Uncertain long-run emissions targets, CO_2 price and global energy transition: a general equilibrium approach*

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Abstract

The persistent uncertainty about mid-century CO_2 emissions targets is likely to affect not only the technological choices that energy-producing firms will make in the future but also their current investment decisions. We illustrate this effect on CO_2 price and global energy transition within a MERGE-type general-equilibrium model framework, by considering simple stochastic CO_2 policy scenarios. In these scenarios, economic agents know that credible long-run CO_2 emissions targets will be set in 2020, with two possible outcomes: either a "hard cap" or a "soft cap". Each scenario is characterized by the relative probabilities of both possible caps. We derive consistent stochastic trajectories - with two branches after 2020 - for prices and quantities of energy commodities and CO_2 emissions permits. The impact of uncertain long-run CO_2 emissions targets on prices and technological trajectories is discussed. In addition, a simple marginal approach allows us to analyze the Hotelling rule with risk premia observed for certain scenarios.

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1 Introduction

This paper shows how the current uncertainty about the 2020-2050 CO_2 emissions targets may affect CO_2 and energy prices as well as technological choices in the energy sector.
To assess the cost of reducing GHG emissions, applied general-equilibrium models linking aggregated descriptions of economies and detailed energy sectors together[1] have been developed. Some of them, for instance MERGE (Manne et al., 1995), GEMINI (Bernard and Vielle, 2003), IGSM (Sokolov et al., 2005) and WITCH (Bosetti et al., 2006), have been used by IPCC (2007) and USCCSP (2007) to evaluate climate change policies. So far, the issue of agents' behavior under uncertainty has been addressed in these models through sensitivity analysis (Löschel and Otto, 2009; Magné et al., 2010), Monte-Carlo simulation (Kypreos, 2006) and stochastic formulations where agents hedge themselves against some probabilistic outcomes. This last approach was first introduced by Manne and Richels (1992) and Manne and Olsen (1996) who studied the effect of a low-probability climate catastrophe on agent's behavior. More recently[2], Bosetti and Tavoni (2009) investigate the impact of uncertain energy-related R&D activities and Loulou et al. (2009) derive different EMF 22 radiative forcing scenarios by assuming an uncertain sensitivity of climate to emissions.
In this paper, we use a stochastic approach to illustrate how the persistent uncertainty about the 2050 CO_2 emissions caps impacts prices and technological choices in the energy sector[3]. These energy prices are especially useful to understand agents' behavior and assess the relevance of our model's results.
In a deterministic model, the agents plan their actions with a perfect knowledge of the future, and the efficient (or clean) technologies expand at the optimal rate in the economy. In our model, until 2020, the agents have to invest before knowing the full sequence of emissions caps imposed to regional economies, by trading off the gain in postponing the adoption of efficient but expensive technologies against the risk of being tied to some detrimental technological choice once the actual emissions caps are set.
The model we use is a modified stochastic version of the MERGE model[4]. For the sake of illustration, here uncertainty only involves two political outcomes, with, at the end of 2020, the setting of either a "hard-cap" policy or a "soft-cap" policy for energy-related CO_2 emissions. Each policy de-

[1]The so-called "top-down/bottom-up" models.
[2]See also the survey by Labriet et al. (2009).
[3]The energy sector represents 76% of total direct CO_2 emissions in 2005 (IEA, 2008b)
[4]See Manne et al. (1995) for a presentation of the MERGE model.

fines series of regional quotas which are linearly-decreasing until 2050 and constant after this date. Until 2050 the hard-cap and soft-cap quotas are respectively consistent with the IPCC (2007)'s 450 and 550 ppm atmospheric-GHG-concentration scenarios. However, over the model's whole horizon, the hard-cap and soft-cap policies are less stringent than the two IPCC's scenarios since complying with these scenarios would involve post-2050 emissions reductions (IPCC, 2007; IEA, 2008b).
In our model, all agents (i.e., firms and households) are forward looking, in the sense that firms (households) always act so as to maximize their expected present value (expected sum of discounted utilities) under rational expectations. In other words, in each date firms base their current decisions on consistent subsequent prices of inputs and outputs (or, in the case of decisions made until 2020, consistent subsequent prices in each possible outcome), i.e., prices that precisely result from the decisions currently made. Firstly, our approach makes possible an explicit modelling of agents behavior in the presence of long-run CO_2 policy uncertainty. Secondly, it yields stochastic scenarios of energy prices - for CO_2, oil, gas, power - with two possible sequences for post-2020 prices, that are consistent with the stochastic political scenario under consideration. Note that the unique pre-2020 sequence and the two possible post-2020 sequences obtained for the price of a given energy commodity may broadly differ from the two deterministic sequences of prices that would be determined by successively considering each CO_2 target as certain from the beginning (i.e., 2005 in our model). In addition, as illustrated later, a stochastic price scenario is not necessarily bounded by the corresponding two deterministic sequences of prices. This shows the interest of a stochastic-scenario-based approach for studying the energy transition when long-run CO_2 emissions targets are uncertain.

Section 2 presents the stochastic CO_2-emissions policy scenarios under consideration and motivates our approach. The structure, calibration and computation of our stochastic general equilibrium model are discussed in section 3. The simulation results are studied in section 4, with an emphasis on the impact of uncertainty on prices and technology trajectories. The last section concludes.

2 A stochastic-scenario approach for long-run emissions targets

The forthcoming energy transition, that will result from the technological choice made by the economic agents, will crucially depend on CO_2 emission targets. If current negotiations can set credible regional emissions targets on the short and intermediate runs, uncertainty on long-run targets (i.e. up to the middle of the century and beyond) is likely to persist. In addition, economic agents are likely to consider these long-run emissions targets as credible only once they have been transposed into regional energy policies (since, meanwhile, any long-run commitment might be offset by possible political, economic or environmental shocks (Frankel, 2009)). In our model, we therefore assume that the agents have currently an incomplete information. They know the emissions targets set until 2020 but they consider that credible mid-century emissions targets will be set in 2020 only.

Therefore, until 2020 they face an uncertainty which impacts not only their future but also their current technological choices and investments. For example, the uncertainty on long-term emissions targets can lead the firms to delay costly investment in clean technologies, although this might cause very high CO_2 emissions costs if restrictive emissions targets are finally set. Indeed this effect is not taken into account in a deterministic model where agents plan their actions with a perfect knowledge of the future and clean technologies expand at the optimal rates in the economy.

Since our primary goal is to illustrate the effect of uncertain long-run CO_2 emissions targets on CO_2 price and energy transition, we consider here a simple stochastic scenario, in the sense that agents are aware that either a hard-cap or a soft-cap target will be set for mid-century energy-related CO_2 emissions. As earlier explained, agents consider that the political choice between the hard and soft caps will be definitely made in a credible way in year 2020. To better illustrate the effect of uncertainty, different assumptions about the relative probabilities of these two possible caps are considered.

More precisely, in our model, the CO_2 emissions targets are enforced through a cap-and-trade mechanism. There are two successive series of linearly decreasing emissions caps. These series are reported in Table 1. For every OECD region, the first series, which spans from 2010 to 2020, sets an emission cap for every period. These caps decrease linearly so as to converge towards the 2020 emissions target. For each OECD or non-OECD region, the second series of emissions caps concern the post-2020 periods. The caps linearly decrease from 2020 to 2050, so as to reach either the hard-cap or the soft-cap emission stabilization level in 2050, and after remain constant.

The OECD countries commit themselves to known reduction levels of energy-related CO_2 emissions for 2020. The European Union agrees on a reduction of 20% with respect to 1990. North America (USA, Canada and Mexico) agrees to reduce emissions by 17% with respect to 2005 (IHT, 2009). The Pacific OECD countries (Japan, South Korea, Australia and New Zealand) are assumed to commit themselves to the same target as North America. Until 2020, the emissions of the non-OECD countries are not limited.
The climate negotiations for the period 2025-2050 are assumed to be finalized in 2020, and to yield at that date either the hard-cap or the soft-cap climate agreement. Therefore, until 2020, households and firms ignore which one of these two caps will be set. In the hard-cap outcome, every OECD region has to cut emissions in 2050 by a factor 4 with respect to 2005. Every non-OECD region commits to a 27% emission reduction by 2050 with respect to 2005. Globally, these commitments correspond to a halving of energy-related CO_2 emissions by 2050 with respect to 2005.
If the soft cap is set, every OECD region has to cut emissions in 2050 by a factor 3 with respect to 2005. Every non-OECD region commits to increase its emissions in 2050 by no more than 14% with respect to 2005. The soft cap corresponds to a 25% decrease in global emissions in 2050 with respect to 2005.
Until 2050 the emissions corresponding to the hard and soft caps are respectively consistent with the 450 and 550 ppm scenarios proposed by IEA (2008b) on the basis of IPCC (2007). However, when considering the model's whole horizon, the hard and soft caps are less constraining than the 450 and 550 ppm scenarios since here, after 2050, emissions are only assumed to be stabilized.

Unused emissions permits can be banked (ensuring inter-temporal efficiency) from 2010 on for OECD regions and from 2025 on for non-OECD regions. From 2060 on, banked permits can no longer be used. Inter-regional trade of emissions permits (i.e. a global CO_2 emission permits market that ensures spatial efficiency) occurs only after 2020.
In the stochastic CO_2 policy scenarios considered here, the two possible post-2020 series of caps represent two distinct states of the world, as illustrated in plain line on the left-side of Figure 1. As in Manne and Olsen (1996), we can oppose a "Learn then Act" model (where the scenario is deterministic) to an

Region	First series of caps	Second series of caps	
		Soft cap	Hard cap
	2005[a]...2020	2025...2050-2100	2025...2050-2100
North America	6.88 ... 5.71 (-17%)	5.26 ... 2.29 (-67%)	4.91 ... 1.72 (-75%)
European Union	4.10 ... 3.32 (-19%)	3.07 ... 1.37 (-67%)	2.86 ... 1.03 (-75%)
Pacific OECD	2.19 ... 1.82 (-17%)	1.68 ... 0.73 (-67%)	1.57 ... 0.55 (-75%)
China	5.46	7.63 ... 6.22 (+14%)	7.36 ... 4.00 (-27%)
India	1.23	1.72 ... 1.40 (+14%)	1.66 ... 0.90 (-27%)
Russia	1.57	2.20 ... 1.79 (+14%)	2.12 ... 1.15 (-27%)
Middle East	1.32	1.84 ... 1.50 (+14%)	1.77 ... 0.96 (-27%)
Asia non-OECD[b]	1.50	2.09 ... 1.70 (+14%)	2.02 ... 1.10 (-27%)
Latin America	1.00	1.40 ... 1.14 (+14%)	1.35 ... 0.74 (-27%)
Africa	0.86	1.20 ... 0.98 (+14%)	1.16 ... 0.63 (-27%)
rest of the world	1.20	1.68 ... 1.37 (+14%)	1.62 ... 0.88 (-27%)
World	27.3	29.8 ... 20.5 (-25%)	28.4 ... 13.7 (-50%)

Figures in brackets give the relative change with respect to emissions in 2005.

"..." denotes a linear decrease in the cap.

[a] Figures are historical emissions (computed from IEA (2007b)).

[b] Asia non-OECD excludes China and India.

Table 1: CO_2 emissions caps (in billion tons per year)

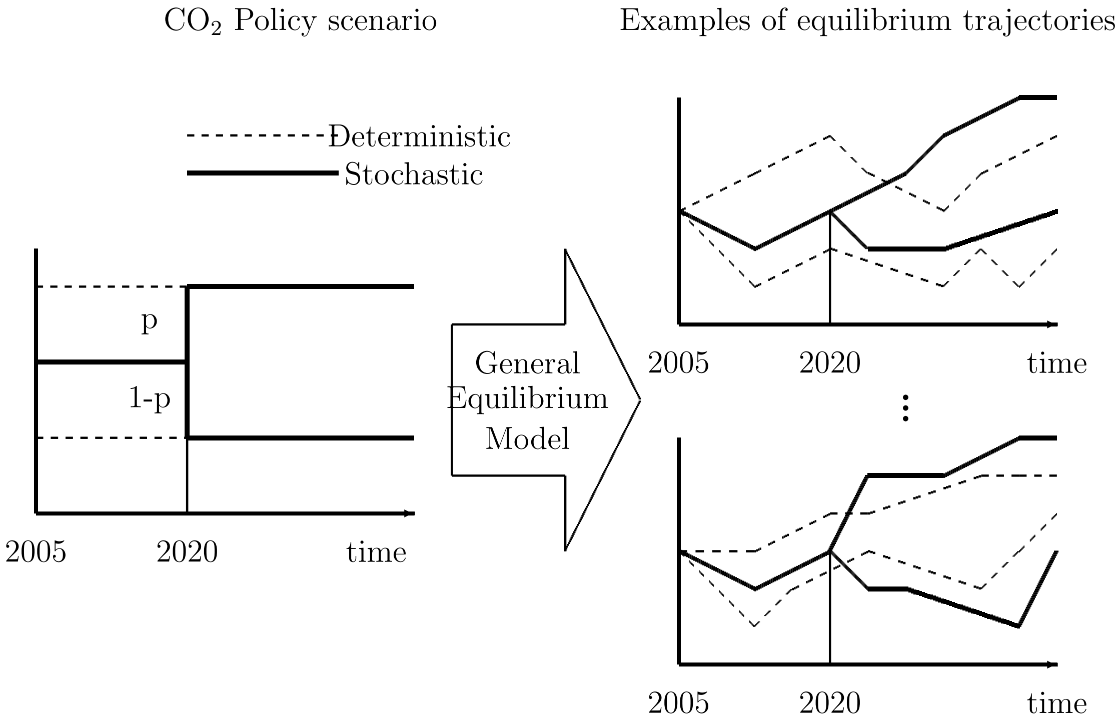

Figure 1: Deterministic and stochastic scenarios with examples of resulting equilibrium trajectories for prices or quantities

"Act then Learn" model (where the scenario is stochastic and takes the form of a probability tree). Our stochastic scenario is common knowledge shared by all agents of the model who are equally informed. These agents - households who maximize expected utilities and firms who maximize expected profits - are forward looking in the sense that they base current decisions on expected prices and quantities. They are assumed to have a perfect foresight, so that their state-conditional expectations are true. In other words, they take their decisions knowing the prices and quantities they would face in each branch, but ignoring until 2020 which branch will materialize. At equilibrium, both price and quantity of every commodity follow a stochastic trajectory, with a unique branch (two possible branches) until 2020 (after 2020), as illustrated in plain line on the right side of Figure 1. Our approach therefore yields stochastic trajectories which are consistent with the underlying stochastic policy scenario. For the sake of illustration, in Figure 1, the one-branch trajectory corresponding to each deterministic CO_2 policy scenario (i.e., when either the hard cap or the soft cap is set from the very start) is also indicated in dashed line.

3 Presentation of the general equilibrium model

To assess the impact of uncertain mid-century CO_2 emissions targets on current and future energy transition, we use a model derived from MERGE (Manne et al., 1995). More specifically, unlike MERGE, our model contains no modelling of the impact of GHG emissions on climate change, but mere accounting relations between CO_2 emissions and energy technology use. The model's horizon extends from 2005 (base year) to 2100, with 5-year time periods. The world is divided into eleven regions: North America, European Union, OECD Pacific, China, India, non-OECD Asia, Russia, Middle East, Latin America, Africa and rest of the world. Recent data (e.g., IEA (2008a), IEA (2008b), EIA (2007)) have been used to calibrate the model. In addition, our model is stochastic as it allows agents to consider different possible outcomes for long-run CO_2 emissions targets.

Following Manne et al. (1995), an intuitive solution would be to introduce uncertainty in our model by means of non-anticipativity constraints[5]. However, in the wake of Meeraus and Rutherford (2005), we use a tighter formulation which limits the number of variables and constraints by taking into account the recursive structure of the model. Apart these elements, the formulation and the solution methods for the deterministic and the stochastic versions of our model are quite similar. For this reason, the following section is devoted to a presentation of the model in a deterministic framework.

3.1 Description of the model

In each region, a representative household sells its labor force, owns four firms[6], the whole capital stock, the stock of *in-situ* natural resources (underground reserves) and the quota of emissions permits (i.e., the volume of emissions that satisfies the targeted cap.) Therefore, the household's revenue consists in firms' profits, interests on capital, rents from natural resource exploitation, and the revenue from the emission permits market[7]. Each region

[5]Let us for instance consider that mid-century CO_2 emissions targets are assumed to be set in 2020, and that agents (correctly) anticipate two possible outcomes. This stochastic scenario could then be handled by duplicating every variable, as there are two possible states of the world. The non-anticipativity constraints would force every variable and its duplicate to be equal until 2020.

[6]Each firm represents one of the following four industrial sectors : final sector producing the composite good, electric production, non-electric energy production, natural resources (oil, gas and coal) extraction.

[7]The quota of emissions permits is sold by the household to the two energy firms of the region. Since the household owns these firms, this is equivalent to ignoring this

i maximizes the sum of its discounted utilities of consumption, defined as follows :

$$\sum_{t=0}^{T} \beta_{i,t} L_{i,t} \log(\frac{C_{i,t}}{L_{i,t}})$$

$C_{i,t}$ is the total consumption in region i at period t. $L_{i,t}$ is the population of region i at period t (the size of the household). The utility function therefore depends on the logarithm of the per-capita consumption, with :

$$\frac{\partial(L_{i,t} \log(\frac{C_{i,t}}{L_{i,t}}))}{\partial C_{i,t}} = \frac{1}{(C_{i,t}/L_{i,t})}$$

In every period, the region's marginal utility is thus inversely proportional to its per-capita consumption. $\beta_{i,t}$ is the discount factor for utility in region i for period t, with $\beta_{i,t} = \beta_{i,t-1} e^{-\rho_{i,t}}$, where $\rho_{i,t}$ is the region's rate of time preference for utility.

The good consumed by the households *represents a composite of all items*[8] *produced outside the energy sector* (Manne et al., 1995). It serves as numraire in the model, and it is measured in terms of units of purchasing power for the year 2005. This composite good can be used for consumption (by households), capital accumulation (investment in firms), or for intermediate consumption (in the four industrial sectors).

The composite good is produced in the final industrial sector by using different generations (vintages) of equipment. Each of them produces the same composite good and requires capital (k), labor (l), electric (e) and non-electric energy (n) as inputs. At each period, to increase its production capacity, the firm of the final sector can install a new vintage with flexibility in the relative quantities of inputs. However, it can no longer adjust the quantity of inputs once the vintage is installed. As a result, at every period, the substitution between inputs is only possible for the new generation of equipment. Thus, the final sector is somehow locked in the short-run by previous technical choices. Each vintage undergoes an (exogenous) exponential scrapping. The production function corresponding to a new vintage at period t is described by a nested Constant-Elasticity-of-Substitution function (for ease of notation, the subscript i is here omitted):

$$F_t(k, l, e, n) = \left[a_t [k^{\alpha} (A_t l_t)^{1-\alpha}]^{\frac{\sigma-1}{\sigma}} + b_t [e^{\beta} n^{1-\beta}]^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}$$

revenue and considering firm's profits on a before-CO_2-emission-cost basis. Nevertheless, the model implicitly considers a regional CO_2 emission permit market, which influences the technological choices made by the firms.

[8]This includes all intermediate and consumption goods and services, as well as all the final energy needs of the economy (firms and households).

The parameter A_t introduces an exogenous improvement in labor productivity. α is the optimal value share of capital in the labor/capital pair and β is the optimal value share of electric energy in the electric/non-electric energy pair. The elasticity of substitution between energy and non energy inputs is σ. This can be considered as a long-run elasticity, whereas in every period the short-run elasticity depends on existing vintages. The time-dependent scaling factors a_t and b_t reflect exogenous energy-efficiency improvements.
Electric and non-electric inputs are supplied by two distinct industrial sectors that use different Leontief technologies to transform fossil fuels and composite goods (used as intermediate goods) into energy for the final sector. The technologies available in these sectors are presented in Tables 2 and 3. The combustion of fossil fuels produces CO_2 emissions which must be covered by the emissions quota available for the period. Each technology is characterized by a type of fuel input (oil, coal, gas, or none[9] for renewable), a fuel efficiency, an emission rate and a non-fuel cost. Unlike Magné et al. (2010) and Manne and Richels (2004), we consider exogenously given non-fuel costs (with no learning-by-doing effect). Some constraints render technologies not perfectly substitutable in both electric and non-electric energy sectors. Firstly, the use of technologies can be subject to some exogenous caps reflecting, for example, technological bottlenecks. Secondly, the market share of some technologies can be limited, as is the case for the wind technologies in order to maintain a stable electric supply. Last, there are constraints on the expansion and decline of each technology. The constraints on maximum expansion (which take the form of a maximum growth rate in technology use from one period to the other) reflects real-world frictions for installing new capacity. The maximum decline constraints limit unrealistic massive abandonment of already-installed capacities. These constraints smooth the activity levels of the various technologies and facilitate the coexistence of technologies with different marginal costs in the electric and non-electric sectors. Furthermore, they generate irreversibility[10] in the model since pre-2020 technological trajectories constrain post-2020 trajectories. Note that the coexistence of different vintages in the final sector implies another type of irreversibility, since pre-2020 investments impact the possible substitutions between capital and energy - and between

[9]Nuclear is a special case in the model since there is no explicit modelling of uranium production.

[10]According to Pindyck (2006), "irreversibility will affect current decisions if it would constrain future behavior under plausible outcomes". Let us take the example of a clean-but-expensive technology. The constraint on its maximum expansion (contraction) rate should favor a greater (lower) optimal pre-2020 use of this technology as a precaution against possible high (low) post-2020 CO_2 prices. A similar analysis, with constraints working in opposite directions, can be made for cheap-but-highly-emitting technologies.

electric and non-electric energies - after 2020.
The electric and non-electric energy firms are supplied in fossil fuels by a mining sector which extracts oil, coal and gas. This extraction requires *in situ* reserves, as well as composite goods to pay the extraction costs. All these mineral reserves are finite and can be exhausted. Moreover, extraction is subject to an upper limitation in every period. This reflects the complexity of undertaking new development projects in the oil and gas industry.
All regions are linked together by the international trade[11] of composite goods[12], oil, gas and (after 2020) emission permits. Transportation costs generate differences between certain regional prices.
In any period, the emissions of the electric and non-electric energy sectors must be smaller than the regional quota (i.e. the cap endowed to the region for the period considered) increased by the emission permits banked in previous periods and (after 2020) by the purchase of emissions permits from other regions.

3.2 Calibration

The exogenous level of effective labor is adjusted so as to obtain at steady state a level of economic growth close to IEA (2008b) assumptions. The rates of time preference for utility are chosen so as to obtain some pre-specified levels of interest rate at steady state (Manne et al., 1995). The elasticity of substitution σ between non-energy and energy inputs is set [13] to .5 in every region. The value share α of capital in the capital-labor input bundle is set to .28. The value share of electricity β in the energy bundle is set to .30. The scaling factor a_t and b_t are calibrated along a benchmark trajectory derived from institutional projections and assumed to result from cost minimization in the final sector. In particular, the gross regional products stem from IMF (2008) and IEA (2008b), the energy consumptions and prices are taken from IEA (2008b) reference scenario.
The decay rate of vintages in the the final sector is 5% per year. The maximum annual expansion and contraction rates are set to 10% for electric and

[11]No interregional coal trade is taken into account, since every region is assumed to own sufficient reserves.

[12]Because of the absence of distinction between capital and consumption goods, the perfect mobility of the composite goods is equivalent to the perfect mobility of capital. Therefore, at equilibrium, all regional interest rates are equal.

[13]This remains in line with the elasticities of substitution of .4 to .5 used by Richels et al. (2007) in MERGE.

Technology	Non-Fuel Cost[a] ($/Mwh)		Heating Rate (Gj/Mwh)		Emission Rate (TCO_2/MWh)	
	2005	2050	2005	2050	2005	2050
hydro	36- 40	40	-	-	0	0
remaining oil	20	20	9	-	0.62	-
remaining nuclear	45-50	50	-	-	0	-
new nuclear	80-90	90	-	-	0	0
remaining gas	5.4-6	6	6.6-11.1	-	0.38-0.63	-
new gas	27-30	30	6.2-6.7	5.7	0.35-0.38	0.33
new gas CCS[b]	61-66	55	6.63-7.05	6.20	0.02	0.02
remaining coal	22-25	25	9.3-14	-	0.85-1.13	-
remaining coal CCS[b]	60-65	65	10.9-18.3	-	0.09-0.12	-
new coal	45-50	50	8.2-8.8	7.7	0.75-0.81	0.7
new coal CCS[b]	79-86	75	9-9.6	8.6	0.04	0.04
on-shore wind	70-80	80	-	-	0	0
solar[c]	300-600	60-120	-	-	0	0
biomass	92-102	85	-	-	0	0

Sources: IEA (2008a,b); EIA (2007).

"-" separates the lowest and highest regional values.

[a] Non-fuel costs include investment and operating costs but exclude fuel costs.

[b] CCS technologies are available from 2015 on in the model.

[c] Solar technology also embodies off-shore wind, geothermal and ocean energy.

Table 2: Non-fuel cost, heating and emission rates of electric technologies

non electric technologies. The exceptions are nuclear, with an annual growth rate limited to 2.5%, and non-electric oil and gas technologies whose annual expansion and contraction rates are limited to 5% in the OECD regions. In addition, prior to 2030, the uses of fossil-fuel-fired technologies are capped. During the first periods, these caps are close to the level of technology use in IEA (2008b) reference scenario. This reference scenario is also used to define upper bounds for oil and gas extraction (in addition to constraints expressed as maximum production-to-reserves ratios). The costs of electric and non electric energy technologies are calibrated from IEA (2008b), IEA (2007a) and IEA (2008a). Initial inter-regional cost differences are assumed to fade away throughout time[14] (due to global economic convergence). As shown by Tables 2 and 3, the cost of certain new technologies is assumed to decrease throughout time.
Using IEA (2008a), a technical progress improving the heating rate of the various energy technologies has been introduced. The base-year regional heating rates have been computed from the observed fuel consumptions and electricity production. In each region, the fossil fuel resources are split into 10 different categories, according to their production cost. The breakdown of resources is derived from IEA (2008b), EIA (2007), and WoodMackenzie (2007). In dollars per barrel, the cost of oil production ranges from 10 (Middle East) to 100 (Arctic regions). In dollars per barrel of oil equivalent, the cost of gas production ranges from 3 to 40. According to the region considered, the production cost of coal in dollars per barrel of oil equivalent varies from 10 to 20. The production cost of synthetic fuel is 80 $ per barrel. Emissions rates, that account for the CO_2 emissions, are estimated on the basis of IEA (2008b) projections.

3.3 Computational issues

The model is solved as a non-linear program[15] using GAMS and the CONOPT3 solver. Nevertheless, as the model is not integrable, there is no means to derive analytically a maximization problem whose primal and dual solutions would yield the consumptions, activity levels and prices of the competitive

[14]Except in the case of solar technologies since the cost of solar photovoltaic energy depends on solar irradiation intensity.

[15]This model could also be solved as a Mixed Complementary Problem, including the first-order conditions of each agent's maximization problem, the absence of excess demand and the satisfaction of budgets constraints. However, this formulation would complicate the maintenance of the model, since lagrangian's derivatives are susceptible to change when a constraint is modified.

Technology	Non-Fuel Cost[a] (\$/Gj)		Emission Rate (TCO_2/Gj)
	2005	2050	
Oil for direct use	0	0	0.07
Gas for direct use	5	5	0.06
Coal for direct use	1	1	0.09
Coal for direct use CCS[b]	4.5	4.5	.005
Bio-fuels	12	12	0
Synthetic fuels[c]	18.3	18.3	0.15
Backstops[d]	40	25	0

Sources: IEA (2008a,b, 2007a); WoodMackenzie (2007).

[a] Non-fuel costs include investment and operating costs but exclude fuel costs.

[b] Coal for direct use CCS is available from 2015 on in the model.

[c] Synthetic fuels include coal-to-liquid and non-conventional oil.

[d] The backstop technologies include second-generation bio-fuels and hydrogen produced from wind and solar energy.

Table 3: Non-fuel cost and emission rates of non-electric technologies

general equilibrium. However, as in (Manne and Olsen, 1996), we assume that there exist some regional weights such that the maximization of the sum of weighted regional utilities under technological constraints and the absence of excess demand gives the competitive-general-equilibrium consumptions, activity levels and prices[16]. The appropriate regional weights are determined iteratively using the method described by Rutherford (1998).
Another important computational aspect is that albeit the model is in infinite time the use of purely numerical solution methods requires a finite-time horizon approximation. Because of the inter-temporal structure of the model, the approximation of an infinite-time model by a finite-time model can lead to undesired effects at the end of the horizon which, in turn, influence earlier periods of the model. To take this into account, as suggested by Manne (1970), we apply a multiplier for the last-period utility and we introduce a constraint for the investment in the last period so as to mimic the steady state [17].

[16]For more insight about Negishi weights, see Ginsburgh and Keyzer (2002).
[17]See for instance Lau et al. (2002) for an in-depth presentation of this method.

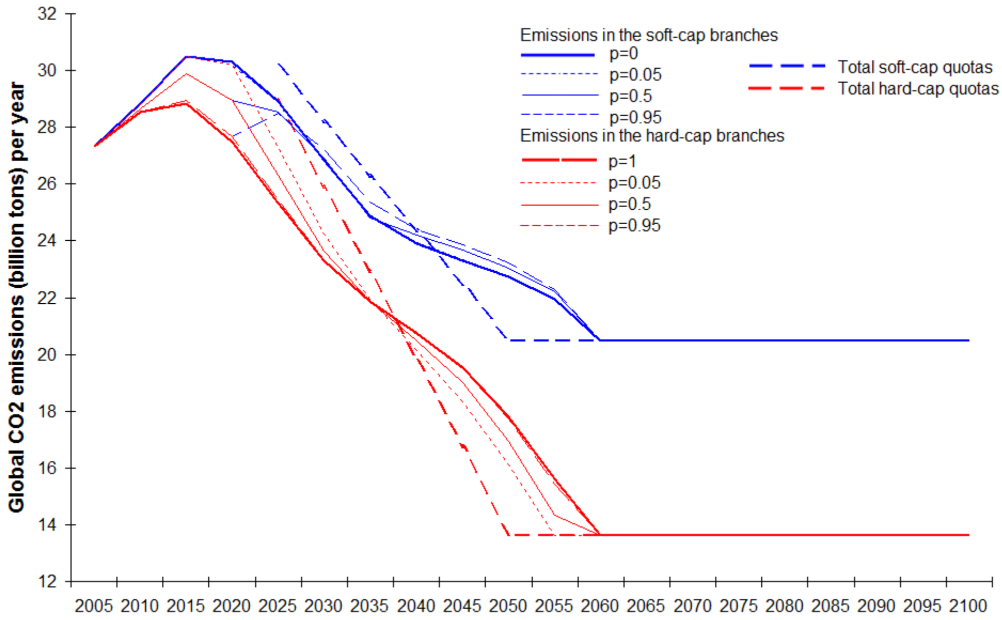

Figure 2: World CO_2 emissions

Figure 3: European Union CO_2 price

4 Analysis and discussion of results

The general equilibrium is computed for various stochastic scenarios, characterized by the probability, denoted as p, that the hard-cap target is enforced in 2020. For the sake of clarity, we consider in most figures the following five scenarios: a deterministic hard cap ($p = 1$), a deterministic soft cap ($p = 0$), equiprobable hard and soft caps ($p = 0.5$), a low-probability hard cap ($p = 0.05$), a low-probability soft cap ($p = 0.95$).

Subsection 4.1 gives a brief overview of CO_2 prices and emissions trajectories. A simple analytical approach is proposed in subsection 4.2 in order to explain the Hotelling rule and risk premia observed in the model. Furthermore, additional comments on CO_2 and energy prices are made. The impact of uncertainty on technological trajectories is discussed in subsection 4.3.

4.1 Preliminary comments on CO_2 prices and emissions trajectories

Figure 2 shows that, in all scenarios, the stock of banked permits is maximum in 2035 in all soft-cap branches and in 2040 in all hard-cap branches, as cheap abatement options (for instance the replacement of old coal-fired plants) are exploited until these dates. During the following periods, the previously-banked permits serve to relax the emissions caps in order to avoid expensive abatement costs such as those incurred in the non-electric energy sector.

The CO_2 price trajectories in the European Union (corresponding to the world price after 2020) are given by Figure 3 for various stochastic scenarios, those in all OECD regions are supplied for the deterministic and the $p = 0.5$ scenarios in Table 4. The 2020 CO_2 prices in the hard-cap and soft-cap deterministic scenarios - equal to \$64 per ton for the hard cap and between \$28 and \$42 per ton for the soft cap - are in line with those obtained by the EMF-22 models[18](Clarke et al., 2009). In general, until 2020, the CO_2 prices yielded by stochastic scenarios are bounded by both deterministic prices. Between periods 2025 and 2055, as one would expect, the CO_2 price is higher in hard-cap than in soft-cap branches. In addition, as could also be expected,

[18]More specifically, we here refer to the EMF-22 scenarios with 450 and 550 ppm targets, concentration overshooting and delayed participation of non industrialized countries to emissions reduction. Prices obtained in the deterministic scenarios in 2030 (\$47 for the soft cap and \$105 for the hard cap) are significantly lower than those proposed by IEA (2008b) at this date for equivalent targets (\$90 for 550 ppm and \$180 for 450 ppm), as, unlike IEA (2008b), we have assumed that all non-OECD regions rejoin the cap-and-trade system for emissions permits, that this cap-and-trade system covers all the energy-related CO_2 emissions, and that no emissions reduction is required after 2050.

scenario	region	regional prices			world price							
		2010	2015	2020	2025	2030	2035	2040	2045	2050	2055	2060
deterministic	European Union	40	33	42								
soft cap	North America	25	32	28	37	47	60	76	96	122	155	299
(p=0)	Pacific OECD	49	37	35								
deterministic	European Union	39	49	64								
hard cap	North America	39	49	64	82	105	135	172	217	276	350	246
(p=1)	Pacific OECD	39	49	64								
equiprobable	European Union	48	35	45	29[a]	38[a]	48[a]	61[a]	77[a]	98[a]	124[a]	334[a]
(p=0.5)	North America	27	35	45								
	Pacific OECD	47	35	45	86[b]	111[b]	142[b]	181[b]	228[b]	290[b]	368[b]	237[b]

[a] Price in the soft-cap branch.

[b] Price in the hard-cap branch.

Table 4: Regional pre-2020 CO_2 prices and world post-2020 CO_2 price (in dollars per ton) in the deterministic and $p = 0.5$ scenarios

prices are higher (lower) in the hard-cap (soft-cap) branches of the stochastic scenarios than in the hard-cap (soft-cap) deterministic scenario. After 2055, in the soft-cap branches, the price sharply increases (with a price peak in 2060) and then slowly decreases before stabilizing, while in the hard-cap branches the price decreases and then stabilizes more rapidly.

4.2 Hotelling rule, risk premia and emission-permits markets convergence

At the general equilibrium of the model, the representative household of each region implicitly considers every possible action (such as the banking of emissions permits, capital investment, or the use of exhaustible natural resources like oil) as a marginal investment decision. Since uncertain long-run emission caps are susceptible to generate uncertainty about economic growth, risk premia may have to be considered by households when discounting revenues expected from these actions. To get further insight about this issue, let us note $C_{i,t}$ the optimal consumption in region i in every period t (observed at the general equilibrium of the model) and x_t the random cash flow (expressed in numeraire) generated in every period t by a given marginal project. This marginal project should be undertaken if it increases the total discounted utility of region i, i.e. if we have:

$$\sum_{t=0}^{T} \beta_{i,t} L_{i,t} E(\log((C_{i,t} + x_t)/L_{i,t})) \geq \sum_{t=0}^{T} \beta_{i,t} L_{i,t} E(\log(C_{i,t}/L_{i,t})) \geq 0 \qquad (1)$$

		2010	2015	2020	2025	2030	2035	2040
Interest rate[a]	soft cap				5.095	5.182	5.183	5.007
			4.875	5.220				
	hard cap				5.096	5.148	5.160	4.989
Consumption growth rate[a]								
European Union	soft cap				1.889	1.922	1.870	2.172
		2.861	1.886	2.064				
	hard cap				1.891	1.889	1.848	2.154
North America	soft cap				2.099	2.132	2.080	2.172
		2.763	1.991	2.274				
	hard cap				2.101	2.099	2.058	2.154
China	soft cap				6.303	5.393	4.394	3.222
		14.797	8.074	7.430				
	hard cap				6.305	5.358	4.372	3.204

[a] In percent, averaged on an annual basis, and calculated with respect to the previous 5-years period in the model.

Table 5: World interest rate and regional consumption growth rates in the $p = 0.5$ scenario

By using a first-order Taylor expansion of the left-hand side of (1), the project is profitable when :

$$\sum_{t=0}^{T} \beta_{i,t} L_{i,t} E(\frac{x_t}{C_{i,t}}) \geq 0 \tag{2}$$

(2) can be rewritten as follows :

$$\sum_{t=0}^{T} (\beta_{i,t} E(\frac{L_{i,t}}{C_{i,t}}))(E(x_t) + cov(x_t, \frac{1}{C_{i,t} E(\frac{1}{C_{i,t}})})) \geq 0 \tag{3}$$

According to (3), the expected cash flow $E(x_t)$, adjusted with the risk premium $-cov(x_t, \frac{1}{C_{i,t}E(\frac{1}{C_{i,t}})})$, is discounted at the social discount factor $\beta_{i,t}E(\frac{L_{i,t}}{C_{i,t}})$. Let us note that whatever the stochastic scenario considered in the model, prices (and therefore cash flows) are certain until 2020 (period 3 of the model). Consequently, let us first consider either a deterministic scenario, or a stochastic scenario with $t \leq 2020$, and let $g_{i,t}$ be the growth rate of per-capita consumption in region i from period $t-1$ to period t, with $\frac{C_{i,t}/L_{i,t}}{C_{i,t-1}/L_{i,t-1}} = e^{g_{i,t}}$. Since there is no uncertainty, the social discount factor from period $t-1$ to period t is then:

$$\frac{\beta_{i,t-1}(\frac{L_{i,t-1}}{C_{i,t-1}})}{\beta_{i,t}(\frac{L_{i,t}}{C_{i,t}})} = e^{\rho_{i,t}+g_{i,t}} \tag{4}$$

In addition, the risk premium is equal to 0. (4) is a standard result[19]: $\rho_{i,t}+g_{i,t}$ is the social discount rate of region i from $t-1$ to t. This social discount rate, which is the rate of interest of the economy, is also equal to the marginal productivity of capital (Ramsey's rule). This equality is ensured by considering a marginal project consisting in consuming one less dollar in $t-1$ to invest this dollar in capital during one period. Furthermore, as long as banking[20] is profitable, one should always consider the marginal project consisting in banking one more ton of CO_2 in $t-1$ in order to release one additional ton in t. By applying (3) to this marginal project, and by using (4), banking in $t-1$ should stop when:

$$Pco_{2,t-1} = Pco_{2,t}e^{-\rho_{i,t}-g_{i,t}} \tag{5}$$

(5) is the Hotelling (1931) rule, which is for instance perfectly followed by the CO_2 price in the European Union from 2010 to 2055 - after this date, banking is no longer possible - in the deterministic hard-cap scenario (as shown by Figure 3 and Table 4). In the deterministic soft-cap scenario, the world CO_2 price follows the Hotelling rule from 2025 to 2055 since there is banking (and use of banked permits) during the whole period at the world level, as shown by Figure 2.

Let us now focus on the stochastic scenarios where the setting of caps at the end of the 2020 period represents an external random shock susceptible to impact the consumption in the various regions. However as shown by table 5, this shock has a very small effect on consumption. For region i, the risk premium to be applied to the CO_2 price expected in 2025 is equal to $-cov(Pco_{2,2025}, \frac{1}{C_{i,2025}E(\frac{1}{C_{i,2025}})})$. By applying (3), banking should stop in 2020 when we have:

$$Pco_{2,2020} = \frac{\beta_{i,2025}E(\frac{L_{i,2025}}{C_{i,2025}})}{\beta_{i,2020}(\frac{L_{i,2020}}{C_{i,2020}})}(E(Pco_{2,2025}) + cov(Pco_{2,2025}, \frac{1}{C_{i,2025}E(\frac{1}{C_{i,2025}})})) \tag{6}$$

[19]Note that the logarithmic utility function considered here has a relative risk aversion equal to 1.

[20]Since there is no inter-temporal emissions "borrowing" allowed in the model, the CO_2 price can decrease or increase at a rate lower than the economy's interest rate during certain periods.

For all regions and stochastic scenarios, this risk premium is positive[21] but extremely small (always less than 0.2 cents per ton of CO_2 for the European Union as indicated in table 6). This is an illustration of the fable of the elephant and the rabbit popularized by Hogan and Manne (1977), i.e. the regional economies are so important that the emissions caps have little effect on consumption[22]. As a result, the expected value of the CO_2 price almost follows a Hotelling law between 2020 and 2025. For instance, if we consider the $p = 0.5$ scenario, from Table 5 let us approximate the effective social discount factor from 2020 to 2025 as follows:

$$\frac{\beta_{i,2025}}{\beta_{i,2020}} \frac{E(\frac{L_{i,2025}}{C_{i,2025}})}{(\frac{L_{i,2020}}{C_{i,2020}})} \simeq (1.05095)^5$$

As expected, the prices given by Table 4 satisfy (6) since we have:

$$45 \simeq \frac{(0.5 \times 29) + (0.5 \times 86)}{(1.05095)^5}$$

Figure 4 shows that emissions permits are banked until 2020 in the European Union when $p \geq 0.4$. Consistently, the expected CO_2 price increases at the social discount rate (economy's rate of interest) between 2020 and 2025. In North America, emissions permits are banked before 2020 even in the deterministic soft-cap scenario ($p = 0$) because of relatively-high pre-2020 emissions quotas and cheap abatement opportunities. In the Pacific OECD region, emissions permits are banked until 2020 when $p \geq 0.2$. Therefore, when $p \geq 0.4$ all the OECD regions bank emissions permits prior to 2025. As illustrated by Table 4, for $p = 0.5$, we then have a convergence of pre-2020 CO_2 prices in all OECD regions (although the inter-regional trade of emissions permits does not yet exist). This convergence of emissions-permits markets is backwardly induced by the Hotelling rule (from a unique world price in 2025). Figure 3 shows that the expected value of CO_2 price follows this Hotelling rule until 2055 in all scenarios (and along each branch of every scenario).

[21] Setting the hard-cap in 2020 leads to more energy conservation in 2025. Since energy and capital are complementary inputs, this (slightly) reduces the marginal productivity of capital (with an interest rate of 5.148% instead of 5.182% in Table 5). Households therefore invest less and consume more in 2025 (CO_2 prices and consumption are positively correlated). However, they consume less in the following periods as shown by Table 5.

[22] This statement has nevertheless to be qualified as both scenarios compared here require a serious curb in emissions. A comparison between a business-as-usual and the hard-cap scenario would probably yield a much bigger impact on consumption.

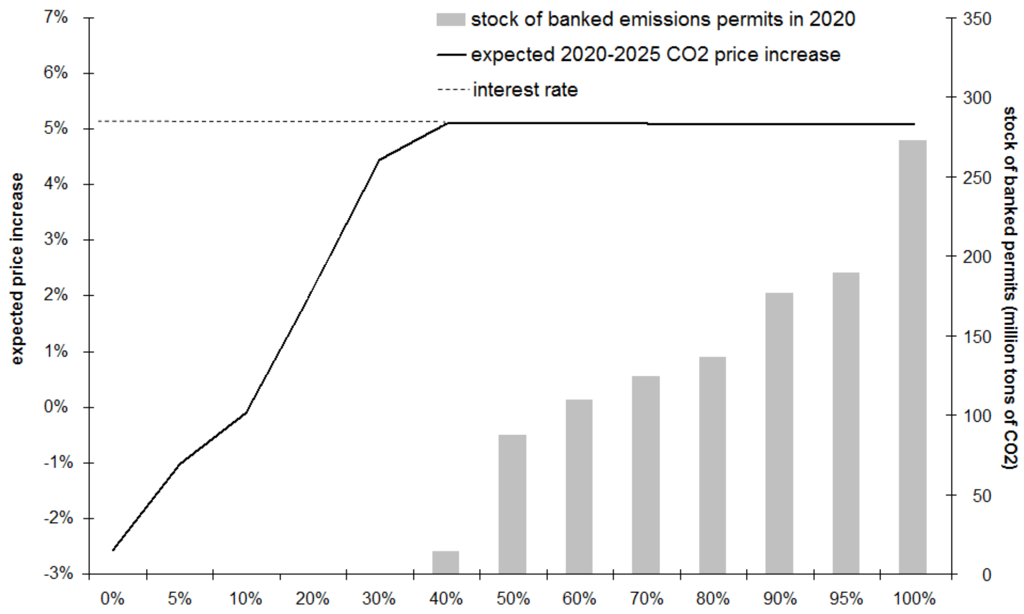

Figure 4: Expected 2020-2025 CO_2 price increase and stock of banked emissions permits in 2020 in the European Union, with respect to the hard-cap probability

For oil and gas, the observation[23] of the Hotelling rule is hindered by constraints imposed on the production of these natural resources (especially maximum production-to-reserve ratios) that limit inter-temporal arbitrage in extraction decisions. Trajectories of price and consumption for oil, gas, coal, and power in various scenarios are provided by A.

Probability of the hard cap	5%	20%	50%	80%	95%
CO_2 risk premium (cents per ton)	0.093	0.186	0.148	0.049	0.039

Table 6: Risk premium on CO_2 price in 2025 for the European Union

[23]Note that, for oil and gas, the Hotelling rule corresponds to a reserve-value increase at the economy's interest rate (if the reserve considered is exhausted at the end of the model's horizon).

4.3 Impact of uncertainty on technological trajectories

Table 7 gives the obtained energy mix in periods 2020 and 2050, for the deterministic and equiprobable ($p = 0.5$) scenarios, at the world scale. Tables 8, 9 and 10 are specific to the European Union, North America and China respectively.

Let us briefly comment on the technological trajectories obtained in deterministic scenarios. Until 2020, reduction in emissions is achieved by decreasing the carbon intensity in both electric and non-electric sectors. In the electric sector, the replacement of coal technologies by nuclear, gas and biomass generation is more pronounced in the hard-cap than in the soft-cap scenario. As a result, in 2020, only 20% of electricity is produced with coal without CCS in the hard-cap scenario, whereas 31% of electricity is produced with coal without CCS in the soft-cap scenario. The non-electric energy sector substitutes gas for oil. As a consequence, in 2020, oil represents less than 50% of non-electric energy production in both scenarios, while it represented 57% in 2005. After 2020, the carbon intensity keeps on decreasing in both energy sectors. In an expanding electric sector, nuclear, coal and gas CCS, wind, solar and biomass replace without-CCS coal and gas generation (which is used for less than 3% of electricity production in 2050). Due to a lower gas price (see Figure 9), gas with CCS is more developed in the hard-cap than in the soft-cap scenario (at the detriment of coal CCS). In the non-electric sector, gas and backstop technologies (hydrogen and second-generation biofuels) substitute for oil and coal. In addition, electricity substitutes for non-electric energy as pre-2020 technological trajectories favor the expansion of new technologies after 2020 in the electric sector. This is not the case in the non-electric energy sector which undergoes the constraints on gas production and where the (expensive) backstop technologies are not competitive prior to 2020. This explains why, after 2020, electricity consumption grows faster than non-electric energy consumption. This evolution is particularly pronounced in the hard-cap scenario where, in 2050, there is more electricity consumed than in the soft-cap scenario (35.8 Tkwh instead of 34.9 Tkwh).

In the hard-cap deterministic scenario, the severity of the emissions target in the intermediate and long runs justifies early (pre-2060) and massive abatement efforts, especially through non-electric energy conservation and development of non-electric backstop technologies (see Figure 6). As a result, when banking is no longer possible, in 2060, the deployed technologies are well-adapted to the long-run emissions target, which makes possible a decrease in CO_2 price as illustrated by Figure 3.

In the soft-cap deterministic scenario, emissions targets in the intermediate and long runs do not necessitate massive pre-2060 abatement efforts, especially regarding non-electric energy conservation and backstop technologies as shown by Figure 6. Therefore, when banking is no longer possible, in 2060, a reduction in non-electric energy consumption is necessary (see Figure 6). This results in a high marginal abatement cost explaining the important upward disruption of CO_2 price in 2060 (with a price peak at almost \$300 per ton in Table 4).

The uncertainty about the long-run emissions targets has a significant impact on the technological trajectories of the energy firms. Especially, the more probable the hard cap, the greater the accumulated stock of banked emissions permits in period 2020, as Figure 4 shows for the European Union. As one could expect, this higher accumulation of banked permits results from a higher expansion (contraction) of less-emitting (more-emitting) technologies prior to 2020. For instance, Figure 5 provides an illustration of this effect for highly-emitting coal-fired power generation (without CCS) which is less used when the hard-cap probability is high.

Let us now turn to the post-2020 periods for which the model yields non-trivial results. Let us first consider the hard-cap branches of stochastic scenarios. Since the setting of the hard cap was initially considered as a mere possibility, the stock of banked permits available in 2025 is lower than that in the deterministic hard-cap scenario. This results in a 2025 CO_2 price higher than in the hard-cap deterministic scenario. However, to compensate for this situation, until 2055 clean technologies expand faster in the stochastic scenarios than in the deterministic one. More specifically, Figure 6 shows that there are more non-electric energy conservation and a grater deployment of non-electric backstop technologies. As a consequence, in 2060, when banking is no longer possible, the CO_2 price is lower in the hard-cap branches of stochastic scenarios than in the deterministic hard-cap scenario. Consistently, this price increases with the probability of the hard-cap target.

Let us now consider the soft-cap branches of stochastic scenarios. In each region, when the soft cap is set at the end of 2020, a stock of banked emissions permits has been previously accumulated as a precaution against a possible hard-cap (at least, if the hard-cap probability was sufficiently high, for instance as Figure 4 shows for the European Union). Using this stock of banked permits results in differing the post-2020 deployment of low-emitting technologies (along with a lower CO_2 price until 2055 in soft-cap branches of stochastic scenarios). Especially, Figure 6 shows that there is more non-electric energy consumed in soft-cap branches of stochastic scenarios than in the deterministic soft-cap scenario. Consequently, when permits are banked in 2020, this results in a 2060 CO_2 price peak higher than that observed

		Deterministic				Equiprobable		
		SC		HC			SC	HC
	2005	2020	2050	2020	2050	2020	2050	2050
Electricity Production								
hydro	16 %	19 %	17 %	20 %	17 %	19 %	17 %	17 %
remaining nuclear	15 %	6 %	0 %	6 %	0 %	6 %	0 %	0 %
new nuclear	0 %	18 %	35 %	20 %	35 %	20 %	35 %	35 %
remaining oil	6 %	1 %	0 %	1 %	0 %	1 %	0 %	0 %
remaining gas	20 %	5 %	0 %	6 %	0 %	6 %	0 %	0 %
new gas	0 %	10 %	2 %	14 %	1 %	12 %	3 %	1 %
new gas CCS	0 %	0 %	2 %	0 %	6 %	0 %	1 %	6 %
remaining coal	41 %	13 %	0 %	9 %	0 %	12 %	0 %	0 %
remaining coal CCS	0 %	0 %	0 %	2 %	0 %	1 %	0 %	0 %
new coal	0 %	18 %	1 %	11 %	0 %	15 %	1 %	0 %
new coal CCS	0 %	1 %	13 %	1 %	7 %	1 %	13 %	7 %
on-shore wind	1 %	8 %	20 %	8 %	20 %	8 %	20 %	20 %
solar	0 %	0 %	8 %	0 %	10 %	0 %	8 %	10 %
biomass	1 %	1 %	1 %	2 %	4 %	1 %	1 %	4 %
Total (Tkwh)	18.5	24.5	34.9	23.6	35.8	24.03	34.84	35.92
Non-Electric Energy Production								
bio-fuels	0 %	1 %	2 %	1 %	3 %	1 %	2 %	3 %
synthetic fuels	2 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %
coal for direct use	17 %	18 %	13 %	17 %	10%	17 %	13 %	8 %
coal for direct use CCS	0 %	1 %	6 %	2 %	7 %	1 %	6 %	7 %
non-electric backstop	0 %	0 %	3 %	0 %	13 %	0 %	3 %	16 %
oil for direct use	57 %	48 %	37 %	49 %	30 %	48 %	37 %	29 %
gas for direct use	24 %	33 %	38 %	31 %	38 %	32 %	39 %	37 %
Total (million tons of oil equivalent)	5400	7247	8550	7089	7880	7186	8644	7835

SC (HC) means in the soft-cap (hard-cap) branch.

Table 7: Technologies used at the world level in the deterministic and equiprobable scenarios

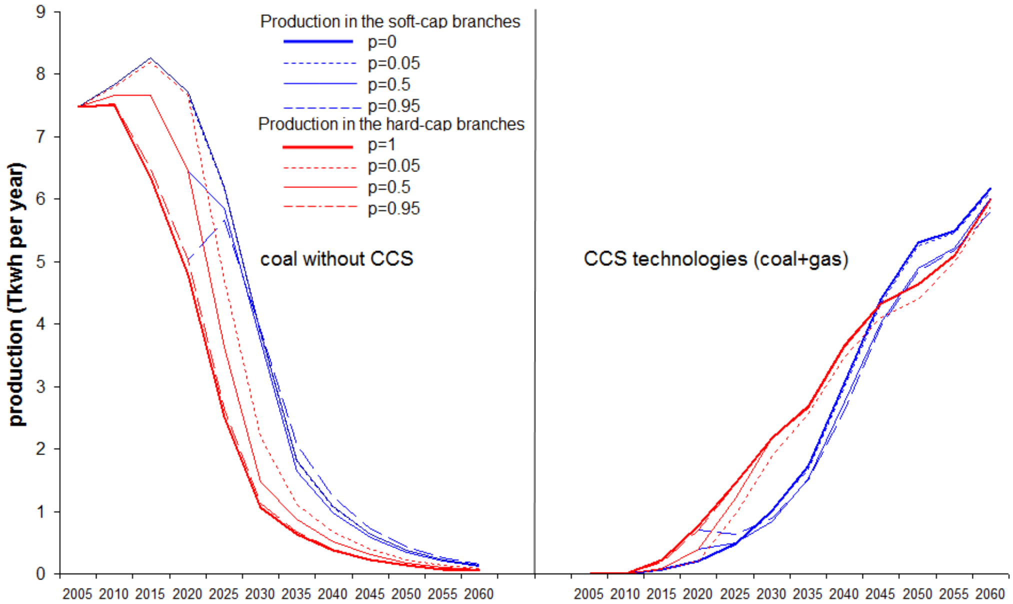

Figure 5: Electricity production from (remaining and new) coal without CCS and from (coal and gas) CCS technologies

in the deterministic soft-cap scenario. This price peak increases with the probability of the hard-cap target.

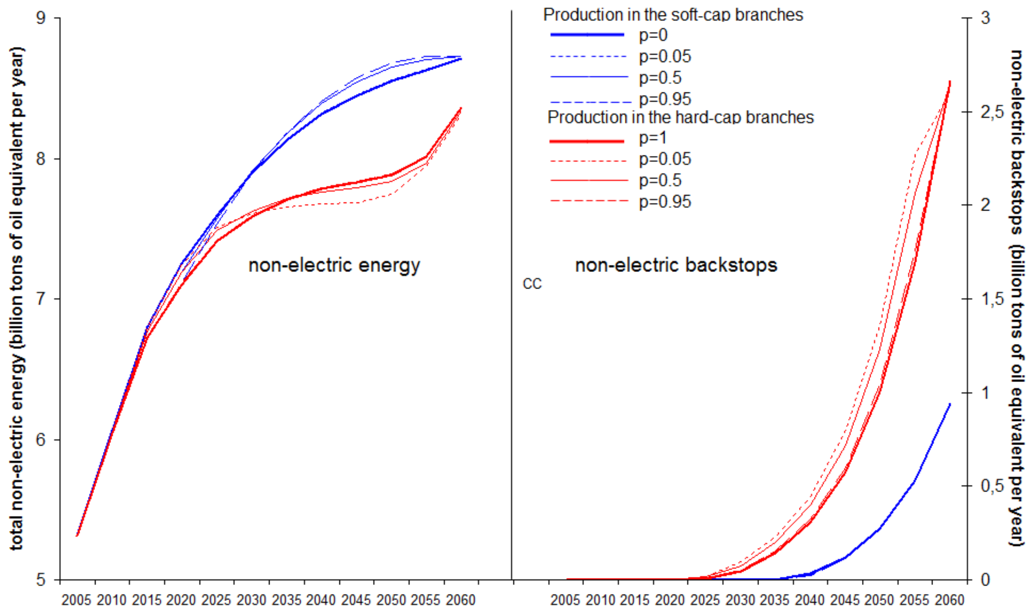

Figure 6: Total non-electric energy production and non-electric production from the backstop technologies

5 Conclusion

Our simulations show that the uncertainty about long-run emissions targets significantly affects the energy transition at both global and regional scales, as well as CO_2 and energy prices. A higher probability for the setting of the hard-cap target at the end of period 2020 leads to more abatement, and therefore more banking, until 2020. In brief, in the electric sector, prior to 2020 coal without CCS declines faster, for the benefit of nuclear and gas technologies. As a higher hard-cap probability leads to a higher stock of banked permits at the start of period 2025, fewer emissions reductions are required in the subsequent periods. More specifically, in all branches, there is less energy conservation in the non-electric sector and, in hard-cap branches, a lower penetration of non-electric backstop technologies. As a result, the technologies deployed in 2060 (when banking is no longer possible) are not fully adjusted to the long-run emissions stabilization targets. Thus, in soft-cap branches of stochastic scenarios, the initial anticipation of a probable hard-cap target results in a 2060 price peak higher than that obtained in the deterministic soft-cap scenario. In addition, since pre-2020 CO_2 prices are sensitive to the hard-cap probability, they reveal information about agents' belief on this probability.

Moreover, a pre-2020 banking of emissions permits occurs for a hard-cap probability greater or equal to 0.4 (0.2) in the European Union (Pacific OECD region), while in North America banking occurs in all scenarios. In every region where such a banking takes place, the regional CO_2 price follows a Hotelling rule with a risk premium between 2020 and 2025. Since the long-run emissions targets have a negligible impact on regional consumptions, this risk premium is very small.
Since a pre-2020 banking occurs in all regions when the hard-cap probability is greater than 0.4, the common belief in a single world CO_2 price from 2025 on then leads to a convergence of CO_2 prices in OECD regions prior to 2020, even if inter-regional trade of emissions permits does not yet exist. For oil and gas, the observation of the Hotelling rule is hindered by constraints imposed on their production (that limit inter-temporal arbitrage in extraction decisions).
Our approach is of course subject to a given number of limitations. One of them relates to the information structure considered. In the model, agents' belief is not assumed to evolve trough time, as information is fully revealed in 2020. Taking into account a more progressive revelation of information on emissions targets would enrich the model and perhaps significantly influence its results.

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A Consumption and price of energy commodities

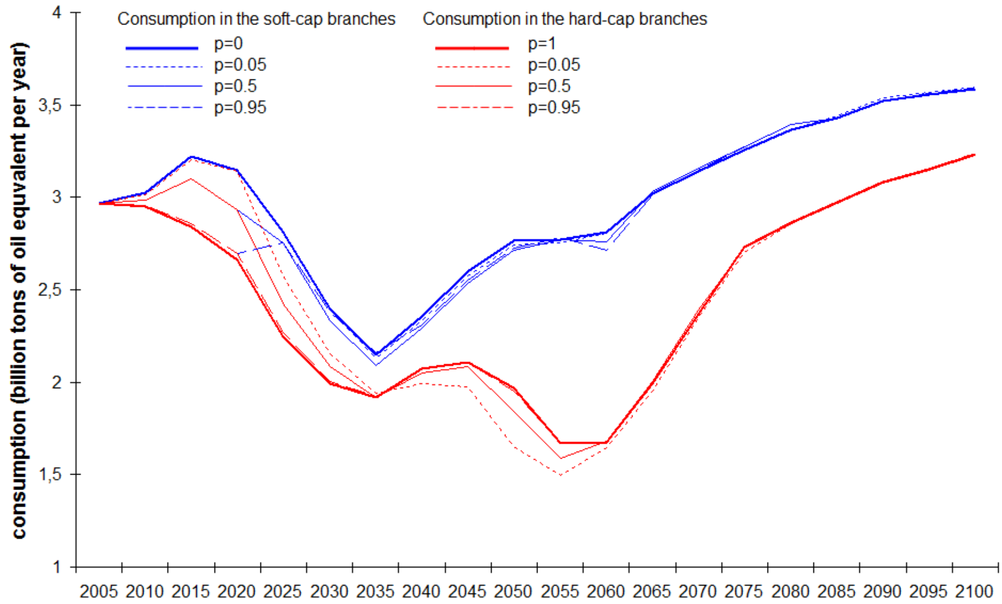

Figure 7: World coal consumption

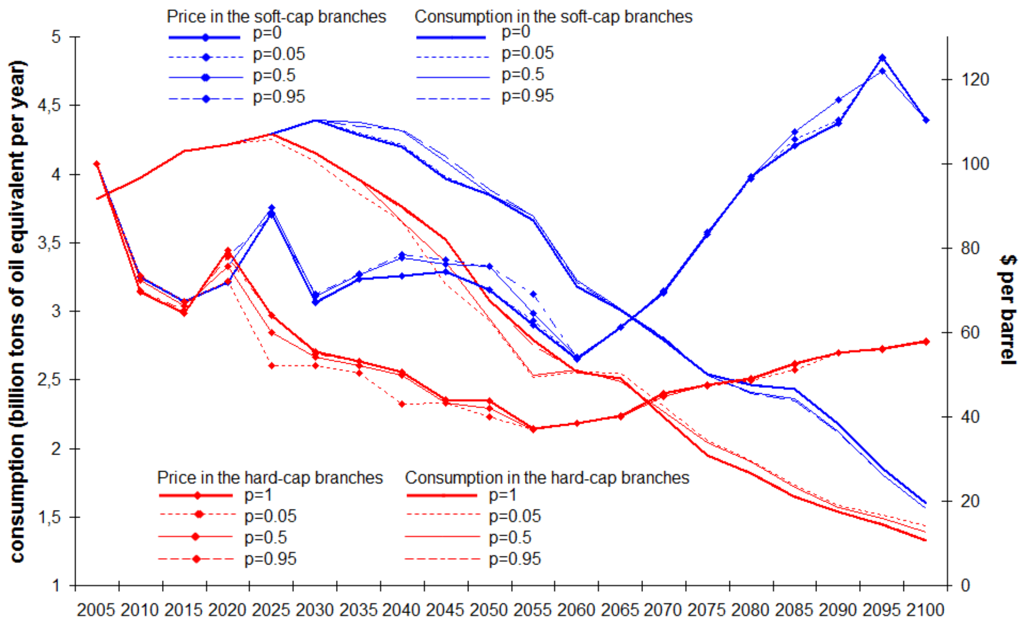

Figure 8: World oil price and consumption

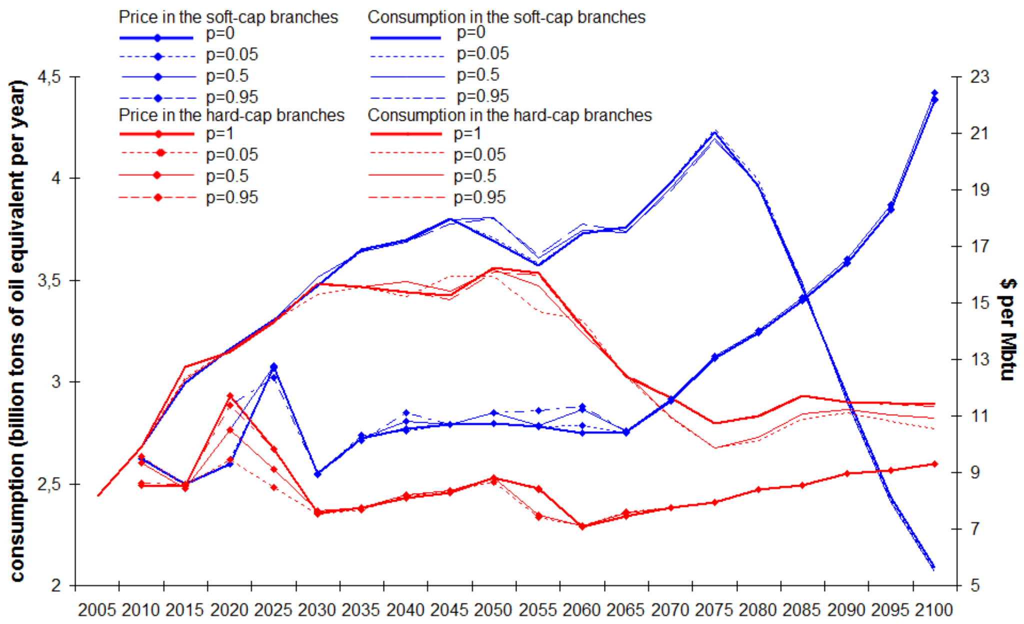

Figure 9: Gas price in the European Union and world gas consumption

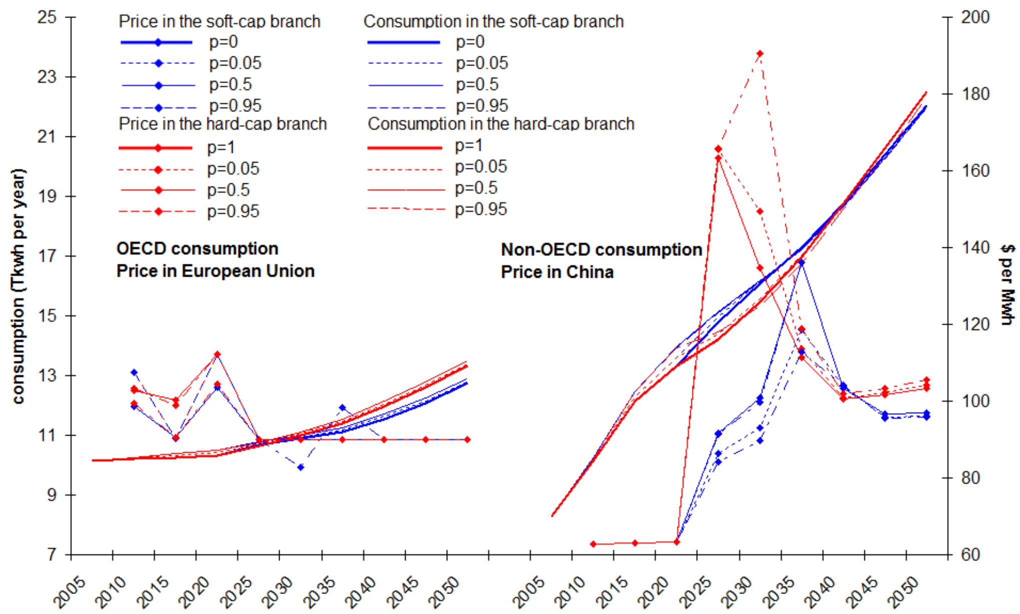

Figure 10: Total electric consumption in OECD and non-OECD regions and power prices in the European Union and China

B Technologies used in the deterministic and equiprobable scenarios

		Deterministic				Equiprobable		
		SC		HC			SC	HC
	2005	2020	2050	2020	2050	2020	2050	2050
Electricity Production								
hydro	9 %	12 %	12 %	12 %	11 %	12 %	12 %	11 %
remaining nuclear	30 %	15 %	0 %	15 %	0 %	15 %	0 %	0 %
new nuclear	0 %	35 %	63 %	35 %	64 %	35	63 %	64 %
remaining oil	4 %	1 %	0 %	1 %	0 %	1 %	0 %	0 %
remaining gas	20 %	10 %	0 %	10 %	0 %	10 %	0 %	0 %
new gas	0 %	8 %	1 %	7 %	0 %	8 %	1 %	0 %
new gas CCS	0 %	0 %	0 %	0 %	5 %	0 %	0 %	5 %
remaining coal	31 %	4 %	0 %	1 %	0 %	3 %	0 %	0 %
remaining coal CCS	0 %	0 %	4 %	3 %	0 %	0 %	0 %	0 %
new coal	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %
new coal CCS	0 %	0 %	0 %	0 %	0 %	0 %	4 %	0 %
on-shore wind	2 %	15 %	20 %	15 %	20 %	15 %	20 %	20 %
solar	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %
biomass	3 %	1 %	0 %	1 %	0 %	1 %	0 %	0 %
Total (Tkwh)	3.29	3.32	3.69	3.30	3.84	3.29	3.66	3.85
Non-Electric Energy Production								
bio-fuels	1 %	2 %	5 %	2 %	6 %	2 %	5 %	6 %
synthetic fuels	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %
coal for direct use	8 %	6 %	5 %	5 %	1 %	5 %	5 %	1 %
coal for direct use CCS	0 %	1 %	3 %	2 %	3 %	2 %	3 %	3 %
non-electric backstop	0 %	0 %	3 %	0 %	10 %	0 %	3 %	18 %
oil for direct use	60 %	71 %	57 %	77 %	52 %	77 %	54 %	49 %
gas for direct use	31 %	20 %	27 %	14 %	28 %	14 %	30 %	24 %
Total (million tons of oil equivalent)	946	995	894	970	828	987	903	826

SC (HC) means in the soft-cap (hard-cap) branch.

Table 8: Technologies used in the European Union for the deterministic and equiprobable scenarios

		Deterministic				Equiprobable		
		SC		HC			SC	HC
	2005	2020	2050	2020	2050	2020	2050	2050
Electricity Production								
hydro	13 %	13 %	10 %	14 %	10 %	13 %	10 %	11 %
remaining nuclear	18 %	9 %	0 %	9 %	0 %	9 %	0 %	0 %
new nuclear	0 %	30 %	65 %	31 %	65 %	30 %	65 %	64 %
remaining oil	3 %	1 %	0 %	1 %	0 %	1 %	0 %	0 %
remaining gas	19 %	7 %	0 %	6 %	0 %	7 %	0 %	0 %
new gas	0 %	10 %	1 %	12 %	0 %	8 %	1 %	0 %
new gas CCS	0 %	0 %	0 %	0 %	5 %	0 %	0 %	5 %
remaining coal	44 %	21 %	0 %	9 %	0 %	20 %	0 %	0 %
remaining coal CCS	0 %	0 %	0 %	3 %	0 %	1 %	0 %	0 %
new coal	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %
new coal CCS	0 %	0 %	4 %	1 %	0 %	0 %	4 %	0 %
on-shore wind	1 %	9 %	20 %	9 %	20 %	9 %	20 %	20 %
solar	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %
biomass	2 %	0 %	0 %	6 %	0 %	2 %	0 %	0 %
Total (Tkwh)	5.10	5.35	7.10	5.21	7.31	5.30	7.05	3.85
Non-Electric Energy Production								
bio-fuels	1 %	2 %	4 %	2 %	5 %	2 %	4 %	5 %
synthetic fuels	4 %	1 %	0 %	1 %	0 %	1 %	0 %	0 %
coal for direct use	4 %	4 %	3 %	3 %	2 %	3 %	3 %	2 %
coal for direct use CCS	0 %	0 %	1 %	1 %	1 %	1 %	1 %	1 %
non-electric backstop	0 %	0 %	4 %	0 %	16 %	0 %	4 %	16 %
oil for direct use	63 %	52 %	21 %	49 %	12 %	48 %	22 %	12 %
gas for direct use	28 %	41 %	66 %	43 %	64 %	45 %	66 %	64 %
Total (million tons of oil equivalent)	1452	1576	1679	1517	1548	1551	1697	1542

SC (HC) means in the soft-cap (hard-cap) branch.

Table 9: Technologies used in North America for the deterministic and equiprobable scenarios

		Deterministic				Equiprobable		
		SC		HC			SC	HC
	2005	2020	2050	2020	2050	2020	2050	2050
Electricity Production								
hydro	15 %	19 %	18 %	20 %	18 %	20 %	18 %	18 %
remaining nuclear	2 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %
new nuclear	0 %	5 %	16 %	6 %	15 %	6 %	16 %	15 %
remaining oil	2 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %
remaining gas	1 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %
new gas	0 %	0 %	0 %	4 %	1 %	3 %	1 %	1 %
new gas CCS	0 %	0 %	0 %	1 %	1 %	0 %	0 %	1 %
remaining coal	80 %	20 %	0 %	20 %	0 %	19 %	0 %	0 %
remaining coal CCS	0 %	0 %	0 %	2 %	0 %	1 %	0 %	0 %
new coal	0 %	47 %	3 %	38 %	1 %	42 %	3 %	1 %
new coal CCS	0 %	2 %	27 %	2 %	17 %	2 %	27 %	17 %
on-shore wind	0 %	4 %	20 %	5 %	20 %	5 %	20 %	20 %
solar	0 %	0 %	13 %	0 %	19 %	0 %	13 %	19 %
biomass	0 %	1 %	3 %	1 %	8 %	1 %	3%	8 %
Total (Tkwh)	2.71	5.41	8.03	5.00	8.07	5.21	8.02	8.13
Non-Electric Energy Production								
bio-fuels	0 %	0 %	1 %	0 %	1 %	0 %	1 %	1 %
synthetic fuels	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %
coal for direct use	61 %	50 %	34 %	50 %	35 %	49 %	34 %	29 %
coal for direct use CCS	0 %	1 %	17 %	2 %	18 %	2 %	17 %	19 %
non-electric backstop	0 %	0 %	5 %	0 %	19 %	0 %	5 %	26 %
oil for direct use	35 %	43 %	41 %	45 %	25 %	44 %	41 %	24 %
gas for direct use	5 %	5 %	3 %	3 %	2 %	3 %	2 %	0 %
Total ((million tons of oil equivalent)	786	1522	1956	1511	1805	1518	1978	1788

SC (HC) means in the soft-cap (hard-cap) branch.

Table 10: Technologies used in China for the deterministic and equiprobable scenarios