portfolio profits (11):

$$log\mathbb{E}[V(\bar{\pi})] = log[(1-\gamma)^{-1}](1-\gamma)\alpha(1-\alpha)\frac{\eta}{2}\;log\mathbb{E}[exp((\Pi_c + \alpha(\Pi_d - \Pi_c))(1-\gamma))].$$

Note that our foregoing assumptions imply that

$$
\begin{aligned}
&(1-\gamma)(\alpha\pi_d + (1-\alpha)\pi_c) \backsim \\
&\qquad \mathcal{N}((1-\gamma)(\alpha\mu_d + (1-\alpha)\mu_c), (1-\gamma)^2(\alpha^2\sigma_d^2 + (1-\alpha)\sigma_c^2 + 2\alpha(1-\alpha)\sigma_{cd})). \quad \text{(A.3)}
\end{aligned}
$$

Hence,

$$
\begin{aligned}
log\mathbb{E}[V(\bar{\Pi})] = &(1-\gamma)\alpha(1-\alpha)\eta/2 + (1-\gamma)(\alpha\mu_d + (1-\alpha)\mu_c) \\
&+ (1+\gamma)^2(\alpha^2\sigma_d^2 + (1-\alpha)^2\sigma_c^2 + 2\alpha(1-\alpha)\sigma_{cd})/2 \quad \text{(A.4)}
\end{aligned}
$$

The investor maximises the expected portfolio profit, adjusted for the risk preferences, by choosing the share of dirty assets in the portfolio α. The share of dirty assets α that maximises the expected portfolio profit maximises also the log of the expected portfolio profits.

The first-order condition $\partial log\mathbb{E}[V(\bar{\pi})]/\partial\alpha = 0$ is thus:

$$(1-\gamma)\left(\left(\frac{1}{2}-\alpha\right)\eta + (\mu_d - \mu_c) + (1-\gamma)(\alpha\eta - \sigma_c^2 + \sigma_{cd}\right) = 0. \quad \text{(A.5)}$$

Solve for α:

$$\alpha = \frac{\mu_d - \mu_c + \eta/2 + (1-\gamma)(\sigma_{cd} - \sigma_c^2)}{\gamma\,\eta} \qquad \forall\,\gamma > 0. \quad \text{(A.6)}$$

A.3 Calibration of cost functions

	Generation [TWh]	Slope [EUR(MWh)$^{-2}$]	CO_2 intensity [t(MWh)$^{-1}$]
Nucl	518.8	1×10^3	0
Biom	172.1	1×10^3	0
Hydr	361.8	1×10^3	0
Wion	673.4	9.60×10^{-8}	0
Wiof	202.8	2.07×10^{-7}	0
Sola	349.3	1.41×10^{-7}	0
Coal	276.8	6.40×10^{-7}	0.90
Ngas	433.2	4.64×10^{-7}	0.36

Table A.1: The model is calibrated to the generated quantities of 2030 in the EU Reference scenario 2020. As nuclear, hydro and biomass have only limited potential for significant adjustments to their output, we fixed supply of these technologies.

A.4 Technology correlations

	Nucl	Biom	Hydr	Wion	Wiof	Sola	Coal	Ngas
Nucl	1	1	1	-0.99	-0.99	-1	1	1
Biom	1	1	1	-1	-0.99	-1	1	1
Hydr	1	1	1	-0.99	-0.99	-1	1	1
Wion	-0.99	-1	-0.99	1	1	1	-1	-0.99
Wiof	-0.99	-0.99	-0.99	1	1	1	-0.99	-0.99
Sola	-1	-1	-1	1	1	1	-1	-0.99
Coal	1	1	1	-1	-0.99	-1	1	1
Ngas	1	1	1	-0.99	-0.99	-0.99	1	1

Table A.2: Technology correlations under the *No Policy* scenario

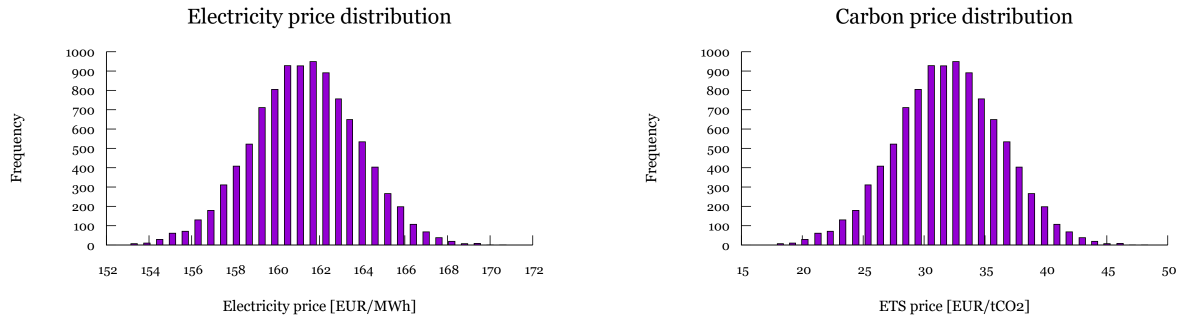
A.5 Results: Output under risk neutrality

Table A.3: Output under risk neutrality [TWh]

	NoPol	ETS	Carb.Tax	Ren.Cert	FiT
Nucl	518.848	518.850	518.850	518.838	518.838
Biom	179.432	179.434	179.434	179.434	179.434
Hydr	361.817	361.819	361.819	361.807	361.807
Wion	652.612	672.363	672.363	677.974	677.974
Wiof	193.198	202.355	202.355	204.956	204.956
Sola	335.124	348.555	348.555	352.370	352.370
Coal	310.230	276.817	276.817	294.129	294.129
Ngas	449.062	433.094	433.094	426.872	426.872

A.6 Benchmark electricity and carbon price distribution

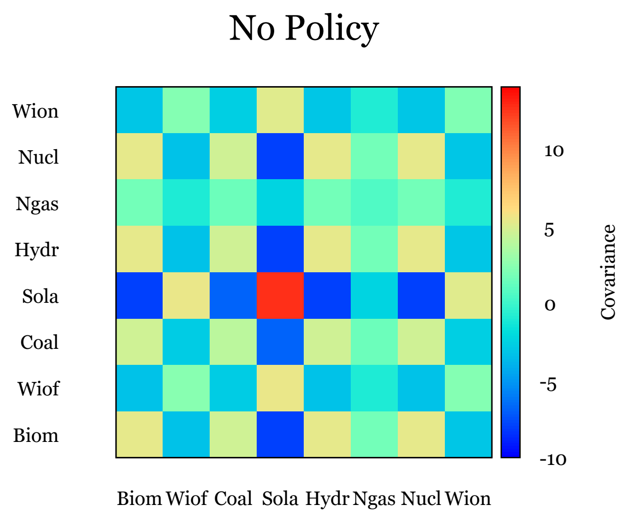
Figure A.1: Electricity and carbon price distribution in benchmark



Distribution of electricity prices (left panel) and of carbon prices (right panel) under benchmark/ETS policy scenario for 2030.

A.7 Covariance of technology profits

Figure A.2: Covariance of profit margins in No Policy Scenario.



Covariance of profit margins of electricity generation technologies in *No Policy* Scenario.

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