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Measuring the effects of environmental policies on electricity markets risk

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ABSTRACT

This paper studies how environmental policies, such as renewable portfolio standards (RPS) and carbon taxes, might contribute to reducing risk exposure in the electricity generation sector. We illustrate this effect by first computing long-term market equilibria of the Chilean generation sector for the year 2035 using a risk-averse planning model, considering uncertainty of hydrological scenarios and fossil fuel prices as well as distinct levels of risk aversion, but assuming no environmental policies in place. We then compare these risk-averse equilibria to generation portfolios obtained by imposing several levels of RPS and carbon taxes in a market with risk-neutral firms, separately. Our results show that the implementation of both policies can provide incentives for investments in portfolios of generation technologies that limit the risk exposure of the system, particularly when high levels of RPS (35%) or high carbon taxes (35 $/tonCO$_2$) are applied. However, we find that in the case of a hydrothermal system, the resulting market equilibria under RPS policies yield expected generation cost and risk levels (i.e. standard deviation of costs) that are more similar to the efficient portfolios determined using a risk-averse planning model than the ones we find under the carbon tax.

1. Introduction

A growing number of studies have proposed that renewable energy sources[1] (RES), such as solar photovoltaic (PV) and wind farms, can contribute to strengthen a country's energy security and resilience due to their independency from volatile international fuel prices, hydrological variability and other types of risks. Since the seminal work of Shimon Awerbuch (Awerbuch, 2006; Awerbuch and Berger, 2003) frameworks and mathematical tools (i.e., risk-averse planning models) capable of determining generation portfolios that are robust to risk have been developed and utilized to analyze several countries' energy mixes considering both expected cost and risk. Moreover, a number of these works have consistently concluded that when renewable energy technologies are selectively added to the generating mix, it is possible to reduce the likelihood that an electric power system will face scenarios of high system costs (Calvo-silvosa et al., 2017).

Furthermore, environmental policies such as carbon taxes, cap-and-trade schemes, renewable portfolio standards (RPS), etc., have been widely established by regulators to incentivize investments in renewables. These policies are normally justified based on benefits regarding global and local pollutants emission reductions, job creation and increased energy security. In effect, regarding energy security and according to the aforementioned studies, increased investment on renewables stemming from these policies may provide benefits on electricity cost risk reduction and energy source diversification. However, this aspect has been scarcely addressed in the literature.

Hence, in this work we contribute to the existing literature by studying in detail risk reduction and diversification incentives provided by two of these environmental policies (i.e. renewable portfolio standards and carbon taxes). We achieve this by calculating several long-term market equilibria of the Chilean generation sector for the year 2035, considering distinct levels of risk aversion of market agents and uncertainty in both hydrological scenarios and fossil fuel prices. These risk-averse equilibria are then compared to generation portfolios

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[1] In this article, we use the term renewable energy to refer to small hydro, wind, solar PV, concentration solar, geothermal and/or biomass energy sources (leaving out large-scale hydro power plants). These are also technologies considered in RPS policies in the paper, as per Chilean regulation.

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obtained by imposing several levels of RPS and carbon taxes in a market with risk-neutral agents, separately.

Through these analyses we conclude that increased levels of either RPS or carbon taxes may reduce risk exposure of generation markets, albeit not always, due to the presence of non-monotonic relations between environmental policies and risk exposure in cases with relatively low levels of RPS or carbon tax (under 35% and 35 \$/tonCO_2 respectively).

Moreover, we carefully study relations between environmental policies and expected cost-risk, demonstrating that RPS policies exhibit certain advantages over carbon taxes in markets where hydro availability risk is relevant, as in Chile, since the latter may result in higher hydro reservoir investment and thus increase risk exposure of portfolios when facing hydrological risk. Alternatively, in cases where fuel price uncertainty is the main driver of risk, we find that under low levels of both RPS and carbon taxes, increased generation by thermal power plants (e.g. LNG plants) that act as a back-up for intermittent renewables such as solar PV, might produce an increase in the generating portfolios risk exposure. However, under higher levels of these policies (above the 35% and 35 ton/CO_2 thresholds), we find a monotonic relationship between the level of the policy and risk reduction in all studied cases.

The present paper is organized as follows. Section 2 summarizes relevant literature regarding methodological advances in risk-averse models, the usage of these models to study several countries' generating portfolios and works that explore the impact of environmental policies in energy security. Section 3 presents the methodological aspects relevant to the present work and Section 4 details cases results and discussion. Finally, Section 5 shows the concluding remarks and policy implications of our study.

2. Literature review

2.1. Study of electricity generation costs and risks under a portfolio optimization lens

The interaction between the level of penetration of renewable generation technologies and risk exposure of an electric power system was first studied by Shimon Awerbuch (Awerbuch, 2006; Awerbuch and Berger, 2003). Borrowing ideas from Harry Markowitz' portfolio theory (Markowitz, 1952), this seminal work proposed a framework where generation technologies are characterized by the reciprocal of their levelized cost of electricity in kWh/US-cent (or "returns"), which is used to select efficient portfolios on the basis of standard deviations and correlations between these returns.

Later on, Jansen et al., (2006) proposed a number of methodological enhancements to Awerbuch's framework. In this approach, expected costs are calculated as the sum of expected investment, fuel, fixed operation and maintenance (O&M), variable O&M and environmental impact costs, while risk is measured as the standard deviation of the sum of all these costs, considering uncertainty and correlations between these cost components.

Building on the latter, Delarue et al., (2011) proposed a model that could optimize both expected cost and risk (i.e. standard deviation of cost), while also accounting for real operating constraints, such as those considered in detailed models for short-term planning of operations.

After Delarue et al., (2011), other studies developed advanced stochastic optimization models capable of determining efficient investments in generation (Inzunza et al., 2016) and both generation and transmission (Munoz et al., 2017a) infrastructure by considering detailed power systems operating constraints, as well as the expectation and risk of investment and operating costs using the conditional value-at-risk (CVaR) as a risk measure. One of the main advantages of the CVaR measure is that it can be used to model non-Gaussian probability distributions of the underlying uncertain parameters in linear optimization models.

Some of the models described above have been used by academics and regulatory agencies to study the tradeoffs between expected cost and risk exposure of generation portfolios in different regions. These works have covered a wide range of jurisdictions, such as: US (Awerbuch, 2006), California (Salazar and Hutchison, 2007), European Union (EU) (Awerbuch, 2006; Calvo-silvosa et al., 2018), United Kingdom (UK) (Roques et al., 2008), Netherlands (Jansen et al., 2006), Belgium (Delarue et al., 2011), Australia (Vithayasrichareon et al., 2015), Chile (Inzunza et al., 2016), China (Zhu and Fan, 2010; Gao et al., 2014), Japan (Bhattacharya and Kojima, 2012) and others (for more examples see Calvo-silvosa et al., (2017); Pérez Odeh et al., (2018)).

Furthermore, several of these analyses have proposed an increase in renewable energy sources in order to draw energy mixes closer to efficient portfolios determined by risk-averse models (Calvo-silvosa et al., 2017). For instance, Calvo-silvosa et al., (2018) concludes that the EU's projected 2030 energy mix is inefficient in terms of its cost-risk balance and that it would benefit from a higher share of RES (especially wind) due to, mainly, their independence from fossil fuels and low carbon emissions; Gao et al., (2014) studies China's projected 2020 and 2030 energy mixes and proposes measures to incentivize investments in solar PV; Inzunza et al.,)2016) concludes that investment in solar PV and wind farms can reduce risk in the Chilean generation sector when considering both hydrological and fossil fuel prices risks; and Bhattacharya and Kojima, (2012) argues that Japan can efficiently increase its RES share from roughly 1.4% to 9% also based on a portfolio optimization framework.

2.2. Studies about the impacts of environmental policies on electricity generation costs and risks

The aforementioned literature regarding the application of portfolio theory to generation investments and the calculation of cost-risk efficient energy mixes, seems to be detached from the environmental policy analysis literature that studies benefits and costs of environmental policies such as carbon taxes and RPS.

Carbon taxation is normally put forward as an economically efficient way to internalize externalities related to carbon emissions and help decarbonize energy systems (Vera and Sauma, 2015). Besides the expected reduction in carbon emissions, other advantages of these policies according to the literature are: their applicability to economic activities beyond the electricity generation sector[2]; their market-based nature, which allows economic agents to privately choose the means via which they will react to the policy[3]; their simplicity; cost certainty[4] (Avi-Yonah and Uhlmann, 2009); generation of tax revenues that can be used to ameliorate some of the side-effects of the policy (e.g., distributional effects) (Callan et al., 2009); and reduced air pollution due to increased reliance on RES (Burtraw et al., 2003).

To our knowledge, only a few authors have studied carbon taxes benefits on increased energy security (in terms of cost-risk) and source diversification (Bazilian et al., 2008; Acevedo et al., 2020). On one hand, Bazilian et al., (2008) states that pricing CO_2 emissions via carbon taxation might enhance energy security in terms of the standard deviation of electricity generation costs, while Acevedo et al., 2020 argues that taxing carbon emissions may reduce risk (measured as the CVaR of yearly investment and operating costs) in the generation sector.

Regarding RPS, benefits commonly associated with these policies, besides potential reductions on carbon emissions, are: reduced local

[2] Which helps to better capture economy-wide emissions, in contrast to electricity generation specific policies such as renewable portfolio standards.

[3] In contrast to command and control policies, where individual emission levels or technology standards for each agent are set by the regulator.

[4] Given that cost increases in goods and services can be easily calculated if the tax value is known. This contrasts with cap-and-trade systems where the emission limit is clear but the increase in cost of goods and services is unclear (Avi-Yonah and Uhlmann, 2009).

pollutants and health benefits (Barbose et al., 2015); creation of jobs (Rouhani et al., 2016); and increased energy security and source diversification (Cory and Swezey, 2007; Farooq et al., 2013).

To our knowledge, the only work that studies effects of RPS policies on electricity cost risk is Acevedo et al., 2020. Authors of this work conclude that RPS, as well as a carbon taxes, can deliver benefits in terms of source diversification and reduction of electricity cost risk.

Departing from the initial exploration of effects of carbon taxes and RPS policies in electricity cost-risk in (Bazilian et al., 2008; Acevedo et al., 2020), we demonstrate that both RPS and carbon tax environmental policies can be effectively used to guide equilibria in the generation market towards outcomes similar to those observed in risk-averse planning models (in terms of expected cost and risk). Additionally and specifically contrasting from initial conclusions drawn by Acevedo et al., 2020, we show that effects of RPS and carbon tax policies might differ and that RPS might be a more adequate policy to provide risk-hedging incentives to agents operating in a hydrothermal system like the one in Chile.

3. Methodology

3.1. *Finding equilibrium investments with risk-neutral and risk-averse agents*

A well-known result from microeconomic theory is that, under perfect competition, a competitive equilibrium can be computed by solving an equivalent Integrated Resources Planning problem that maximizes social welfare (elastic demand) or minimizes total system cost (inelastic demand) (Samuelson, 1952; Hobbs, 1995). Furthermore, if investment decisions are made under uncertainty, investors are risk-neutral, and all agents share the same views about possible future outcomes, then central planning can also be used to find a market equilibrium (e.g., Munoz et al., (2014); Bergen and Muñoz, (2018)).

Unfortunately, the equivalency between central planning and stochastic market equilibrium problems does not hold if investors are risk-averse and the market does not offer enough financial instruments to hedge against all possible scenarios, which is often the case in electricity markets (de Maere d'Aertrycke et al., 2017; Willems and Morbee, 2010). Nevertheless, if investors assess market risks using a coherent risk measure, such as the CVaR, and the market is complete (i.e., there are enough financial securities to hedge against all possible scenarios), then a stochastic market equilibrium exists and it can be computed by solving a risk-adjusted variant of the problem solved by a central planner (Munoz et al., 2017a; Ralph and Smeers, 2015).

Here we employ two of the properties mentioned above to compute market equilibria for different settings by solving the equivalent optimization problems faced by central planners.

The first type of equilibrium problem we formulate is the one for risk-averse agents in a complete market. This equilibrium problem represents the idealized situation where all market risks can be traded and where the views of all agents are aligned with the view of a risk-averse central planner (i.e., they all agree on the set of scenarios that result in the most important downside risks[5]). The Appendix includes a detailed description of the model, with all parameters, variables, and constraints.

Here we provide a high-level description of its most important elements and the most important equations.

The model considers a set of possible scenarios S, each associated to a probability p_s that may represent possible realizations of hydrology (rainfall), future fossil fuel prices or other. Thus, the objective function minimizes the expected fixed and variable costs of installing and operating plants in the target year.

[5] This is an assumption since, in reality, market agents may have different levels of risk aversion and respond to different sets of scenarios that conform their view of downside risk.

Fixed costs include annuitized capital expenses and fixed operation and maintenance (O&M) costs (both included in INV_i parameter) and variable costs are composed by fuel consumption, variable O&M expenses, CO_2 emissions tax and cost of unserved energy, in each modelled scenario.[6]

$$\text{O.F.}: min\sum_{s\in S}\mathrm{p}_s\cdot C_s \tag{1}$$

s.t.:

$$C_s=\sum_{i\in I}\mathrm{INV}_i\cdot c_i+\sum_{i\in I}\sum_{j\in J}\left(\mathrm{FU}_{i,s}+\mathrm{VOM}_i+\epsilon_i\cdot\tau\right)\cdot g_{i,j,s}+\sum_{j\in J}\mathrm{voll}\cdot ll_{j,s},\forall s\in S \tag{2}$$

Additionally, the model is subject to α-CVaR constraints[7] as in Inzunza et al., (2016). These constraints are used to limit the α-CVaR of generation portfolios, meaning that the average installing and operating cost of scenarios in the $(1-\alpha)$ percentile can be bounded by the CV parameter.

If a sufficiently large CV parameter is used, then the minimum expected cost portfolio can be determined. Smaller CV bounds may be employed to compute portfolios with reduced CVaR until minimum risk solution is reached.

$$d_s\geq C_s-z,\forall s\in S \tag{3}$$

$$z+\frac{1}{1-\alpha}\sum_{s\in S}d_s\cdot\mathrm{p}_s\leq\mathrm{CV} \tag{4}$$

Other constraints included in the model are:

- Electricity supply and demand balance.
- Maximum generation limits, considering hourly availability of renewable resources.
- Energy balance constraints for hydro plants with reservoirs, pumped storage units, and concentration solar plants.
- Maximum annual availability factors (i.e. limited by maintenance).
- Minimum levels of operating reserves to accommodate unexpected changes in demand and supply (i.e. variable renewables).

The second type of market equilibrium considered is one where we assume risk-neutral agents that face a certain environmental policy (either RPS or a carbon tax), and which can be solved by finding investment and operating decisions that minimize the total expected system cost. The planning problem employed to compute this equilibrium has the same structure of the one described above, but with two differentiating elements. First, we remove the risk-limiting constraint from the model. Second, we account for environmental policies that can take the form of an RPS, included as a constraint, or a carbon tax, included in the objective function as part of the operating cost. We expect that these policies contribute to diversify generation portfolios, thus reducing risk exposure in the market and driving market equilibria closer to risk-averse portfolios calculated with the first model.

Note that including an RPS policy as a constraint in the planning problem is equivalent to assuming that the regulator allows firms to fulfill the policy using tradable Renewable Energy Certificates (RECs). Under perfect competition, such flexibility ensures that the renewable target is met in the most efficient manner using a combination of the eligible technologies that are available in the system (Perez et al., 2016; Munoz et al., 2017b).

[6] In order for the model to accurately balance fixed and variable costs incurred during the target year, variable costs should be scaled up if any kind of reduction is done regarding the number of hours considered. For simplicity, we have omitted these scaling parameters in Eq. (2).

[7] This constraint can be included, alternatively, in the objective function without changing results.

3.2. A comment about using the CVaR as a risk measure to model risk aversion

The existing literature of microeconomics and financial engineering offers two distinct approaches to model risk aversion. The standard approach used in microeconomics is to employ concave utility functions, such as exponential utility functions with constant absolute risk aversion, which convert expected monetary profits into expected utility (Mas-Colell et al., 1995). While these utility functions have been used to model risk aversion in equilibrium problems in electricity markets (Fan et al., 2010), their nonlinear structure create computational difficulties when applied to realistic problems, with thousands of variables and constraints.

In finance, risk is often quantified with metrics such as the variance or standard deviation of outcomes (Markowitz, 1952) or with risk measures that include the value-at-risk (VaR) and the CVaR (Shapiro et al., 2009). Out of all the alternatives, the CVaR is the most common approach to model risk in partial equilibrium problems because it can be included directly as part of linear optimization programs (Rockafellar and Uryasev, 2000), which makes computation relatively straightforward even for large-scale applications (Inzunza et al., 2016; Munoz et al., 2017a). Furthermore, since the CVaR is a coherent risk measure, it can be used to compute a market equilibrium employing the equivalence result between risk-averse central planning and the equilibrium in a complete market described in the previous section (Ralph and Smeers, 2015). Note that including the CVaR as a constraint in the optimization problem with the objective of minimizing expected system cost is equivalent to minimizing a weighted sum of both terms (i.e., both methods return non-inferior solutions) (Cohon, 1978), the latter of which is also a coherent risk measure.

Nevertheless, we are not claiming that the CVaR is the actual measure of risk used by private investors in the electricity market. For this reason, in our study we also report the standard deviation of cost since it is a common metric to quantify the volatility of returns in finance. Reporting the standard deviation of cost is also useful to compare experiments where a large fraction of the CVaR comes from large capital investments with very low operating costs (e.g., experiments with lots of investments in renewables). Another interpretation of this modelling choice is that we use the CVaR in the optimization model as a heuristic to identify different portfolios of generation investments for different degrees of risk aversion. Using the standard deviation of costs as a risk measure in the optimization would allow us to identify the true Pareto frontier of the problem. However, doing so would result in a non-linear optimization problem that would be much difficult to solve than the linear program that considers the CVaR as a risk measure.

3.3. Cases

The objective of our study is to assess if environmental policies applied to the generation sector can give investors incentives to develop portfolios of generation technologies that are similar to the ones that would result under an equilibrium with risk-averse agents in a complete market (equivalent to a risk-averse central plan). For this purpose, we employ the equilibrium models described in the previous section as follows.

- **First set of cases:** We compute market equilibria assuming that all investors are risk averse and that there is a complete market of insurance products to hedge against all possible scenarios. Following the approach used in Munoz et al., (2017a); Ralph and Smeers, (2015), we compute this equilibrium by solving the equivalent optimization problem of a risk-averse central planner. The resulting portfolios at this stage provide a benchmark to compare the performance of generation portfolios that result from imposing a carbon tax or an RPS[8] in a market with risk-neutral investors. In this case, we employ CVaR[9] as a risk measure (see the Appendix for a complete description) and select investments that minimize risk-adjusted investment and operating costs of generation power plants, facing several fossil fuel prices and/or hydrological scenarios. We run the model described in the Appendix with no carbon tax ($\tau = 0$) and no RPS requirement (RPS $= 0$) assuming different levels of risk aversion. We change the risk tolerance of investors by lowering the upper bound of the allowed CVaR of generation portfolios (right hand side of Eq. (A.4)), which allows us to construct a curve akin to the Pareto efficient frontier for the Markowitz portfolio selection problem.
- **Second set of cases:** We compute market equilibria assuming that investors are risk-neutral, but consider that the regulator imposes a tax on carbon emissions. In this case, we solve the model described in the Appendix without the RPS requirement (RPS $= 0$) and without the CVaR constraint (A.4). We compute multiple market equilibria for a range of carbon tax levels (τ) and evaluate the resulting portfolios of generating technologies in terms of expected cost and risk exposure.
- **Third set of cases:** As in our second set of cases, we consider risk-neutral investors, but assume that the regulator enacts an RPS requirement instead of a carbon tax. We compute market equilibria by solving the planning model described in the Appendix without the CVaR constraint (A.4) and with no carbon tax ($\tau = 0$). We compute multiple market equilibria considering a broad range of RPS requirements and evaluate the resulting portfolios of generation investments in terms of expected cost and risk exposure.

We repeat these three set of cases for two type of experiments. In the first type of experiments we consider uncertainty of both hydro resources for electric power generation and fossil fuel prices. In the second type we only consider uncertainty of fossil fuel prices and assume average hydro conditions based on historical data.

3.4. Input data

We model the main electric power system in Chile, the Sistema Eléctrico Nacional (SEN), in year 2035. Table 1 summarizes the list of generation technologies available in the system, as well as the main input data used in the model for new developments. We use the same investment costs and CO_2 emission rates employed by the Chilean National Energy Commission (NEC) in recent policy studies (Ministry of Energy, 2015; National Energy Commission, 2017a). Fixed and variable maintenance costs, on the other hand, were taken from the most recent Annual Energy Outlook report (Energy Information Administration, 2017) and lifespans from Escenarios Energéticos, (2013). For current installed capacity, we used the total installed capacity at the beginning

[8] In Chile and in this paper, RPS is understood as a requirement for the total generation of certain renewable energy sources to stay above a determined percentage of the total demand, during each year. In this case, renewable sources that participate in the RPS requirement are: small hydro, wind, solar PV, concentration solar, geothermal and biomass.

[9] As in Inzunza et al., (2016), we use an α parameter of 95%, which means that the CVaR considers the 5% scenarios with the highest cost. We recognize that this is an arbitrary value for α, however, in Munoz et al., (2017a) the authors conduct a sensitivity analysis on the impact of using different values of this parameter using a model that is very similar to the one used in this paper. They find that most of the trends observed when changing the weight between the expected system cost and the CVaR in the objective function remain valid for all the values considered in the sensitivity analysis. Furthermore, they also observe that changing the value of α in a way that increases the number of scenarios considered in the CVaR reduces the difference between the results of the risk-neutral case and the planning model that considers risk-aversion.

Table 1
Input data.

	Investment cost	Fixed maintenance cost	Variable maintenance cost	Lifespan	Emissions rate	Current installed capacity	Resource potential
	[$/kW]	[$/kW-year]	[$/MWh]	[years]	[tonCO_2/MWh]	[MW]	[MW]
Coal	2765	31.2	4.7	35	0.95	4721	∞
Oil	666	17.1	3.4	25	0.78	3116	∞
Hydro reservoir	3472	14.7	2.6	45	0.00	3393	6720
Wind	1491	46.0	0.0	20	0.00	1289	37,639
Solar PV	1200	21.3	0.0	25	0.00	1603	∞
Gas combined cycle (LNG)	1090	9.8	2.0	25	0.44	5091	∞
Run-of-river	3472	14.7	2.6	45	0.00	2826	5582
Pumped storage hydro	1283	14.7	2.6	30	0.00	0	∞
Biomass	2621	108.6	5.4	40	0.00	375	1540
Geothermal	5800	116.1	0.0	40	0.00	0	3350
Small hydro	3646	14.7	2.6	45	0.00	426	6033
Concentration solar (CSP)	4977	69.2	0.0	25	0.00	0	15,607

of year 2017 for each technology (National Energy Commission, 2018). Resource potentials were taken from a study prepared by the *Deutsche Gesellschaft für Internationale Zusammenarbeit* (GIZ) agency for the Ministry of Energy (Santana et al., 2014). There is also a set of technologies that present an extremely high potential relative to the size of the electricity market (e.g., solar PV) and for which we do not impose limits on investments (referred to as "∞" in the resource potential column of Table 1).

We model annual operations using one representative day for each month of year 2035. These representative days are composed by 24 h in chronological order, which allows us to capture the variability of demand and renewable generation using hourly profiles.[10] The demand profile for year 2035 is a projection based on the hourly demand data in 2012. We scaled up the base demand profile based on the NEC's projections for the year 2035 (134 TWh) (National Energy Commission, 2017b), which includes transmission losses. Each of the 12 representative days is an average of the 24-h demand patterns within a month. Since the model can curtail demand if economically efficient, we set the value-of-lost-load (VoLL) at 698 $/MWh, which is the value used by the regulator for adequacy purposes in the most recent indicative generation expansion planning calculation (National Energy Commission, 2017a).

Solar PV, wind and concentration solar radiation profiles were taken from resource assessment tools provided by Universidad de Chile and the Ministry of Energy (Ministry of Energy, 2017; University of Chile, 2017). We extracted hourly profiles from several locations across the SEN and then averaged them considering each location's potential as a relative weight in order to obtain individual profiles that represent each type of technology. We then used the same methodology employed for the demand profile to compute representative 24-h blocks for every month. The resulting average capacity factor (i.e., load factor) for solar PV technology was 30% and 29% for wind technology. For biomass and geothermal technologies we assummed maximum availability factors with a constant profile. For biomass this value was assumed equal to the average capacity factor seen in the SEN during 2016 (57%) (Coordinador Eléctrico Nacional, 2017) and for geothermal generation it was equal to the expected capacity factor declared by the main developer of these projects in Chile (78%) (Environmental Impact Assessment Service, 2017). Note that for completeness, we show detailed demand and renewable resources profiles in Appendix C.

[10] Note that the methodology to determine representative days can be improved in order to find results that would be more appropriate for realistic planning exercises. We address interested readers to check Tejada-arango et al., (2018); Poncelet et al., (2017), where advanced methodologies to determine representative days are described.

We further reduced the computational complexity of the problem by defining equivalent generation units with capacities equal to the sum of the installed capacities of all units of the same technology in the system. Although it has been demonstrated that such simplification can bias our results due to information loss from individual units, we believe that it is a reasonable simplification since in our study we do not account for transmission constraints. The latter has been assumed in similar studies such as in Inzunza et al., (2016).

For large hydro we considered the same reservoir characteristics as the one employed in Inzunza et al., (2016). We assumed an average inflow-to-power rate of 1.936 MW/m^3/s, lower and upper bounds of storage levels equal to 1556 hm^3 and 10,321 hm^3 respectively (these values are scaled for new investments) and losses caused by evaporation and seepage equal to 0.002% of the stored level in each hour. For pumped storage hydro technology, we modelled a reservoir capable of storing 24 h of generation at rated power and used the same losses parameter as in the case of hydro reservoir technology. Additionally, we assumed a 75% roundtrip efficiency for the pump-turbine equipment, which is in line with average values for this type of power plants. For concentration solar (see the Appendix for a full description of CSP modelling) we assumed a solar multiple of 3 based on Santana et al., (2014) and an 18 h thermal storage system (TES), since this is the storage capacity of the first project being constructed in Chile (Pérez Odeh et al., 2018). Power block, charging and discharging efficiencies of the TES system were assumed to be 40%, 98% and 98% respectively, based on Ehrhart and Gill, (2013); Jorgenson et al., (2013). Additionally, a minimum storage level was set to 10% of the maximum storage capacity.

Moreover, certain baseload technologies require major maintenance every year. For coal and gas power plants we defined a maximum annual capacity factor of 85% (International Energy Agency, 2015) and assumed that maintenance of technologies with storage capabilities does not affect their annual capacity factor. Since we are modelling an aggregated generation mix, maintenance in any particular plant will not affect overall systemic storage capability and, as these set of plants can withhold their energy for later usage, the aggregated capacity factor should not be affected significantly by maintenance of an individual unit. Maintenance periods for biomass and geothermal technologies are accounted in their generation profiles based on historical data from existing units. Finally, solar PV, wind, run-of-river and small hydro plants can schedule maintenance during low generation periods, thus diminishing the impact on their overall capacity factor.

3.5. *Scenario modelling*

We modelled hydro scenarios using real data of inflows from the past

50 years provided by the system operator in Chile. From these data we selected three hydrological series that represent dry, medium and wet scenarios and assigned equal probability to each of them. With these data we generated hourly inflow profiles for hydro reservoir and hourly capacity factor profiles for run-of-river and small hydro technologies. Table 2 shows average capacity factors for hydro reservoir (i.e. as if all energy from hourly inflows was used for generation), run-of-river and small hydro in each hydrological scenario.

Fossil fuel prices scenarios were computed by following the methodology proposed by Inzunza et al., (2016). In broad terms, the methodology assumes that annual changes in fossil fuel prices follow a correlated Brownian motion. Thus, we use historical mean of price returns and their correlation as used by Inzunza et al., (2016), to compute the probability distribution of fuel prices by assuming a 6-year lag between the investment decision and the commercial operation date of plants. Prices forecasted by the Chilean regulator for the year 2029 were used as base prices for the estimation of their probability distributions in 2035.

Table 3 shows the main statistical parameters of the log-normal distributions used to generate scenarios of fossil fuel prices. These distributions were then sampled to create 25 perfectly correlated scenarios.

These 25 fossil fuel prices scenarios are combined with the 3 hydrological scenarios described previously to form a set of 75 scenarios used in the model. Note that detailed data for all these scenarios are available in Appendix C.

We recognize that there are other sources of uncertainty that could also have a large impact on decisions and that we did not consider in our work. For example, in some regions, there could be large inter-annual variability of wind and solar generation. Furthermore, a large number of, say, wind sites, could have a high degree of correlation in terms of wind speeds, making it difficult to diversify a portfolio of wind generators. However, in Chile, solar resources present little inter-annual variability and wind farms are diversified across a large geographical region, with little correlation between wind sites that are far apart.

We also chose not to consider uncertainty about demand growth because its effect on a system without transmission constraints is very similar to the effect of different hydro scenarios. Nevertheless, this is a simplification and future studies should also consider additional sources of uncertainty, including different scenarios about the future investment cost of new technolgies (e.g., large- and small-scale energy storage) as well as different possible designs of environmental policies, and the option to delay some investment decisions until new information becomes available.

4. Results and discussion

We divide the results and their respective analysis into two main sections. The first section presents the results and discussions regarding cases that consider 75 different scenarios of hydro conditions and fossil fuel prices. The second section presents the results obtained by only considering fossil fuel price uncertainty, via 25 scenarios, all accompanied by the H2 hydrological scenario (see Table 2).

4.1. Uncertainty in hydrological conditions and fossil fuel prices

4.1.1. Determining a pareto efficient frontier in a complete market

Fig. 1 shows the resultant Pareto frontier, calculated by solving the CVaR constrained model described in the Appendix, without introducing the RPS constraint or a carbon tax. The figure shows the CVaR and expected cost of five different portfolios in the Pareto frontier, denoted with capital letters A to E. Portfolio A corresponds to the risk-neutral market equilibrium, which results from solving the planning problem without the CVaR constraint (i.e., the CVaR limit is high enough such that, in the optimum solution, the constraint is not binding). Portfolios B through E on the other hand, are points in the efficient frontier where the CVaR constraint is binding. Note that going from point A to point E implies results in a 10.6% reduction of the CVaR, but at the expense of a 30.5% increase of total system cost.

Table 4 shows the optimal portfolios of generation technologies as well as the expected system cost, CVaR, and the resulting share of generation from renewable energy sources for points A through E. In the case of portfolio A, capacity additions include solar PV and coal. Solar PV in Chile exhibits high capacity factors (30% and higher), especially in the Atacama Desert, where the bulk of solar projects are currently being developed. Additionally, investment costs of these plants have dropped significantly and continue to do so (Bloomberg New Energy Finance, 2016), hence, this technology appears as an economically efficient alternative under the risk-neutral framework. As solar power is intermittent, coal technology is added to cover additional demand at night.

As expected, reducing the maximum limit on the CVaR constraint yields different portfolios of generation investment. Portfolio E, of minimum risk, only includes investments in solar PV, wind, biomass and pumped storage hydro,[11] without any capacity additions of coal units. In this case, capital intensive technologies with low variable costs are preferred because they reduce the long-term volatility of the operating costs of the system. Note that this is not unique to portfolio E. As Table 4 shows, in general, the more we reduce the CVaR limit, the larger the share of renewables and pumped storage hydro in the system, in line with previous findings in Awerbuch, (2006); Delarue et al., (2011); Inzunza et al., (2016). However, investments in coal capacity are non-monotonic for high CVaR limits (portfolio B). This occurs because when risk is slightly constrained, coal generation is an economic

Table 3
Statistical properties of log-normal distributions of fossil fuel prices.

	Coal	LNG	Oil
Base price (2029) [$/MWh]	27	73	202
Expected price (2035) [$/MWh]	31	82	193
Standard deviation (2035) [$/MWh]	10	29	122

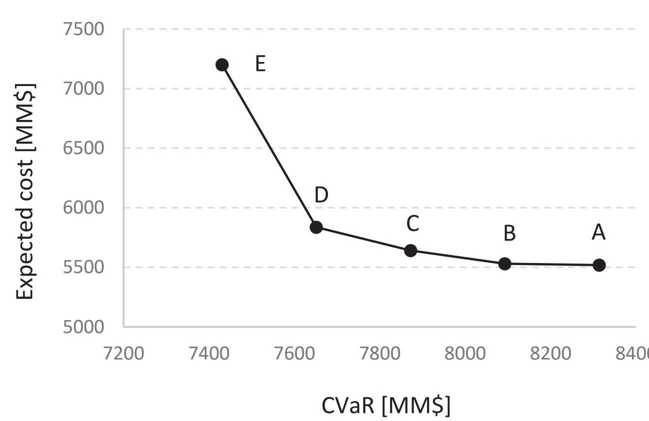

Fig. 1. Pareto frontier considering hydrological and fossil fuel prices scenarios.

Table 2
Scenarios of hydro conditions.

	H1	H2	H3
Hydro reservoir equivalent average capacity factor	16%	52%	71%
Run-of-river and small hydro average capacity factor	42%	55%	59%

[11] Energy storage capacity increases when considering risk aversion of agents, mainly because its capacity to shave yearly demand peaks has greater relative value in scenarios where peaking plants' fuel costs are high. See Diaz et al., (2019) for more details.

Table 4
Capacity composition of portfolios.

	A	B	C	D	E
Installed capacity [MW]					
Coal	7156	7942	7231	6026	4721
Oil	3116	3116	3116	3116	3116
Hydro reservoir	3393	3393	3393	3393	3393
Wind	1289	1289	4099	10,420	17,214
Solar PV	12,865	12,681	11,271	9940	11,619
Gas	5091	5091	5091	5091	5091
Run-of-river	2826	2826	2826	2826	2826
Pumped storage hydro	0	0	0	0	1711
Biomass	375	375	1540	1540	1540
Geothermal	0	0	0	0	0
Small hydro	426	426	426	426	426
Concentration solar	0	0	0	0	0
Expected renewable generation [%]	31%	30%	37%	47%	59%
Expected cost [MM$]	5519	5532	5642	5838	7200
CVaR [MM$]	8313	8093	7872	7651	7431

alternative to mitigate the availability of hydro resources to some extent. Nevertheless, further reducing the CVaR reduces the economic incentives to invest in coal capacity and increases the incentives to develop renewable generation technologies, the latter of which reduce the system exposure to volatile fuel prices and hydro scenarios. More detail on these effects can be found in Inzunza et al., (2016).

4.1.2. The effect of RPS policies on risk-neutral investors

As stated in Section 3, we evaluate the effect of different RPS requirements in a market with risk-neutral agents by solving a planning problem that finds the portfolio of generation investments that minimizes the expected system cost subject to an RPS constraint. Here we report the resulting portfolios for different RPS levels and assess their performance using the CVaR and standard deviation as two different measures of risk.

The plot in Fig. 2 (a) shows the expected cost and CVaR of seven different portfolios of generation that result from different RPS requirements varying from 0% to 85%. Here we observe that, in the range of 0% to 65% renewable targets, increasing the RPS target yields a reduction in the CVaR of the generation portfolio and an increase in expected system cost. Nevertheless, for RPS levels above 65%, increasing the renewable target results in portfolios of generation technologies with increasing CVaR and expected cost.

As explained in Section 3.2, comparing the CVaR of different portfolios of generation technologies can result in misleading conclusions about risk because the CVaR includes operation and investment costs, which exaggerates the risk exposure of portfolios of generating technologies with high investment but low operating cost. Nevertheless, a high CVaR does not necessarily imply an increase in the volatility of costs.[12] Fig. 2 (b) shows the performance of the same portfolios shown in Fig. 2 (a), but using the standard deviation instead of the CVaR as a measure of volatility. In this graph, we see that as the RPS requirements increase, the volatility of total system cost decrease.

Table 5 shows generation portfolios for a selection of three different RPS targets, 0%, 65%, and 85%. We observe that increasing the RPS target results in a replacement of coal generation by a mix of solar PV, wind, biomass and pumped storage hydro.

4.1.3. The effect of a carbon tax on risk-neutral investors

We now study the effect of increasing levels of a carbon tax on investment choices assuming risk-neutral agents. As in the case of RPS policies, we assess the effect of a carbon tax ranging from 0 $/Ton to 85 $/Ton. Fig. 3 (a) and 3 (b) show the performance of the resulting portfolios using both the CVaR and the standard deviation, respectively, as measures to assess risk and volatility.[13]

Our first observation is that the curves depicted in Fig. 3 (a) and Fig. 3 (b) present a highly non-monotonic response to changes in the carbon tax level. While in the case of the RPS policy we found that both the expected cost and CVaR of expected system cost can increase for renewable targets above 65% (Fig. 2 (a)), the curve that depicts the standard deviation versus expected cost is monotonic on the renewable target (Fig. 2 (b)), meaning that an increase in the RPS target always achieves a reduction of the standard deviation of cost at the expense of an increase in the expected system cost. However, in the case of the carbon tax, both figures are non-monotonic in the low range of carbon taxes, from 0 $/Ton to 35 $/Ton.

This effect can be explained by studying the composition of the resulting portfolios of generation technologies in Table 6. For instance, in portfolio J (carbon tax of 35 $/Ton), which exhibits the highest cost volatility, coal capacity is replaced by hydroelectric power plants with reservoirs that become attractive when carbon taxes are introduced. This technology minimizes expected costs under a 35 $/tonCO$_2$ tax, nevertheless it also increases cost volatility since in a dry hydrology, large hydroelectric power plants with reservoir plants can only generate with a maximum annual capacity factor of 20%, making system operating costs escalate in those scenarios.

For tax levels above 35 $/Ton only Fig. 3 (b) presents a monotonic behavior, where an increase in the carbon tax reduces the standard deviation of cost at the expense of an increase in expected system cost. In those cases, the installed capacity of renewables increases and reduces the participation of fossil fuel-based technologies and hydropower, thus reducing the volatility of total system cost.

4.1.4. Comparing the outcomes from risk-averse equilibria in a complete market versus risk-neutral equilibria subject to environmental policies

Our study aims at understanding if the implementation of environmental policies in a market with risk-neutral investors can give investors economic incentives to achieve portfolios of generating technologies that would achieve a similar performance to the ones attained by risk-averse investors in a complete market. For this purpose, in Fig. 4 we present the performance of all the portfolios studied in the previous three subsections in terms of standard deviation (volatility) and expected cost.

In this case, we find that the performance of the portfolios of generation technologies that result from imposing an RPS policy in a market with risk-neutral investors (dashed curve) is very similar to the performance of portfolios that result from risk-averse investors in a complete market (solid black curve). This observation is particularly accurate for low to medium RPS levels, where the differences are negligible. Nevertheless, for RPS levels above 75%, the renewable target achieves portfolios that are strictly dominated by the portfolios that result from risk-averse investors in a complete market.[14]

On the other hand, the portfolios that result from imposing increasing levels of a carbon tax in a market with risk-neutral investors

[12] Indeed, a dataset with a large mean value and a large CVaR may present small deviations between the extreme values (those included within the CVaR) and the expected value.

[13] We do not include the social cost of emissions in these graphs with the objective of comparing portfolios from different exercises, by using the same cost streams. Ignoring the social cost of emissions in these figures does not alter our conclusions.

[14] An important observation here is that the curve constructed using portfolios of generation that result from the planning problem with the CVaR constraint is not necessarily the Pareto efficient curve if risk is measured using the standard deviation of cost. That curve can only be computed by solving a planning problem using a constraint on the maximum standard deviation instead of using the CVaR. However, that would result in a much more complicated nonlinear problem than the one we solve in this paper.

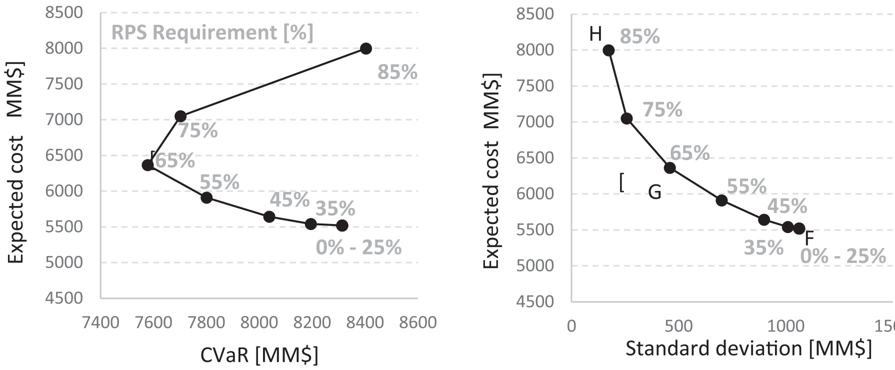

Fig. 2. (a) Expected cost vs CVaR for different RPS targets. (b) Expected cost vs Standard deviation for different RPS targets.

Table 5
Selected generation portfolios for three RPS targets.

	F (0%)	G (65%)	H (85%)
Installed capacity [MW]			
Coal	7156	4721	4721
Oil	3116	3116	3116
Hydro reservoir	3393	3393	3393
Wind	1289	14,883	18,870
Solar PV	12,865	15,225	22,091
Gas combined cycle	5091	5091	5091
Run-of-river	2826	2826	2826
Pumped storage hydro	0	1019	5766
Biomass	375	1540	1540
Geothermal	0	0	0
Small hydro	426	426	426
Concentration solar	0	0	0
Expected renewable generation [%]	31%	65%	85%
RPS [%]	0%	65%	85%
Expected cost [MM$]	5519	6364	7997
S.Dev. [MM$]	1064	460	175

(grey curve) are all dominated by the portfolios that result from a market with risk-neutral investors and a complete market (solid black curve). This occurs because, as stated in the previous section, a carbon tax can trigger an increase in investments in large hydroelectric power plants with reservoir, which are not eligible to meet the RPS target in the country. Since the availability of hydropower for electricity generation is stochastic, including more capacity of this type of technology in the generation mix yields more volatile portfolios than the ones that result under the RPS constraint or in a market with risk-neutral investors.

Consequently, in a market where both fossil fuel and hydrological uncertainties are important, and where investors are risk neutral, both an RPS and a carbon tax could give investors incentives to reduce the risk exposure of the resulting portfolio of generation technologies. These results suggest that, for a regulator concerned about the risk exposure of an electric power system, these two types of environmental policies could provide benefits beyond reductions in carbon emissions and spillover externalities for renewable energy technologies. In addition, of both instruments, it is the RPS constraint the one that selectively augments the installed capacity of technologies that do reduce the volatility of total system cost in a manner akin to what a risk-averse central planner would do.

Also, methods employed here can be highly valuable for policy-makers interested in quantifying the broad range of cost and benefits of environmental policies in the generation sector. As we have shown in this section, widespread stochastic modelling techniques can be used by regulators and policy makers to develop benchmarks to which market equilibria under environmental policies can be compared, and thus allow them to systematically evaluate economic benefits of diversification in the generation sector when assessing these policies. Thanks to the developed approach, we showed that an RPS, which can be deemed as costly in terms of its expected performance, can actually drive market equilibria towards efficient outcomes when risk aversion is taken into account. The latter could be overlooked under traditional methods of evaluating environmental policies, leading to an underestimation of the benefits that result from adopting these types of policies.

4.2. *Uncertainty in fossil fuel prices*

4.2.1. *Determining a pareto efficient frontier in a complete market*

We now repeat the previous analysis but assume that the only sources of uncertainty are fossil fuel prices (please refer to Appendix B for further analysis and results pertaining to these calculations). Fig. 5

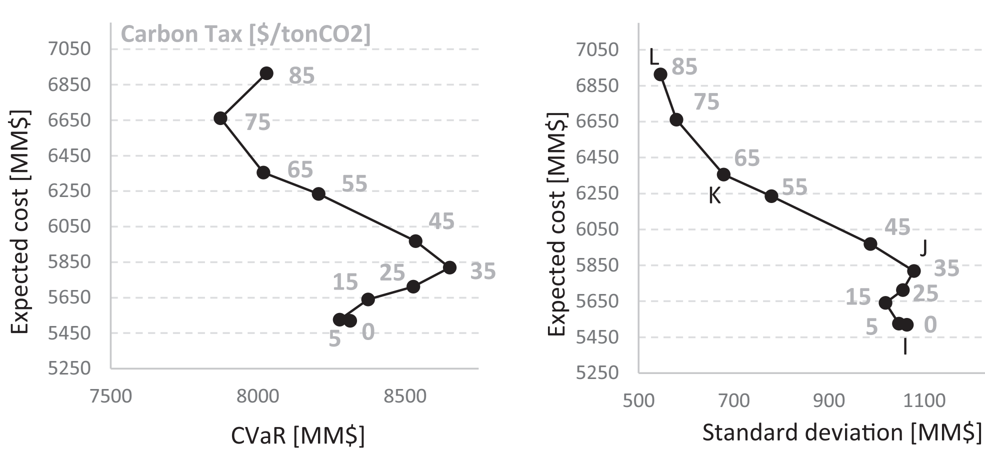

Fig. 3. (a) Expected cost vs CVaR for different carbon tax levels. (b) Expected cost vs Standard deviation for different carbon tax levels.

Table 6
Selected portfolios of generation technologies for four different carbon tax levels.

	I (0 $/Ton)	J (35 $/Ton)	K (65 $/Ton)	L (85 $/Ton)
Installed capacity [MW]				
Coal	7156	4721	4721	4721
Oil	3116	3116	3116	3116
Hydro reservoir	3393	6720	5610	4479
Wind	1289	3180	11,648	13,878
Solar PV	12,865	15,739	12,883	12,527
Gas combined cycle	5091	5091	5091	5091
Run-of-river	2826	2826	3595	5582
Pumped storage hydro	0	0	20	993
Biomass	375	1540	1540	1540
Geothermal	0	0	0	0
Small hydro	426	426	426	426
Concentration solar	0	0	0	0
Expected renewable generation [%]	31%	44%	54%	57%
Carbon tax [$/tonCO2]	0	35	65	85
Expected cost [MM$]	5519	5819	6355	6914
S.Dev. [MM$]	1064	1078	679	546

shows the Pareto frontier built based on five different limits on the CVaR constraint in the optimization problem that computes the risk-averse equilibrium in a complete market. Unlike the previous case, where we also considered hydro uncertainties, here we find that the risk-neutral equilibrium, portfolio M, can be further optimized in terms of risk, with a small increment of expected system cost, until reaching portfolio P. However, forcing a reduction of the CVaR below the level set for portfolio P has a rather large trade off with expected system cost.

4.2.2. *The effect of RPS policies on risk-neutral investors*

In contrast to our previous experiments where we considered both fuel price and hydro uncertainty, Fig. 6 shows that when only considering fuel price uncertainty we no longer observe a monotonic behavior of the curve of the standard deviation and expected system cost. In other words, increasing the RPS requirement does not necessarily lead to reductions of the standard deviation of system cost and an increase in expected cost for the whole range of renewable targets. For instance, increasing the RPS target from 0% (portfolio R) to 35% (portfolio S) increases both the standard deviation of system cost and its expectation. Nevertheless, in this case, increasing the RPS requirement above 35% of total supplied demand always reduces risk (standard deviation of cost) at the expense of an increase in expected system cost.

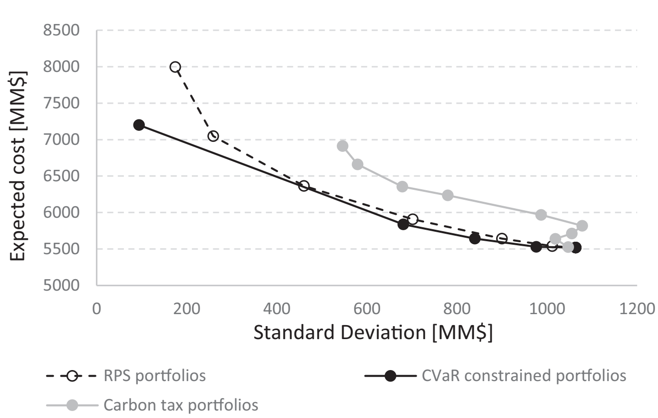

Fig. 4. Comparison of performance of the resulting portfolios under risk-aversion as well as under risk-neutral agents with an RPS policy or a carbon tax.

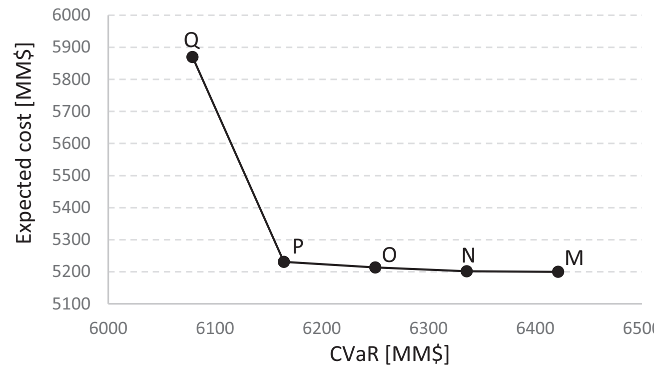

Fig. 5. Pareto frontier considering fossil fuel price uncertainty (see Appendix B for portfolio composition details).

4.2.3. *The effect of a carbon tax on risk-neutral investors*

In the case of carbon tax portfolios, Fig. 7 shows again that an increment in the carbon tax does not necessarily imply a decrease in volatility. Nevertheless, this relationship holds in a major number of portfolios. In portfolios U and V (see Appendix B for more details on portfolio composition), coal generation is replaced by run-of-river hydro and solar PV. As in the case with the RPS target, the variability of renewables in the system is firmed with existing gas units that operate mostly at night-time, increasing the volatility of system cost due to fuel price uncertainty. This is similar to the prior case we described in Section 4.1.3, in which the introduction of carbon taxes incentivized investments in new hydro units with reservoirs in exchange for reduced investments in coal generation. However, this also increased volatility because of hydro uncertainty.

4.2.4. *Comparing the outcomes from risk-averse Equilibria in a complete market versus risk-neutral Equilibria subject to environmental policies*

In Fig. 8 we compare all the equilibrium portfolios computed considering fossil fuel price uncertainty only. In this case, both environmental policies, RPS and carbon tax, generate portfolios that are similar in terms of performance with respect to what it would it would result from an equilibrium with risk-averse investors in a complete market. Unlike what we observed in Fig. 4, here a carbon tax yields results that are closer in performance to the portfolios that result from the CVaR-constrained planning model than the ones that result from the implementation of an RPS target in a market with risk-neutral investors. Nevertheless, the differences are rather small.

According to the graph, high renewable targets or carbon tax levels can drive risk-neutral investors to very low-risk portfolios. Interestingly,

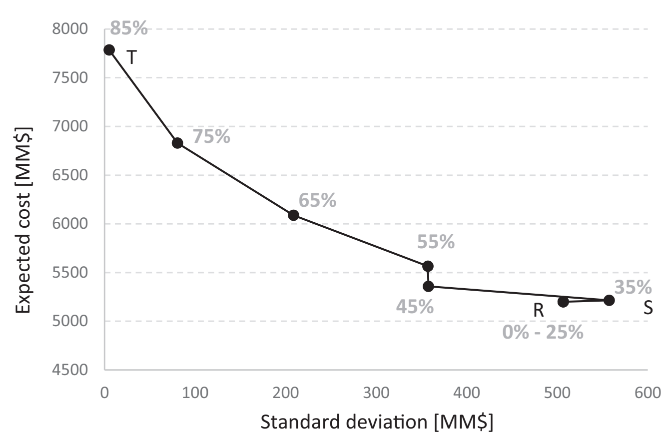

Fig. 6. Expected cost vs Standard deviation for different RPS targets (see Appendix B for portfolio composition details).

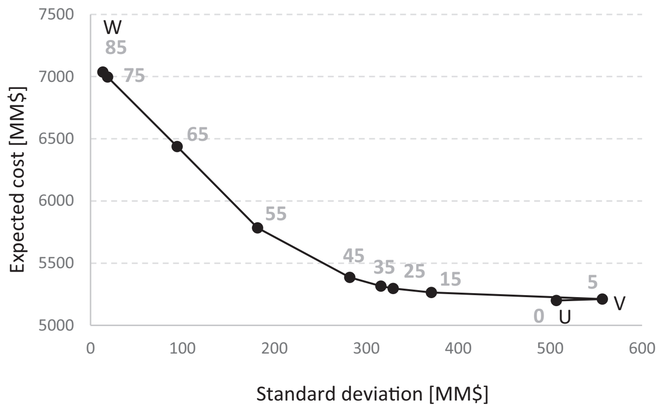

Fig. 7. Expected cost vs Standard deviation for different carbon tax levels *(see Appendix B for portfolio composition details)*.

because in this case we are not considering hydro uncertainty, it is theoretically possible to achieve a portfolio of generation with no risk (i.e., zero standard deviation) using only renewables plus large-scale hydro units. However, such equilibria can be economically inefficient considering high investment costs of such portfolios. This is why our CVaR-constrained model does not reach such low levels of risk.

5. Policy implications and conclusions

Existing research suggests that investments in a diversified portfolio of various types of renewable energy technologies can reduce the exposure of a power system to volatile fossil fuel prices and hydro availability. Indeed, according to the literature, a selective addition of renewables to poorly diversified generating portfolios might enhance energy security and economic efficiency from a risk perspective. This is particularly relevant for electric power systems that rely heavily on imported fossil fuels and hydropower.

In this work, we illustrate how environmental policies that are typically used in response to the threat of climate change can be also utilized to steer generation investments towards a more diversified and economically efficient outcome from a risk-averse planning perspective. We illustrate our point by employing two types of equilibrium models, one where we assume risk-averse investors and a complete market, and another one where we assume risk-neutral investors subject to some form of environmental policy. Under perfect competition, both equilibrium models can be solved by using optimization. We compute several long-term market equilibria of the Chilean generation sector for year 2035, considering distinct levels of risk aversion of market agents

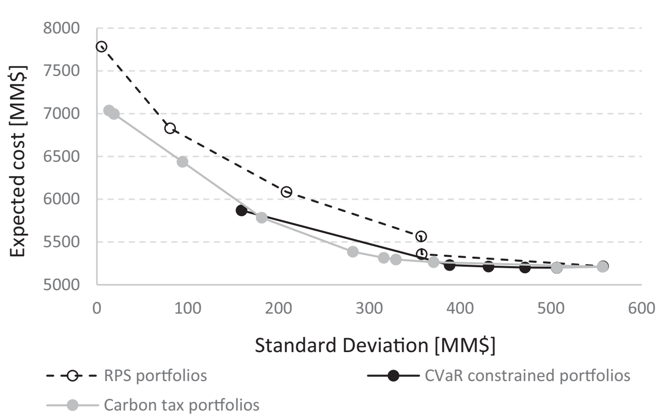

Fig. 8. Comparison of performance of the resulting portfolios under risk-aversion as well as under risk-neutral agents with an RPS policy or a carbon tax.

and uncertainty in both hydrological scenarios and fossil fuel prices. These risk-averse equilibria are then compared to generation portfolios that result from imposing different levels of RPS targets and carbon taxes in the market with risk-neutral agents, separately.

Through these calculations, we find that both RPS and carbon tax policies can be utilized to incentivize investments in generation portfolios that decrease the risk exposure of the generation sector to fuel price and hydrological uncertainties. Our results consistently show that when these policies are sufficiently strict (i.e. above 35% RPS or 35 $/ton$CO_2$), both policies contribute to reducing the risk exposure of the electric power system by triggering investments in renewable energy generation technologies with respect to a no-policy scenario. However, we also find that lower RPS or carbon tax values could actually increase portfolio risk in markets where hydro generation uncertainty is relevant (due to their effect on increased hydro investment) and in markets where fossil fuel price risk is dominant (due their effect on increased thermal generation to back-up renewables).

Additionally, we find that RPS policies present some advantages in terms of providing incentives to risk-neutral investors to achieve an efficient portfolio of generation technologies from a centralized risk-averse planning perspective in hydrothermal systems, such as the one in Chile. Our results indicate that when both fuel price and hydrological uncertainty are considered, RPS policies lead to generation portfolios that are very similar to the ones determined by a CVaR-constrained planning model, which is equivalent to the equilibrium in a complete market with risk-averse investors. In contrast, the generation investment portfolios that result from the implementation of a carbon tax, include investments in hydro reservoir capacity that reduce the efficiency of the resulting portfolio compared to the outcomes from the CVaR-constrained model. However, when hydrological risk is ignored, both policies achieve results that are comparable to the optimal generation portfolios that result from the CVaR-constrained planning model.

The main implication of our results is that, depending on the power system, both RPS and carbon tax policies can have economic benefits other than reductions of greenhouse gas emissions and cost reductions due to the early adoption of new technologies. Our results indicate that they could also be used to incent diversification of the generation portfolio in a country and, potentially, reduce the reliance of a system on imports of fossil fuels from foreign regions.

Finally, we want to acknowledge that our results are not general and that our conclusions could change if this analysis is applied to a different system. For example, in power systems affected by other sources of uncertainty it is possible that increasing the share of wind or solar generation could increase risk when measured as the standard deviation of total system costs. This could be the case for systems where the output of wind and solar resources presents large inter-annual variations or where these resources are all highly correlated across large geographical areas. In those cases, our conclusions would not necessarily hold since the implementation of environmental policies such as carbon taxes or renewable targets could result in generation portfolios exposed to volatile system conditions in the long term (e.g., years or seasons with abnormally-low wind speeds that affect most wind farms in the system). For those situations, the methodology that we describe in this paper could be used to measure the potential impact on risk that would result from imposing stringent emissions or renewable policies.

We also want to highlight that our study considers risk from a system-wide perspective, because the measures of risk we employed in our study (i.e., the CVaR and the standard deviation) are applied to the total cost of investments and operations. This means that we are not explicitly accounting for the impact of environmental policies on the generation portfolios or financial positions of each individual firm in the market. A future study should also consider market structure and how environmental policies could impact the risk exposure of firms with different portfolios of assets in the market. Such study could also be used to measure how environmental policies create new opportunities for risk trading among market participants.

Declaration of Competing Interest

Andrés Inzunza acknowledges being currently employed at Engie Impact, sustainability consulting branch of the Engie group. Additionally, Andrés Inzunza is a minor shareholder of the energy storage company Valhalla, based in Chile. Francisco Muñoz acknowledges being Director of Research at Generadoras de Chile AG, the views expressed in this paper are those of the author(s) and do not necessarily represent the views of Generadoras de Chile AG.

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Appendix A. Mathematical appendix

A.1. Nomenclature

A.1.1. Sets

I:	Set of all generation technologies.
I^R:	Set of renewable technologies that contribute to the RPS target (subset of I).
I^{NR}:	Set of technologies that do not contribute to the RPS target (subset of I).
J:	Set of hours in the simulated year.
J_k^D:	Set of hours included in stage k (subset of J).
K:	Set of stages in the simulated year.
S:	Set of scenarios.

A.1.2. Parameters

CV:	Maximum CVaR of generation portfolio costs.	[$]
D_j:	Demand in hour j.	[MWh]
$FU_{i,s}$:	Fuel cost of technology i in scenario s.	[$/MWh]
h_i:	Storage hours of technology i. Measured as the maximum time a certain technology may sustain its rated output without charging.	[hours]
$inf_{j,s}$	Normalized water inflow of hydro reservoir technology in hour j under scenario s.	[hm^3/MW]
INV_i:	Annuitized investment cost of technology i (this includes yearly fixed maintenance costs).	[$/MW-year]
n:	Number of simulated hours.	[hours]
p_s:	Probability of occurrence of scenario s.	[p.u.]
$RP_{i,j}$:	Generation availability of renewable technology i at hour j.	[p.u.]
RPS:	Renewable portfolio standard. Minimum percentage of renewable generation relative to total demand, in the simulated year.	[%]
$RRP_{i,j,s}$:	Run-of-river generation availability at hour j in scenario s for technology i (small-hydro and large scale run-of-river generation).	[p.u.]
RD_j:	Normalized hourly solar radiation incident in CSP plants solar collectors.	[p.u.]
SM:	Solar multiple of CSP technology.	[p.u.]
$\overline{SP}$:	Maximum power of solar field.	[MW]
$\overline{v}$:	Upper bound of stored water in hydro reservoir technology.	[hm^3]
voll:	Value of lost load.	[$/MWh]
VOM_i:	Variable O&M cost of technology i.	[$/MWh]
α:	CVaR parameter that defines the $(1-\alpha)$% highest cost scenarios.	[p.u.]
β_i:	Maximum availability of technology i due to scheduled maintenance.	[p.u.]
ϵ_i:	Emission coefficient of technology i.	[tonCO_2/MWh]
λ_i:	Hourly losses of stored energy/water of technology i.	[p.u.]
η:	Production coefficient of hydro reservoir technology.	[MWh/hm^3]
ρ^{PB}:	CSP technology power block efficiency.	[p.u.]
ρ_i^+:	Charging efficiency of storage technology i.	[p.u.]
ρ_i^-:	Discharging efficiency of storage technology i.	[p.u.]
τ:	Tax applied to CO_2 emissions.	[$/ton$CO_2$]

A.1.3. Decision variables

c_i:	Installed capacity of technology i.	[MW]
C_s:	Total investment and operating costs in scenario s.	[$]
d_s:	α – CVaR auxiliary variable that represents the right deviation of the cost in scenario s with respect to the value of variable z.	[$]
$g_{i,j,s}$:	Generation of technology i in hour j under scenario s.	[MWh]
$ll_{j,s}$:	Lost load in hour j under scenario s.	[MWh]
$v_{i,k,j,s}$:	Stored energy/water in technology i at the end of hour j, included in stage k, under scenario s. In MWh for CSP and PSH technologies and hm^3 for hydro reservoir.	[MWh] or [hm^3]
$p_{j,s}^{PB}$:	Power sent to power block in CSP technology.	[MW]
$p_{i,j,s}^+$:	Charging power of storage technology i in hour j under scenario s.	[MW]
$p_{i,j,s}^-$:	Discharging power of storage technology i in hour j under scenario s.	[MW]
$sp_{j,s}$:	Water lost through spillage in hour j under scenario s.	[hm^3]
z:	α – CVaR (auxiliary) variable that represents $VaR_\alpha(C_s)$.	[$]

A.1.4. Abbreviations

Concentration solar:	CSP
Hydro reservoir:	HRR
Pumped storage hydro:	PSH
Run-of-river:	RRH
Small hydro:	SH

A.2. Optimization model

In the present section, the CVaR constrained cost minimization model used for calculations is described. Here, we include all constraints that are added to the model throughout the study, nevertheless, a subset of these constraints will be simultaneously employed in the different experiments, as explained in prior sections.

The model considers the first four equations explained in the body of the paper (Eqs. (1)–(4)), which we repeat next.

$$\text{O.F.}: \min \sum_{s\in S} \mathrm{p}_s \cdot C_s \tag{A.1}$$

s.t.:

$$C_s = \sum_{i\in I} \mathrm{INV}_i \cdot c_i + \sum_{i\in I}\sum_{j\in J} \left(\mathrm{FU}_{i,s} + \mathrm{VOM}_i + \epsilon_i \cdot \tau\right) \cdot g_{i,j,s} + \sum_{j\in J} \mathrm{voll} \cdot ll_{j,s}, \forall s \in S \tag{A.2}$$

$$d_s \geq C_s - z, \forall s \in S \tag{A.3}$$

$$z + \frac{1}{1-\alpha} \sum_{s\in S} d_s \cdot \mathrm{p}_s \leq \mathrm{CV} \tag{A.4}$$

Moreover, an RPS constraint imposes a lower bound for renewable generation, relative to the total demand of the target year, for each scenario. Different technologies may contribute to the standard, depending on the jurisdiction being modelled.

$$\sum_{i\in I^R}\sum_{j\in J} g_{i,j,s} \geq \mathrm{RPS} \bullet \sum_{j\in J} \mathrm{D_j}, \forall \mathrm{s} \in \mathrm{S} \tag{A.5}$$

Eq. (A.6) sets that generation of power plants should match hourly demand and pumped storage pumping consumption in each scenario. Here, the $ll_{j,\,s}$ variable represents unserved energy.

$$\sum_{i\in I\setminus\{PSH\}} g_{i,j,s} + p^-_{PSH,j,s} = \mathrm{D}_j - ll_{j,s} + p^+_{PSH,j,s}, \forall j \in J, s \in S \tag{A.6}$$

Certain renewable generation technologies are modelled through unitary profiles that represent resource availability. (A.7) sets the hourly availability of renewable technologies that are not subject to hydrological variability and (A.8) sets the availability of renewable sources depending on hydrology (small hydro plants and large-scale run-of-river plants).

$$g_{i,j,s} \leq \mathrm{RP}_{i,j} \cdot c_i, \forall i \in I^R \setminus \{SH\}, j \in J, s \in S \tag{A.7}$$

$$g_{i,j,s} \leq \mathrm{RRP}_{i,j,s} \cdot c_i, \forall i \in \{SH, RRH\}, j \in J, s \in S \tag{A.8}$$

For every other generation technology (thermal power plants, hydro reservoir, etc.) generation must not surpass installed capacity, as constrained by (A.9). Also, minimum (or initial) and maximum installed capacities are considered in the model, so existent power plants and limited resource potentials can be included.

Eq. (A.12) on the other hand, limits total generation in the simulated period according to the average time units of a certain technology undergo planned maintenance. The maximum availability parameter β_i can be set to 1 for technologies which overall capacity factor is not affected by planned maintenance periods.

$$g_{i,j,s} \leq c_i, \forall i \in I^{NR} \setminus \{RRH\}, j \in J, s \in S \tag{A.9}$$

$$\underline{c_i} \leq c_i, \forall i \in I \tag{A.10}$$

$$c_i \leq \overline{c_i}, \forall i \in I \tag{A.11}$$

$$\sum_{j\in J} g_{i,j,s} \leq c_i \cdot \beta_i \cdot \mathrm{n}, \forall i \in I, s \in S \tag{A.12}$$

Technologies with storage capability such as hydro reservoir, pumped storage hydro and concentration solar power have also been included in the model. To reduce computation times, stages of 24 h can be used to represent days within the same month or season. For this, we employ a formulation considering a set of K stages, each of which contain a subset of hours of the year, J_k^D.

For each storage technology, we consider a single representative reservoir in the same fashion of Inzunza et al., (2016). Constraint (A.13) models the storage of water for hydro reservoir technology (HR). Here, inflows are normalized and considered to grow as installed capacity of hydro reservoir power augments. Losses of water through seepage and/or evaporation are included via the λ_i parameter.

Although not shown here for simplicity, hourly upper and lower bounds of reservoir level are considered, as well as initial and final conditions of reservoirs. Also, reservoir level decision variables ($v_{i,\,k,\,j,\,s}$) of the different consecutive stages are linked, so chronological interdependence of stages can be included.

$$v_{i,k,j,s} = v_{i,k,j-1,s} \cdot (1-\lambda_i) + inf_{j,s} \cdot c_i - \frac{g_{i,j,s}}{\eta} - sp_{j,s}, \forall i \in \{RH\}, j \in J_k^D, k \in K, s \in S \tag{A.13}$$

$$v_{i,k,j,s} \leq c_i \cdot \overline{v}, \forall i \in \{RH\}, j \in J_k^D, k \in K, s \in S \tag{A.14}$$

The block diagram in Fig. 9 shows our modelling of CSP technology, which is based on Denholm and Hummon, (2012); Godoy, (2017). Here, a design parameter, which represents the ratio between the maximum power that the solar field (array of collectors of solar radiation) provides to the power block (steam turbine) is considered. This parameter is called the Solar Multiple (SM). Also, we employ a normalized radiation profile (RD_j).

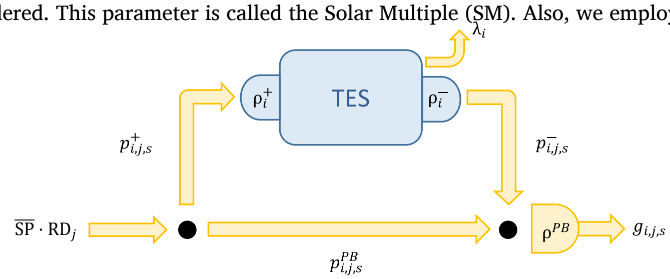

Fig. 9. CSP model used in our study.

The Solar Multiple, the installed capacity of CSP technology and the hourly radiation determine the amount of power than can be either sent to the power block or stored in the thermal energy storage system (TES), as in (A.16).

$$\overline{\mathrm{SP}} = \frac{\mathrm{SM} \cdot c_i}{\rho^{PB}}, \forall i \in \{CSP\} \tag{A.15}$$

$$\overline{\mathrm{SP}} \cdot \mathrm{RD}_j \geq p_{i,j,s}^+ + p_{j,s}^{PB}, \forall i \in \{CSP\}, j \in J, s \in S \tag{A.16}$$

Generation of CSP technology can then be determined as the amount of power drawn from the TES system or the power sent to the power block directly from the solar field. Also, a certain power block efficiency is considered:

$$g_{i,j,s} = \left(p_{i,j,s}^- + p_{i,j,s}^{PB}\right) \cdot \rho^{PB}, \forall i \in \{CSP\}, j \in J, s \in S \tag{A.17}$$

With the above considerations, storage of energy in the TES system can be modelled through similar equations as in the case of pumped storage hydro. Thus, (A.18) models the storage for both technologies.

$$v_{i,k,j,s} = v_{i,k,j-1,s} \cdot (1-\lambda_i) + p_{i,j,s}^+ \cdot \rho_i^+ - \frac{p_{i,j,s}^-}{\rho_i^-}, \forall i \in \{CSP, PSH\}, j \in J_k^D, k \in K, s \in S \tag{A.18}$$

Also, storage capacity for PSH and CSP technologies is modelled through a certain maximum number of hours that plants can generate at rated capacity without charging. This is determined by Eq. (A.19).

$$v_{i,k,j,s} \leq c_i \cdot \mathrm{h}_i, \forall i \in \{CSP, PSH\}, j \in J_k^D, k \in K, s \in S \tag{A.19}$$

In the case of PSH, a very big lower reservoir and no inflows are considered, since the pumped storage hydro potential in Chile is mainly composed by sea-water pumped storage plants. For this technology, (A.20) and (A.21) limit the amount of power that can be generated or consumed for pumping, relative to the installed capacity of the technology.

$$p_{i,j,s}^+ \leq c_i, \forall i \in \{PSH\}, j \in J, s \in S \tag{A.20}$$

$$p_{i,j,s}^- \leq c_i, \forall i \in \{PSH\}, j \in J, s \in S \tag{A.21}$$

Appendix B. Additional analyses on results considering fossil fuel price uncertainty alone

In this section we provide further details on results from Section 4.2.

B.1. Determining a pareto efficient frontier in a complete market

The most interesting effect of only considering fuel price uncertainty is what occurs to the generation investment portfolios as we change the maximum level of CVaR in the risk-averse planning model. In contrast to the previous exercises with hydro uncertainty, in the new set of results where hydro uncertainty has been removed, the optimal risk-neutral portfolio includes large investments in hydroelectric power plants with storage capabilities, depleting the technology's potential in the case study. This is reasonable, since there is no longer a dry scenario in which hydro reservoir plants reduces their energy and capacity contributions. Additionally, in this case, we find that it is also optimal to expand investments in solar PV and reduce coal capacity with respect to the risk-neutral case that considers all uncertainties (see Table 7 and Table 4).

Table 7
Equilibrium portfolios of generation technologies for the case with risk-averse agents in a complete market.

	M	N	O	P	Q
Installed capacity [MW]					
Coal	5676	6242	5847	5293	4721
Oil	3116	3116	3116	3116	3116
Hydro reservoir	6720	6720	6720	6720	6720
Wind	1289	1289	1289	1289	1289
Solar PV	13,881	13,306	12,817	12,253	13,703
Gas combined cycle	5091	5091	5091	5091	5091
Run-of-river	2826	2826	3827	5055	5582
Pumped storage hydro	0	0	0	0	0
Biomass	375	375	375	375	553
Geothermal	0	0	0	0	0
Small hydro	426	426	426	426	426
Concentration solar	0	0	0	0	0
Expected renewable generation [%]	33%	31%	31%	29%	31%
Expected cost [MM$]	5200	5202	5213	5231	5870
CVaR [MM$]	6421	6336	6250	6165	6079

On the other hand, we find that the portfolio of generation technologies with the lowest CVaR (portfolio Q) includes capacity additions of hydro units with reservoir, solar PV, run-of-river hydro, biomass and pumped storage hydro, all of which are risk-free technologies in this case. As in the previous case where we considered hydro uncertainty, we find that in the portfolio of minimum risk exposure it is not optimal to invest in new coal capacity. We also find that reducing the CVaR limit yields an initial increase in coal capacity (i.e., going from portfolio M to N), but further reducing the risk exposure of the portfolio results in reductions of investment in coal capacity (i.e., going from portfolio N to Q). This behavior occurs for the same reasons discussed in Section 4.1.1. In this case, since the price of coal in international markets is less volatile than gas or oil prices, it is optimal to initially employ coal generation to replace gas units, mitigating the price risk of natural gas (see Table 8). However, further reducing the limit on the CVaR eliminates coal from the investment portfolio, leaving only the existing capacity of this technology available for operation.

Table 8
Expected share of generation per technology for portfolios M and N.

	M	N
Expected generation [%]		
Coal	32%	35%
Oil	0%	0%
Hydro reservoir	22%	22%
Wind	2%	2%
Solar PV	27%	26%
Gas combined cycle	3%	1%
Run-of-river	10%	10%
Pumped storage hydro	0%	0%
Biomass	1%	1%
Geothermal	0%	0%
Small hydro	2%	2%
Concentration solar	0%	0%

5.1. *The effect of RPS policies on risk-neutral investors*

As we show in Table 9, in portfolio S (35% RPS), coal capacity is replaced by solar PV to increase renewable generation levels and comply with the RPS constraint. Since solar PV is an intermittent energy source, new capacity should be backed with other technologies to generate at night-time. In this case, gas generation plays this role and increases its participation in the energy dispatch, as shown in Table 10. Nevertheless, because LNG prices are volatile, increased generation of this technology to balance the variability of renewables increases the risk performance (CVaR and standard deviation) of the generation portfolio.

Table 9
Selected generation portfolios for three RPS targets.

	R	S	T
Installed capacity [MW]			
Coal	5676	4761	4721
Oil	3116	3116	3116
Hydro reservoir	6720	6720	3393
Wind	1289	1289	14,627
Solar PV	13,881	14,982	15,714
Gas combined cycle	5091	5091	5091
Run-of-river	2826	2826	2826
Pumped storage hydro	0	0	3347
Biomass	375	423	1540

(*continued on next page*)

Table 9 (*continued*)

	R	S	T
Geothermal	0	0	0
Small hydro	426	426	6033
Concentration solar	0	0	0
Expected renewable generation [%]	33%	35%	85%
RPS [%]	0%	35%	85%
Expected cost [MM$]	5200	5215	7785
S.Dev. [MM$]	507	557	5

Table 10
Expected generation of portfolios R and S.

	R	S
Expected generation [%]		
Coal	32%	26%
Oil	0%	0%
Hydro reservoir	22%	22%
Wind	2%	2%
Solar PV	27%	29%
Gas combined cycle	3%	6%
Run-of-river	10%	10%
Pumped storage hydro	0%	0%
Biomass	1%	2%
Geothermal	0%	0%
Small hydro	2%	2%
Concentration solar	0%	0%
Expected renewable generation [%]	33%	35%
RPS [%]	0%	35%
Expected cost [MM$]	5200	5215
S.Dev. [MM$]	507	557

5.2. *The effect of a carbon tax on risk-neutral investors*

Table 11
Selected generation portfolios for three carbon tax levels.

	U	V	W
Installed capacity [MW]			
Coal	5676	4721	4721
Oil	3116	3116	3116
Hydro reservoir	6720	6720	6720
Wind	1289	1289	10,111
Solar PV	13,881	14,500	9996
Gas combined cycle	5091	5091	5091
Run-of-river	2826	3096	5582
Pumped storage hydro	0	0	0
Biomass	375	375	1540
Geothermal	0	0	0
Small hydro	426	426	4160
Concentration solar	0	0	0
Expected renewable generation [%]	33%	34%	59%
Carbon tax [$/tonCO2]	0	5	85
Expected cost [MM$]	5200	5211	7037
S.Dev. [MM$]	507	557	13

Please refer to Section 4.2.3 for analysis on these portfolios.

Appendix C. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2021.105470.

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