Giannousakis, A., Baumstark, L., Kriegler, E. (2020): En route to China's mid-century climate goal: comparison of emissions intensity versus absolute targets. - Climate Policy, 20, 10, 1274-1289.

DOI: https://doi.org/10.1080/14693062.2020.1798734

En route to China's mid-century climate goal: Comparison of emissions intensity versus absolute targets

Anastasis Giannousakis[1], Lavinia Baumstark, Elmar Kriegler

Potsdam Institute for Climate Impact Research (PIK), Member of the Leibniz Association, P.O. Box 60 12 03, D-14412 Potsdam, Germany

Abstract

We compare the effectiveness of absolute vs. intensity targets in preparing China for progressive climate action under the Paris Agreement. The Agreement requires countries to submit nationally determined contributions (NDCs) every five years and in addition calls for submission long-term low greenhouse gas emission development strategies up to 2050. This study conducts a multi-criteria comparison of the adoption of an absolute vs. an intensity interim target in 2030, followed by an absolute target in 2050, for China. In doing so, we explicitly consider economic growth uncertainty as it is the main motivation behind China's and other developing countries' adoption of intensity targets for 2030. We perform the target comparison analytically, as well as using the stochastic version of a large-scale integrated assessment model. The stochastic model is based on expected utility theory and explicitly accounts for uncertainty.

Key policy insights:

- If China wants to hedge against higher than expected economic growth, it is reasonable to adopt an intensity target. However, in case of lower economic growth, this choice becomes problematic as policy costs will rise while the economy grows slow
- The difference in costs due to the 2030 target choice can be of the same order of magnitude as the overall climate policy costs themselves
- An interim absolute target performs better than an equivalent intensity target, under multiple criteria

Keywords: intensity target, economic growth uncertainty, China NDC

1. Introduction

With the contribution of China and India, more than one third of global greenhouse gas (GHG) emissions are currently controlled by targets indexed to future gross domestic product (GDP). This means that, instead of aiming to limit the amount of annual emissions by a given year by an absolute number, China and India are aiming for a reduction in the emission intensity of their economy, i.e. CO_2 emissions per unit of GDP by 2030, as part of nationally determined contributions (NDCs) under the Paris Agreement. Chinas NDC also contains a target to peak GHG emissions before 2030, but this does not describe an absolute reduction compared to a reference

[1]Corresponding author, giannou@pik-potsdam.de

year, and could thus lead to different emission pathways depending on how the economy grows. In addition, Chinas NDC includes two secondary absolute targets for forestry and non-fossil fuel use. In climate policy design, emission intensity targets are used as alternatives to emission quantity targets are used as alternatives to absolute (or quantity) emission targets in order to hedge against economic growth uncertainty, which is particularly large in rapidly developing countries like China and India. At the same time, research (IPCC (2018),Luderer et al. (2018)) shows that the next decade of mitigation action up to 2030 will determine the chances of staying below the warming limits set out in the Paris Agreement. Thus, it is important to explore the implications of the choice of target type in 2030 in preparing the economy and energy system for mid-century (2050) targets, toward the Paris Agreement ambition of holding global mean warming "well below" 2 °C. We do so here for the world's largest emitter, China, applying a state-of-the-art stochastic energy-economy model that explicitly accounts for economic growth uncertainty.

China is currently implementing its first emissions trading system, the first one in history formulated with an emissions intensity cap instead of an absolute cap (Goulder et al., 2017). At the same time, its economy is undergoing structural changes (Wang et al., 2019c; Mi et al., 2017a), thereby reducing its GHG emissions (Guan et al., 2018; Zheng et al., 2019). It is also taking measures to reduce air pollution (Li et al., 2019), and investing heavily in renewables. Yet, these actions alone are not sufficient to rapidly decarbonize the Chinese economy, simply due to the country's sheer size and its dependence on coal, reflecting continued dependence on coal in several emerging economies (Edenhofer et al., 2018; Wang et al., 2019a). While global coal demand dropped in 2015 for the first time this century, the International Energy Agency forecasts that demand will increase again and will not return to 2014 levels until 2021 (IEA/OECD, 2018). Since China currently accounts for 50% of global coal demand—and almost half of coal production—global coal demand in the next decade will depend greatly on the trajectory of China, itself highly uncertain like the future economic growth of China.

Economic growth is an important indicator to which projected CO_2 emissions are sensitive (Marangoni et al., 2017; Mouratiadou et al., 2016). Economic growth is in turn also affected by CO_2 emissions (Mi et al., 2017b). In the presence of a target indexed by economic growth this effect is further strengthened. It is expected to intensify even more with growing regional rivalry in trade (Neuenkirch and Neumeier, 2015). Motivated by the above, we address the following research question. Under growth uncertainty, does an intensity or a quantity target for 2030 perform better in preparing the Chinese economy for a mid-century target and ultimately a 2 °C pathway? Given that a growth-indexed (intensity) target makes the amount of emissions at the target heavily dependent on economic output, we conduct the analysis to explicitly account for growth uncertainty by deploying a state-of-the-art stochastic integrated assessment model.

The remainder of the paper is structured as follows. Section 2 gives a short overview of how the two target types and target sequencing emerged in the Paris Agreement process, section 3 provides a literature review on the comparison of intensity versus quantity targets, and section 4 describes the scenarios and methods we use for the present comparison. Section 5 begins the target comparison with an analytical method and shows results of deterministic and stand-alone numerical scenarios, which motivate the stochastic analysis on sequential 2030 and 2050 targets under growth uncertainty, on which the final target comparison is based. Section 6 concludes and discusses policy implications. In the Appendix a description of the models and additional methods used in the study is provided, as well as a literature review on uncertainty considerations in energy-economy models of climate change.

2. NDCs and target sequencing after Paris

Under the Paris Agreement, participating countries have announced their NDCs, with most pledging emission reductions up to 2030. Apart from the variation in the level of ambition between countries, there is also a distinction in the chosen types of emission reduction targets. The Paris Agreement calls on developed countries to adopt "economy-wide absolute emission reduction targets", aiming to reduce domestic emissions by a fixed amount compared to a base-year, e.g. 2005 (UNFCCC, 2015). Based on this, many developing countries, including China and India, have chosen to adopt an emission intensity target. This is because an intensity target T hedges against not achieving the desired reduction in absolute emissions E because of unexpected accelerated growth in the economy, as the allowed emissions would increase in lockstep with economic growth Y:

$$T = \frac{E}{Y} \tag{1}$$

An intensity target also helps to avoid "hot-air", which might occur if the absolute target no longer imposed a constraint, because of slow economic growth resulting in lower than expected emissions. With an intensity target, however, the amount of allowed emissions decreases with slower growth (Equation 1). The possibility of hot-air can harm a country's credibility towards other participants of an agreement. Finally, there is also a political stance reflected in the choice of a target indexed to economic output; an acknowledgement that the willingness to act against climate change exists, but is combined with a statement that penalizing growth of developing countries does not correctly reflect the responsibilities associated with historical emissions. Intensity targets are believed to effectively limit economic growth losses from climate policy in contrast to quantity (Pizer, 2005). However, intensity targets are problematic, as they allow emissions to continue to increase(Vuuren et al., 2002), imposing no overall cap. In the case of China and India, which are responsible for over one third of global emissions, the choice of target could have a substantial impact on global decarbonization pathways(Zhu et al., 2015). Progress made in the implementation of NDCs will be monitored and reviewed every 5 years, with a first global stocktake scheduled for 2023. Mid-century strategies are already being discussed, as countries are invited in the decision accompanying the Paris Agreement to submit these strategies by 2020 (UNFCCC, 2015). This means that, once these mid-century targets are in place, the NDCs will, in effect, become interim targets, and a situation of target sequencing will emerge. Compatibility of NDCs and 2050 targets is important and will play a decisive role in paving the way for long term climate stabilization (Pahle et al. (2018); Kriegler et al. (2018)). An analysis of the dynamics of this succession of targets under uncertainty is pursued in this study.

3. The literature on target comparison

Intensity targets can be indexed to output or input and are well established in environmental regulation. In the climate change context, they gained more attention when the US decided against ratification of the 1997 Kyoto Protocol (which included absolute targets), and instead took on an intensity target. The debate following the collapse of negotiations at the 2009 Copenhagen Climate Conference—when it became clear that a Kyoto-like global agreement including absolute targets with permit trading was not achievable—has focused on a wider range of national and progressively strengthened commitments.

Overall, the scientific literature on comparison between intensity and absolute targets in environmental regulation can be divided into two main categories: literature on economy-wide regulation, and literature on regulation at firm or sectoral level, see e.g. Quirion (2005). The focus of this paper will be the category of economy-wide regulation, which we divide further into 3 subcategories: (I) analyses of policies for a specific country or region and discussion of which target performs better; (II) discussions of the implications of the target choice on international bilateral (or broader) agreements in terms of willingness to participate and commit; and (III) target sequencing, i.e. situations where in multi-stage policy design either choice of target can be implemented sequentially.

Marschinski and Edenhofer (2010) discuss (I), (II) as well as (III) using formal analyses with simple analytic models, including also the concepts of hot-air and banking/borrowing of emission permits. They find intensity targets to perform better than absolute targets only under very specific conditions, e.g. a significant positive correlation between shocks in emissions and output. Ellerman and Wing (2003) also touch on all 3 subcategories, and find hybrid targets including only some reduced form of indexation—which they analyse in detail—to have advantages over pure absolute or intensity targets, but conclude in making the case that willingness to act is more important than the target type.

In the subcategory of single country studies (I), Lu et al. (2013) analyse China's previous intensity targeting for 2020 and conclude that the advantage of flexibility offered by intensity targets is reduced by the prospect of a low growth scenario, which would incur high costs. Wang (2014) calls for a Chinese shift to an absolute emissions cap in order to break the link between emissions and growth. This is based on the grounds of an expected coal import increase under an intensity target following a reduction in coal usage in big coal exporting countries (e.g USA). Zhu et al. (2018) propose a hybrid control scheme based on quantity (energy consumption and CO_2 emissions) and intensity (energy intensity and carbon intensity). Webster et al. (2010) also propose a hybrid instrument consisting of a quantity target combined with a safety valve, and perform a Monte-Carlo analysis for the US economy using a CGE model. They include uncertainty in 3 parameters: GDP, the rate of autonomous energy efficiency improvement, and the elasticities of substitution of the production functions. Their analysis results in favoring intensity targets depending on parameter values and only in combination with a safety valve instrument. Pizer (2005) makes the case for intensity targets on the grounds of preserving developing countries' right to near-term emission growth.

In the subcategory (II) of interacting participants in agreements, Akimoto et al. (2008) propose a scheme based on sectoral intensity targets, as opposed to country-specific ones, thus reducing the overall energy transformation costs. However, they do not consider the welfare implications and do not account for uncertainty. Dudek and Golub (2003) reject the concept of intensity targets arguing that it could add yet another hurdle to the implementation of already difficult to achieve international agreements.

Authors address the subcategory of target sequencing (III) the least. Sue Wing et al. (2006) find intensity control more suitable under a broad range of emission targets, especially for developing countries. Their analysis is based on two indicators arising from consideration of uncertainty: preservation of expectations and temporal stability.

Here we discuss subcategories (I) and (III) of target comparison studies. We also contribute to the literature on China's climate and energy policy in the post-Paris Agreement era. We do so by explicitly accounting for economic growth combined with short- and long-term climate targets (sequencing), thereby proposing a framework for dealing with these two types of uncertainties. Additionally, in order to address target achievability, the target comparison criteria found in the literature are extended with our multi-criteria analysis.

4. Study design

As growth uncertainty drives the choice of intensity targets, we use methods for explicitly accounting for uncertainty in our modelling. Moreover, to capture the importance of current targets in paving the way for future climate policy we consider target sequencing scenarios. Finally, since reduction of fossil fuel resource use is crucial in shaping China's emissions future, we use a model of large technological detail to capture realistic energy system configurations. We run all scenarios with the integrated assessment model REMIND (Luderer et al., 2015), in its stochastic version called REMIND-S, which is presented here for the first time (see Appendix A.1 and Appendix A.2 for the descriptions of REMIND and REMIND-S, respectively). An overview of the scenarios considered in our study is given in Table 1. Scenarios unfold in two dimensions: a) Learning about 2050 climate targets, and b) Learning about economic growth. By "learning", we mean to the information available to (energy) investors under uncertainty, see also Appendix A.3. Concerning the first dimension we consider the following four scenarios: a no-target scenario (BASE); a scenario (Q50) with a "stand-alone" (as opposed to "sequencing") quantity target in 2050, that assumes learning has already happended in 2010[2], (that is, Q50 is known to the investors); and scenarios with intensity (I30) or quantity (Q30) target types in 2030, which assume that announcement of Q50 happens later than 2010 (target sequencing scenarios) and investors are constrained by their earlier actions after the announcement. The second dimension represents different years where learning about economic growth occurs: 2010 or 2030. Here, "learning in 2010" describes the situation where the investors take decisions accounting for China's best-guess growth path in the period 2010-2030. The different scenario dimensions are explained in further detail below.

4.1. Climate policy scenarios

We define sequencing scenarios as cases with a 2 °C-compatible GHG emissions quantity[3] reduction target in 2050 (mid-century strategy), that has been announced in the year 2030, which we call the learning point. Before the learning point, the investor "sees" only the 2030 target; only for the period after the learning point decisions can be tailored to the updated information (i.e. the Q50 target). To set the stage for these sequencing scenarios we also run stand-alone scenarios with the 2030 Chinese climate target formulated as either a GHG intensity target[4]—reflecting the current situation—or an equivalent GHG quantity target (I30 and Q30). Before 2030, the

[2] Initial point of the model's time horizon.

[3] Because the long-term goal of 2 °C adopted by the Paris Agreement corresponds to a quantity target (i.e. an absolute limit on cumulative CO_2 emissions), we formulate the 2050 target solely as a quantity target and do not consider 2050 intensity target scenarios.

[4] Our formulation of China's intensity target encompasses also China's peaking target.

2050 target is unknown and only a 2030 target exists, reflecting the current level of information. The technique to implement the sequencing scenario in a model with perfect foresight such as REMIND is as follows: a scenario with only the 2030 target (stand-alone scenario) is run in a first step and then the sequencing scenario is optimized over the period 2030-2050 to achieve the mid-century target, with the energy and mitigation investment trajectory fixed to the stand-alone run until 2030. We also consider a hypothetical scenario of full information, where both the Q50 target and growth uncertainty are considered to have been resolved already in 2010 and no interim target in 2030 is needed. This deterministic scenario (Q50-L10-medium) with fixed expectations about economic growth ("medium") is then used to derive the optimal 2030 interim targets (Figure 1), thereby ensuring that they are aligned with the 2050 quantity target for China, which in turn is fixed to a global below 2 °C scenario based on results from the CD-LINKS project (Kriegler et al., 2018). It is important to note that our calculation of optimal interim targets leads to a more stringent intensity target in 2030 (72% reduction relative to 2005; 0.91 Mt CO_2-e/billion US$2005) than provided in the official Chinese NDC (60-65% reduction relative to 2005), which reflects the fact that the cost-efficient pathway towards the 2050 emission quantity target—and the overall below 2 °C target—typically lies below China's NDC intensity target in 2030 (UNEP, 2017), see Figure 3. For the comparison of interim target types, we adopt the emissions in 2030 (13.4 Gt CO_2eq, within the uncertainty range found in studies using also national Chinese models like TIMES Grubb et al. (2015) and Roelfsema et al. (2020)) of the cost effective mid-century strategy (Q50-L10-medium) as the quantity target (Q30) equivalent to I30.

Climate policy in all scenarios is enforced via an economy-wide lump-sum carbon tax, covering also CH_4 and N_2O emissions, however excluding land-use change[5] CO_2 emissions. The carbon tax takes an initial value in 2020 and then rises with a 5% annual increase. To derive the optimal carbon tax path, the model is solved iteratively (with updating of the initial carbon tax value between iterations) until the climate target, i.e. the reduction of GHG emissions or GHG intensity, is met. Decision variables in REMIND are investments in the macroeconomic capital stock as well as into energy generation technologies (optimal allocation). Technological change is an important driver of the evolution of energy systems. For mature technologies, such as coal-fired power plants, the evolution of techno-economic parameters in the production function of REMIND is prescribed exogenously. For less mature technologies with substantial potential for cost decreases via learning-by-doing, investment costs are determined via an endogenous one-factor learning curve approach that assumes floor costs. In the presence of a national target, a carbon tax is used so that the optimal investments shift to cleaner energy sources, but REMIND fully accounts for path dependencies (e.g. past investments in power plants that have not yet reached the end of their lifetime), as well as increasing marginal costs in the case of rapid expansion of technologies (adjustment costs).

4.2. Economic growth scenarios

The SSP2[6] "middle-of-the-road" GDP path (Kriegler et al., 2014a) is our central, medium growth scenario. Then, by increasing labor productivity[7]—the main driving force of economic growth in the REMIND model (Luderer

[5] These are also reduced in policy scenarios, but by prescribed scenarios.

[6] Shared socio-economic pathways (SSPs, ONeill et al. (2014)).

[7] By designing the growth scenarios via labor productivity—rather than directly prescribing GDP paths—we capture macro-economic effects of different policy choices.

Table 1: Overview of the scenarios considered. There are 2 dimensions in the study, reflected in the scenario names as follows: "Climate target(s)"-"Year where learning about growth uncertainty occurs". Example names: Q50-L10 means stand-alone quantity target in 2050 (i.e. no 2030 target) - learning about growth in 2010, I30-L30 denotes a sequencing scenario with intensity target in 2030 and quantity target in 2050 - learning about growth in 2030, etc. In cases where the focus is on a particular growth scenario (low, medium or high), it will be added to the scenario name as follows: Q50-L10-medium. Notes: The 2050 target is formulated solely as a quantity target, because the long-term 2 °C target is also of the same kind.

			Economic Growth	
		2030 Target	**Learn 2010**	**Learn 2030**
2050 Target	**No Target**	**No Target**	BASE-L10	BASE-L30
	Stand-alone	**No Target**	Q50-L10	Q50-L30
	Sequencing	**Intensity**	I30-L10	I30-L30
		Quantity	Q30-L10	Q30-L30

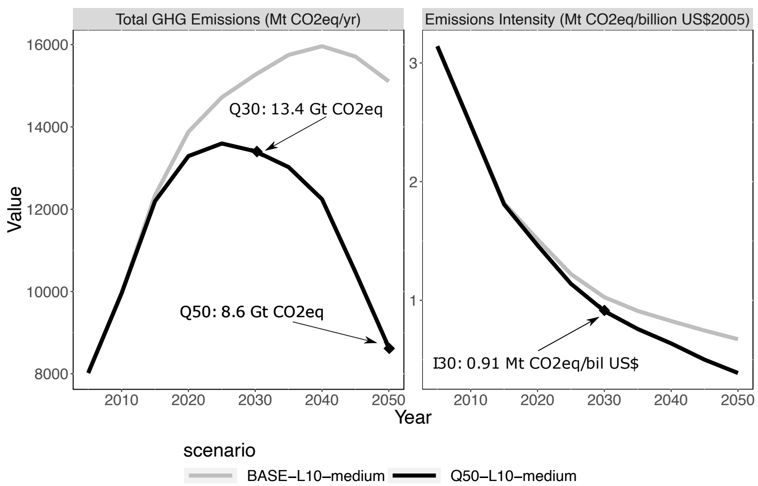

Figure 1: Calculation of China's Q30 and I30 targets, based on **full information**, i.e. medium growth assumptions and full target information. We derive the optimal 2030 quantity target for China (Q30) as well as the equivalent intensity target (I30) from the optimal emissions path of a policy scenario (black line) compatible with the 2 °C long-term target featuring the 2050 cost-efficient emissions from the CD-LINKS project (Q50) as target.

et al., 2015)—by 25% and by decreasing it by 25% we generate the "High" and "Low" scenarios. All three scenarios are assumed to have equal probability. Figure 2 shows the resulting baseline GDP paths for China. For comparison, current growth estimates from other sources: SSP1, SSP5, the OECD, and Price-Waterhouse-Coopers are also shown. This illustrates the difficulty of deriving solid predictions of Chinese economic growth (Morgan, 2018; Christensen et al., 2018).

5. Results

5.1. The importance of target type

5.1.1. Analytical results

Here, a discussion is provided on how each target type shapes the optimal carbon price differently. This is important because different incentives and investment dynamics are reflected in the optimal carbon price paths,

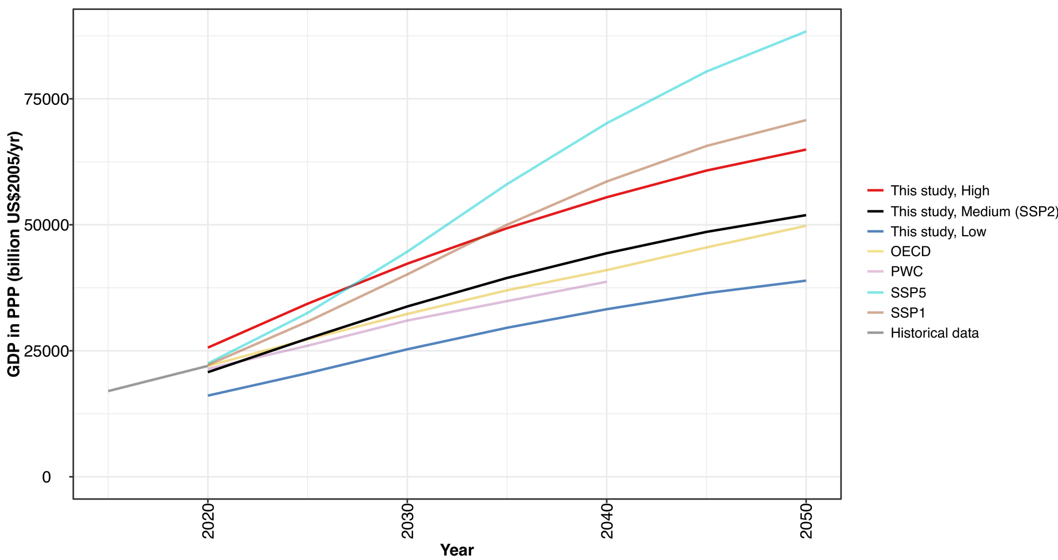

Figure 2: Uncertainty in economic growth of China, measured in purchasing power parity (PPP) GDP. A 25 percent variation around the medium growth scenario (SSP2, O'Neill et al. 2014) is used for the labor efficiency parameter in our scenarios (Low, Medium, High). For reference, SSP1 and SSP5 (based on OECD projections; Kriegler et al. (2017)) as well as other scenarios from the OECD (OECD, 2018), and Price-Waterhouse-Coopers Hawksworth et al. (2017) are shown.

and subsequently different hedging strategies against uncertainty (e.g. a preventive strategy versus a wait-and-see approach). We will show that when emission intensity decreases with economic growth—as is commonly the case—the target type has a strong effect on how economic growth shapes the optimal carbon price paths, i.e. different incentives for investment are generated. More precisely, we show that in the presence of a quantity target, the optimal carbon price increases with economic growth, whereas under an intensity target it decreases.

We define the emissions reduction in each case as $\Delta E \equiv E_{base} - E_{pol}$. In a single period setting (stand-alone target), and under an emissions quantity target Q, we obtain (comparing the medium with the low growth scenario):

$$\Delta E_M = E_{M,base} - Q > E_{L,base} - Q = \Delta E_L, \tag{2}$$

because $E_{M,base} > E_{L,base}$ (see Figure 3). Thus, since abatement in the medium scenario is larger than in the low scenario (the target Q is fixed, but baseline emissions are higher under medium growth than under low growth), the medium scenario will feature a higher carbon price.

In the case of an intensity target I, we get (Y stands for GDP):

$$\Delta E_L = E_{L,base} - I \cdot Y_{L,pol} = E_{M,base} \cdot \frac{E_{L,base}}{E_{M,base}} - I \cdot Y_{M,pol} \cdot \frac{Y_{L,pol}}{Y_{M,pol}} > E_{M,base} - I \cdot Y_{M,pol} = \Delta E_M \tag{3}$$

The inequality in eq. 3 holds only if

$$\frac{E_{L,base}}{E_{M,base}} > \frac{Y_{L,pol}}{Y_{M,pol}} \Rightarrow \frac{I_{L,base}}{I_{M,base}} \cdot \frac{Y_{L,base}}{Y_{M,base}} > \frac{Y_{L,pol}}{Y_{M,pol}} \Rightarrow I_{L,base} > I_{M,base} \tag{4}$$

(GDP cancels out because $Y_{base} \approx Y_{pol}$; climate policy has very little impact on GDP). The last inequality of eq.

4 holds for China and most countries, because emissions intensity is commonly reduced faster in a higher growth compared to a lower growth scenario, see Figure 3. Thus from eq. 3 it holds that $\Delta E_M < \Delta E_L$

Summarizing, in the presence of an intensity target the optimal carbon price will be highest for the low growth scenario, as seen also in Figure 4. As the carbon price is a proxy for costs of policies, this has serious implications in how the hedging strategies of the early years are shaped, which we will quantify numerically in the following.

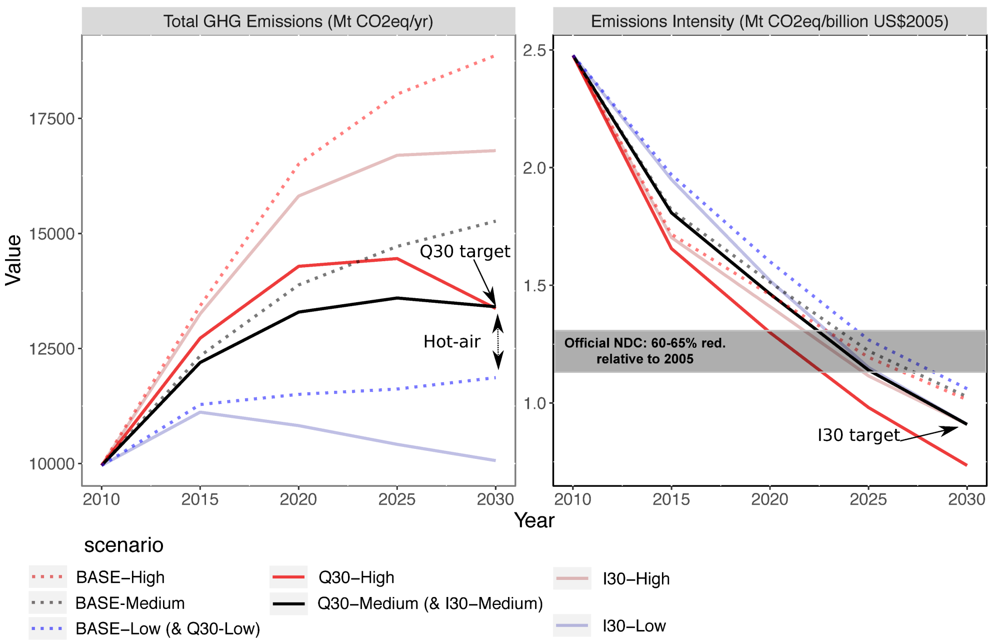

Figure 3: Overview of the deterministic case (learn about growth in 2010). Left: GHG emissions scenarios for China. The 13.4 Gt CO_2eq target is not constraining for the low growth Q30 scenario (hot-air is the difference in 2030 between the dashed blue and the continuous black line), and the indexed target (I30 scenarios) is not unique. Without uncertainty (medium growth) it makes no difference whether an intensity or quantity target is chosen. Right: GHG intensities for the same scenarios. The converging Q30 emission scenarios are now diverging, and the I30 scenarios are converging to our 2 °C-compatible intensity target. The official NDC intensity target of China is depicted in the grey area. It is not posing a constraint, as it lies above the baseline intensities in 2030. Note: L10 has been omitted from the scenario names

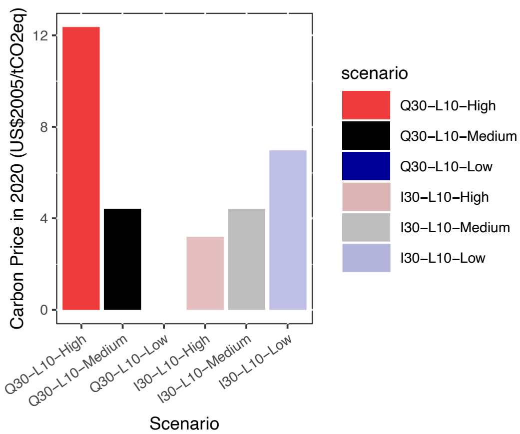

Figure 4: How economic growth scenarios shape the optimal carbon price paths in China, i.e. the policy costs; Q30 and I30 targets have reversed behavior in response to the high and low growth scenarios, whereas they are equal in the absence of uncertainty (medium growth).

5.1.2. Numerical results

To motivate the use of a stochastic modelling framework in the upcoming sections, we start the numerical analysis by investigating the deterministic modelling—i.e. assuming that learning about growth uncertainty has occurred already in 2010, see Appendix A.3—of the targets in 2030. We compare the medium with the high and low growth scenarios, and discuss environmental implications in terms of total GHG emissions. Differences in marginal abatement costs are expressed in terms of carbon prices. Finally, we discuss welfare effects in terms of differences in *balanced growth equivalents* (BGE), as proposed by Stern (2007), and further analysed and used by Anthoff and Tol (2009), and Drouet and Emmerling (2016), see Appendix A.5 for details.

The optimal emissions of the deterministic cases are given in Figure 3. Without uncertainty, it makes no difference whether an intensity or quantity target is chosen, which can be proven also analytically (Ellerman and Wing, 2003). Since we have chosen equivalent quantity and intensity targets for the medium growth scenario, optimal emissions are identical in this case, as seen by the coinciding paths (black line). This is no longer true for the high and low growth scenarios. If a higher than expected growth is observed, emissions in 2030 will be higher regardless of target choice, seen by the difference in the red and the black curves. An intensity target (I30-L10) has increased emissions in total and in absolute value in 2030, whereas a quantity target (Q30-L10) meets the 2030 target of 13.4 Gt CO_2eq but with increased total emissions. In the case of low growth the quantity target is not posing a constraint as the baseline emissions are already below it (dashed blue line). The average annual growth rate of GDP in the period 2010-2030 is assumed to be 6.7% in the medium growth SSP2 scenario (historical data: ca. 6.5% in 2017-2020). By conducting a sensitivity analysis of emissions on the GDP growth rate we find that emissions under a quantity target are the same as in the medium growth baseline (i.e. the target is not posing a constraint) at an average annual growth rate of GDP of 6.1%[8]. The non-constraining target could give rise to hot air and climate policy costs can drop to zero. In contrast, an intensity target can impose a stringent emissions

[8]For reference, our low growth scenario features a GDP growth rate in the period 2010-2030 of 5.5%, and the average annual growth rate of long-term OECD projections for 2020-2050 is ca. 2.5%.

Table 2: Comparison of welfare effects until 2030 measured as percent changes in *balanced growth equivalents* (BGE, see Appendix A.5) for the different target types of the stand-alone 2030 scenarios. The last two rows are the corresponding climate policy costs (i.e. comparison with the baseline) for each target and for the same period, which we use for reference.

Scenarios compared	**ΔBGE 2030 (%)**
High growth (I30-L10-High vs. Q30-L10-High)	1.0
Medium growth (I30-L10-Medium vs. Q30-L10-Medium)	0
Low growth (I30-L10-Low vs. Q30-L10-Low)	-0.97
Quantity (BASE-L10 vs. Q30-L10)	0.6
Intensity (BASE-L10 vs. I30-L10)	0.75

constraint on a slow growing economy (weak blue line), i.e. an additional challenge.

In terms of marginal abatement costs, Figure 4 shows that under high growth, to reach a quantity target they can increase almost 3-fold, whereas they would decrease under an intensity target. On the other hand, in the low growth case, there is a significant increase in marginal abatement costs for reaching the intensity target, while the quantity target produces hot-air, i.e. no costs (the target is not posing a constraint as baseline emissions are already below it). Regarding the welfare effects, Table 2 shows how the differences in welfare between target types compare with each other and—for reference—with the costs of climate policy. In the case of high growth, an intensity target performs better than a quantity target, whereas in the case of low growth only an intensity target incurs costs (as the quantity target is not posing a constraint), so quantity has an advantage. Our sensitivity analysis of emissions on the GDP growth rate (see Appendix A.6) suggests that these effects are monotonous, meaning that an intensity target has a lower BGE than quantity under low growth already at a marginal variation in GDP growth around the medium scenario (because the intensity target is a "moving" emissions target), and a higher BGE in the case of high growth, which means it provides cost containment compared to a quantity target. In the medium growth case, there is no difference in welfare, due to the equivalence of the two targets in the absence of uncertainty. It is important to note that the differences in welfare between the targets in the high and low growth scenarios could reach the same order of magnitude as the costs of climate policy (last two rows of Table 2). This observation, combined with the case-dependent advantage that each target exhibits—depending on what growth scenario materializes—motivates us to perform the stochastic analysis of the upcoming sections, in order to compare intensity and quantity targets.

5.2. How hedging strategies shape the target sequencing

5.2.1. Target sequencing scenarios

In the remainder of the paper we perform decision-making under uncertainty (see Appendix A.3) with the REMIND-S model, as opposed to the deterministic analysis of the previous section. We do so by performing an expected value welfare maximization across all three growth cases (low-medium-high) at once. We thus derive one single optimal emissions path instead of one for each growth scenario, which is the main feature of the stochastic model. This allows us to identify hedging strategies (hedging strategies are characterized by a lower emissions pathway due to taking into account all three possible economic growth outcomes simultaneously, compared to simply assuming medium growth in a deterministic optimization, see Figure A.9).

The implementation of the stochastic optimization problem describes the situation of an investor who has to decide on a single energy sector investment strategy for the period 2010-2030 until the uncertainty about economic growth is resolved. The REMIND-S model also accounts for investments in industrial capital stock as an additional optimization variable. This decision remains freely adjustable to the individual economic growth scenario from 2010 onward, assuming that capital markets can learn immediately about the actual growth path as it unfolds. To implement the target sequencing, we calculate the optimal emission paths for cases where, initially, decisions up to a certain point are taken with only the 2030 targets being known (stand-alone scenarios), and an announcement of a "follow-up" 2050 quantity target taking place in the same year. This myopic behavior describes a situation of unanticipated learning in 2030. We simulate two types of sequencing scenarios, one that follows after the 2030 intensity target case, which is denoted with I30-L30, and one that follows after the 2030 quantity target case, which we denote with Q30-L30 (see also Table 1). REMIND-S calculates the optimal paths that emerge around mid-century, resulting from investment decisions pre-2030 taken under growth uncertainty and without information about the follow-up 2050 target.

In Figure 5, we show how target sequencing shapes optimal emissions paths, and plot these next to the hypothetical, full-information case of the 2 °C compatible stand-alone[9] target in 2050, which we used to derive the optimal 2030 targets. Due to the stronger hedging (i.e. the deviation from the Q50-L10-medium scenario, which we analyse in detail in the next section) in the I30-L30 scenario, decarbonization starts earlier and thus total emissions (area under emissions curve) are lower than in the quantity target case (483 Gt CO_2 in I30Q-L30 vs. 527 Gt CO_2eq in Q30-L30). In Figure 6, a more detailed representation of the same scenarios is shown, focusing on key variables and adding the baseline scenario. An intensity target scenario has a higher net present value (in year 2020) carbon price (27.7 \$/tCO_2 vs. 18.6 \$/tCO_2). This leads to over-investment in energy in the early years (energy investment curve). The 2050 target announcement leads to jumps in the optimal carbon price paths. It can also lead to substantial early retirement of coal capacities in the power sector up to 2050 (aggregated over time) of up to 2500 GW, i.e. nearly 40% of total projected coal capacity in the baseline (6,400 GW), and 66% more than the idle capacity in the quantity target scenario (these estimates are in the lowest range of estimated stranded capacities from Wang et al. (2019a),Wang et al. (2019b)). Finally, a quantity target could lead to less welfare losses as seen in the *certainty- and balanced-growth equivalent* curves. Figures A.16 and A.17 in the Appendix show further numerical results, including for GDP, energy demand, and energy mixes.

[9]The Q50-L10-medium scenario features no growth uncertainty, and has full long-term target information; thus an interim target is obsolete.

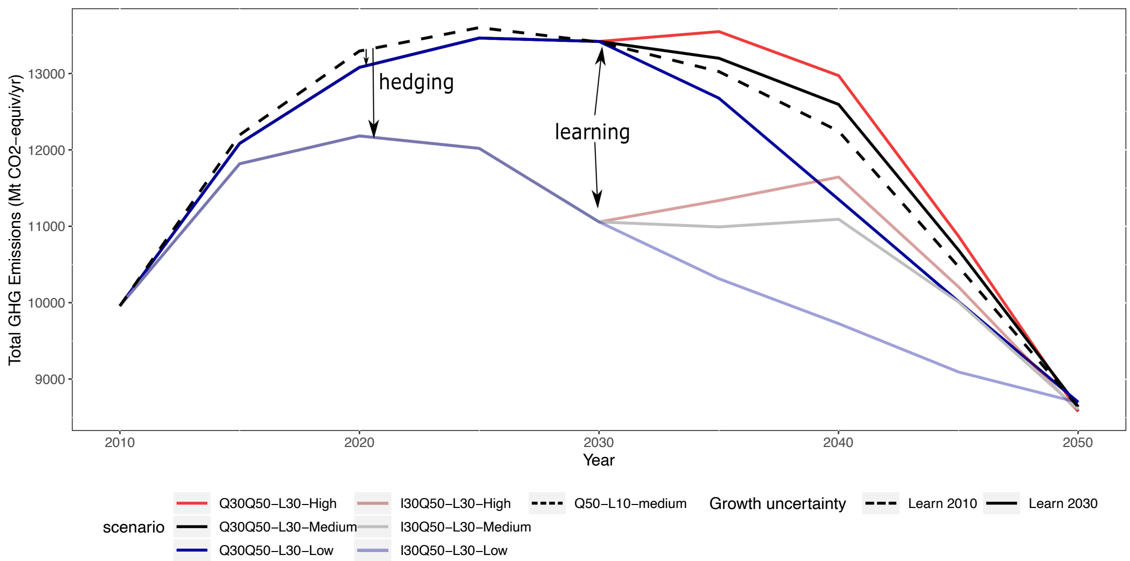

Figure 5: Optimal emissions of the target sequencing scenarios for China (featuring uncertainty about growth and 2050 target until 2030), compared to the stand-alone medium-growth Q50 deterministic scenario (full information about 2050 target and economic growth). In 2030 uncertainty is resolved (learning point) and the 2050 absolute emissions target is announced (myopic behavior). The decisions prior to the learning point are equal across the growth scenarios (one line for each target type) whereas after the learning point they can be tailored to the individual growth scenarios, see Appendix A.3. In the graph the intensity target's stronger hedging is shown.

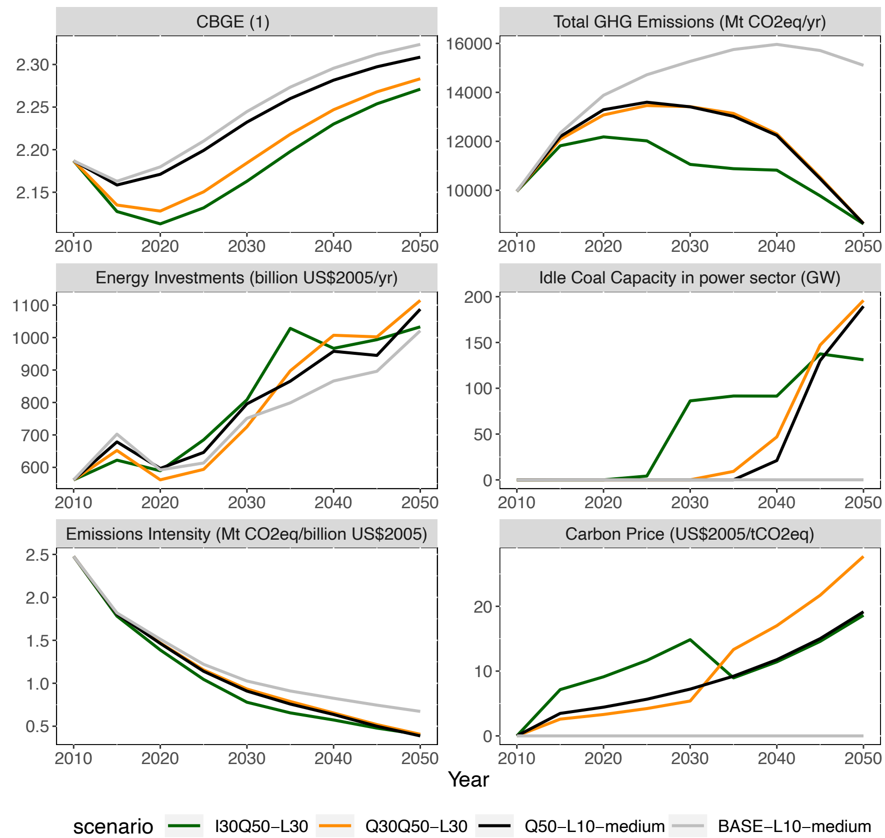

Figure 6: Optimal paths of the sequencing scenarios for China, under uncertainty. The same graphs with each growth scenario plotted separately are found in Figure A.15 of the Appendix. CGBE: *certainty- and balanced-growth equivalent*.

Sue Wing et al. (2006) discuss the theoretical property stating that intensity targets lead to a slower decoupling of growth and emissions. In our stochastic analysis, however, where hedging strategies against growth uncertainty are identified, we find that it is the intensity target that could lead to a faster—but more costly—reduction in emissions.

5.2.2. Hedging strategies in the energy system

The sequencing scenarios of the previous section exhibit a different behavior depending on whether the 2030 target is an intensity or absolute target. We showed analytically that this is due to different incentives generated by each target type. With the sectoral and technological detail of REMIND-S we are able to quantify the optimal hedging strategies dictated by the different incentives of the previous sections. Hedging is the result of seeking the best compromise between all the possible growth scenarios, and exists also in the baseline case (see Appendix A.4). However, it unfolds differently in the case of climate targets under growth uncertainty. Under an intensity target the low growth scenario poses a challenge for the economy if realized, as the 2030 intensity target becomes more stringent if GDP grows slowly (see Figure 3). The dominance of the low growth scenario leads to the hedging strategy of further reduced emissions when comparing a full-information with an uncertainty scenario (Q50-L10-Medium vs. I30-L30 in Figure 5), describing a preventive strategy. This happens via increased renewable energy capacity additions in the power sector—alongside increased energy investment in general—compared to the quantity target case (see Figure A.13 for a comparison of energy investment strategies). However, this comes at an increased price for energy, as seen on the same figure. Under a quantity target the hedging strategy differs substantially; now the high growth scenario poses a challenge—due to high policy costs if the target is fixed (see again Figure 3)—and the least-cost possible energy system in the presence of the short-term 2030 target is one characterized by moderate energy investment, pointing to a wait-and-see strategy and less hedging in emissions. This is reflected also in the average price paid for energy, as seen in Figure A.13.

5.2.3. The role of coal

The power sector plays an important role in the transition to a low-carbon economy. In China, this sector is dominated by coal. An illustration of how coal shapes the hedging in emissions is shown in Figure 7, where it is seen that until 2020 in the quantity target scenario optimal coal usage follows a similar path as the deterministic policy case, only to be reduced further under an intensity target. This is not the case for the other two important fossil fuel energy sources, gas and oil, as seen on the same figure. The coal reduction under the intensity scenario is driven by the retired coal capacities in the power sector (see Figure 6 and section 5.2.1).

We examine also the stylized case of anticipated learning about uncertainty, described by the introduction of a learning step in a perfect foresight model like REMIND-S, which greatly reduces the target effect and leads to similar strategies for each target. As seen in Appendix A.4.2, anticipated learning reduces the importance of target choice and leads to almost the same amount of uncertainty-driven emissions reduction for a quantity and an intensity target.

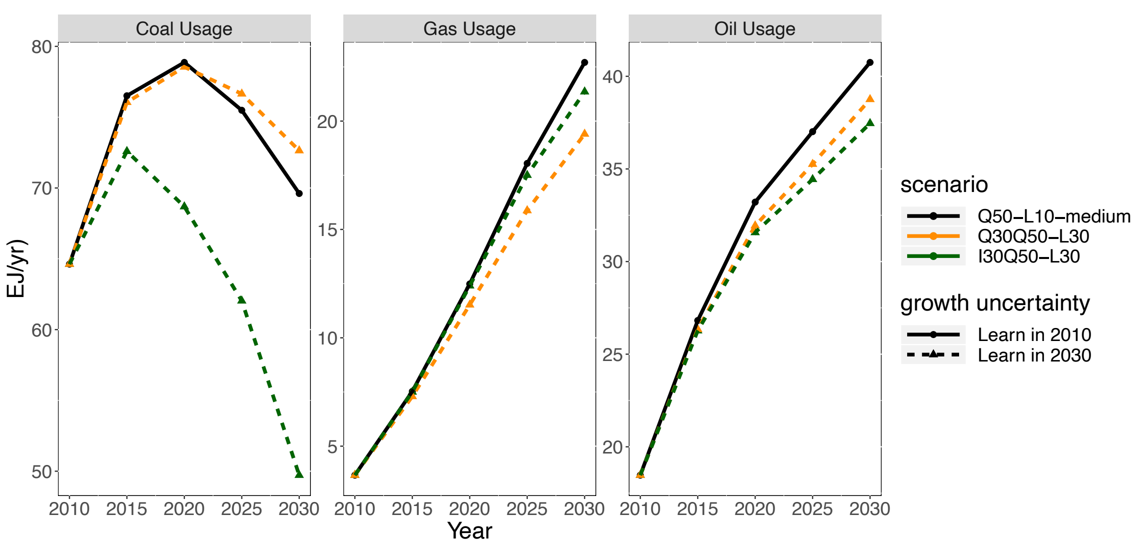

Figure 7: Optimal fossil resource usage in China under uncertainty compared to the scenario of full information. The quantity scenario features no further uncertainty-driven decrease in coal usage whereas oil and gas are reduced.

5.3. Multi-criteria comparison of intensity vs. quantity targets

Climate targets, as policy objectives, need to be evaluated in terms of more than one property to achieve political and social acceptance; climate policy will affect the environment (GHG concentration, air pollution, etc.), but it can also create winners and losers depending on the direction of investment streams. It can even be the

Table 3: Overview of criteria for target comparison. A detailed description of the indicators is provided in Appendix A.7.

Criterion	Short description	Category
GHG emissions	Total GHG emissions in the period 2005-2050	Environmental
Carbon price	The size of the carbon price that has to be exerted on the economy for the target to be met	Efficiency
Welfare loss	Indicator based on total discounted social welfare loss until 2050. Measured in *balanced growth equivalents*	Efficiency
Idle coal capacity	Total retired coal capacity in the power sector that has not reached the end of its lifetime	Disruptiveness
Cost volatility	Expressed by the volatility of the carbon price around 2030, the year of learning about the mid-century target	Disruptiveness
Expected Value of Information	Describes the difference in the value of learning about growth uncertainty between the two target types	Expectation Stabilization
Non-optimal investment	The amount by which investment in energy deviates from the medium-growth full-information path	Expectation Stabilization

reason why capacities are retired earlier than expected (due to unanticipated strengthening of policies), giving rise to sunk investments. Moreover, different target types can give rise to completely different response strategies. For example, a preventive strategy can incentivise high investment in energy early on, whereas a wait-and-see strategy can have the opposite effect. This will affect how costs are distributed over time. Furthermore, as targets will inevitably be sequential, the above mentioned effects will become more complex, as it is also the type of the second target and the time of its announcement that will play an important role. Lastly, the fact that economic growth cannot be predicted with certainty already affects the baseline case (over- or under-investment), and this effect intensifies in the presence of climate policy.

To address these implications and take into account the findings of the analytical discussion and the deterministic and stochastic analyses, we compare intensity and quantity targets under multiple criteria. We choose four categories of criteria: the **environment**, economic **efficiency** (relating to costs of policies and their distribution over time), **disruptiveness** (relating to abrupt changes in the system caused by the announcement of targets) and **expectation stabilization** (relating to how targets under growth uncertainty affect investors' optimal behavior). Overall, we use seven criteria. Environmental criteria are expressed in terms of GHG emissions, while target efficiency is measured in terms of carbon prices and welfare. As indicators addressing disruptiveness, we use idle coal capacity and climate policy cost volatility. To assess the robustness of targets for stabilizing expectations, we rate them according to the Expected Value of Information (EVOI) (see Table A.4 for a description of the EVOI) and non-optimal investment. The criteria are summarized in Table 3, and explained in detail in Appendix A.7.

Figure 8 illustrates the multi-criteria comparison between a quantity and an intensity target, taking into account target sequencing and growth uncertainty. The quantity target performs better in five out of seven criteria, whereas intensity is better under one. The individual values of the indicators are discussed in section 5.2.1. Regarding the criteria classification, an intensity target features leads to slightly lower total emissions but the quantity target features more economic efficiency (lower carbon price and less welfare losses) and favors stabilization of expectations (less non-optimal investment). In terms of disruptiveness, a sudden switch to a quantity target after 2030 could cause many coal capacities in the power sector to become idle. Under a quantity target the idle capacities would be lower, with the additional benefit of a smaller jump in the carbon price due to the announcement of the 2050 target. In the EVOI case there is no clear advantage of either a quantity or intensity target, highlighting the dominant role of growth uncertainty. The reduction of growth uncertainty largely eliminates the target effect, as shown in Appendix A.4.2. Summarizing, a 2030 quantity target features an easier low carbon transition, e.g. with less costs and less idle capacities in the energy sector. The overall effect of the quantity target performing better can be interpreted as a manifestation of the optimal response to the risk of realization of the low growth scenario in the case of an intensity target, which outweighs the risk of a high growth scenario under a quantity target (because under high growth the extra climate policy costs are more easily borne). It is thus more beneficial to hedge against growth uncertainty with a 2030 quantity target because in the case of low growth it provides cost containment and, at the same time, offers a smoother transition to the mid-century quantity target.

We acknowledge that the absence of indicators relating to interaction with other countries (incentives, cooperation, etc.) and the absence of an indicator based on air quality constitute limitations for our study. To capture these, a stochastic model with regional interaction (and high spatial resolution) would be needed, which currently involves a prohibitive computational burden. Moreover, the model's sensitivity related to the utility function's constant relative risk aversion could be explored in a further analysis.

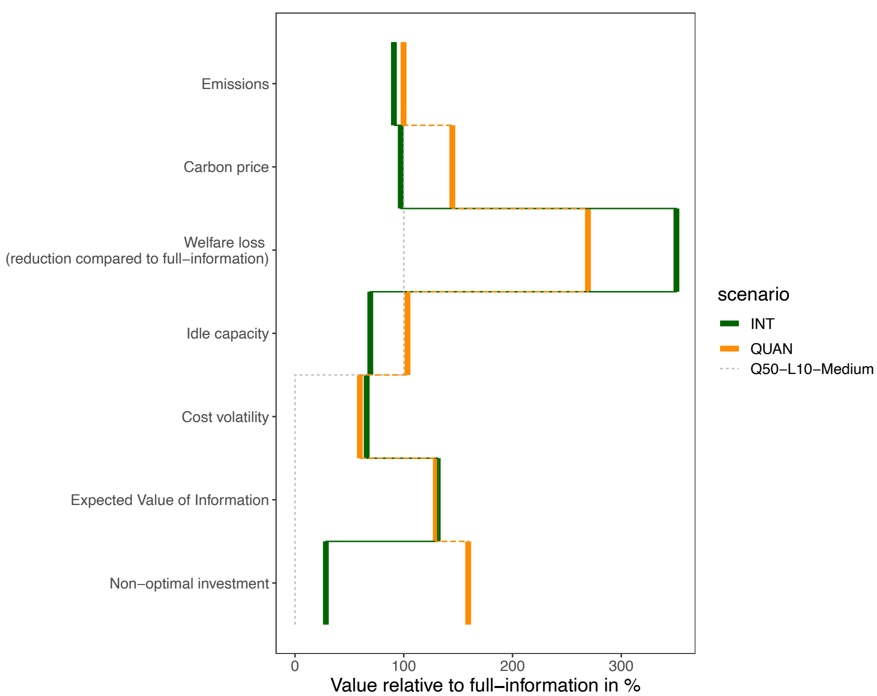

Figure 8: Multi-criteria comparison of quantity and intensity targets for China. Indicators are listed along the y-axis and their values are given on the x-axis as percentages relative to the medium-growth full-information scenario value (Q50-L10-Medium), for harmonization. A lower indicator value indicates a more positive effect, i.e. reduced risk. A quantity target generally performs better than an intensity target. In one case there is no clear advantage for the one or the other type of target (EVOI). Note: the full-information value is 100% for the four upper indicators. For the three indicators at the bottom where scaling with the full-information value is not possible (it is zero by definition), we scale with the respective lower value. A detailed explanation of the criteria is given in Appendix A.7.

6. Conclusions and Policy Implications

We performed an empirical study of China's climate policy to assess if its 2030 emission intensity target performs better than an absolute target in preparing the economy for a 2 °C compatible mid-century target, i.e. in a target sequencing situation.

China and India expect high economic growth, and hence adopted an intensity target providing cost containment. But this becomes problematic in the low growth scenario as increased climate policy costs will occur on top of lower than expected growth. In contrast, a quantity target has more costs than an intensity target in a high growth scenario, but may come at very low cost in the case of low growth. This means that each target has its advantages, but no single optimal strategy can be identified if future growth is uncertain. Additionally, the costs related to the choice of intensity vs. quantity target for China are of the same order in magnitude as climate policy itself. Taking into account all possible growth scenarios shows that an interim 2030 absolute target en route to a 2 °C compatible mid-century quantity target performs better than an intensity target in our multi-criteria comparison for the case of China; costs are lower and it also reduces uncertainty. As an explanation for the advantage a quantity target over an intensity one, we show analytically that the target type has a strong effect on how growth scenarios shape the optimal carbon price, i.e. different incentives for investment are generated for each target type. The analytic results enhance the robustness of the findings, as the form of the probability distribution describing the uncertainty does not play any role there.

China's climate targets constitute an important part of the Paris Agreement, reflecting the country's key role in the negotiations and the international effort to combat climate change. As such, their performance needs careful analysis both for the sake of China's economy and for a successful agreement. Ellerman and Wing (2003) suggest that—in a theoretical and perfectly flexible system—intensity and quantity targets can be interchanged infinitely and eventually lead to the same costs and emissions. This is challenged here due to the fact that in reality, energy investment cycles and power plant lifetimes have time scales longer than the target updating (e.g. China's official 5-year plans, or the Paris Agreement process for mid-century strategies); that is, the system shows inertia rather than flexibility. Consequently, successions of different types of targets will lead to a discontinuity and should be avoided. A strengthening of China's climate ambition is underway, driven by the fact that, in the current 5-year plan climate targets were easily met through energy saving policies and economic structure adjustments. The adoption of a 2030 absolute target is more suitable for China, as the long-term 2 C target is also, in effect, an absolute target. The switch from the current interim intensity target to absolute emissions control could happen gradually, taking advantage of the Agreements updating of targets every five years.

Code and data availability. REMIND is open-source: https://github.com/remindmodel/remind. The source code of the models used (REMIND and REMIND-S) as well as the data are available by the authors upon request.

Declarations of interest: none.

Appendix A.

Appendix A.1. The integrated assessment model REMIND

REMIND (REgional Model of INvestment and Development) is a multi-sector, multi-region integrated assessment model used for global and regional climate policy analysis (Luderer et al., 2015). REMIND has been used extensively in IPCC reports, e.g. IPCC (2014) and IPCC (2018), and major model intercomparison projects, e.g. Kriegler et al. (2014b), Pietzcker et al. (2017), Bauer et al. (2018), Luderer et al. (2018), Riahi et al. (2017). It combines a top-down Ramsey-type growth model with a bottom-up energy system model of large technological detail. In the macro-economic core of REMIND, aggregated and discounted intertemporal social welfare is maximized for a number of regions spanning the whole globe, while pathways are derived for savings and investments, factor incomes, as well as energy and material demand. The utility function of REMIND exhibits constant relative risk aversion and has a logarithmic form on consumption. Regions interact by trade in primary energy carriers, emission permits, and a composite good. The detailed representation of the energy system in each region consists of capital stocks for more than 60 technologies for energy conversion, including technologies that are able to generate negative emissions, like bioenergy combined with carbon capture and sequestration.

In REMIND, economic activity results in demand for energy services, which in turn results in GHG emissions from extraction and burning of fossil fuels in different sectors (buildings, industry, transport) and levels (primary, secondary, and final energy). Mitigation scenarios analyse optimal strategies for decarbonization with the use of a carbon tax applied on the economy, resulting in a shift from fossil use to renewable energy. A full portfolio of GHG is considered (CO_2, CH_4, N_2O, NH_3, F-gases, etc.), either via emissions from energy use or via exogenous marginal abatement cost curves (e.g. land-use). Adjustment costs in energy investment and deployment account for policy realism and path dependency. REMIND usually runs in so-called cost-effectiveness mode, not internalizing potential economic damages of climate change, but rather analyzing energy technology portfolios and investment dynamics under given climate targets (GHG budgets, reduction relative to a baseline, carbon taxes, etc.)

Appendix A.2. Decision-making under uncertainty in energy-economy models — Description of the REMIND-S model

There are several approaches in the literature to tackle uncertainty in climate policy analysis, reviewed extensively by Golub et al. (2014), Traeger (2009), Kann and Weyant (2000), Heal and Millner (2014), Heal and Kristrm (2002), Peterson (2005), and Baker and Shittu (2008). In energy-economy models, the first approach is called uncertainty propagation, and includes the methods of scenario analysis and sensitivity analysis. Although as methods they do not derive unique optimal decision paths, they provide important means for the design of climate policy. They do so by thoroughly exploring the scenario space and deriving detailed insights for each case, and by identifying which parameters contribute the most to uncertainty. A recent application of scenario analysis in the context of climate change are the SSPs (ONeill et al., 2014)), where self-consistent scenarios for the most important socio-economic drivers (population and economic growth, etc.) were developed for the future and a big body of studies was carried out shedding light on the implications of these socio-economic drivers for energy and land-use, emissions, climate change and mitigation of climate change (Riahi et al. (2017), Kriegler et al. (2017)). In other applications, Marangoni et al. (2017) use a sophisticated sensitivity analysis method to test various different parameters influencing emissions projections in the context of the SSPs, and conclude that economic growth and energy intensity are the most important drivers of uncertainty.

As a second approach to tackling uncertainty, methods performing decision-making under uncertainty are used. These include the methods of real option analysis (Anda et al., 2009) and stochastic modelling, e.g. discrete stochastic programming (Bosetti and Tavoni, 2009) and dynamic stochastic programming (Jensen and Traeger (2014) provide detailed estimates of optimal carbon taxes under long-term economic growth uncertainty using a dynamic stochastic integrated assessment model).

The model REMIND-S (REMIND-Stochastic) is presented here for the first time. It is the version of REMIND (see Appendix A.1) that explicitly accounts for uncertainty in one or more parameters. REMIND-S solves a Discrete Stochastic Programming (DSP) problem. DSP is a common method to explicitly account for uncertainty in integrated assessment models of climate change. It is widely used due to its moderate computational cost and useful insights, as well as the fact that it provides means for inclusion of stochasticity and multi-stage decision modelling. The key concept of DSP is to allow for the identification of one single optimal strategy under uncertainty (illustrated on the right panel of Fig. A.9), as opposed to multiple state-dependent optimal paths in a learn-then-act framework which can be explored by standard Monte Carlo, or simple deterministic scenario analysis (left panel of Fig. A.9). Thus, in DSP, the decision maker is exposed to a range of values of the uncertain parameter(s) in different "states-of-the-world" (realizations of the uncertain parameter), and still derives a single optimal path. The range of values of the uncertain parameter is described by a probability distribution running over the full set of states-of-the-world. This probability distribution can take any form and this is what gives the method the characterization "stochastic". REMIND-S features the exact same technological and sectoral detail as REMIND (the same holds for the rest of the model structure), but in REMIND-S expected utility is maximized, i.e. the weighted sum of utilities in each state-of-the-world, using the probabilities as weights, see equations describing the No-Learn and Act-Then-Learn cases in Fig. A.9. Thus, each state-of-the-world of REMIND-S is actually an instance of REMIND with different values for the uncertain parameters.

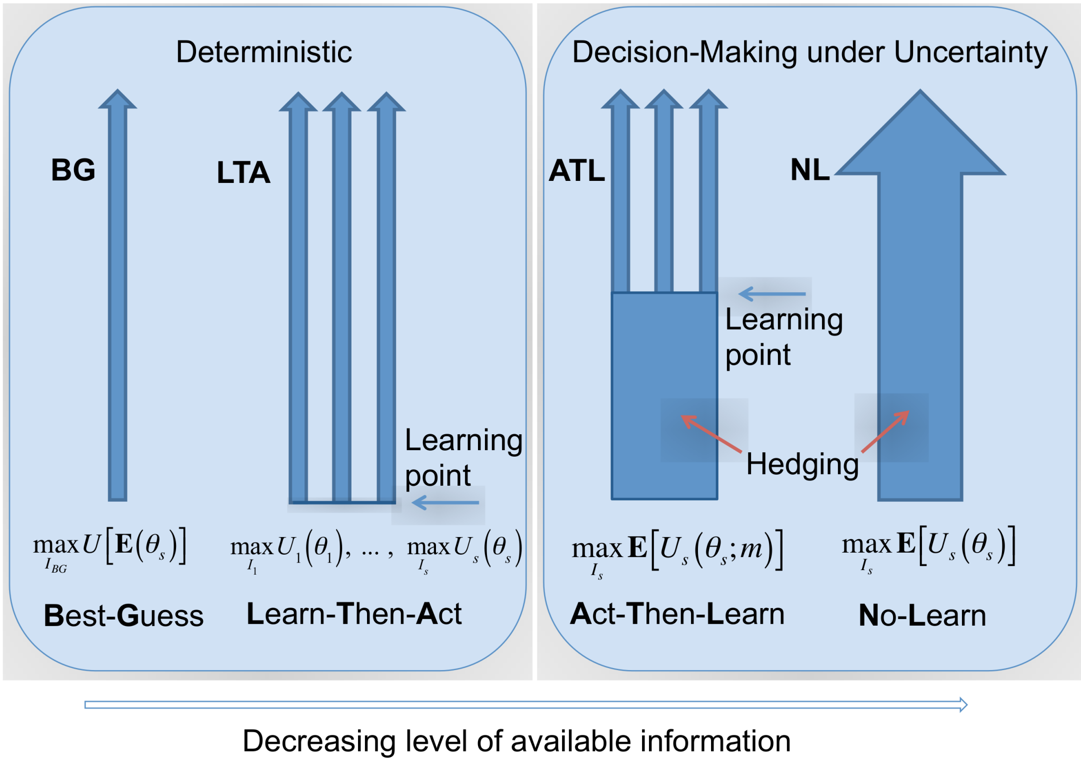

Figure A.9: Schematic representation of the various levels of uncertainty consideration applied here, and the respective objective functions. $\mathbf{E}$ is the expected value operator, U is the utility, s stands for state-of-the-world, I are the investment decisions, θ is the uncertain parameter, and m a message containing information about θ. "Learning" refers to the point in time where the message m is received. Hedging is defined as the decision path that responds to uncertainty, driven by the decision maker's risk aversion.

As mentioned above, the main feature of DSP is deriving a single optimal strategy under uncertainty. But capturing one single decision path poses a challenge in a complex model like REMIND-S, where various different investments and choices can be made. Thus, in REMIND-S, energy investments, fossil extraction rates and trade, as well early retired capacities are equalized across the states-of-the-world using special constraints, which leads to equal emissions across the states-of-the-world; this is what is defined as one single optimal strategy. The presence of these constraints in an expected utility optimization framework gives rise to hedging strategies (the red arrows of Fig. A.9 show where the hedging takes place), as the best compromise between conflicting optimal decisions in each state-of-the-world is sought after. This happens before uncertainty is resolved (learning point of Fig. A.9), as the decision maker should be unaware of the state-of-the-world that will materialize. After the learning point the constraints are fully relaxed so that decisions can be tailored to individual growth scenarios, and emissions differ across the different states-of-the-world.

Risk aversion is described by the elasticity of intertemporal substitution (EIS), which describes also the decision maker's preference towards intertemporal equality, as we do not consider separate preferences (this would require a different type of modelling, as intertemporal optimization cannot be easily combined with separate preferences). In REMIND-S, EIS is equal to unity, giving the utility function its logarithmic form with diminishing returns of consumption, see Appendix A.1.

Appendix A.3. Uncertainty scenarios

A schematic of the approaches to uncertainty considered here is given in Figure A.9. First, in the presence of a symmetrical probability distribution, the medium growth or best-guess (BG) case is the situation where—given an uncertain parameter θ described by a known probability distribution—an optimal decision path can be derived under complete information using the best-guess value of θ, $\mathbf{E}(\theta)$, where $\mathbf{E}$ is the expected value operator. With "decision path" we refer to optimal energy planning configurations (i.e. investments, fuel extraction and trade, and capacity retirement decisions). The second case of Figure A.9, learn-then-act (LTA), describes a counterfactual, where uncertainty about θ is completely resolved before energy planning is performed, thus it can be fully adapted to each state-of-the-world (a "state-of-the-world" describes one realization of θ). Third, act-then-learn (ATL) is the case where all θ values remain possible and the decision path takes into account all of them at once. But the decision makers will eventually learn or be able to make better assumptions about the uncertain parameter; at a certain point in time uncertainty is resolved and the decisions after that point can be tailored to the individual messages received. Last, no-learn (NL) is a special case of ATL where learning never happens and decisions are taken under uncertainty throughout the time horizon.

Appendix A.4. How to hedge against growth uncertainty

Appendix A.4.1. Hedging in the absence of climate policy

Hedging is defined as the deviation of the single optimal decision path—produced with REMIND-S—when compared with the path of the deterministic case. But why does hedging appear in the first place, i.e. why is the single optimal path not simply the mean value between the growth scenarios (i.e. the medium growth—or best-guess—result in the case of a symmetrical probability distribution, like in this study)? The latter can be obtained by a simple scenario analysis, without stochasticity. In mathematical form (using the same notation as in Figure A.9):

$$\arg\max_{I} \mathbf{E}[U(\theta)] \quad \neq \quad \arg\max_{I_{BG}} U[\mathbf{E}(\theta)] \tag{A.1}$$

To answer this question we look into how uncertainty affects optimal investments. Uncertainty in economic growth leads to changes in optimal investment decisions already in the baseline case, in investments in the macroeconomic capital stock as well as energy investments. These changes occur while seeking one single energy investment path, i.e. the best compromise between all the possible growth scenarios (only one is allowed in REMIND-S because energy planning decisions cannot be tailored to individual growth scenarios prior to learning), when the decision maker necessarily ends up with a trajectory that lies somewhere between the optimal paths of the deterministic scenarios. This is the solution that includes the lowest sacrifice: the least possible overinvestment in case a low growth scenario realizes, the least possible underinvestment in case a high growth scenario realizes, and, if possible, neither overinvestment nor underinvestment in case the medium growth realizes. Indeed, as seen in Figure A.10 the overall result is an investment path (grey line) that lies between the High- and Low-growth scenarios, but lower than the medium growth path (black line), as the effect of uncertainty does not propagate linearly through the growth scenarios, see Equation A.1. More specific, if optimal investments were to lie above the medium growth case and a low growth scenario materialized, this suboptimality turns out to be more expensive than if the investments lie under the medium growth case, because in the high growth case the society is wealthier.

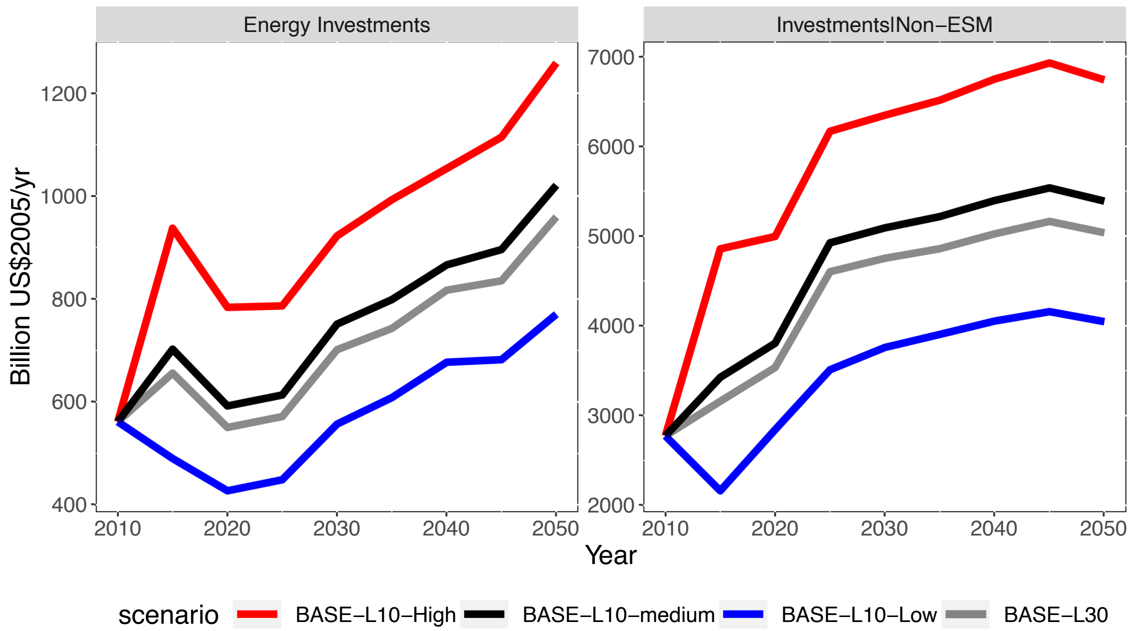

Figure A.10: Hedging in investments in the baseline case for China. Left: Energy investments. Right: Macro-economic investments. Note: macro-economic investments in the stochastic case are not equal across the growth scenarios, the grey line of the right graph describes the average. Energy investments are equalized in REMIND-S by definition.

Furthermore, as seen in Figure A.11, the percent reductions in optimal energy technology investments under uncertainty are not the same for each technology, showing a) energy-specific robust strategies in the baseline, and b) highlighting the necessity to use a technology-rich model for the present analysis.

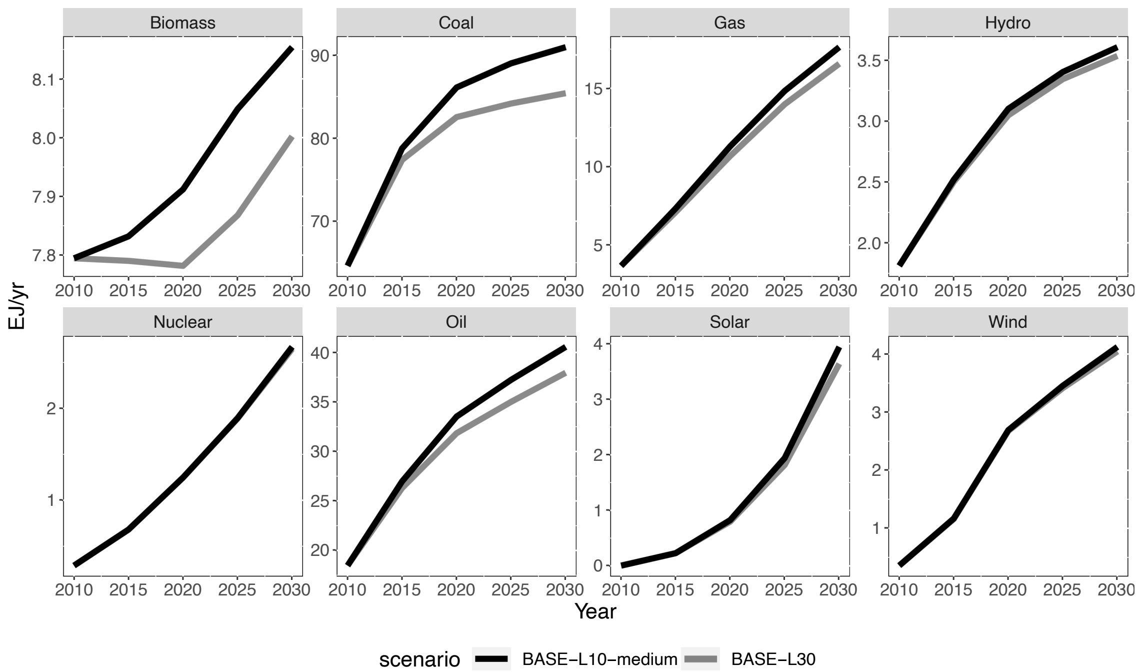

Figure A.11: Variation in the optimal use of key energy sources between the medium-growth/full-information and the BASE-L30 case (both without climate policy) in China. percent reduction is not the same for all energy types.

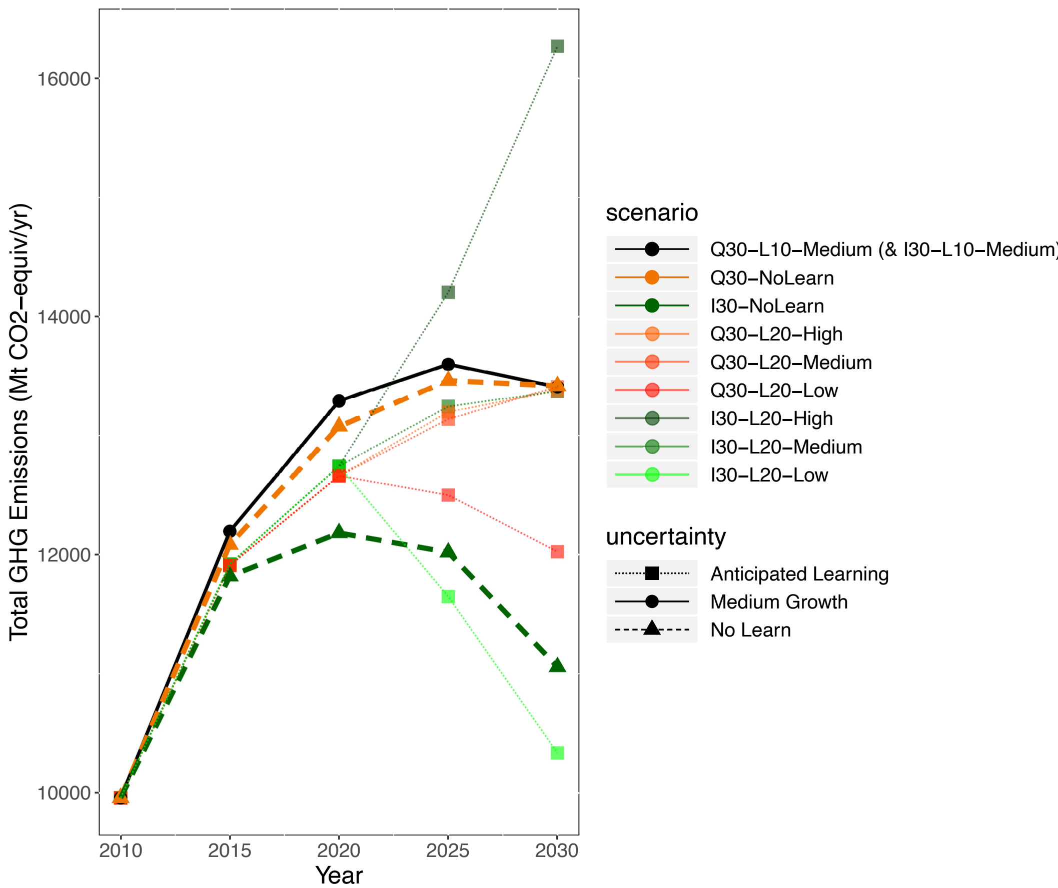

Figure A.12: Hedging (defined as the deviation from the medium-growth full-information line) in emissions in the scenarios with and without anticipated learning for stand-alone 2030 targets in China. Hedging is given by the difference between circles and triangles and is much stronger in the case of an intensity target (dark green vs. orange dashed lines), but is almost equalized when learning in 2020 is considered (squares in 2020). The separate paths after 2020 exist because energy planning can adapt to individual growth scenarios only after the learning point.

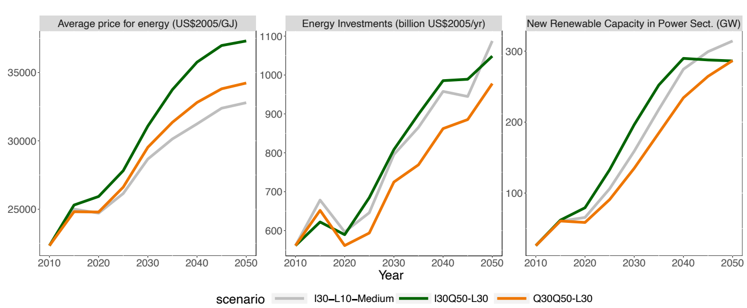

Figure A.13: Left: Energy is cheaper in the case of a quantity target in China, as a result of a wait-and-see strategy. Right: Optimal energy investments increase under uncertainty in the intensity target case, but decrease for a quantity target.

Appendix A.4.2. The effect of anticipated learning

When anticipated learning is considered (with a learning step in 2020, see A.12), more hedging (compared to the no-learn case) takes place in the quantity target scenario, as the available information after 2020 allows for the energy planner to respond to the upcoming target in 2030 individually, thus increasing investment and subsequently,

Table A.4: Effect of uncertainty and target type on welfare (expressed as percent changes in aggregate policy costs and measured in *certainty-equivalent balanced growth equivalents; CBGE*) for China: In the left column, a comparison of policy costs until 2030 between the deterministic and the scenarios with and without anticipated learning is shown. We see that anticipated learning about uncertainties increases welfare significantly (difference between Expected Value of Perfect Information; EVOPI, and Expected Value of Information; EVOI), and quantity targets can generate less costs than intensity targets. In the far right column, as reference, we show the corresponding climate policy costs until 2030, i.e. BASE-L30 vs. I30-L30 and Q30-L30, and baseline vs. policy with anticipated learning

	Target Type	EVOPI	Reference Costs
No-Learn	Quantity	3.16	0.62
	Intensity	4.1	1.6
		EVOI	
Anticipated Learning	Quantity	1.23	-0.06
	Intensity	1.32	-0.03

welfare, see Table A.4 (more on this in the next paragraph). All the Q30-L20 scenarios meet the 13.4 Gt target in 2030, except for the low growth scenario, where the target is not constraining, because overinvestment prior to the learning point combined with low growth result in a pathway with emission reductions stronger than what the target dictates. Overall, we see that learning eliminates to a great extend the difference between a quantity and intensity target. This is reflected also in the respective coal usage as seen in Figure A.14

The welfare losses due to uncertainty, measured in *certainty- and balanced-growth equivalents* (CBGE), sum up to 4.1 percent of net present value of total consumption, see Appendix A.5 for a detailed definition of the CBGE. This is called expected value of perfect information (EVOPI), and is reduced when learning is considered, as seen in Table A.4. The associated metric is called expected value of information (EVOI). This shows that with reduced uncertainty (learning), the target type choice plays less of an important role in the decision-making process.

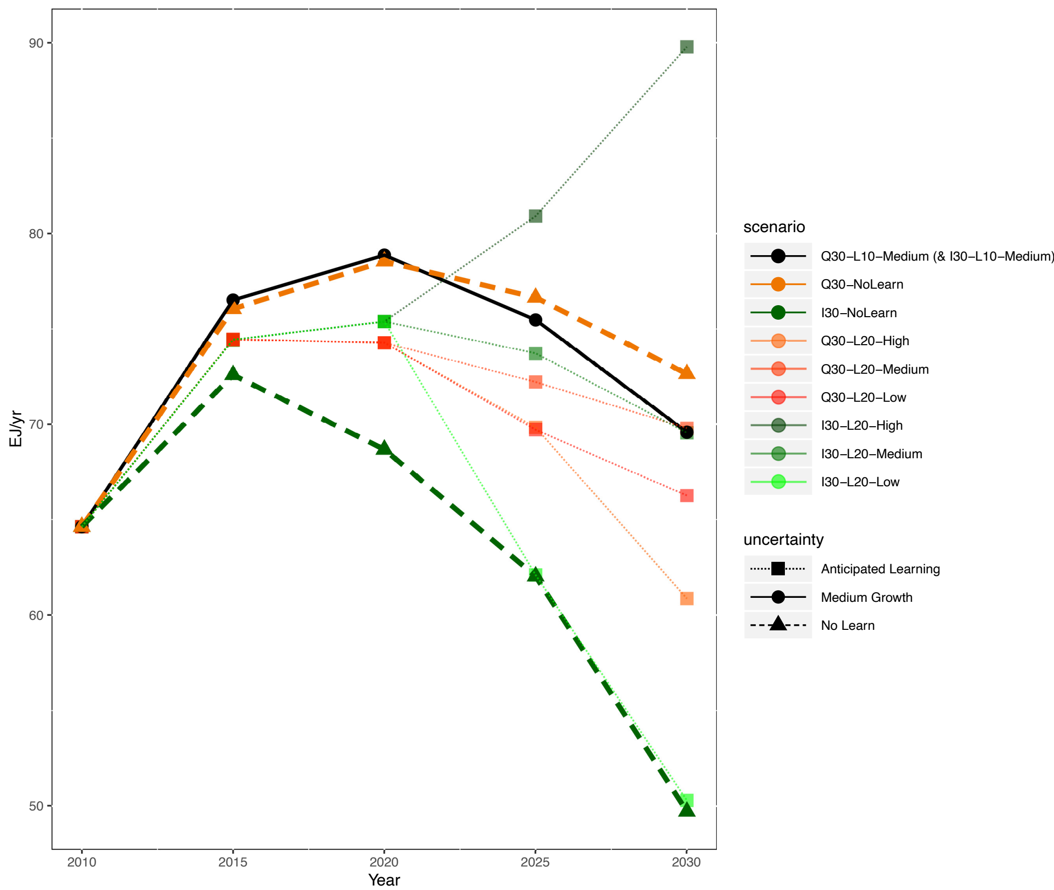

Figure A.14: Coal usage in China in the 2030 target case. The quantinty no-learn scenario features no decrease in coal consumption, compared to the deterministic medium-growth, but with anticipated learning (L20) coal is reduced. There is only one no-learn scenario for each target because all 3 scenarios have the same optimal energy planning, by definition (the same happens for the L20 scenarios prior to learning).

Appendix A.5. Policy costs measured in balanced growth equivalents

Climate policy costs in integrated assessment models are usually formulated in terms of relative differences in intertemporal, aggregated, and discounted consumption (or GDP) between cases with and without policy. When comparing climate policy costs across different baselines, as happens here where different growth scenarios are considered, this method of comparison fails to capture the welfare effects correctly, as for each case one ends up using a different yardstick. A measure that is more adequate is the *balanced growth equivalent* (BGE), which describes the amount of today's consumption, that, when extended into the future with a growth rate α, results in the same amount of utility U as the scenario in question. In mathematical form the BGE is the solution of the following equation with respect to γ:

$$\sum_{t=0}^{T} U[\gamma(\omega)(1+\alpha)^t]P_t(1+\rho)^{-t} = W(\omega) \tag{A.2}$$

where ω is the policy in question, P is population, t is the time and T the time horizon, ρ is the discount rate and W is the welfare. For a standard constant relative risk aversion utility function we get:

$$\gamma(\omega) = [(1-\eta)W(\omega)]^{\frac{1}{1-\eta}} \Big[\sum_{t=0}^{T} \frac{(1+\alpha)^{t(1-\eta)} P_t}{(1+\rho)^t} \Big]^{-\frac{1}{1-\eta}} \text{ , for } \eta \neq 0 \tag{A.3}$$

and

$$\gamma(\omega) = \exp\Big(\frac{W(\omega) - \ln(1+\alpha) \sum_{t=0}^{T} t P_t (1+\rho)^{-t}}{\sum_{t=0}^{T} P_t (1+\rho)^{-t}} \Big) \text{ , for } \eta = 0 \tag{A.4}$$

where η is the intertemporal elasticity of consumption.

Using the BGE relative differences between scenarios with different baselines are easily and intuitively comparable. For scenarios where expected utility is maximized the *certainty- and balanced-growth equivalent* is defined as the expected value of the BGE and used as adequate policy measure:

$$\text{CBGE} \equiv \mathbf{E}(\text{BGE}) = \sum_{i=1}^{s} \text{BGE}_i p_i \tag{A.5}$$

Appendix A.6. Sensitivity of policy costs on the growth of GDP

Here the results of a sensitivity analysis on the GDP growth rate in the deterministic case are presented (Table A.5).

Appendix A.7. Description of target rating criteria

We discuss the relative attractiveness of sequential intensity and quantity targets in terms of the criteria listed below (the respective categories are provided in brackets), based on the sequencing scenarios (Q30-L30 and I30-L30) of section 5.2.1. The expected value, i.e. the average between the three possible growth scenarios is taken for the calculation of all indicator values. The Q50-L10 medium-growth/full-information scenario—with which we normalize where noted—features full information about growth and 2050 target, and no 2030 target. For plots of the indicators see Figure 8. For a detailed view of the optimal paths in each growth scenario see Figure A.15.

GHG emissions [Environmental]

We describe the emissions indicator in terms of the total amount of GHG emissions emitted by each target type scenario in the period 2005-2050. The indicator is harmonized with the total GHG emissions reduction of the full-information scenario in the period 2005-2050.

Carbon price [Efficiency]

The size of the carbon price that has to be exerted on the economy for the target to be met. To account for time variability we take the net present value in 2020 (discounted at 5%) of the price path until 2050, and express the indicator as percentage of the medium-growth full-information case.

Welfare loss [Efficiency]

The welfare loss indicator measures which target features a smaller reduction of social welfare against the baseline in the period 2005-2050, relative to the reduction of the medium-growth full-information path (which thus has a value of 100%). We use BGE values in 2050 in order to account for baseline variability, see Appendix A.5.

Idle coal capacity [Disruptiveness]

Table A.5: Expansion of Table 2: Comparison of welfare effects until 2030 measured as percent changes in *balanced growth equivalents* (BGE, see Appendix A.5) for the different target types of the stand-alone 2030 scenarios. The GDP growth rate is increased gradually (in 10% steps) until the value that corresponds to the scenarios considered in our study in order to examine the sensitivity of policy costs to the GDP growth rate. The last two rows are the corresponding climate policy costs (i.e. comparison with the baseline) for each target and for the same period, which we use for reference.

Scenarios compared	**ΔBGE 2030 (%)**
High growth (I30-L10-High vs. Q30-L10-High)	1.00
High growth 90% (I30-L10-High vs. Q30-L10-High)	0.90
High growth 80% (I30-L10-High vs. Q30-L10-High)	0.82
High growth 70% (I30-L10-High vs. Q30-L10-High)	0.73
High growth 60% (I30-L10-High vs. Q30-L10-High)	0.67
High growth 50% (I30-L10-High vs. Q30-L10-High)	0.60
High growth 40% (I30-L10-High vs. Q30-L10-High)	0.48
High growth 30% (I30-L10-High vs. Q30-L10-High)	0.37
High growth 20% (I30-L10-High vs. Q30-L10-High)	0.25
High growth 10% (I30-L10-High vs. Q30-L10-High)	0.12
Medium growth (I30-L10-Medium vs. Q30-L10-Medium)	0
Low growth 10% (I30-L10-Low vs. Q30-L10-Low)	-0.09
Low growth 20% (I30-L10-Low vs. Q30-L10-Low)	-0.20
Low growth 30% (I30-L10-Low vs. Q30-L10-Low)	-0.27
Low growth 40% (I30-L10-Low vs. Q30-L10-Low)	-0.41
Low growth 50% (I30-L10-Low vs. Q30-L10-Low)	-0.55
Low growth 60% (I30-L10-Low vs. Q30-L10-Low)	-0.65
Low growth 70% (I30-L10-Low vs. Q30-L10-Low)	-0.75
Low growth 80% (I30-L10-Low vs. Q30-L10-Low)	-0.80
Low growth 90% (I30-L10-Low vs. Q30-L10-Low)	-0.90
Low growth (I30-L10-Low vs. Q30-L10-Low)	-0.97
Quantity (BASE-L10 vs. Q30-L10)	0.6
Intensity (BASE-L10 vs. I30-L10)	0.75

Expected retired coal capacity in the power sector (i.e. retired capacity that has not reached the end of its lifetime). To take into account also the years a power plant would spent in idle mode, we aggregate over time. The indicator is normalized with the medium-growth full-information scenario value.

Cost volatility [Disruptiveness]

The sequencing scenarios with unanticipated announcement of the 2050 target, exhibit a myopic behavior which can lead to jumps in costs. To capture these we calculate the difference in the carbon price across the various growth scenarios in the time before and after the target announcement (2030). Since each growth scenario has an independent carbon price, we take the expected value of the differences for each scenario in order to derive the cost volatility indicator.

Expected Value of Information [Expectation Stabilization]

Describes the value—in terms of welfare gains—of learning about growth uncertainty in 2030, i.e. it compares the BGE of the I30-L30 and Q30-L30 scenarios with the BGE of scenarios with no learning. See Table A.4 for more information on this indicator.

Non-optimal investment [Expectation Stabilization]

Acting under uncertainty necessarily leads to a suboptimal allocation of resources, as explained in section Appendix A.4. Thus, prior to the learning point, energy investment will be suboptimal. We measure this suboptimality by comparing the absolute difference between the net present value (with a discount rate of 5%) of the total energy investment of the period 2010-2030, i.e. up to the learning point, in the full-information case and each target scenario. Thus, medium-growth full-information has a zero value by definition, and we scale with the baseline value.

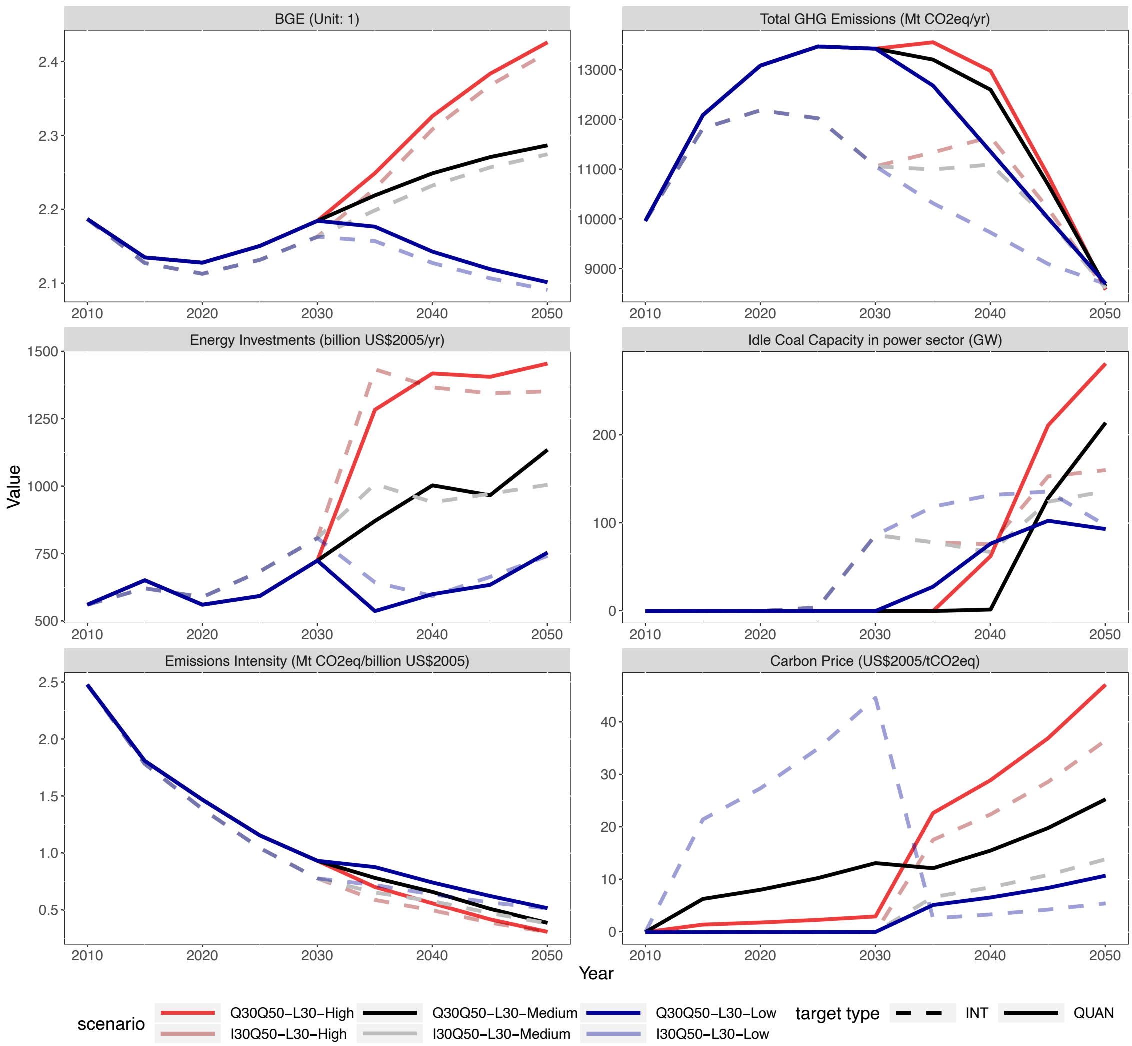

Figure A.15: Target sequencing scenarios for China: detailed view (with each growth scenario plotted separately) of the variables used for deriving the indicators for target comparison.

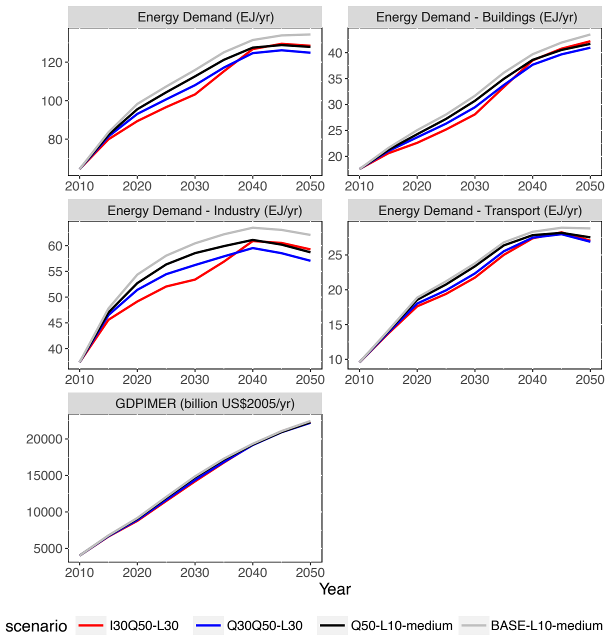

Figure A.16: Optimal paths of energy demand (total, and by sector) and GDP for the sequencing scenarios for China, under uncertainty. The graph shows how target sequencing shapes optimal emissions paths, plotted next to the hypothetical, full-information case of the 2 °C compatible stand-alone target in 2050—which we used to derive the optimal 2030 targets—and the counterfactual baseline scenario.

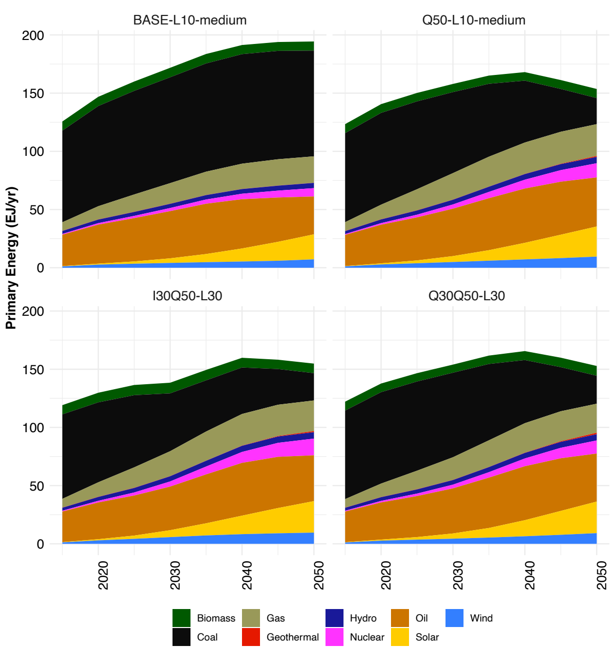

Figure A.17: Optimal energy mixes for the sequencing scenarios for China, under uncertainty. The graph shows how target sequencing shapes optimal emissions paths, plotted next to the hypothetical, full-information case of the 2 °C compatible stand-alone target in 2050—which we used to derive the optimal 2030 targets—and the counterfactual baseline scenario.

References

Akimoto, K., Sano, F., Oda, J., Homma, T., Rout, U.K., Tomoda, T., 2008. Global emission reductions through a sectoral intensity target scheme. Climate Policy 8, S46–S59. URL: http://dx.doi.org/10.3763/cpol.2007.0492, doi:10.3763/cpol.2007.0492.

Anda, J., Golub, A., Strukova, E., 2009. Economics of climate change under uncertainty: Benefits of flexibility. Energy Policy 37, 1345–1355. URL: http://www.sciencedirect.com/science/article/pii/S0301421508007155, doi:10.1016/j.enpol.2008.11.034.

Anthoff, D., Tol, R.S.J., 2009. The Impact of Climate Change on the Balanced Growth Equivalent: An Application of FUND. Environmental and Resource Economics 43, 351–367. URL: https://doi.org/10.1007/s10640-009-9269-5, doi:10.1007/s10640-009-9269-5.

Baker, E., Shittu, E., 2008. Uncertainty and endogenous technical change in climate policy models. Energy Economics 30, 2817–2828. URL: http://www.sciencedirect.com/science/article/pii/S0140988307001211, doi:10.1016/j.eneco.2007.10.001.

Bauer, N., Rose, S.K., Fujimori, S., van Vuuren, D.P., Weyant, J., Wise, M., Cui, Y., Daioglou, V., Gidden, M.J., Kato, E., Kitous, A., Leblanc, F., Sands, R., Sano, F., Strefler, J., Tsutsui, J., Bibas, R., Fricko, O., Hasegawa, T., Klein, D., Kurosawa, A., Mima, S., Muratori, M., 2018. Global energy sector emission reductions and bioenergy use: overview of the bioenergy demand phase of the EMF-33 model comparison. Climatic Change URL: https://doi.org/10.1007/s10584-018-2226-y, doi:10.1007/s10584-018-2226-y.

Bosetti, V., Tavoni, M., 2009. Uncertain R&D, backstop technology and GHGs stabilization. Energy Economics 31, Supplement 1, S18–S26. URL: http://www.sciencedirect.com/science/article/pii/S0140988308000455, doi:10.1016/j.eneco.2008.03.002.

Christensen, P., Gillingham, K., Nordhaus, W., 2018. Uncertainty in forecasts of long-run economic growth. Proceedings of the National Academy of Sciences 115, 5409–5414. URL: http://www.pnas.org/content/115/21/5409, doi:10.1073/pnas.1713628115.

Drouet, L., Emmerling, J., 2016. Climate policy under socio-economic scenario uncertainty. Environmental Modelling & Software 79, 334–342. URL: http://www.sciencedirect.com/science/article/pii/S1364815216300305, doi:10.1016/j.envsoft.2016.02.010.

Dudek, D., Golub, A., 2003. Intensity targets: pathway or roadblock to preventing climate change while enhancing economic growth? Climate Policy 3, S21–S28. URL: http://www.tandfonline.com/doi/abs/10.1016/j.clipol.2003.09.010, doi:10.1016/j.clipol.2003.09.010. 12.

Edenhofer, O., Steckel, J.C., Jakob, M., Bertram, C., 2018. Reports of coals terminal decline may be exaggerated. Environmental Research Letters 13, 024019. URL: http://stacks.iop.org/1748-9326/13/i=2/a=024019, doi:10.1088/1748-9326/aaa3a2.

Ellerman, A.D., Wing, I.S., 2003. Absolute versus intensity-based emission caps. Climate Policy 3, S7–S20. URL: http://www.tandfonline.com/doi/abs/10.1016/j.clipol.2003.09.013, doi:10.1016/j.clipol.2003.09.013. 34.

Golub, A., Narita, D., Schmidt, M.G.W., 2014. Uncertainty in Integrated Assessment Models of Climate Change: Alternative Analytical Approaches. Environmental Modeling & Assessment 19, 99–109. URL: http://link.springer.com/article/10.1007/s10666-013-9386-y, doi:10.1007/s10666-013-9386-y.

Goulder, L.H., Morgenstern, R.D., Munnings, C., Schreifels, J., 2017. China's National Carbon Dioxide Emission Trading System: An Introduction. Economics of Energy & Environmental Policy 6. URL: http://www.iaee.org/en/publications/eeeparticle.aspx?id=175, doi:10.5547/2160-5890.6.2.lgou.

Grubb, M., Sha, F., Spencer, T., Hughes, N., Zhang, Z., Agnolucci, P., 2015. A review of Chinese CO2 emission projections to 2030: the role of economic structure and policy. Climate Policy 15, S7–S39. URL: https://doi.org/10.1080/14693062.2015.1101307, doi:10.1080/14693062.2015.1101307. publisher: Taylor & Francis _eprint: https://doi.org/10.1080/14693062.2015.1101307.

Guan, D., Meng, J., Reiner, D.M., Zhang, N., Shan, Y., Mi, Z., Shao, S., Liu, Z., Zhang, Q., Davis, S.J., 2018. Structural decline in Chinas CO 2 emissions through transitions in industry and energy systems. Nature Geoscience , 1URL: https://www.nature.com/articles/s41561-018-0161-1, doi:10.1038/s41561-018-0161-1.

Hawksworth, J., Audino, H., Clarry, R., 2017. The World in 2050. Technical Report. PwC.

Heal, G., Kristrm, B., 2002. Uncertainty and Climate Change. Environmental and Resource Economics 22, 3–39. URL: https://link.springer.com/article/10.1023/A:1015556632097, doi:10.1023/A:1015556632097.

Heal, G., Millner, A., 2014. Uncertainty and Decision Making in Climate Change Economics. Review of Environmental Economics and Policy 8, 120–137. URL: https://academic.oup.com/reep/article/8/1/120/1590265/ReflectionsUncertainty-and-Decision-Making-in, doi:10.1093/reep/ret023.

IEA/OECD, 2018. IEA/OECD Coal statistics. URL: https://www.oecd-ilibrary.org/energy/data/iea-coal-information-statistics/oecd-coal-statistics_data-00554-en.

IPCC, 2014. Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel of Climate Change. Technical Report.

IPCC, 2018. Global warming of 1.5C. An IPCC Special Report on the impacts of global warming of 1.5C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change, sustainable development, and efforts to eradicate poverty. Technical Report.

Jensen, S., Traeger, C.P., 2014. Optimal climate change mitigation under long-term growth uncertainty: Stochastic integrated assessment and analytic findings. European Economic Review 69, 104–125. URL: http://www.sciencedirect.com/science/article/pii/S0014292114000105, doi:10.1016/j.euroecorev.2014.01.008.

Kann, A., Weyant, J.P., 2000. Approaches for performing uncertainty analysis in large-scale energy/economic policy models. Environmental Modeling & Assessment 5, 29–46. URL: https://link.springer.com/article/10.1023/A:1019041023520, doi:10.1023/A:1019041023520.

Kriegler, E., Bauer, N., Popp, A., Humpender, F., Leimbach, M., Strefler, J., Baumstark, L., Bodirsky, B.L., Hilaire, J., Klein, D., Mouratiadou, I., Weindl, I., Bertram, C., Dietrich, J.P., Luderer, G., Pehl, M., Pietzcker, R., Piontek, F., Lotze-Campen, H., Biewald, A., Bonsch, M., Giannousakis, A., Kreidenweis, U., Mller, C., Rolinski, S., Schultes, A., Schwanitz, J., Stevanovic, M., Calvin, K., Emmerling, J., Fujimori, S., Edenhofer, O., 2017. Fossil-fueled development (SSP5): An energy and resource intensive scenario for the 21st century. Global Environmental Change 42, 297–315. URL: http://www.sciencedirect.com/science/article/pii/S0959378016300711, doi:10.1016/j.gloenvcha.2016.05.015.

Kriegler, E., Bertram, C., Kuramochi, T., Jakob, M., Pehl, M., Stevanovic, M., Hhne, N., Luderer, G., Minx, J.C., Fekete, H., Hilaire, J., Luna, L., Popp, A., Steckel, J.C., Sterl, S., Yalew, A.W., Dietrich, J.P., Edenhofer, O., 2018. Short term policies to keep the door open for Paris climate goals. Environmental Research Letters URL: http://iopscience.iop.org/10.1088/1748-9326/aac4f1, doi:10.1088/1748-9326/aac4f1.

Kriegler, E., Edmonds, J., Hallegatte, S., Ebi, K.L., Kram, T., Riahi, K., Winkler, H., Vuuren, D.P.v., 2014a. A new scenario framework for climate change research: the concept of shared climate policy assumptions. Climatic Change 122, 401–414. URL: http://link.springer.com/article/10.1007/s10584-013-0971-5, doi:10.1007/s10584-013-0971-5.

Kriegler, E., Weyant, J.P., Blanford, G.J., Krey, V., Clarke, L., Edmonds, J., Fawcett, A., Luderer, G., Riahi, K., Richels, R., Rose, S.K., Tavoni, M., Vuuren, D.P.v., 2014b. The role of technology for achieving climate policy objectives: overview of the EMF 27 study on global technology and climate policy strategies. Climatic Change 123, 353–367. URL: http://link.springer.com/article/10.1007/s10584-013-0953-7, doi:10.1007/s10584-013-0953-7. 00138.

Li, N., Chen, W., Rafaj, P., Kiesewetter, G., Schpp, W., Wang, H., Zhang, H., Krey, V., Riahi, K., 2019. Air Quality Improvement Co-benefits of Low-Carbon Pathways toward Well Below the 2 C Climate Target in China. Environmental Science & Technology 53, 5576–5584. URL: https://doi.org/10.1021/acs.est.8b06948, doi:10.1021/acs.est.8b06948. publisher: American Chemical Society.

Lu, Y., Stegman, A., Cai, Y., 2013. Emissions intensity targeting: From China's 12th Five Year Plan to its Copenhagen commitment. Energy Policy 61, 1164–1177. URL: http://www.sciencedirect.com/science/article/pii/S030142151300582X, doi:10.1016/j.enpol.2013.06.075.

Luderer, G., Leimbach, M., Bauer, N., Kriegler, E., Baumstark, L., Bertram, C., Giannousakis, A., Hilaire, J., Klein, D., Levesque, A., Mouratiadou, I., Pehl, M., Pietzcker, R., Piontek, F., Roming, N., Schultes, A., Schwanitz, V.J., Strefler, J., 2015. Description of the REMIND Model (Version 1.6). SSRN Scholarly Paper ID 2697070. Social Science Research Network. Rochester, NY. URL: https://papers.ssrn.com/abstract=2697070.

Luderer, G., Vrontisi, Z., Bertram, C., Edelenbosch, O.Y., Pietzcker, R.C., Rogelj, J., Boer, H.S.D., Drouet, L., Emmerling, J., Fricko, O., Fujimori, S., Havlk, P., Iyer, G., Keramidas, K., Kitous, A., Pehl, M., Krey, V., Riahi, K., Saveyn, B., Tavoni, M., Vuuren, D.P.V., Kriegler, E., 2018. Residual fossil CO 2 emissions in 1.52 C pathways. Nature Climate Change 8, 626. URL: https://www.nature.com/articles/s41558-018-0198-6, doi:10.1038/s41558-018-0198-6.

Marangoni, G., Tavoni, M., Bosetti, V., Borgonovo, E., Capros, P., Fricko, O., Gernaat, D.E.H.J., Guivarch, C., Havlik, P., Huppmann, D., Johnson, N., Karkatsoulis, P., Keppo, I., Krey, V., Broin, E., Price, J., van Vuuren, D.P., 2017. Sensitivity of projected long-term CO2 emissions across the Shared Socioeconomic Pathways. Nature Climate Change advance online publication. URL: http://www.nature.com/nclimate/journal/vaop/ncurrent/full/nclimate3199.html, doi:10.1038/nclimate3199. 00000.

Marschinski, R., Edenhofer, O., 2010. Revisiting the case for intensity targets: Better incentives and less uncertainty for developing countries. Energy Policy 38, 5048–5058. URL: http://www.sciencedirect.com/science/article/pii/S0301421510003071, doi:10.1016/j.enpol.2010.04.033. 12.

Mi, Z., Meng, J., Guan, D., Shan, Y., Song, M., Wei, Y.M., Liu, Z., Hubacek, K., 2017a. Chinese CO 2 emission flows have reversed since the global financial crisis. Nature Communications 8, 1–10. URL: https://www.nature.com/articles/s41467-017-01820-w, doi:10.1038/s41467-017-01820-w. number: 1 Publisher: Nature Publishing Group.

Mi, Z., Wei, Y.M., Wang, B., Meng, J., Liu, Z., Shan, Y., Liu, J., Guan, D., 2017b. Socioeconomic impact assessment of China's CO2 emissions peak prior to 2030. Journal of Cleaner Production 142, 2227–2236. URL: http://www.sciencedirect.com/science/article/pii/S0959652616318935, doi:10.1016/j.jclepro.2016.11.055.

Morgan, M.G., 2018. Uncertainty in long-run forecasts of quantities such as per capita gross domestic product. Proceedings of the National Academy of Sciences 115, 5314–5316. URL: http://www.pnas.org/content/115/21/5314, doi:10.1073/pnas.1805767115.

Mouratiadou, I., Luderer, G., Bauer, N., Kriegler, E., 2016. Emissions and their drivers: sensitivity to economic growth and fossil fuel availability across world regions. Climatic Change 136, 23–37. URL: http://link.springer.com/10.1007/s10584-015-1368-4, doi:10.1007/s10584-015-1368-4.

Neuenkirch, M., Neumeier, F., 2015. The impact of UN and US economic sanctions on GDP growth. European Journal of Political Economy 40, 110–125. URL: http://www.sciencedirect.com/science/article/pii/S0176268015000816, doi:10.1016/j.ejpoleco.2015.09.001.

OECD, O., 2018. Domestic product - GDP long-term forecast - OECD Data. URL: http://data.oecd.org/gdp/gdp-long-term-forecast.htm.

ONeill, B.C., Kriegler, E., Riahi, K., Ebi, K.L., Hallegatte, S., Carter, T.R., Mathur, R., Vuuren, D.P.v., 2014. A new scenario framework for climate change research: the concept of shared socioeconomic pathways.

Climatic Change 122, 387–400. URL: http://link.springer.com/article/10.1007/s10584-013-0905-2, doi:10.1007/s10584-013-0905-2.

Pahle, M., Burtraw, D., Flachsland, C., Kelsey, N., Biber, E., Meckling, J., Edenhofer, O., Zysman, J., 2018. Sequencing to ratchet up climate policy stringency. Nature Climate Change 8, 861–867. URL: https://www.nature.com/articles/s41558-018-0287-6, doi:10.1038/s41558-018-0287-6.

Peterson, S., 2005. Uncertainty and economic analysis of climate change: A survey of approaches and findings. Environmental Modeling & Assessment 11, 1–17. URL: http://link.springer.com/article/10.1007/s10666-005-9014-6, doi:10.1007/s10666-005-9014-6.

Pietzcker, R.C., Ueckerdt, F., Carrara, S., de Boer, H.S., Desprs, J., Fujimori, S., Johnson, N., Kitous, A., Scholz, Y., Sullivan, P., Luderer, G., 2017. System integration of wind and solar power in integrated assessment models: A cross-model evaluation of new approaches. Energy Economics 64, 583–599. URL: http://www.sciencedirect.com/science/article/pii/S0140988316303395, doi:10.1016/j.eneco.2016.11.018.

Pizer, W.A., 2005. The case for intensity targets. Climate Policy 5, 455–462. URL: http://www.tandfonline.com/doi/abs/10.1080/14693062.2005.9685570, doi:10.1080/14693062.2005.9685570. 49.

Quirion, P., 2005. Does uncertainty justify intensity emission caps? Resource and Energy Economics 27, 343–353. URL: http://www.sciencedirect.com/science/article/pii/S0928765505000382, doi:10.1016/j.reseneeco.2005.05.002. 23.

Riahi, K., van Vuuren, D.P., Kriegler, E., Edmonds, J., ONeill, B.C., Fujimori, S., Bauer, N., Calvin, K., Dellink, R., Fricko, O., Lutz, W., Popp, A., Cuaresma, J.C., KC, S., Leimbach, M., Jiang, L., Kram, T., Rao, S., Emmerling, J., Ebi, K., Hasegawa, T., Havlik, P., Humpender, F., Da Silva, L.A., Smith, S., Stehfest, E., Bosetti, V., Eom, J., Gernaat, D., Masui, T., Rogelj, J., Strefler, J., Drouet, L., Krey, V., Luderer, G., Harmsen, M., Takahashi, K., Baumstark, L., Doelman, J.C., Kainuma, M., Klimont, Z., Marangoni, G., Lotze-Campen, H., Obersteiner, M., Tabeau, A., Tavoni, M., 2017. The Shared Socioeconomic Pathways and their energy, land use, and greenhouse gas emissions implications: An overview. Global Environmental Change 42, 153–168. URL: http://www.sciencedirect.com/science/article/pii/S0959378016300681, doi:10.1016/j.gloenvcha.2016.05.009.

Roelfsema, M., van Soest, H.L., Harmsen, M., van Vuuren, D.P., Bertram, C., den Elzen, M., Hhne, N., Iacobuta, G., Krey, V., Kriegler, E., Luderer, G., Riahi, K., Ueckerdt, F., Desprs, J., Drouet, L., Emmerling, J., Frank, S., Fricko, O., Gidden, M., Humpender, F., Huppmann, D., Fujimori, S., Fragkiadakis, K., Gi, K., Keramidas, K., Kberle, A.C., Aleluia Reis, L., Rochedo, P., Schaeffer, R., Oshiro, K., Vrontisi, Z., Chen, W., Iyer, G.C., Edmonds, J., Kannavou, M., Jiang, K., Mathur, R., Safonov, G., Vishwanathan, S.S., 2020. Taking stock of national climate policies to evaluate implementation of the Paris Agreement. Nature Communications 11, 1–12. URL: https://www.nature.com/articles/s41467-020-15414-6, doi:10.1038/s41467-020-15414-6. number: 1 Publisher: Nature Publishing Group.

Stern, N., 2007. The Economics of Climate Change by Nicholas Stern. URL: /core/books/economics-of-climate-change/A1E0BBF2F0ED8E2E4142A9C878052204, doi:10.1017/CBO9780511817434.

Sue Wing, I., Ellerman, A.D., Song, J., 2006. Absolute vs. Intensity Limits for CO2 Emission Control: Performance Under Uncertainty. Technical Report. MIT Joint Program on the Science and Policy of Global Change. URL: http://dspace.mit.edu/handle/1721.1/31204. 9.

Traeger, C.P., 2009. Recent Developments in the Intertemporal Modeling of Uncertainty. Annual Review of Resource Economics 1, 261–286. URL: http://dx.doi.org/10.1146/annurev.resource.050708.144242, doi:10.1146/annurev.resource.050708.144242.

UNEP, 2017. The Emissions Gap Report 2017: A UN Environment Synthesis Report. URL: https://wedocs.unep.org/handle/20.500.11822/22070.

UNFCCC, 2015. Paris Agreement. UNFCCC URL: https://unfccc.int/process-and-meetings/the-paris-agreement/the-paris-agreement.

Vuuren, D.v., Elzen, M.d., Berk, M., Moor, A.d., 2002. An evaluation of the level of ambition and implications of the Bush Climate Change Initiative. Climate Policy 2, 293–301. URL: https://doi.org/10.3763/cpol.2002.0235, doi:10.3763/cpol.2002.0235.

Wang, H., Chen, W., Bertram, C., Malik, A., Kriegler, E., Luderer, G., Desprs, J., Jiang, K., Krey, V., 2019a. Early transformation of the Chinese power sector to avoid additional coal lock-in. Environmental Research Letters URL: http://iopscience.iop.org/10.1088/1748-9326/ab5d99, doi:10.1088/1748-9326/ab5d99.

Wang, H., Chen, W., Zhang, H., Li, N., 2019b. Modeling of power sector decarbonization in China: comparisons of early and delayed mitigation towards 2-degree target. Climatic Change URL: https://doi.org/10.1007/s10584-019-02485-8, doi:10.1007/s10584-019-02485-8.

Wang, J., Wu, Y., Zhao, Y., He, S., Dong, Z., Bo, W., 2019c. The population structural transition effect on rising per capita CO2 emissions: evidence from China. Climate Policy 19, 1250–1269. URL: https://doi.org/10.1080/14693062.2019.1664381, doi:10.1080/14693062.2019.1664381.

Wang, Q., 2014. China should aim for a total cap on emissions. Nature News 512, 115. URL: http://www.nature.com/news/china-should-aim-for-a-total-cap-on-emissions-1.15705, doi:10.1038/512115a.

Webster, M., Sue Wing, I., Jakobovits, L., 2010. Second-best instruments for near-term climate policy: Intensity targets vs. the safety valve. Journal of Environmental Economics and Management 59, 250–259. URL: http://www.sciencedirect.com/science/article/pii/S0095069610000240, doi:10.1016/j.jeem.2010.01.002. 16.

Zheng, J., Mi, Z., Coffman, D., Milcheva, S., Shan, Y., Guan, D., Wang, S., 2019. Regional development and carbon emissions in China. Energy Economics 81, 25–36. URL: http://www.sciencedirect.com/science/article/pii/S0140988319300829, doi:10.1016/j.eneco.2019.03.003.

Zhu, B., Jiang, M., Wang, K., Chevallier, J., Wang, P., Wei, Y.M., 2018. On the road to China's 2020 carbon intensity target from the perspective of double control. Energy Policy 119, 377–387. URL: http://www.sciencedirect.com/science/article/pii/S0301421518302416, doi:10.1016/j.enpol.2018.04.025.

Zhu, B., Wang, K., Chevallier, J., Wang, P., Wei, Y.M., 2015. Can China achieve its carbon intensity target by 2020 while sustaining economic growth? Ecological Economics 119, 209–216. URL: http://www.sciencedirect.com/science/article/pii/S0921800915003638, doi:10.1016/j.ecolecon.2015.08.015.