Intentionally Holding Potential Stranded Assets in the Portfolio —Policy Uncertainty and Investments in the Power Market*

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Abstract

Modern Portfolio Theory tells us that, inter alia, the expected correlation between returns of different investments options shapes the composition of portfolios. In the transition to a low-carbon economy, an important determinant of the risk-return profile of energy sector investments is climate policy —either via direct policy interventions or through market equilibrium adjustments. Hence, climate policy and in particular the uncertainty around its stringency and design shape the asset portfolio an investor holds. In this paper, we explore the consequences of carbon pricing schemes and fixed remuneration renewable energy support policies for investments into clean and dirty assets under uncertainty and show that it might be optimal for hedging purposes in certain cases to invest in fossil-fuel plants even if their relative return is lower due to a more stringent environmental policy but with asymmetric consequences on variances of the returns. Using the European power sector as a case study, we calibrate a stochastic electricity market model to analyse the impact of policy instruments on investment. We find that uncertainty about the continuation of fixed remuneration policies for renewable energy deployment leads to more potentially stranded investments in fossil fuel generation capacities —ranging from 1% to 35% of a risk-averse investor' investment budget. In comparison, a carbon price instrument is less affected by policy discontinuation risk. Moreover, fixed remuneration for clean power generation assets significantly lowers clean assets' risk and their return correlation with dirty assets —thus attracting both moderately and highly risk-averse investors. This effect remains when fixed remuneration policies coexist with carbon pricing schemes.

Keywords: Investment under Uncertainty, Risk Aversion, Mean-Variance Portfolio, Climate Policy, Electricity Market, Stranded Assets.

JEL Codes: D81, E22, G11, P48

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1 Introduction

To transit to a low-carbon economy, enormous investments in clean technologies are necessary. Global power sector investment was at USD 0.82 trillion in 2021; but to reach net-zero emissions by 2050, clean energy investments need to triple the current level by 2030 (IEA, 2021). In the European Union, a total of EUR 3 trillion renewable energy investment is required by 2050 to reach climate neutrality (Hainsch et al., 2020). These paradigms of "shifting the trillions" aim to mobilise finance for a just transition to a clean and green economy in a timely manner.

Power generation investments in the energy sector have a lifetime of several decades. They are therefore exposed to substantial uncertainty as these investments take place in a stochastic environment. Sudden demand fluctuations, as observed during the pandemic, or changes in the input costs, as it is currently observed with natural gas, lead to ex-ante uncertain return realisations of electricity market projects.

In order to stimulate clean energy investments, governments worldwide implemented a fleet of policies. Carbon pricing —either as a cap-and-trade system or as a carbon tax —aims at lowering the returns of greenhouse gas emitting projects relative to the returns of low-carbon alternatives. Renewable deployment policies such as Feed-in Tariffs (FiT) or Renewable Tax Credits directly raise the returns of low-carbon technologies and thus make the investment into these technologies relatively more attractive. The design and implementation of policy instruments might affect both the mean and the standard deviations of expected return realisations. In addition, policies can also affect the correlation between the expected returns of different electricity-generating technologies.

Investors might be aware that policy regimes are subject to change. Egli (2020) identifies that policy risk —the risk of generating lower than expected revenues due to retroactive renewable energy support policy changes —is one of the most important and most frequently mentioned risks by investors interviewed in the study. Kempa et al. (2021) show evidence that financing costs of firms engaged in renewable energy technologies are decreasing if the stringency of environmental policies it is exposed to is increasing, even when controlling for the direct policy effect on profits —in other words, the increased policy stringency signals a decrease in the perceived policy risk by lenders.

The risk from sudden policy changes can be substantial, as several examples in Europe and other countries show. Austerity measures following the European debt crisis induced a retroactive change on renewable support measures in several European countries including Italy, Spain, Greece, Bulgaria, Slovakia, Romania and the Czech Republic (BNEF, 2013, 2015). Investors filed arbitration claims against the respective country authorities (Patrizia et al., 2020). In certain cases, the court ruling favoured the investors, but it is not certain when the developers will be compensated (Kenning, 2016). Not surprisingly, these sudden policy regime changes discouraged investor confidence substantially. Directly after the retroactive policy changes, renewables investments decreased by 55% in Spain (BNEF, 2011) and by 71% in Italy (BNEF, 2015). Most recently, the French parliament approved retroactive cuts for solar FiT (Scully, 2021). Outside

Europe, there have been substantial uncertainties around the tax credits for renewable energy after Biden took office; the support measure was subject to a makeover, which brings uncertainties to clean energy investments (Moran et al., 2021).

Investors might be aware of these policy risks and take them into account with important, to the best of our knowledge so far not thoroughly examined consequences for investment decisions in the electricity sector. Investors can respond to this risk by diversification as shown by the Modern Portfolio Theory (MPT) (Markowitz, 1952). MPT provides an analytical framework to analyse the relationship between returns, individual investment risk and the correlation of returns between investment opportunities. It is therefore an ideal tool to understand how climate policy instruments and the uncertainty about their implementation and stringency affect these three key parameters for low-carbon investments and thus portfolio allocation of investments.

In this paper, we thus analyse —both analytically and numerically —how climate policy instruments affect the variance of expected returns of specific generation technologies and their correlation by means of an analytical model and a numeric model. The analytical model allows for a stylised investigation of climate policy effect on portfolio investment decisions and serves as a theoretical foundation for the numeric model. Within the electricity sector, the expected returns of different assets are correlated through the mediation of market mechanisms. We show how policies —intended to decarbonise the electricity sector —can induce investments into fossil fuel technologies due to portfolio-optimisation consideration.

Assessing the effectiveness of climate policy instruments given (policy) uncertainty and risk-aversion for incentivising investments provides important new insights. Ex-ante assessments of climate policy is often based on so-called techno-economic models. In these models, investment pathways resulting under a certain climate policy scenario are determined assuming cost-minimisation of the energy system (Hall and Buckley, 2016; Trutnevyte, 2016; Hirth and Steckel, 2016; McCollum et al., 2018). The cost-minimisation approach assumes that investors are risk-neutral.

However, investors are generally recognised as risk-averse (Markowitz, 1952). This even holds if the investment is undertaken by a firm, as it is the case for most investments into energy-sector infrastructure. The reluctance to bear risk is empirically evidenced in the extent of corporate hedging activity (Géczy et al., 1997). Moreover, factors such as non-diversified owners, liquidity constraints, and costly financial distress can all drive firms to behave in a risk-averse manner (Asplund, 2002).

As we show in this paper, the aspects mentioned earlier have important consequences for investment decisions that need to be taken into account when using these techno-economic models to provide guidance for policymakers. Recently, there is increasing attention on the limitation of the techno-economic models and better integration of financing issues into the models are called for (Battiston et al., 2021; Peng et al., 2021). Accounting for finance and real investor decisions in climate policy models would likely improve the models' ability to inform policy and investment decisions.

Our paper is related to two strands of the literature. The first strand is the literature on environmental and climate policy instruments uncertainties (Sen and von Schickfus, 2020; van der Ploeg and Rezai, 2021). Weitzman (1974) discusses price and quantity setting in policy instruments and shows that the policy instrument of choice is determined by the relative steepness of the marginal abatement benefit and cost curves when there are risks and uncertainties on the costs of pollution control. With an investment model calibrated to the global oil and gas industry, van der Ploeg and Rezai (2020) show that the uncertain climate policy changes would cause discrete jumps in the evaluation of assets today and reevaluation of assets in the future. By studying a partial equilibrium model of the energy sector, Kalkuhl et al. (2020) demonstrate how lobbying power or fiscal considerations can lead the government to deviate from its previously announced carbon tax, thus creating stranded assets. In another study, it is shown that carbon price may prompt premature retirement of existing polluting capacities, but mandates and feebates can attract new investments without inducing stranded assets (Rozenberg et al., 2018). More recent research has also learned from macroeconomics adopting real business cycle models (Garth, 2012; Heutel and Fischer, 2013). For instance, a emission cap and a tax can induce equivalent outcomes in expectation (Fischer and Springborn, 2011). Furthermore, there is the extended issue of overlapping regulatory policies and uncertainties. When studying the policy portfolio containing a cap and trade scheme and a renewable share target under different states of aggregate electricity demand, Flues et al. (2014) find that there would be unintended consequences on efficiency and effectiveness, especially when aggregate demand is low and carbon prices and sensitive to economic activity changes.

The second strand is the established literature on the optimisation of electricity planning using MPT. When assessing the efficiency of the Brazilian electricity generation mix proposed, Losekann et al. (2013) find that a higher share of fossil fuel in the portfolio is observable when CO2 is not priced and higher CO2 prices can increase the share of renewables in the generation mix. FiT requires lower direct support levels than feed-in premiums because they expose investors to fewer market risks (Kitzing, 2014). Laurikka and Koljonen (2006) show that emission trading impacts investment decisions by affecting the expected allowance prices and their volatility and correlation with electricity and fuel prices. Most of the papers in this strand come from a social welfare maximisation perspective, optimising the electricity generation portfolio of the whole electricity system for policy analysis purposes. However, portfolio optimisation from a private energy corporate investor point of view is not well studied. We fill this research gap by investigating the direct effects of climate policy instruments on the investment decision of private utilities investors. Our paper is the first of its kind to conduct this type of assessment using the MPT approach.

Additionally, in one paper closely related to ours, the findings show a relationship between portfolio optimisation in the financial market and climate actions —a trade-off between diversification and climate action due to climate system uncertainties —with uncertain timing of climate disasters, investors hedge these uncertainties by keeping a portion of dirty assets in the portfolio (Hambel et al., 2020). Thus, in general, brown generation assets are not shut down completely. Similar to our findings, Hambel et al. (2020) find that hedging used to minimise the effects of uncertainty can lead to stranded assets. In contrast to their paper, we focus on a different source of uncertainty, which is not caused by the climate system, but rather the uncertainty in the economy, such as demand and price shocks and policy risk.

In our paper, we show that uncertainty about the continuation of fixed remuneration policies for renewable deployment leads to more potentially stranded investments in fossil fuel generation capacities —ranging from 1% to 35% of a risk averse investors' budget. On the contrary, a carbon price instrument is less affected by policy discontinuation in comparison. Both fixed remuneration and carbon price policies can crowd out dirty asset investments in an investor's portfolio; however, for the same amount of clean energy in the portfolio, the investors have to bear more investment risks under carbon pricing policies. If implemented as an overlapping policy, a fixed remuneration scheme reduces investment risks and thus can serve as a complementary tool to make the investment risk profile more attractive for the more risk-averse investors to broaden the investor base for clean energy.

Our paper has the following contributions. By going beyond cost-minimisation in the techno-economic models and taking portfolio optimisation consideration into account, we contribute to examining a mechanism of how policies affect real investment decisions —investors are more likely to construct diversified portfolios to manage risks and potential losses using MPT, rather than following investment pathways resulted from cost minimisation of the electricity system. In addition, we analyse multiple climate policy instruments in the same framework —thus contributing to the discussions of the trade-off among the instruments. Policymakers should take uncertainties well into policy design considerations because uncertainties beyond policy instruments lead to investors' adjustment of portfolios and investment assets that can lead to potentially stranded assets. Our recommendations and argumentation hold in other sectors. Our primary model is about policy uncertainty in the power market, but policy uncertainty is essentially a tax on capital, with the end effect of higher-than-expected capital cost on the policy-supported technologies. Where one technology is more capital intensive than the other in investment choices, our analysis framework could be adopted, and similar results are likely in developing country contexts and in other goods markets, e.g. the hydrogen capacity market.

In the remainder of the paper, we show our analytical model in Section 2 and the numeric model in Section 3. The calibrated stochastic numeric model for the European Union (EU) power sector demonstrates case studies of what risk-averse investors' portfolios look like under different policy schemes. The policy effect results are summarised in Section 4, where an extension on the effect of uncertain policies on investment decisions is examined. This is followed by a discussion of key findings in Section 5. Finally, Section 6 concludes.

2 Analytical Model

We develop a simple model on investing in the energy sector where the risk-return profile of the investments, as well as their correlation is shaped to a large extent by policy instruments. This model allows for identifying the main mechanisms of how policy design governs the investment portfolio composition.

Let us assume for the moment that electricity can be produced by only two different technologies. There are fossil-fuel burning and pollution emitting power plants (called "dirty") d. Alternatively, electricity can be produced with renewable energy (in short "clean") c. Technologies can be indexed by $j \in \{c, d\}$.

We assume that these plants use capital as their only production factor in our stylised model, ignoring other input costs for the moment (the input costs will be considered later in the numeric model). This simplification is reasonable in the simple model because the costs will be reflected indirectly in the returns of the assets. We abstract from the accumulation of capital stocks of multiple periods and assume that there are two periods only[1]. In period t an investor can invest either dirty or clean projects or divide its wealth w_t between both technologies. We think of the investor as a power utility, or another entity whose purpose is generating electricity and that is exclusively investing in the power market. There are, therefore, no other options available such as government bonds or other assets outside the electricity market.

In order to produce one unit of electricity with technology j, $c_{j,t}$ units of capital are necessary in period t. Electricity producers face a given electricity price p_t. This equilibrium price is set on the electricity market. In the simplified model here, we are agnostic about explicit demand and supply considerations, but we capture this more explicitly in the numerical model in Section 3 of the paper. Due to externalities, the electricity market is ripe with policy interventions. Dirty, fossil-fuel burning plants may need to pay carbon taxes or are included in cap and trade schemes. Clean renewables may be supported by tax credits, feed-in tariffs or other forms of support mechanisms. We denote the regulative price intervention per unit of electricity with $\varrho_{j,t}$. Thus, electricity producers make per-unit profit $\pi_{j,t} = p_t + \varrho_{j,t} - c_{j,t}$, where $\varrho_{j,t}$ is positive if the policy intervention is a subsidy and negative if it is a tax or another cost.

Hence, the return on capital in t is $\pi_{j,t}/c_{j,t}$. In the end, the invested unit of capital in technology j has thus a value of

$$R_{j,t+1}(p_t, \varrho_{j,t}) = \frac{p_t + \varrho_{j,t}}{c_{j,t}},$$

which we call the return factor. The return is increasing in prices and subsidies, decreas-

[1]Thus we assume implicitly that the capital is fully depreciated after the end of the second period. The uncertainty of the investment comes from return uncertainties. The period index t is only necessary because we care about expected returns in the future.

ing in taxes or other policy costs.

However, when investing at time t, the utilities do not know the the return the respective projects generate in period $t+1$. Building and investing in a power plant are long-term decisions, and the returns of a project are ex-ante unknown as (i) electricity demand changes due to changes in aggregate demand, preferences or technology, (ii) an asset's average remuneration changes as its location on the merit order changes due to changes in the marginal costs of other plants in the market, or as policies changes. Though the exact return realisation is ex-ant unknown to the investor, we assume that the investor has expectations about the distribution of potential returns as well as the covariance of returns between the projects. [2]

A key determinant of the capital return expectation formation in the energy sector is policy instruments. They can either affect the variance of expected returns; for example, Feed-in-Tariffs provide a fixed remuneration per produced unit of electricity, independent of market prices. Obviously, many policies also affect the expectation of mean returns. A carbon tax, for instance, increases marginal costs and reduces profits and thus returns of fossil-fuel plants. In addition, policies can also affect the correlation between clean and dirty assets. This becomes obvious if renewable power plants get a Feed-in-Tariff such that their remuneration becomes independent from market prices and less correlated with returns of fossil-fuel power plants.

We will model these power market asset returns and their correlation more explicitly in the next section. For the moment, we remain agnostic about the source of the underlying risks and just assume that both assets have lognormally distributed return factors $R_{j,t+1}$ with $j \in \{c, d\}$ and thus: $logR_{j,t+1} = r_{j,t+1} \sim \mathcal{N}(\mu_j, \sigma_j^2)$. [3] The covariance matrix is given by $\left(\begin{smallmatrix} \sigma_c^2 & \sigma_{cd} \\ \sigma_{cd} & \sigma_d^2 \end{smallmatrix}\right)$, where σ_j^2 denotes the variance of return factors and σ_{cd} is the covariance.

We assume that investors are risk-averse, an assumption that can be justified even if the investor is a firm. The delegation of investment decisions to a risk-averse manager, whose pay is linked to firm performance, can cause the firm to behave in a risk-averse manner (Wiseman and Gomez-Mejia, 1998; Asplund, 2002). The manager's risk aversion is one of the key factors that make safer projects relative more desirable than risky projects for a firm (Parrino et al., 2005).

On this basis, we adopt and adjust the constant relative risk aversion (CRRA) framework to model the risk aversion characteristics of the firm investors and their preferences,

$$V = W_{t+1}^{1-\gamma}/(1-\gamma),$$

where V is the risk-preference adjusted valuation for a firm, W_{t+1} is the expected value of the firm's investment portfolio in $t+1$ and with $\gamma \geq 1$.[4] The value of the investment portfolio in $t+1$ depends on the its value in the previous period times the

[2] Real power market investors consider return uncertainties in their investment assessments Egli (2020)

[3] A log-normal distribution is commonly used in finance to characterise investment returns

[4] In the limit with $\gamma = 1$, $V = log(V_{t+1})$.

portfolio return factor $\bar{R}_{t+1}$, hence

$$W_{t+1} = \bar{R}_{t+1} W_t. \tag{1}$$

As the investor can allocate her resources on two different assets, the lognormally distributed portfolio return factor is the weighted average of both assets' returns, weighted by their portfolio weight $0 \leq \alpha_j \leq 1$. As we have only two assets, we express everything in terms of the portfolio weight of dirty assets $\alpha_d = (1 - \alpha_c)$, i.e. the clean asset as benchmark.

$$\bar{R}_{t+1} = \alpha_d R_{d,t+1} + (1 - \alpha_d) R_{c,t+1}.$$

The portfolio rate of return $r_{p,t+1}$ can be approximated from a second-order Taylor expansion (Campbell and Viceira, 2002b). We demonstrate this in the Appendix A.1 and obtain

$$\bar{r}_{t+1} = r_{c,t+1} + \alpha_d (r_{d,t+1} - r_{c,t+1}) + \frac{1}{2} \alpha_d (1 - \alpha_d) \eta, \tag{2}$$

where $\eta = \sigma_c^2 + \sigma_d^2 - 2\sigma_{cd}$. Note that $\bar{r}_{t+1} = log(1 + \bar{R}_{t+1})$ is the normally distributed log return on the portfolio. [5] Generally, we denote log variables in small letters and write the firm investors' budget constraint in (A.1) in log-form:

$$w_{t+1} = \bar{r}_{t+1} + w_t$$

Using the approximation of the portfolio rate of return in (2), the expectation of the investment value adjusted by risk-preferences as of date t is:

$$\mathbb{E}[V(W_{t+1})] \approx (1-\gamma)^{-1} \mathbb{E}\left[(w_t e^{r_{c,t+1} + \alpha_d (r_{d,t+1} - r_{c,t+1}) + \alpha_d \alpha_c \eta /2})^{1-\gamma} \right]. \tag{3}$$

The rate of return realisations $r_{c,t+1}$ and $r_{d,t+1}$ in $t+1$ are stochastic. In fact, $(1-\gamma)(\alpha_c r_{c,t+1} + \alpha_d r_{d,t+1}) \sim \mathcal{N}((1-\gamma)(\alpha_c \mu_c + \alpha_d \mu_d), (1-\gamma)^2 (\alpha_c \sigma_c^2 + \alpha_d \sigma_d^2 + 2\alpha_c \alpha_d \sigma_{cd}))$. We therefore take the deterministic variables w_t as well as the third summand in the exponential function out of the expectations. Thus,

$$\mathbb{E}[V(W_{t+1})] \approx (1-\gamma)^{-1} w_t^{1-\gamma} e^{(1-\gamma)\alpha_d \alpha_c \eta/2} \mathbb{E}\left[(e^{(r_{c,t+1} + \alpha_d (r_{d,t+1} - r_{c,t+1}))(1-\gamma)} \right].$$

the investor aims at maximising the risk-preferences adjusted valuation of the portfolio by choosing the asset allocation through α_c and $\alpha_d = 1 - \alpha_c$. Following Carroll (2013), we show the derivation of the problem's first-order conditions in the Appendix A.1 and obtain the valuation-maximising portfolio weight α_d for dirty power plant assets:

$$\alpha_d = \frac{\mu_d - \mu_c + (\sigma_c^2 + \sigma_d^2 - 2\sigma_{cd})/2 + (1-\gamma)(\sigma_{cd} - \sigma_c^2)}{\gamma(\sigma_c^2 + \sigma_d^2 - 2\sigma_{cd})}. \tag{4}$$

Equation (4) shows that the share that an investor is willing to invest in dirty assets is

[5] This is the so-called continuously compounded portfolio return in financial terms

governed by five parameters. Obviously, the portfolio share of dirty assets is increasing in the mean return difference $\mu_d - \mu_c$ between dirty and clean assets. A greater markup on returns of dirty relative to clean assets increases the portfolio weight of dirty assets. Under deterministic returns, the asset allocation would be driven by return considerations only. However, given uncertainty on the realisation of future returns, the investment decision is more complex depending also on variances and covariances of asset returns.

This leads to the question if there are conditions that lead to an increase in α_d even if the expected returns of clean assets are increasing? Since policy instruments may shape these conditions in the power market, it is important to understand these mechanisms.

A risk-averse investor with $\gamma > 1$ chooses her portfolio weights with respect to variances and covariance. Further assuming $\mu_c = \mu_d$ and $\sigma_{cd} = 0$, and the partial derivative of (4) with respect to σ_c gives $(2(\gamma-1)\sigma_c\sigma_d^2)/(\gamma(\sigma_c^2+\sigma_d^2)^2)$. Under risk aversion with $\gamma > 1$ both numerator and denominator are positive. Thus, if both assets are uncorrelated, an increase in σ_c (more volatility in clean assets) leads to an increase in the share of dirty assets. In case of an increasing volatility of the dirty asset σ_d, everything else equal, the investor reduces her holding of dirty assets at the margin.

Additionally, the dirty asset share α_d also depends on the covariance between both assets' returns. Assuming $\mu_d > \mu_c$,one can see that a marginal rise in the covariance σ_{cd} leads to an increase in α_d if $\sigma_c > \sigma_d$.[6] On the contrary, a marginal decrease in σ_{cd} leads to an decrease in α_d given the same conditions.

If a policy intervention that supports clean renewables such that μ_c is (marginally) increasing, the policy intervention can still lead to an increase in dirty asset holdings if the variance of clean (or dirty assets) is (marginally) increasing and $\frac{\partial^2\alpha_d}{\partial\mu_c\partial\sigma_{cd}^2} > 0$.

From (4) we see that

$$\frac{\partial^2\alpha_d}{\partial\mu_c\partial\sigma_{cd}^2} = \frac{1}{\gamma(\sigma_c^2+\sigma_d^2-2\sigma_{cd})^2} \tag{5}$$

Proposition 1. *[Potential Stranded Assets] A policy instrument ϱ_j that marginally increases the expected return of clean assets μ_c leads still to an marginal increase of the portfolio weight of dirty asset α_d if σ_c marginally increases and $\sigma_c^2+\sigma_d^2-2\sigma_{cd} \neq 0$.*

A proof of the proposition is in the Appendix A.2. This shows that it potentially possible that policy instruments that generally improve the expected profitability of clean assets still induce additional investments into dirty assets if the the policy at the same time increases the variance sufficiently. Although with good intentions, an instrument to support clean assets can thus lead to more potentially stranded assets that are mainly bought for hedging purposes.

By evaluating the changes of signs and magnitude of the various terms in the equations after a climate policy is implemented, the policy effects of two sorts are analysed in a stylised manner:

[6] $\frac{\partial\alpha_d}{\partial\sigma_{cd}} = \frac{2(\mu_d-\mu_c)+(\gamma-1)(\sigma_c-\sigma_d)(\sigma_c+\sigma_d)}{\gamma(\sigma_c^2+\sigma_d^2-2\sigma_{cd})^2}$.

Will the climate policy instrument lead to decreased share of dirty asset in the portfolio? α_c, the optimal clean asset holding is the rest of the share not invested in α_d. To transit to a low-carbon economy, clean energy technologies should have a higher share than the dirty ones. We find that the difference between the clean and dirty asset holding is

$$\alpha_c - \alpha_d = 2\frac{(\mu_d - \mu_c)}{\gamma(\sigma_c^2 + \sigma_d^2 - 2\sigma_{cd})} + (1-\gamma)\frac{(\sigma_c^2 + \sigma_d^2)}{\gamma(\sigma_c^2 + \sigma_d^2 - 2\sigma_{cd})}. \tag{6}$$

From equation (6), it can be seen that if climate policies are to improve the expected returns of clean assets, which is $\mu_d > \mu_c$, it is only a necessary condition, not a sufficient condition for the clean asset share to be larger than the dirty asset share in the portfolio. In fact, the risk aversion level, riskiness and the variance-covariance relations of the assets all play a role.

Will the instrument result in a portfolio with more clean assets than dirty assets? Equation (4) can be rewritten as

$$\alpha_d = \frac{1}{\gamma}\left(\frac{\mu_d - \mu_c}{\sigma_c^2 + \sigma_d^2 - 2\sigma_{cd}}\right) + \frac{1-\gamma}{\gamma}\left(\frac{\sigma_{cd} - \sigma_c^2}{\sigma_c^2 + \sigma_d^2 - 2\sigma_{cd}}\right) + \frac{1}{2\gamma}. \tag{7}$$

Depending on whether a climate policy instrument affects the market though quantity or price, we study two types of instruments. The first type is the fixed remuneration policies, which provide a guaranteed remuneration for clean electricity generation. This includes the Feed-in Tariffs, Feed-in Premiums, and auctions that pay fixed clearing price. The second is the price instruments, which penalises dirty assets by putting a price on it. This includes the carbon taxes and emission trading scheme.

To investigate the above two questions, we make use of the insights from our numerical model results in Section 4 of the paper. The risk aversion of an investor is assumed to be stable in the long-term; therefore the risk preference of the investor does not change with market conditions.Under fixed remuneration policies, the risk-return profile of dirty assets does not change, whereas that of clean assets is improved —meaning that the fixed remuneration policy leads to higher expected returns and lower risks in clean assets. The correlation between dirty and clean assets is reduced, providing better diversification effect. Under price instruments, the expenses for dirty assets are increased by carbon tax or emission trading scheme. The expected returns of dirty assets become lower than those of clean assets. As electricity price is pushed up though the carbon pricing instruments, clean assets gain higher expected returns but also have higher return volatility along with the price fluctuations —becoming similar to that of dirty assets in financial characteristics, thus the correlation between both assets increases. Taking these observations into Equation 6 and Equation 7, we find that the fixed remuneration policies will lead to a portfolio with reduced dirty asset share and larger clean asset share. The price instruments have similar effects. Retroactive changes in both types of instruments would reduce the promotional effect for clean assets.

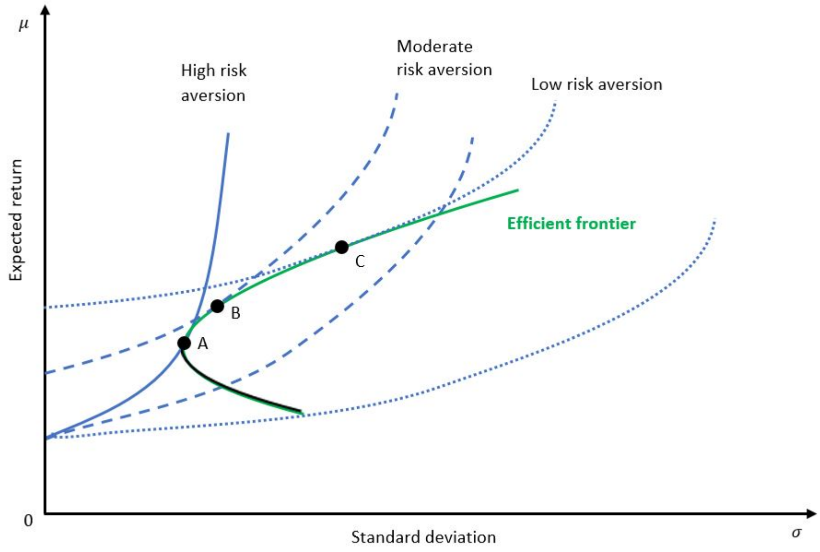

Figure 1: Portfolio choices of representative risk averse investors

The above analytical model has provided insights into stylised policy effects on investments. However, it is still limited in analysing investment decisions in the economy in more concrete terms and does not give more details into how fixed remuneration and carbon pricing instruments' policy effects on investor choices differ. In order to further study market interactions and uncertainties, portfolio allocation decisions and climate policy effects, a calibrated stochastic numerical model of energy market investments is developed in the section below. The theoretical foundation for the numeric modelling is based on Markowitz modern portfolio theory (Markowitz, 1952). Seen in Figure 1, the optimal portfolio choice for an investor is determined by the indifference curves and the efficient frontier of investments jointly, essentially when investor preference meets market opportunities. On each indifference curve, the various combinations of dirty and clean assets give the investor the same amount of utility (satisfaction). The rational investor, however, can and will only invest in portfolio combinations with the least variance at each possible level of expected portfolio return — the efficient frontier illustrating the trade-off between the expected return and risk on a portfolio level. Given the risk preference of a investor, she is best-off at the point where the slope of the efficient frontier equals the marginal utility.

In the following, we will study risk averse investors in our paper, in particular, investors with high, moderate and low risk aversion in stylised case studies. The three points on the efficient frontier line represent the portfolio choice of three different investors with different risk preferences. An investor with higher risk tolerance is willing to accept more risks for higher expected returns.

3 Calibrated Stochastic Model of Energy Market Investments

As seen in the analytical model above, optimal portfolio composition depends on several key parameters, including expected returns, variance and correlation of the assets in the portfolio. We use a calibrated model to generate these key parameters to study the optimal investment portfolios for a representative risk-averse investor into clean and brown generation assets in the EU power market in a mean-variance portfolio approach.

The mean-variance portfolio (MVP) approach is chosen because it is applied by utilities in the real world. Oil & gas companies have been systematically deploying MVP for capital allocation and risk management purposes (Walls, 2004). The electric utility industry has also moved towards a more efficient portfolio since the 1980s (Roques et al., 2008). An example of an electricity utility using MVP for investment decision guidance is E.ON, one of the largest power utility company in Europe. Optimising E.ON's electricity generation portfolio using MVP was conducted by the E.ON Energy Research Centre (Madlener et al., 2010) and it concluded that the optimal portfolio could include more renewables. Subsequently, E.ON stated in its 2011 annual report a renewables expansion plan worth EUR 7 billion in investments (E.ON, 2011). E.ON has invested more and more in renewable energy generation in recent years (SE, 2021) .

3.1 Model description

The modelling framework developed below is grounded in literature. The mean-variance portfolio analysis approach in our model is consistent with that in Laurikka and Koljonen (2006), Losekann et al. (2013) and Kitzing (2014). In particular, the framework is based on the methods recommended by Gross et al. (2010), which states that modelling based on cost estimates is of limited use in designing policies for promoting investments. Instead, a simple model should be used to calculate potential returns to investment in technologies, then taking market and policy uncertainties in different scenarios to conduct policy analysis.

Our numeric model aims to answer the question: If there are additional financing sources available for new investments, what would the investment allocation to different power generation technologies look like for a representative risk-averse investor in the EU power market?

We assume that there is one representative investor and she represents the market. Later in the case studies, we will choose a representative investor with different risk aversion levels, however, the assumption of one representative market investor does not change. We further assume that there is no feedback effect between the portfolio allocation and the power market.

The standard model consists of three parts. The three sub-models are executed sequentially. As shown in Figure 2, the outputs from the power market model are used as part of the inputs in the cash flow model, and the outputs from the cash flow

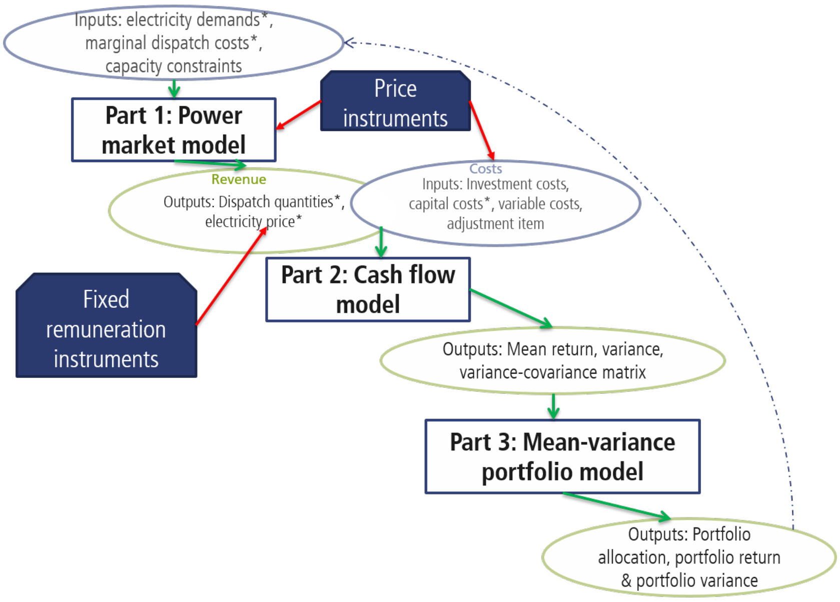

Figure 2: Model flow chart (Source of uncertainties marked by *star: electricity demands, dispatch costs, capital costs, policy uncertainties)

valuation are used to calculate the optimal mean-variance portfolio. Moreover, climate policy instruments affect the investment decisions through the first two parts of the model. Fixed remuneration instruments directly guarantee a stable electricity price, enhancing the revenue stream of renewable energy producers. Carbon price instruments differs from these two approaches by not only increasing costs for dirty assets, but also changing the power market equilibrium as the carbon costs are factored in dispatch decisions.

The sources of uncertainties in the model are marked by stars (*). Market uncertainties come from electricity demands and marginal dispatch costs, affecting market electricity price and dispatch quantities through the power market. Financing costs uncertainties are captured by uncertain capital costs. Policy uncertainties exist as climate policies supporting clean assets have a mid to long term horizon and retroactive changes due to fiscal deficit, lobbying and other political factors occur.

Part 1: Power market model. The power market model generates optimal electricity dispatch. We extend an electricity dispatch model (Rutherford, 1995). In equilibrium, electricity demands and marginal dispatch costs by power plant technologies determine dispatch amounts and the electricity price in the power market.

The electricity dispatch model is highly simplified, providing equilibrium prices and quantities of dispatch. It is compact enough to run a large number of Monte Carlo Simulations. There are three load segments, which are peak load, intermediate load and baseload. The time framework for the investment plan is assumed from 2015 to 2035. Power generation technologies are solar, wind, hydro, biomass, nuclear, coal, and gas. The demand side is divided into three segments: residential, commercial and industrial.

The model does not capture the intermittent nature of renewable energy sources. This shortcoming only affects our research objectives marginally because our electricity dispatch model's purpose is not to realistically project power market dispatches but to serve as a simplified market equilibrium experiment so that the equilibrium parameters generated in the model can be used as inputs for the next step's cash flow model. The key input parameters for the power market model are reference demand in Megawatt (MW), the marginal cost of dispatch in EUR per Megawatt hours (MWh), capacity constraint in MW, and the demand shares for different loads by segment.

In the first step, reference prices and quantities of electricity for each segment are calculated with linear programming. The objective function is to minimise the total dispatch costs in the power system in the total cost function (Equation 8) while satisfying the demand function (Equation 9).

Cost refers to the total costs of power supply, s is the load segments, Y is the unit power supply, βref_s is the baseline reference demand for loads in the year 2015.

$$cost = \sum_{j,\,s,\,t} (c_{j,t} \cdot Y_{j,\,s}) \tag{8}$$

$$\sum_{j} Y_{j,\,s} = \beta ref_s \tag{9}$$

In the second step, electricity supply, profits and capacities are calculated in an equilibrium model, with additional three binding conditions: market-clearing condition (Equation 10), zero profit condition (Equation 11) and capacity constraint condition (Equation 12), while satisfying the aggregate demand function (Equation 13). The model is solved as a mixed complementarity problem.

B is the power demand, p is the electricity price, i refers to the demand categories, K refers to the capacity constraints of technologies, π is the unit profits, tax is the taxes, ϵ is the elasticity of demand, $\bar{p}$ refers to the reference price of demand.

$$\sum_{j} Y_{j,\,s} \geq \sum_{i} B_{i,\,s}(p) \quad \perp \quad p_s \geq 0 \tag{10}$$

$$c_{j,t} + tax_j + \pi_{j,\,s} \geq p_s \quad \perp \quad Y_{j,\,s} \geq 0 \tag{11}$$

$$K_j \geq Y_{j,\,s} \quad \perp \quad \pi_{j,\,s} \geq 0 \tag{12}$$

The three complementarity conditions above are written in the orthogonal form with $\perp$ to indicate the orthogonal relationship between the two.

$$B_{i,\,s} = \bar{\beta} ref_{i,\,s}(1 - \epsilon_i(p_s/\bar{p}_s - 1)) \tag{13}$$

In the third step, market uncertainties are taken into consideration. The models are looped through simulated stochastic input variables. Volatilities come from demand and marginal dispatch costs. The model is run 10,000 times in the Monte Carlo simulation. The 10,000 states of equilibrium market prices and quantities are stored as inputs to be used in the cash flow model.

Part 2: Cash flow valuation. The second part is a cash flow valuation used to calculate the Net Present Values (NPVs) and the power plant projects' returns. The investment return calculation is assumed based on a 1 MW power plant, as there are fixed and variable costs. Power generation assets' key cost items are captured by investment costs, capital costs and variable costs (Río and Cerdá, 2014). The key input parameters for the cash flow valuation are investment costs, capacity factor, operation & maintenance (O&M) costs, other costs as adjusting factors, and the weighted average cost of capital (WACC); WACC is a firm's cost of capital indicator, where each capital type such as debt and equity are proportionally weighted.

In the cash flow valuation, there is an initial investment in 2015. From the year 2016, the investment generates revenues but also result in costs. The sum of the discounted cash flow is the NPVs. The net cash inflows are calculated by deducting cash outflows from cash inflows. The WACC then discounts the cash flows within the project's lifetime. NPV is a key financial indicator for judging a project's investment attractiveness. A positive NPV is desired; the higher the NPV, usually the more financially a project is. The discounted total costs are obtained by discounting the total costs by the WACC. Returns are defined and calculated as the NPV of a generation asset type divided by its discounted total costs.

NPV is the net present value, θ is the different states, inv is the initial investment cost,wacc is the weighted average cost of capital, $cashflow$ is the cash flows starting from period 1, p* is the equilibrium market price, τ is other costs —other inputs and financing costs, $unitcost_j$ is the marginal costs of production, h is the operating hours, capacity is the capacity factor, totinvestcost is the discounted total investment costs, investcost refers to the investment costs, μ is the return. 1MW capacity is considered.

$$\begin{aligned}
NPV_{\theta,\, j} &= -inv_j + \sum_{t=1}^{T} \frac{cashflow_{\theta,\, t,\, j}}{(1+wacc_j)^t} \\
cashflow_{\theta,\, t,\, j} &= \sum_{s} (p^*{}_{s,\, \theta} - unitcost_j - \tau_j) \cdot h_s \cdot capacity_j \\
totinvestcost_{t,\, j} &= inv_j + \sum_{t=1}^{T} \frac{investcost_{\theta,\, t,\, j}}{(1+wacc_j)^t} \\
investcost_{\theta,\, t,\, j} &= \sum_{s} (unitcost_j + \tau_j) \cdot h_s \cdot capacity_j \\
\mu_{\theta,\, j} &= \frac{NPV_{\theta,\, j}}{totinvestcost_{\theta,\, j}}
\end{aligned}$$

For each type of generation asset, we calculate the returns under 10,000 different power market outcome states. To capture the uncertainties in financing costs, we build uncertainties in the WACCs using stochastic variables generated by following a normal distribution. The simulated returns' mean and standard deviation and the variance-covariance matrix between asset types' returns are calculated. These parameters will be used as inputs in the mean-variance portfolio model.

Part 3: Mean-variance portfolio model. The third part is a mean-variance portfolio model, which calculates the optimal portfolio allocation of investments into different power plants. The mean-variance portfolio theory is well established (Markowitz,1952; Markowitz, 2016). We follow the standard theory in this part of the model.

The mean-variance portfolio model's key input parameters are mean return, variance, and variance-covariance matrix of each power generataion asset's returns calculated.

$\bar{\mu}$ is the mean return, which is the average of the returns generated in the simulation. σ^2 is the variances. λ represents the variance-covariance matrix.

$$\bar{\mu}_j = \sum_{\theta} \frac{\mu_{\theta,\, j}}{\theta}$$

$$\sigma_j^2 = \sum_{\theta} \frac{(\mu_{\theta,\, j} - \bar{\mu}_j)^2}{\theta}$$

$$\lambda_{j,jj} = \sum_{\theta} \frac{(\mu_{\theta,\, j} - \bar{\mu}_j) \cdot (\mu_{\theta,\, jj} - \bar{\mu}_{jj})}{\theta}$$

The objective function is to minimise portfolio variance function (Equation 14). The portfolio return function calculates the portfolio return based on the optimal allocation and the expected returns (Equation 15). The sum of all portfolio allocation weights is equal to 1, which is the normalisation constraint (Equation 16).

$port_{\sigma^2}$ is the portfolio variance, α is the optimal portfolio share in a technology,$port_{\mu}$ is the portfolio return.

$$port_{\sigma^2} = \sum_{j,\, jj} {\alpha_j}^2 \cdot {\sigma^2}_j + {\alpha_{jj}}^2 \cdot {\sigma^2}_{jj} + 2 \cdot \alpha_j \cdot \alpha_{jj} \cdot \sigma_j \cdot \sigma_{jj} \cdot \lambda_{j,\, jj} \tag{14}$$

$$port_{\mu} = \sum_{j} \bar{\mu}_j \cdot \alpha_j \tag{15}$$

$$\sum_{j} \alpha_j = 1 \tag{16}$$

This part of the model is solved by non-linear programming. The model's outcome is the optimal portfolio composition, consisting of shares in percentages in different types of power generation assets.

3.2 Data and calibration

The power market model is calibrated based on EU-28 power market data, taking 2015 as the base year. The key data source is the EU reference scenario 2016 (Capros et al., 2016).

Table 1: Reference demand data (Capros et al., 2016)

Load segment	βref_s (MW)	h_s	r(%)	c (%)	i(%)
Peak load	115743	310	0.70	0.20	0.10
Intermediate load	97468	1780	0.45	0.25	0.30
Base load	98841	6670	0.25	0.30	0.45

Table 1 shows the demand side of the power market. There are three loads: peak, intermediate and base loads and three demand categories: residential (r), commercial (c) and industrial (i). The reference demand βref_s denotes the adjusted baseline demand in the year 2015. The demand hours h_s add up to 8760 hours, which correspond to a standard year of operation.

Table 2 shows the power generation-related data by technology. Marginal costs of production ($unitcost_j$) and carbon intensities (ξ_j) are estimated values based on Lazard (Lazard, 2015) and Annex III: Technology-specific cost and performance parameters in the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (Schlömer et al., 2014). Capacity constraints (K_j) are adjusted in order to calibrate electricity market price and the power generation profile, where the price levels (p_s) are calibrated to EU electricity price level in 2015. Power generation profile imitates the composition of technologies to that in the EU's power generation portfolio in 2015.

The power generation calibration is consistent with the following aspects of the real electricity market. The market price in the base load is not greater than that of the peak load, and renewables appear in all three types of load. However, due to the simplicity of the dispatch model structure and disregard of the intermittent nature of renewable energy, we cannot calibrate solar and wind to take a greater share in the peak load.

Technology	$unitcost_j$ (EUR/MWh)	K_j (MW)	ξ_j(kg/MWh)
Solar	5	3950	0
Wind	5	10437	0
Hydro	5	13791	0
Biomass	225	1796	0
Nuclear	12	33006	0
Coal	175	32224	900
Natural gas	75	21540	700

Table 2: Reference electricity generation technology data (Capros et al., 2016)

The reference investments data are presented in Table 3. The cash flow model is calibrated based on the investment data from the year 2015. Key data source are Lazard (Lazard, 2015) and fifth IPCC assessment annex (Schlömer et al., 2014). In addition, we use Damodaran cost of capital for firms data (Damodaran, 2021). The calibration follows market observations of the investment attractiveness of clean and brown generation assets. Nuclear technology usually is planned as a national program and receives support from the public sector (Jewell, 2011); we account for this by adjusting the extra costs into support to reduce nuclear power plant costs. In a market without climate support policies, the risk-return profiles of renewables are not as attractive for investors as that of coal or natural gas.

	inv_j (mEUR/MW)	$capacity_j$ (%)	$unitcost_j$ (EUR/MWh)	tau_j (EUR/MWh)	$wacc_j$
Solar	1.3	0.25	85	10	0.065
Wind	1.6	0.35	70	30	0.065
Hydro	1.8	0.40	38	65	0.065
Biomass	3	0.60	55	45	0.065
Nuclear	5.5	0.94	82	-2	0.087
Coal	0.5	0.48	46	75	0.087
Natural gas	0.4	0.10	32	50	0.087

Table 3: Reference investment data: Lazard (2015); Schlömer et al. (2014); Damodaran (2021)

The parameters used in the model are summarised in Table 4. Volatilities (vol) characterise a normal distribution random number generators to capture uncertainties in demand (β), marginal costs ($unitcost$) and WACC ($wacc$). The reference level in Tables 1, 2 and 3 with respect to each variables are taken as the mean. The demand shock is chosen at 0.1%, imitating a mild demand fluctuation. The volatility of the marginal costs is calibrated to take high values to obtain price differences in different states.

Parameters (selected from all sections of the model)	Value
vol_β	0.001
$vol_{unitcost}$	5
vol_{wacc}	0.005
ϵ_r	0.1
ϵ_c	0.2
ϵ_i	0.5
ϱ (EUR/MWh)	200
$carbon_{price_{scale1}}$ (EUR/ton CO2eq)	25 to 35 to 45 to 55

Table 4: An overview of the key parameters

The elasticity of demand (ϵ) for residential (r), commercial (c) and industrial (i) sectors take the values from the original power dispatch model (Rutherford, 1995). The fixed remuneration policy support levels (ϱ) are set at 0,2 EUR/kWh for solar, wind, hydro and biomass, a reasonable level as seen in the historical average support levels in the EU countries (LEGAL, 2021). Carbon taxes are assumed to rise from 25 EUR to 55

EUR; the increase happens every 5 years.

Technology	Mean returns	Variance
Solar	18%	0.0111
Wind	20%	0.0144
Hydro	20%	0.0144
Biomass	18%	0.0111
Nuclear	18%	0.0111
Coal	25%	0.0221
Natural gas	28%	0.0266

Table 5: Characteristics of the benchmark returns

Table 5 shows the mean and variance of the assets returns in the benchmark case. In our benchmark calibration, dirty assets have higher mean return and variance levels than the clean assets. Table 6 shows the covariance relations between the dirty and clean assets.

	SL	WN	HD	BM	NC
CL	0.00115	0.00124	0.00122	0.00120	0.00120
GS	0.00118	0.00128	0.00125	0.00123	0.00122

Table 6: Benchmark case variance-covariance matrix of assets
Note: SL,WN,HD,BM,NC,CL,GS are solar, wind, hydro, biomass, nuclear, coal and natural gas technologies.C is covariance relation.

Statistically, the return distributions of different assets are close to normal distributions. The mean-variance approach used in the modelling part does not require returns to be strictly normal. Thus the simulated data under policy shocks are all suitable for analysis using this modelling framework.

4 Policy Instruments Analysis: Modelling Results

This section is structured to answer two layers of questions. Firstly, how do mean returns, variance and variance-covariance relations among assets change with a fixed remuneration instrument? Secondly, what does this mean for portfolio allocation? We investigate the fixed remuneration instruments, carbon pricing instruments with case studies, and selected cases of overlapping instruments.

4.1 Fixed Remuneration Instruments

Fixed remuneration instruments like Feed-in Tariffs guarantee a fixed compensation to generators per unit of electricity sold. The payment is usually guaranteed for a period of time, ensuring predictable cash inflows for the investors. This instrument's support level is incorporated in the cash flow equation. The level of support is denoted by ϱ, whereas τ is other costs —other inputs and financing costs. The cash flows for clean assets are therefore:

$$cashflow_{\theta,\,t,\,j_c} = \sum_s (\varrho_{fixed_remuneration_{j_c}} - unitcost_{j_c} - \tau_{j_c}) \cdot h_s \cdot capacity_{j_c}$$

Retroactive policies that put taxes on the remunerated clean technology systems reduce cash flows. Using tax_{retro} to denote this tax rate, we have:

$$cashflow_{\theta,\,t,\,j_c} = \sum_s ((\varrho_{fixed_remuneration_{j_c}} - unitcost_{j_c} - \tau_{j_c}) \cdot h_s \cdot capacity_{j_c})(1 - tax_{retro})$$

Potential stranded asset share is denoted by δ_{Policy}. α_{uncer} and α_{cer} refer to the shares of assets given policy uncertainty vs. those under uncertain policies. $(\alpha_{uncer} - \alpha_{cer})$ is then the estimated potential stranded assets value.

$$\delta_{Policy} = \alpha_{uncer} - \alpha_{cer}$$

Policy effect on assets' variance and covariance. Fixed remuneration instruments increase the expected returns of clean assets while reducing their risks (see Table 7).

	SL	WN	HD	BM	NC	CL	GS
R_{no}	18%	20%	18%	16%	16%	32%	35%
R_{yes}	34%	36%	34%	32%	16%	32%	35%
V_{no}	0.0012	0.0014	0.0013	0.0013	0.0014	0.0014	0.0017
V_{yes}	0.0004	0.0003	0.0003	0.0003	0.0014	0.0014	0.0017

Table 7: Assets' expected returns and variance before and after a fixed remuneration instrument is implemented
Note: SL,WN,HD,BM,NC,CL,GS are solar, wind, hydro, biomass, nuclear, coal and natural gas technologies. R is return. V is variance. No indicates no policy. Yes indicates policy is in place.

In addition, the instruments reduce the covariance correlation between clean and dirty assets (see Table 8).

Policy Effect on Optimal Portfolio. The policy effect on assets' variance and covariance is reflected in the investor's choice of the optimal portfolio. We test three risk tolerance level of tolerated portfolio variance: 0.001, 0.002 and 0.003 respectively for three different representative risk averse investors. With fixed remuneration policy in place, the optimal portfolio for all three risk averse investors have improved risk-return characteristics, e.g., the portfolio variance changes from 0.0028 to 0.0009, whereas portfolio return changes from 21.65% to 33.01% compared to with no policy. From $P_{no_{vara}}$ and $P_{yes_{vara}}$ in Table 9, we see dirty assets CL (coal) and GS (natural gas) are reduced by

	SL	WN	HD	BM	NC
C_{no}: CL	0.00115	0.00124	0.00122	0.00120	0.00120
C_{yes}: CL	-0.00008	0.00001	0.000004	0.000006	0.00120
C_{no}: GS	0.00118	0.00128	0.00125	0.00123	0.00122
C_{yes}: GS	-0.00008	0.00002	0.000004	0.000003	0.00122

Table 8: Assets' covariance relations before and after a fixed remuneration instrument is implemented
Note: SL,WN,HD,BM,NC,CL,GS are solar, wind, hydro, biomass, nuclear, coal and natural gas technologies.C is covariance relation. No indicates no policy. Yes indicates policy is in place.

17.3% together. This effect of dirty asset reduction is stronger in portfolios of investors with risk tolerance of 0.001 and 0.002. As investors are willing to accept slightly more volatility in their portfolio returns (portfolio variance of 0.003), the clean assets prove to be the better choices than dirty assets and in this case, dirty assets can be largely excluded from the portfolio —note that we ignore the technical requirements of dirty assets in the power plants, but only discuss it from an investment portfolio construction perspective.

	SL	WN	HD	BM	NC	CL	GS
$P_{no_{var_a}}$	15.81%	14.54%	15.15%	15.18%	13.78%	14.24%	11.30%
$P_{yes_{var_a}}$	18.40%	23.12%	24.14%	21.40%	4.53%	4.69%	3.72%
$P_{no_{var_b}}$	13.46%	12.38%	12.89%	12.91%	11.73%	12.12%	9.61%
$P_{yes_{var_b}}$	21.05%	65.23%	7.77%	0%	0%	0%	5.95%
$P_{no_{var_c}}$	17.10%	20.65%	21.15%	13.18%	10.03%	10.12%	7.77%
$P_{yes_{var_c}}$	74.6%	25.4%	0%	0%	0%	0%	0%

Table 9: Investors' optimal portfolio choice before and after fixed remuneration instrument is implemented
Note: SL,WN,HD,BM,NC,CL,GS are solar, wind, hydro, biomass, nuclear, coal and natural gas technologies. R is return. P is policy implementation. No indicates no policy. Yes indicates policy is in place. var: variance, indicating the risks the investor willing to tak, var_a=0.001, var_b=0.002, var_c=0.003.

4.2 Carbon Pricing Instruments

Carbon pricing instruments put a price on carbon emissions. We incorporate carbon pricing in our model through a progressing carbon tax. Equation 11 becomes:

$$unitcost_j + tax_j + carbon_{taxj} + \pi_{j,\,s} \geq p_s \quad \perp \quad Y_{j,\,s} \geq 0$$

Cash flows for dirty assets are reduced to:

$$cashflow_{\theta,\,t,\,j_d} = \sum_s (p^* - \xi_j \cdot carbon_{tax} - unitcost_j - \tau_j) \cdot h_s \cdot (1 \cdot capacity_j)$$

Policy Effect on Assets' Variance and Covariance. Carbon pricing can take different forms. In Sweden, the initial carbon tax was issued at EUR 25 per tCO2 with incremental increases in tax rate (Ackva and Hoppe, 2018). [7] Following this, in our study, we assume that the implementation of carbon pricing instrument takes a progressive method —the level of the carbon tax rate is increased steadily. The assumed carbon tax rates have intervals of price increases of every five years. The carbon tax pricing scheme assumes to increase from 25, 35, 45 to 55 EUR per tCO2.

Given carbon price, there is cost transfer of the increased generation costs to consumers, thus the market electricity prices increase. The expected returns of clean assets increase —and expected returns of the dirty assets decrease (see Table 10). At the same time, the expected returns of clean assets become more volatile, while those of the dirty assets become less volatile.

	SL	WN	HD	BM	NC	CL	GS
R_{no}	18%	20%	18%	16%	16%	32%	35%
R_{yes}	40%	41%	39%	37%	36%	25%	33%
V_{no}	0.0012	0.0014	0.0013	0.0013	0.0014	0.0014	0.0017
V_{yes}	0.0015	0.0016	0.0014	0.0015	0.0017	0.0009	0.0012

Table 10: Assets' expected returns and variance before and after a carbon pricing instrument is implemented
Note: SL,WN,HD,BM,NC,CL,GS are solar, wind, hydro, biomass, nuclear, coal and natural gas technologies. R is return. V is variance. No indicates no policy. Yes indicates policy is in place. Carbon price assumes to rise from 25 to 55 EUR/tCO2.

Moreover, carbon pricing reduces the covariance correlation between clean and dirty assets (see Table 8).

		SL	WN	HD	BM	NC
C_{no}	: CL	0.00115	0.00124	0.00122	0.00120	0.00120
C_{yes}	: CL	0.00097	0.00104	0.00097	0.00094	0.00100
C_{no}	: GS	0.00118	0.00128	0.00125	0.00123	0.00122
C_{yes}	: GS	0.00105	0.00112	0.00108	0.00103	0.00107

Table 11: Assets' covariance relations before and after a carbon pricing instrument is implemented
Note: SL,WN,HD,BM,NC,CL,GS are solar, wind, hydro, biomass, nuclear, coal and natural gas technologies.C is covariance relation. No indicates no policy. Yes indicates policy is in place.

Policy Effect on Optimal Portfolio. Carbon price instruments give incentives for reducing dirty asset holding in portfolios. Same as in the analysis of fixed remuneration instruments, we test three risk tolerance level for each pricing scheme: the tolerated

[7] Today Sweden's power sector is included in the EU ETS and the carbon tax covers Non-EU ETS sectors only.

portfolio variance is assumed to be 0.004, 0.007 and 0.009 respectively. These indicate three different levels of risk aversion.

Table 12 demonstrates the policy effect of a carbon pricing instrument. Carbon pricing instrument has similar effect as the fixed remuneration instrument. However, the efficient frontier line (thus the investment opportunities, the possible portfolio combinations)in both cases are different. The least risky investment option under carbon pricing scheme is riskier than that under fixed remuneration instrument. The investors thus have to accept more risks in comparison under carbon pricing scheme for higher returns, while fixed remuneration instrument takes away partial market risks making it a safer investment for the investor.

	SL	WN	HD	BM	NC	CL	GS
$P_{yes_{var_a}}$	22.00%	23.01%	20.98%	15.39%	11.78%	0%	6.84%
$P_{yes_{var_b}}$	32.35%	39.23%	25.41%	3.00%	0%	0%	0%
$P_{yes_{var_c}}$	33.38%	52.84%	13.78%	0%	0%	0%	0%

Table 12: Investors' optimal portfolio choice before and after a carbon pricing instrument is implemented
Note: SL,WN,HD,BM,NC,CL,GS are solar, wind, hydro, biomass, nuclear, coal and natural gas technologies. P is policy implementation. Yes indicates policy is in place. var: variance, indicating the risks the investor willing to take, var_a=0.004, var_b=0.007, var_c=0.009.

4.3 Overlapping policies

Overlapping climate policies refer to situations where fixed remuneration instrument, carbon pricing instrument and other types of instruments co-exist to reduce emissions. In the following case study, the fixed remuneration instrument and carbon pricing in the above sessions are implemented together.

Policy Effect on Assets' Variance and Covariance Overlapping policies have the combined characteristics of both policy instruments. Together the instruments stabilise the cash flows, reducing portfolio risks and reducing assets correlations, but not to the extent as under fixed remuneration instruments (see Table 13 and Table 14).

Policy Effect on Optimal Portfolio As seen in Table 15, overlapping instruments reduce dirty assets holding in the portfolio. The possibilities of constructing portfolio with risk as low as 0.001 portfolio variance level is achievable again thanks to the fixed remuneration instrument. With portfolio variance level of 0.001, 0.0012 and 0.0014, it is already possible to achieve similar level of dirty asset reduction that require risks of 0.004, 0.007 and 0.009 under carbon pricing instrument alone.

	SL	WN	HD	BM	NC	CL	GS
R_{no}	18%	20%	18%	16%	16%	32%	35%
R_{yes}	35%	36%	34%	32%	36%	25%	33%
V_{no}	0.0012	0.0014	0.0013	0.0013	0.0014	0.0014	0.0017
V_{yes}	0.0003	0.0003	0.0003	0.0003	0.0017	0.0009	0.0012

Table 13: Assets' expected returns and variance before and after a fixed remuneration instrument and a carbon pricing instrument are implemented
Note: SL,WN,HD,BM,NC,CL,GS are solar, wind, hydro, biomass, nuclear, coal and natural gas technologies. R is return. V is variance. No indicates no policy. Yes indicates policy is in place.

	SL	WN	HD	BM	NC
C_{no}: CL	0.28792	0.44222	0.330918	0.343518	0.5554
C_{yes}: CL	0.00005	0.00007	0.00001	-0.00006	0.0010
C_{no}: GS	0.10513	0.14298	0.098025	0.119170	0.2834
C_{yes}: GS	0.00002	0.00008	0.00005	0.00002	0.0011

Table 14: Assets' covariance relations before and after a fixed remuneration instrument and a carbon pricing instrument are implemented
Note: SL,WN,HD,BM,NC,CL,GS are solar, wind, hydro, biomass, nuclear, coal and natural gas technologies.C is covariance relation. No indicates no policy. Yes indicates policy is in place.

	SL	WN	HD	BM	NC	CL	GS
$P_{no_{var_a}}$	15.81%	14.54%	15.15%	15.18%	13.78%	14.24%	11.30%
$P_{yes_{var_a}}$	20.33%	28.95%	29.44%	12.46%	3.24%	2.84%	2.74%
$P_{no_{var_b}}$	13.46%	12.38%	12.89%	12.91%	11.73%	12.12%	9.61%
$P_{yes_{var_b}}$	26.57%	31.85%	32.18%	9.40%	0%	0%	0%
$P_{no_{var_c}}$	17.10%	20.65%	21.15%	13.18%	10.03%	10.12%	7.77%
$P_{yes_{var_c}}$	32.83%	33.19%	33.22%	0.77%	0%	0%	0%

Table 15: Investors' optimal portfolio choice before and after a fixed remuneration instrument and a carbon pricing instrument are implemented
Note: SL,WN,HD,BM,NC,CL,GS are solar, wind, hydro, biomass, nuclear, coal and natural gas technologies. R is return. P is policy implementation. No indicates no policy. Yes indicates policy is in place. var: variance, indicating the risks the investor willing to take, var_a=0.001, var_b=0.0012, var_c=0.0014.

4.4 Extension: Effect of Retroactive Policies

Given retroactive policy changes happened in the past, investors may not trust climate policies will be consistent through the project's life time (Egli, 2020).The expectation of policy change would be considered by investors in the investment evaluation. In this section that extends the paper, we aim to answer the question: how does the policy effect in the first two layers change given investor distrust and policy uncertainties?

Uncertainty in Fixed Remuneration Instruments The long-term "survival" of the fixed remuneration policy are largely dependent on the ability of the government to pay out the promised remuneration levels throughout time. Retroactive renewable energy support changes happened many times in different European countries. For the development of stylised case studies, we have selected policy uncertainty scenarios based on the generalisation of the real retroactive policy changes in the past.

- Scenario 1: The complete suspension of the fixed remuneration instrument [8].
- Scenario 2: 15% cut on fixed remuneration support level [9].
- Scenario 3: 25% tax on renewable energy systems to get partially paid-out remuneration back due to fiscal and financial difficulties [10].

For a clean energy investor, the retroactive policy change could happen any time in the middle of the project life-time. Therefore, to take this into consideration, we model the above three scenarios at the early, middle and late life-time of the project —we define them as at the 5th, 10th and 15th year into the project. We present the results of the case when the uncertainty occurs in the middle of the project life (10th year). The changes of expected returns, variance and covariance are time period dependent and we omit the report of these changes here, but directly show the effect of retroactive policies on the portfolio optimisation.

Under all cases of retroactive policies, the investors with three different levels of risk aversion all decide to include dirty assets in their portfolios —in most cases they include significantly more dirty assets (see in Table 18). The retroactive policy through system taxation has more influence on the highly risk averse investors to hold on to dirty assets than reducing fixed remuneration levels.

Assuming that the amount of new funds for investments from a risk averse investor is 1,000,000 EUR, we estimate the potential stranded assets value for this investor by comparing her portfolio choice given policy uncertainty with that of no uncertainty. As seen in Table 17, unreliable fixed remuneration policy result in potential stranded asset of values range from 12,000 million EUR to 66,600 million EUR for a high risk aversion investor, 24,400 million EUR to 352,600 million EUR for an investor with relatively low risk aversion. For a moderate risk aversion investor, though stranded dirty assets in the portfolio may not occur in the first two scenarios, the nuclear asset share has significantly increased in these cases, crowding out shares in clean assets.

[8] Based on the real case: Italy suspended Feed-in Tariff system in 2013.

[9] Based on the real case: Slovakia decreased Feed-in Tariff level with 1 month notice; Bulgaria reduced FiT with 3 weeks notification time.

[10] Based on the real case: Czech Republic and Greece issued a tax of 26-28% for system > 30kw, and a tax of 25-30% for system > 10kw.

	SL	WN	HD	BM	NC	CL	GS
$P_{uncer_{sce1_{var_a}}}$	20.79%	21.25%	22.42%	20.74%	5.19%	5.36%	4.25%
$P_{uncer_{sce1_{var_b}}}$	58.00%	5.00%	17.00%	5.00%	5.00%	5.00%	5.00%
$P_{uncer_{sce1_{var_c}}}$	76.08%	3.33%	7.26%	3.34%	3.33%	3.33%	3.33%
$P_{uncer_{sce2_{var_a}}}$	18.70%	24.31%	25.64%	22.12%	32.32%	3.34%	2.65%
$P_{uncer_{sce2_{var_b}}}$	73.92%	5.56%	5.57%	5.55%	4.59%	4.63%	0.17%
$P_{uncer_{sce2_{var_b}}}$	92.93%	1.11%	1.11%	1.11%	1.11%	1.11%	1.52%
$P_{uncer_{sce3_{var_a}}}$	8.13%	7.99%	8.25%	8.40%	23.56%	24.35%	19.32%
$P_{uncer_{sce3_{var_b}}}$	55.46%	10.08%	10.22%	10.04%	5.81%	5.94%	2.45%
$P_{uncer_{sce3_{var_c}}}$	71.83%	5.15%	5.17%	5.15%	4.63%	4.66%	3.41%

Table 16: Investors' optimal portfolio choices under certain vs. uncertain fixed remuneration instrument, uncertainty in midlife of the project
Note: SL,WN,HD,BM,NC,CL,GS are solar, wind, hydro, biomass, nuclear, coal and natural gas technologies. P is policy implementation. cer: certain. uncer: uncertain.sce: scenario. var: variance, indicating the risks the investor willing to tak, var_a=0.001, var_b=0.002, var_c=0.003.

	Dirty assets in %	Dirty assets	Nuclear in %	Nuclear
$Str_{sce1_{var_a}}$	1.20%	$12,000$	0.66%	$6,600$
$Str_{sce1_{var_b}}$	4.05%	$40,500$	5.00%	$50,000$
$Str_{sce1_{var_c}}$	6.66%	$66,600$	3.33%	$33,300$
$Str_{sce2_{var_a}}$	−2.42%	$-24,200$	27.79%	$277,900$
$Str_{sce2_{var_b}}$	−1.15%	$-11,500$	4.59%	$45,900$
$Str_{sce2_{var_c}}$	2.63%	$26,300$	1.11%	$11,100$
$Str_{sce3_{var_a}}$	35.26%	$352,600$	19.03%	$190,300$
$Str_{sce3_{var_b}}$	2.44%	$24,400$	5.81%	$58,100$
$Str_{sce3_{var_c}}$	8.07%	$80,700$	4.63%	$46,300$

Table 17: Potential stranded assets in percentage and absolute terms for risk averse investors, uncertainty in midlife of the project
Note: SL,WN,HD,BM,NC,CL,GS are solar, wind, hydro, biomass, nuclear, coal and natural gas technologies. uncer: uncertain policy. cer: certain policy. Str is potential stranded assets. Sce is scenarios of retroactive fixed remuneration policies. Calculation based on Table 9 and Table 18. Table 9 serves as benchmark.

Uncertainty in Carbon Pricing Instruments Different from fixed remuneration instruments, a retroactive policy change of carbon tax in the midlife of the project does not necessarily lead to more dirty asset holding in the portfolios as seen in Table 18. We do not observe policy uncertainty costs in this case because a carbon pricing scheme makes the volatility of the clean and dirty assets increased significantly. According to our Proposition 1 in the analytical section, the scheme would unintentionally lead to the inclusion of more dirty assets in the portfolio. The halfway implementation of the scheme therefore does not have negative effect on the clean asset share in the portfolio.

	SL	WN	HD	BM	NC	CL	GS
$P_{uncer_{var_a}}$	23.74%	43.63%	32.63%	0%	0%	0%	0%
$P_{uncer_{var_b}}$	13.18%	73.63%	13.19%	0%	0%	0%	0%
$P_{uncer_{var_c}}$	7.45%	85.11%	7.44%	0%	0%	0%	0%

Table 18: Investors' optimal portfolio choices under certain vs. uncertain fixed remuneration instrument, uncertainty in midlife of the project
Note: SL,WN,HD,BM,NC,CL,GS are solar, wind, hydro, biomass, nuclear, coal and natural gas technologies. P is policy implementation. cer: certain. uncer: uncertain.sce: scenario. var: variance, indicating the risks the investor willing to take, var_a=0.004, var_b=0.007, var_c=0.009.

4.5 Robustness check

Our modelling results hold under different levels of fixed remuneration, or under retroactive policies occurring at different stage of the project's lifetime, when everything else is equal. Higher carbon pricing would have different effect on the risks and covariance correlation of the dirty and clean assets, but the general results still hold.

5 Discussion

Due to the low correlation between clean and dirty assets, one of them is frequently used as a hedging device in the portfolio while the other asset has a dominating share. About one decade ago, when renewable energy had high investment risks around the world and considered to be a niche, renewable energy sources were served as a hedge against fossil fuel plants in the power plant portfolios (Tietjen et al., 2016; Arnesano et al., 2012; Bhattacharya and Kojima, 2012). We explained this phenomenon in our analytical model: when the dirty asset has comparatively higher expected returns and lower risks, a marginal decrease in the correlation between dirty and clean asset returns can lead to an increase in clean asset shares. This situation is changing. Though renewable energy is still considered riskier and less attractive in many developing nations for financing reasons (Shimbar and Ebrahimi, 2020) , in many markets where there are commercially viability renewable investment opportunities, good sustainable policy environment and high investor confidence, the dirty asset is mixed in the portfolio to serve potentially a hedging purpose. This may explain the current renewables development situation in the EU, where there is commercial maturity of solar and wind technologies, the EU's strong commitments to financing sustainable growth and Non-Governmental organisations (NGO) pressure on corporations. Some observations show that RWE, one of the largest electricity generators worldwide, plans new investments are predominantly shifted towards renewable energy generation alongside investments into natural gas power plants (Bünder, 2021).

The portfolio risk of two assets depends on the asset shares, their variance, and the correlation between assets' returns. Changes in portfolio risks affect investment decisions significantly —not surprisingly —for risk-averse investors. Thus there is potential in designing policy incentives considering this effect. For instance, increasing the riskiness of the dirty asset will incentivise a risk-averse investor to reduce her dirty asset holding, given that the two assets are identical in expected returns and their returns are independent of each other. In our analytical model of two assets, we further showed that policies that increase mean returns of clean energy assets but at the same time increase their risks might not yield the desired policy effect. This could happen, as illustrated in Proposition 1, and lead to an increase of dirty asset holdings in the portfolio if the risk level of clean assets marginally increase and the variance of return difference between both assets are not equal to 0. This is in line with the literature, which says that climate policies that reduce market uncertainties could reduce the risks related to an investment decision (Masini and Menichetti, 2012).

Our calibrated stochastic model of the EU power sector further demonstrated and extended the points made in the analytical framework. In comparing individual policy instruments, we find that de-risking policies that guarantee certainties for investors have similar effects in incentivising clean investments as carbon pricing instruments. The merit of the fixed remuneration instrument is its power to reduce asset risks and reduce correlation among clean and dirty assets, thus offering risk-averse investors a safe zone and the possibility to construct portfolios suitable to their preferences. Carbon pricing instruments are less affected by policy discontinuation, whereas remuneration policies have to be trustworthy to fulfil their purposes. The merits of the different policy instruments have to be considered together with their costs. In terms of policy costs, fixed remuneration policies, as well studied in literature, if set at a very high support level, may not be sustainable. This is because fixed remuneration instruments promote investments quickly in a large scale and the financial burden of supporting all of the projects become immense. Carbon pricing instrument, in particular, carbon tax is a fiscal instrument that brings cash inflows to the public sector, thus not subjecting to fiscal risks in comparison.

6 Conclusion

Asset stranding caused by climate-related policy issues affects the sustainable development of both developed and developing countries (Ansari and Holz, 2020); it could lead to losses of wealth and employment linked to fossil fuels in fossil resource-reliant countries (Jin et al., 2021) . Moreover, in the lower-carbon transformation, the unanticipated policy changes could cause discrete jumps in the evaluation and reevaluation of assets and capital (van der Ploeg and Rezai, 2020) . These policy risks, as shown in our paper, have serious consequences on power market investors' portfolio composition choices. Electric utility company investors intentionally hold dirty assets to manage uncertainties and risks from the market and from policy uncertainties. Given that fossil fuel power generation assets have a long lifetime, the dirty assets in the portfolio will likely lock in carbon-intensive technologies for an extended period of time.

Uncertainty about the continuation of fixed remuneration policies for renewable deployment leads to more potentially stranded investments in fossil fuel generation capacities —ranging from 1% to 35% of a risk-averse investors' budget. On the contrary, a carbon price instrument is less affected by policy discontinuation in comparison. Both fixed remuneration and carbon price policies can crowd out dirty assets. However, the investors have to bear more investment risks under carbon pricing policies. The investment risk profile becomes more attractive for risk-averse investors if fixed remuneration policies coexist.

Policymakers should pay attention to how climate policies affect the risks and correlation of dirty and clean assets. In designing climate policies, an evaluation of policy instruments on the asset stranding potential is recommended.

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A Appendix

A.1 Portfolio return and expected utility

A risk-averse firm investor has the following constant relative risk aversion (CRRA) preferences:

$$V = W_{t+1}^{1-\gamma}/(1-\gamma),$$

with $\gamma \geq 1$.[11] The initial value in $t+1$ depends on the value in the previous period times the portfolio return factor $\bar{R}_{t+1}$, hence

$$W_{t+1} = \bar{R}_{t+1} W_t. \tag{A.1}$$

$\bar{R}_{t+1}$ is the Log-normally distributed portfolio return factor realised in $t+1$. The portfolio is a composite of clean and dirty assets.α_d is the portfolio weight of the dirty assets and $\alpha_c = (1-\alpha_d)$ is the share of clean assets.

$$\bar{R}_{t+1} = \alpha_d R_{d,t+1} + (1-\alpha_d) R_{c,t+1}.$$

With some manipulation we get

$$\frac{1+\bar{R}_{t+1}}{1+R_{c,t+1}} = 1 + \alpha_d \left(\frac{1+R_{d,t+1}}{1+R_{c,t+1}} - 1 \right).$$

Taking logs —and again denoting log variables in small letters — gives

$$\bar{r}_{t+1} - r_{c,t+1} = log\left[1 + \alpha_d(exp(r_{d,t+1} - r_{c,t+1}) - 1)\right] \tag{A.2}$$

This relation can be approximated using a second-order Taylor expansion (Campbell and Viceira, 2002a) around the point $r_{d,t+1} - r_{c,t+1} = 0$:

$$f(r_{d,t+1} - r_{c,t+1}) \approx f(0) + f'(0)(r_{d,t+1} - r_{c,t+1}) + \frac{1}{2} f''(0)(r_{d,t+1} - r_{c,t+1})^2.$$

The Taylor approximation of (A.2) is thus (more details are in the appendix campbell file we citepd)

$$\bar{r}_{t+1} = r_{c,t+1} + \alpha_d \left(r_{d,t+1} - r_{c,t+1}\right) + \frac{1}{2}\alpha_d \; \alpha_c \; \eta \tag{A.3}$$

According to Carroll (2013) , $(r_{d,t+1} - r_{c,t+1})^2$ is approximated and replaced by $\eta = (\sigma_d^2 + \sigma_c^2 - 2\sigma_{cd})$, which is the variance for the difference between the two variables $r_{c,t+1}$ and $r_{d,t+1}$.

Using the approximation to the portfolio rate of return, the expectation of utility at

[11] In the limit with $\gamma = 1$, $U = log(W_{t+1})$.

t+1 is

$$\mathbb{E}[V(W_{t+1})] \approx (1-\gamma)^{-1} w_t^{1-\gamma} e^{(1-\gamma)\alpha_d \alpha_c \eta/2} \mathbb{E}\left[(e^{(r_{c,t+1}+\alpha_d(r_{d,t+1}-r_{c,t+1}))(1-\gamma)} \right]. \quad \text{(A.4)}$$

Given

$$r_{t+1} = (r_{c,t+1}, r_{d,t+1})' \backsim (\mathcal{N}(r_c, {\sigma_c}^2), \mathcal{N}(r_d, {\sigma_d}^2))'$$

This implies that

$$(1-\gamma)(\alpha_c r_{c,t+1} + \alpha_d r_{d,t+1}) \backsim \mathcal{N}((1-\gamma)(\alpha_c r_c + \alpha_d r_d), var((1-\gamma)(\alpha_c r_{c,t+1} + \alpha_d r_{d,t+1})))$$

Which is

$$(1-\gamma)(\alpha_c r_{c,t+1}+\alpha_d r_{d,t+1}) \backsim \mathcal{N}((1-\gamma)(\alpha_c r_c+\alpha_d r_d), (1-\gamma)^2({\alpha_c}^2 {r_c}^2+{\alpha_d}^2 {r_d}^2+2\alpha_c\alpha_d\sigma_{cd})))$$

According to the log form manipulation rule If $log\hat{R}_{t+1} = \gamma log R_{t+1}$ where $log R_{t+1}\ \mathcal{N}(r, {\sigma_r}^2)$, then $\mathbb{E}_t[\hat{R}_{t+1}] = e^{\gamma r + \gamma^2 {\sigma_r}^2/2}$, we obtain the log of the expectation

$$log\mathbb{E}[e^{(r_{c,t+1}+\alpha_d(r_{d,t+1}-r_{c,t+1}))(1-\gamma)}] = (1-\gamma)(\alpha_c r_c+\alpha_d r_d)+(1-\gamma)^2(\alpha_c^2\sigma_c^2+\alpha_d^2\sigma_d^2+2\alpha_c\alpha_d\sigma_{cd})/2$$

According to Carroll (2013), the expected utility of the investor with two risky assets is

$$\mathbb{E}[V(W_{t+1})] \approx (1-\gamma)^{-1} W_t^{1-\gamma} e^{(1-\gamma)\alpha_d\alpha_c\eta/2} * e^{(1-\gamma)(\alpha_c r_c+\alpha_d r_d)} * e^{(1-\gamma)^2(\alpha_c^2\sigma_c^2+\alpha_d^2\sigma_d^2+2\alpha_c\alpha_d\sigma_{cd})/2} \quad \text{(A.5)}$$

The constant item $(1-\gamma)^{-1} W_t^{1-\gamma}$ in $\mathbb{E}[V(W_{t+1})]$ is less than zero; to maximise the expected utility level, the log of the non-constant item is minimised. The FOC for this condition is

$$(1-\gamma)\alpha_d\alpha_c\eta/2 + (1-\gamma)(\alpha_c r_c + \alpha_d r_d) + (1-\gamma)^2(\alpha_c^2\sigma_c^2 + \alpha_d^2\sigma_d^2 + 2\alpha_c\alpha_d\sigma_{cd})/2 = 0$$

That is,

$$(1-2\alpha_d)\eta/2 + r_{d,t+1} - r_{c,t+1} + (1-\gamma)(\alpha_d\eta + (\sigma_{cd} - {\sigma_c}^2)) = 0$$

Thus, the portfolio weight α_d for dirty power plant assets is

$$\alpha_d = \frac{\mu_d - \mu_c + (\sigma_c^2 + \sigma_d^2 - 2\sigma_{cd})/2 + (1-\gamma)(\sigma_{cd} - \sigma_c^2)}{\gamma(\sigma_c^2 + \sigma_d^2 - 2\sigma_{cd})}. \quad \text{(A.6)}$$

A.2 Proposition One - Potential stranded assets

We show that the dirty asset holdings α_d will increase if the stated two conditions 1) increasing μ_c; and 2) $\sigma_c^2 + \sigma_d^2 - 2\sigma_{cd} \neq 0$ hold.

The cross partial derivative of α_d with respect to μ_c and σ^2 is

$$\frac{\partial^2 \alpha_d}{\partial \mu_c \partial \sigma^2} = \frac{1}{\gamma(\sigma_c^2 + \sigma_d^2 - 2\sigma_{cd})^2} \tag{A.7}$$

Since $\gamma >= 1$, if $\sigma_c^2 + \sigma_d^2 - 2\sigma_{cd} \neq 0$, the denominator is > 0. If μ_c is (marginally) increasing, the change in α_d with respect to changing μ_c changes as σ_c changes. The change is positive but decreasing with increasing σ_c.