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Optimal international technology cooperation for the low-carbon transformation

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Abstract

Research on low-carbon transformation pathways has focused on carbon pricing as a means for climate stabilization. By contrast, technology policies remain the more prominent national climate policy instruments today: renewable energy subsidies amount to more than US$100 billion per year globally – more than twice the value of priced carbon in 2016. Given technology spillovers and global learning effects it remains unclear how technology policies can be coordinated internationally as part of climate stabilization policy. Our study is the first to derive optimal technology and climate policy for the 2°C target using an energy-economy-climate model. We show an economic rationale to include an international technology protocol alongside carbon pricing: Cumulative low-carbon subsidies of more than US$1 trillion from 2020 until the end of the century mainly support solar power as well as electric- and hydrogen-powered passenger vehicles. Higher carbon pricing could replace subsidies at very low cost, but mitigation cost increases from delayed carbon pricing can be reduced only somewhat by stepping up subsidies. Our study suggests that existing low-carbon subsidies must be complemented by full carbon pricing to achieve 2°C cost-efficiently: Alongside the optimal carbon price, low-carbon subsidies should amount to no more than ∼6% of the value of priced carbon.

Policy insights :

- international spillovers in low-carbon technologies may slow their deployment
- we derive optimal technology and climate policy for 2C in an energy-economy-climate model

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- subsidies of more than US$1 trillion support mainly solar and advanced car technologies
- replacing all subsidies by carbon pricing barely increases mitigation costs

Keywords: climate change mitigation; technology subsidies; optimal policy instruments; learning-by-doing; Integrated Assessment

1 Introduction

The international community agrees that global warming should be limited to "well below" 2°C above the pre-industrial temperature (UNFCCC 2015), but negotiations so far have not resulted in commitment to sufficient emissions reduction (Luderer et al. 2013b; Tavoni et al. 2014; Spencer et al. 2015). Technology cooperation and technology policy continue to play an important role in the UNFCCC process. Meanwhile, policies supporting renewable energy have been enacted in more than 100 countries (International Energy Agency 2016): Subsidies for renewable energy production were around US$120 billion in 2015 (International Energy Agency 2016), much higher than the value of priced carbon at around US$50 billion in 2016 (World Bank; Ecofys; Vivid Economics 2016). Most of these subsidies supported solar and wind power (International Energy Agency 2016). Even though these subsidies have multiple objectives, reducing emissions is their primary aim in many countries, especially among countries that subsidize the most in global comparison: In Germany, the country where most renewable energy support was paid out in 2013, climate protection is named as the most important objective among stakeholders (Joas et al. 2014). Still, it is controversial whether for example the German renewable subsidies actually contribute to reducing greenhouse gas (GHG) emissions, given overlaps with EU policies and international interactions (Frondel et al. 2010).

Consequently, coordinating technology policies internationally has the potential to advance climate policy by increasing efficiency and opening up technology support to public funds such as the Green Climate Fund (Coninck et al. 2008; Asselt and Zelli 2013). It is not clear, however, how large a role technology subsidies can play in cooperative international climate policy, and which low-carbon technologies should be supported the most (Aldy et al. 2010).

One economic rationale for technology policy are market failures in the development and deployment of energy technologies (Jaffe et al. 2005). Optimal technology policy as a means to correct these market failures under carbon pricing has so far been characterized using stylized models (Fischer and Newell 2008). The standard result is that subsidizing the dynamically superior technologies can prevent costly lock-ins in the energy system, as for example shown in single-region growth models with simple technology representation (Schneider and Goulder 1997; Kverndokk and Rosendahl 2007; Kalkuhl et al. 2012). Obviously, the results obtained in these studies depend strongly on the modeling detail in energy technologies. Technology-rich energy-economy-climate models did not include optimal technology policies, but rather relied on guesstimated combinations of technology policies (Rao et al. 2006; Kahouli-Brahmi 2008; Bauer et al. 2012b; Kypreos and Turton 2011; Marcucci and Turton 2013; Bertram et al. 2015). Some studies using technology-rich models derived the optimal spending on public research and development (R&D) for energy technologies (Bosetti et al. 2008; Bosetti et al. 2009). Current levels of public R&D spending are, however, much lower than technologies subsidies: Member countries of the International Energy Agency, which includes most advanced economies around the world, spent just US$17 billion on public energy R&D in 2014, of which only around a fifth goes to renewable energy research (Internation Energy Agency 2015). Consequently, our contribution focuses on technologies subsidies instead of public R&D, as public R&D spending is only such a small fraction of the funds spent on renewable energy production subsidies.

Knowing the optimal policy instruments is a requirement to implement the low-carbon transformation cost-efficiently, and assessing the compatibility of current levels of renewable energy subsidies with climate policy is of pressing concern. Our study is the first to calculate optimal technology subsidies as part of cooperative climate stabilization using an integrated energy-economy-climate model with high technological resolution in the energy and transport sector. We close a gap in the literature between optimal policy models and technology-rich models – informing policy design about the cost-efficient mix of carbon pricing and technology subsidies for climate stabilization. This study thus addresses the structure and timing of technology subsidies: When and where should emerging low-carbon technologies be subsidized? To what extent can technology subsidies substitute for carbon pricing?

2 Methodology

2.1 Model

To identify optimal climate stabilization policies we use the integrated energy-economy-climate model REMIND (Leimbach et al. 2010; Bauer et al. 2012a; Luderer et al. 2013a). REMIND is a global model integrating the energy and the climate system into the macro-economy in a coherent way, and has elements of a top-down macro-economic and a bottom-up technology model. There are eleven model regions[1], connected by trade in generic goods, and energy resources. Our modeling results are by no means predictions of future developments, but rather a tool to assess the trade-offs between different long-term policy scenarios. We use the Shared Socioeconomic Pathways scenario SSP2 for assumptions on GDP and population growth (Dellink et al. 2017; KC and Lutz 2017). The model is described in full detail by Luderer et al. (2015).

[1] The eleven regions in REMIND are: The individual countries China (CHN), India (IND), Japan (JPN), The United States of America (USA), and Russia (RUS), as well as the aggregated regions European Union (EUR), Latin America (LAM), Sub-Saharan African countries with the exception of South Africa (AFR), Middle East and North Africa (MEA), Other Asia (OAS), and Rest of the World (ROW).

The energy system captures inertia and path-dependencies by representing more than 50 energy-conversion technologies as capital stocks with vintaging. Investments into these technologies are subject to adjustment costs. Energy prices reflect resource scarcities, as well as final energy taxes and subsidies (Schwanitz et al. 2014). Final energy is an input to the production process, where it is combined with labour and capital in a nested constant elasticity of substitution production function to produce GDP. Energy is used in a stationary and a transport sector: In the transport sector, mobility demand for light-duty passenger vehicles is derived within the nested production function. Demand is met by three vehicle propulsion technologies that are perfect substitutes (up to a maximum share of around 90% for the latter two): internal combustion engine, battery electric, and fuel cell (hydrogen). In the stationary sector, fossil and non-fossil technologies are good substitutes in the supply of each final energy type.

Induced technological progress is captured through learning-by-doing for some technologies with the highest learning rates – the emerging low-carbon technologies. In the literature, induced technological progress is usually attributed to either learning-by-doing, research and development, or a combination of both (Goulder and Mathai 2000). It has been argued though that research and development with finite patent lifetimes has dynamics similar to learning-by-doing (Gerlagh et al. 2009). That, and the much smaller extent of R&D spending compared to spending on low-carbon subsidies, as cited in the introduction, motivate our choice of including cost reductions through learning-by-doing effects only. Investment costs decrease endogenously due to learning-by-doing in some technologies: wind power, photovoltaics (PV), concentrated solar power (CSP), energy storage, and electric- and hydrogen-powered (fuel cell) passenger vehicles in the transport sector. Specifically, investment costs decrease with cumulative capacities through global learning curves in these six low-carbon technologies, approaching floor costs.

The learning rate – the decrease in specific investment cost for every doubling of cumulative capacity – is highest for PV. We use the estimate by Pietzcker et al. (2014) for the PV learning rate of 20%, who also describe in detail the solar energy potentials data we use. In our model calibration, reducible costs are ∼70% of the specific investment cost for PV in 2015 (Pietzcker et al. 2014). Reducible costs are the share of initial cost that can be reduced by learning over time, while the rest of the costs are floor costs. CSP learns at a initial rate of 8%, with a ∼80% share of reducible costs (Pietzcker et al. 2014). Wind power is a more mature technology, with only 16% of reducible costs in 2015, but still learns at 10%. The two technologies for non-fossil passenger vehicles are assumed to have learning rates of 10%, and their share of reducible costs is around 50% in 2015.

GHG emissions from the energy system and land-use[2] are translated into radiative forcing levels and global mean temperature using the MAGICC climate model (Meinshausen et al. 2011).

2.2 External effects

All of our climate policy scenarios stabilize the climate at a radiative forcing level in 2100 consistent with the RCP2.6 scenario – which corresponds to limiting the global mean temperature increase to below 2°C above pre-industrial levels with a probability of $> 66\%$ (Stocker et al. 2013). The necessary emission reductions are implemented by a carbon tax on GHG emissions that rises at a rate of 5% p.a., potentially, in some policy scenarios, along with subsidies on low-carbon technologies. Depending on the specific scenario, carbon pricing is assumed to be available to different degrees (see Tab. 1): Immediate, globally uniform, and optimal carbon pricing; regionally differentiated carbon pricing in the near future; permanently sub-optimal carbon pricing.

Additionally to the climate externality, we model an externality in technological progress. This is motivated by the evidence that firms fail to appropriate the full benefits of learning in emerging low-carbon technologies (Jaffe et al. 2005; Bollinger and Gillingham 2014; Benthem et al. 2007). We model a spillover externality in learning-by-doing. An investment by the representative firm of a model region in a technology that is subject to learning-by-doing causes a global spillover: A part of this global spillover accrues in the representative firm's own region, but most of it accrues to firms in all other world regions. Seen the other way around, parts of the spillover from the investment of other countries' firms accrues to each respective region[3]. The representative firm in each region thus fails to anticipate the spillover in form of future reductions in investment cost through learning-by-doing, both through their own investment (intertemporal externality) and through the investment of other regions' firms (interregional externality).

Reliable estimates for how much of the spillover, be it onto their own region and onto other regions, firms are unable to appropriate are not available. We assume that firms cannot appropriate any of of the spillover that accrues in regions other than their own. This is a reasonable assumption, as for example a European firm

[2] Land-use and agricultural emissions as well as bioenergy supply and other land-based mitigation options are represented via reduced-form emulators derived from the detailed land-use and agricultural model MAgPIE.

[3] Technically, the spillover externality is implemented as follows: The cumulative capacities of low-carbon technologies that drive the learning curves are not endogenously linked to the control variables describing investment into these technologies in this optimization problem. Instead, we calculate cumulative capacities ex-post and iterate the model to its fixed point. In effect, firms do not anticipate but still enjoy the positive effect of learning-by-doing. For more details see Leimbach et al. (2017).

would not consider the beneficial spillovers onto firms overseas in their investment decision. Additionally, we assume that firms also fail to appropriate the part of the spillover that accrues to themselves. This can be understood as myopic behaviour of the representative firm. While this might seem an extreme assumption, its impact on our results is limited, as we discuss further later in this section. This means that the smaller part of the spillover is external because the representative firm is myopic, and does not anticipate being able to appropriate future benefits from learning-by-doing – the intertemporal externality. The largest part of the spillover, however, is caused by firms' failure to appropriate today's and future benefits of learning-by-doing that accrue in regions other than their own – the interregional externality.

Assuming that firms cannot appropriate the spillovers, an underinvestment in emerging low-carbon technologies results – learning is a global public good. We find the non-cooperative solution (named NoSub) with respect to this spillover, where regions play a Nash game in choosing their learning investments – the details of the underlying algorithm are described by Leimbach et al. (2017). The resulting equilibrium shows a Pareto-inefficiently low investment in technologies subject to learning-by-doing. While there is no technology policy in the NoSub scenario, co-operative climate policy in the form of carbon pricing is enacted from 2020 on to reach the 2°C target.

By contrast, in the first-best scenario (named Optimal), carbon taxation from 2020 on internalizes the emissions externality and an optimal subsidy protocol internalizes the spillover. The main methodological innovation of this paper is to identify the set of technology- and region-specific subsidies on investment costs that internalizes the spillover. These subsidies quantify the technology support to be mandated by an optimal international technology protocol.

We determine the globally uniform per unit subsidy as the sum over the spillovers of a unit of capacity investment on all regions. The spillovers at time t for technology T on region r are the capitalized marginal benefits of learning $M_{r,t,T}$[4]. We then calculate the subsidy for technology T at time t, denoted by $S_{t,T}$, as the sum over the regional capitalized benefits of learning:

$$S_{t,T} = \sum_{r \in \text{all regions}} M_{r,t,T} \tag{1}$$

After the initial adoption of the technology the per unit subsidy declines rapidly,

[4] In our implementation, we calculate the capitalized marginal benefits of learning from the shadow price of the equation that describes the capacity build up. Conversion of this shadow price to a monetary value (dollar per watt) is achieved by normalizing with the shadow price of the budget restriction equation. We iterate the model until the the capitalized marginal benefits, and hence the subsidy, do not change anymore.

reflecting decreasing learning effects with cumulative capacities. Capacity additions $c_{r,t,T}$ in each region r are subsidized at the per unit subsidy, such that the subsidy paid out is $S_{t,T} \cdot c_{r,t,T}$. Each region subsidizes its own capacity additions, and finances the subsidy by a lump-sum tax on households. In effect, this technology subsidy protocol transforms the non-cooperative solution into the first-best Optimal scenario, where regions cooperate to internalize the spillover alongside the climate externality.

We assume here that firms cannot appropriate any of the spillover, but the results are robust in this respect: Assuming instead that at least the spillover in each region due to its own investment is completely internal decreases the aggregate global subsidy by around 15% only, as most of the spillovers accrue to other regions anyway. Thus, our results may be considered an upper bound on the low-carbon subsidies due to learning-by-doing spillover. However, other external effects that we do not model in this study – such as learning-by-searching (i.e. research and development) – may justify additional subsidies for low-carbon technologies.

All climate policy scenarios are listed in Tab. 1. Mitigation costs are given as consumption losses from 2015 until 2100 with respect to a baseline scenario without climate and technology policy, discounted at the baseline interest rate of around 5% p.a.[5].

All but the Optimal scenario are second-best in one or the other respect: With no subsidy protocol in the NoSub scenario, a slightly higher carbon tax enforces the same climate target from 2020 on. In the delayTaxNoSub scenario, on the contrary, full carbon pricing is delayed: in a first phase, emissions are priced at regionally differentiated rates from 2015 on, reflecting today's varying ambitions in climate policy. The global average carbon price is 7 US$/tCO2 in 2015, and there is no technology policy in this scenario. Full carbon pricing only starts from 2035 on, which is not anticipated in the model during the first phase.

In addition to delayed carbon pricing, there is technology policy in the delayTaxHighSub scenario: An optimal subsidy internalizes the spillover in the second phase starting in 2035. Until 2035, high technology subsidies act as a second-best instrument to substitute for too low carbon pricing. This reflects that technology subsidies are the most common – and largest as measured by value – climate policy instruments globally today. We implement exogenous subsidies until 2035 above the level that internalizes the spillover. Using our method, we cannot identify the optimal level of subsidies in the case of delayed carbon pricing. Consequently, we specify low-carbon subsidies during the delay phase exogenously at a level that minimizes mitigation

[5] The baseline interest rate of around 5% p.a. results through the Ramsey rule from an exogenous utility discount rate (or rate of pure time preference) of 3% p.a. and an endogenous average growth rate of consumption of around 2% p.a..

cost.

3 Results and Discussion

3.1 Optimal policy

In the cost-efficient policy for the 2°C target – the Optimal scenario (Tab. 1) – regions agree on a globally uniform carbon price and a technology protocol. Full carbon pricing starts in 2020 at the global tax rate of US$31 per tonne of CO_2, realizing a tax revenue of US$1 trillion in 2020 alone. Subsidy expenditures are much smaller at ∼US$60 billion in 2020. The subsidy rises to US$370 billion in 2080 in constant terms (Fig. 1), which is still below 8% of the value of priced carbon in that year. Cumulated from 2020 to 2100, subsidies make up 6% of the value of priced carbon.

The cumulative present value of all subsidies under this protocol is US$1.4 trillion. Cost optimization implies that ∼60% of the cumulative present value is spent on solar power, and ∼30% on non-fossil passenger vehicles.

In 2020, PV subsidies are ∼US$50 billion; this figure stays roughly the same over the century, as increasing deployment volumes are balanced by decreasing per unit subsidies. For CSP, subsidies grow from ∼US$4 billion in 2020. The split between PV and CSP in total solar subsidies is 60% to 40%, but as PV and CSP are good substitutes, this technology split could be varied at low additional cost. Most of the solar subsidies are paid out in China, the United States, India, and the model region Sub-Saharan Africa, as seen from the regional allocation of subsidies in Fig. 2.

For non-fossil passenger vehicle technologies, two thirds of the cumulative subsidies go to electric cars and one third to hydrogen passenger vehicles – but again, these two non-fossil passenger vehicles are good substitutes in our model. More than half of the passenger vehicle subsidies until 2030 are carried by Europe.

Wind power subsidies, which decline from US$8 billion in 2020 on, and storage subsidies make up the rest of the bill. For every dollar in subsidies to variable renewables, 6 cent are spent on storage capacities in aggregate.

3.2 The technology protocol

In the scenario NoSub (see Tab. 1), regions do not agree on a technology protocol, and there are no subsidies from 2020 on. Instead, regions cooperatively price carbon at a slightly higher rate to reach the same climate target. Compared to this second-best NoSub scenario, the technology protocol of the Optimal scenario speeds up the low-carbon transformation: Variable renewables exceed the 25% share in total electricity generation around a decade earlier, and the adoption of non-fossil passenger vehicles is accelerated as well (Fig. 3).

Cumulative use of solar energy until 2100 increases by 15% through the optimal subsidy: This allows for a reduction of the use of wind power and of low-carbon technologies that face public opposition due to risks and sustainability issues such as nuclear power generation and technologies using carbon capture and storage by 5%.

Therefore, the subsidy protocol increases the efficiency of the low-carbon transformation: The carbon price required for climate stabilization in the Optimal scenario is 6% below the one in the NoSub scenario, but mitigation costs are only reduced marginally (Tab. 1).

The technical and economical potential of low-carbon technologies differs a lot between regions. We use the regional share of low-carbon subsidies in the fossil fuel carbon rent[6] as an indicator for the regional potential. The share ranges from 3% to 11% across regions: Sub-Saharan Africa has the highest share at 11% due to the large potential for solar power; the share is above 7% in Latin America and India. In Europe, China, and the USA the share is slightly above 6%, close to the global average. Rather little potential for low-carbon subsidies is found in Russia and Japan at below 4%.

If regions agree on the international climate and technology protocol, and pay for the subsidies in their respective region, the global public good of learning is optimally provided. Despite large regional differences in the subsidies, the technology protocol in the Optimal scenario does not result in large income shifts between regions: In aggregate, most of the benefits accrue to the regions that implement most of the subsidies. In other words, the net spillovers between regions due to the technology protocol are small. In fact, we find that the net spillovers are less than 5% of the total subsidy volume in the Optimal scenario, and mostly benefit today's developing regions. Note that no explicit transfer of technology or money is part of our climate policy scenarios: The net spillover in our model caused by the technology protocol is an implicit transfer through a decrease in the investment costs for low-carbon technologies.

In effect, taking into account not only the net spillovers but also including the reaction on international markets, the Optimal policy scenario increases welfare over the NoSub scenario for most model regions. Explicit transfer schemes may change the incentives such that all regions are better off through the Optimal policy, but this study rather outlines the optimal global agreement in a first step.

[6] The fossil fuel carbon rent is the aggregate value of priced carbon, collected through the tax in our model.

3.3 Subsidies cannot replace carbon pricing

Beyond internalizing the spillover, subsidies could substitute for too low carbon pricing, but this increases mitigation costs significantly. Higher subsidies still accelerate the adoption of low-carbon technologies, but rebound effects prevent effective emission reductions: If the carbon tax is permanently only 7% below the Optimal level, as in the LowTax scenario (Tab. 1), large low-carbon subsidies are required to still reach the same level of climate stabilization. However, this suboptimal policy mix increases mitigation costs significantly.

If instead full carbon pricing is delayed, mitigation costs increase strongly. In the DelayTaxNoSub scenario, carbon is only weakly priced – on global average at only US$7 – until full pricing starts in 2035. The resulting lock-in into carbon intensive infrastructure in the near term increases mitigation costs by a hefty 0.40 percentage points (pp) above the first-best level of 1.62% of discounted consumption. Using the method presented here we cannot determine the cost-optimal subsidy protocol when carbon pricing is delayed, but we find that up to some degree an increase in subsidies reduces the costs of the lock-in: Mitigation costs in the DelayTaxHighSub scenario are reduced to 0.31pp above the first-best level by a threefold increase in subsidies until 2030, and total subsidies of ∼US$2 trillion over the century – reducing the cost markup due to the lock-in by only around one-fourth. Additional policies, such as banning the construction of new coal-fired power plants, or an accelerated phase-out of final energy subsidies, have been shown to reduce the cost markup due to delayed carbon pricing further (Bertram et al. 2015).

4 Conclusions and Policy Implications

In summary, we complement the standard result that carbon pricing is by far the most important single element in cost-efficient cooperative climate stabilization (Jaffe et al. 2005; Aldy et al. 2010) by specifying the optimal subsidies for emerging low-carbon technologies. In our model, these subsidies compensate firms for non-appropriable spillovers from learning-by-doing in emerging low-carbon technologies. In total, the optimal subsidies amount to only 6% of the aggregate value of priced carbon if all spillovers are assumed to be external. To our knowledge this is the first such quantification of the optimal amount and structure of low-carbon subsidies for a 2°C pathway in the literature. Knowing about the optimal mix of carbon pricing and low-carbon subsidies is a valuable input to policy making, even though the current policy landscape may be far from it.

Subsidies for solar power make up around 60% of the optimal subsidy portfolio, non-fossil vehicle technologies around 30%, and wind power and energy storage technologies receive around 10%. We note that global solar and wind subsidies in

2013 of around US_{2013}\$80 billion (International Energy Agency 2014) are not much above the optimal value for the year 2020 of US_{2015}\$56 billion found in this study. We assumed here that the only rationale for subsidies is a fully non-appropriable spillover from learning-by-doing, whereas there are other reasons motivating governments to subsidize low-carbon energy. According to our results, current policies, in global aggregate, are unbalanced: low-carbon subsidies are too high and carbon pricing is too low. Although our results show that higher low-carbon subsidies can partially substitute for loo low carbon pricing in achieving a given climate target, such a substitution leads to a strong increase of total mitigation costs.

If full carbon pricing will be below around US\$30 per tonne of CO_2 in 2020, mitigation costs for the 2°C target increase significantly. We find that if full, global carbon pricing were delayed until 2035, mitigation costs rise irrespective of the subsidy policy – subsidies cannot replace carbon pricing. However, the mitigation cost increase can be reduced by a fourth by stepping up subsidies in the near term. Hence, suboptimally low carbon prices could be aided by higher near-term subsidies for low-carbon technologies, but subsidies must in no case replace efforts to price carbon.

Our study focuses on external effects in learning-by-doing, but there are other external effects associated with emerging technologies, giving rationales for additional policy interventions. Such external effects can often be found in research and development, demonstration, or early deployment of emerging energy technologies. Relevant external effects may also be found beyond technological progress itself, for example, in behavioral responses of individuals, or related to large-scale infrastructure investments and lock-ins (Grubb et al. 2014). In this work we assume that all external effects except for non-appropriable benefits from learning-by-doing and climate change are internalized by appropriate policy instruments. If there are external effects related to emerging low-carbon technologies in the real world that are not internalized, our model results underestimate the relative importance of subsidies compared to carbon pricing in optimal climate policy. By the same token, our model would underestimate the cost increase of climate policy relying on carbon pricing only.

The mitigation cost increase for an international climate agreement based only on carbon pricing – in contrast to an optimal mix of carbon pricing and low-carbon subsidies – is found to be very small. Including a subsidy protocol thus has to be, on the one hand, weighted against the uncertainties and difficulties in anticipating, determining, and enacting the technology-specific optimal rates and the resulting risk of cost increases due to failure to do so. On the other hand, most low-carbon technologies with learning externalities are capital-intensive, and thus are penalized by the high financing costs in many emerging economies and developing countries

(Ondraczek et al. 2015; Creutzig et al. 2017). The subsidies could thus take the form of de-risking measures, both financial (loan guarantees) and policy-oriented (improving local institutions, e.g. streamlining permitting processes) (Schmidt 2014). In todays' situation of low capital costs in developed countries, such de-risking measures may come relatively cheap, and policy-oriented de-risking measures may boost local development through financial and administrative capacity-building.

For a globally uniform carbon price to be socially optimal climate policy, transfer payments to compensate countries with high mitigation costs are required. We assume such transfers to be fully available in our model, but one may question their feasibility given the current state of international climate policy. Even if today such international transfers are not fully available yet, they may be a route to incentivize carbon pricing and according subsidy schedules, working towards a more effective global climate policy.

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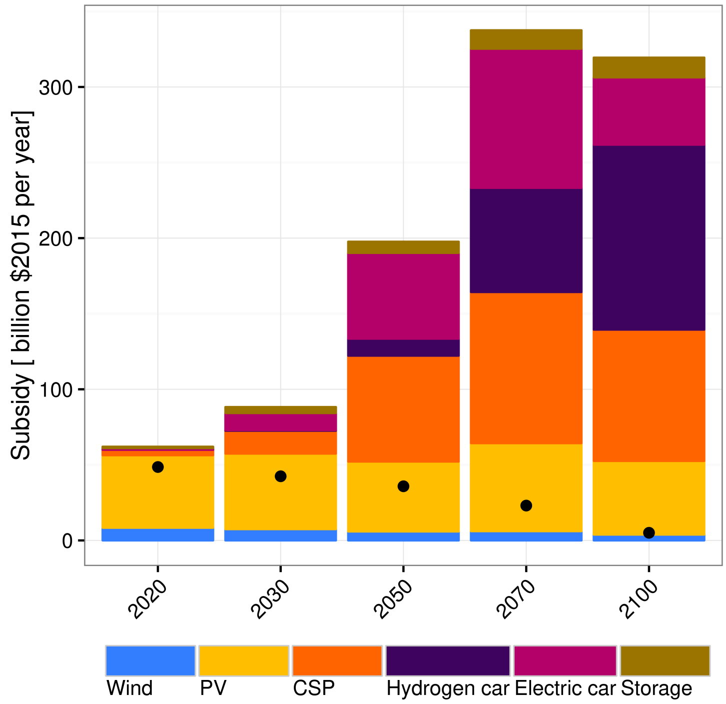

Figure 1: Optimal global subsidy by technology. Stacked bars show subsidy by technology in constant value terms, the black dots indicate the present value in US$$_{2015}$.

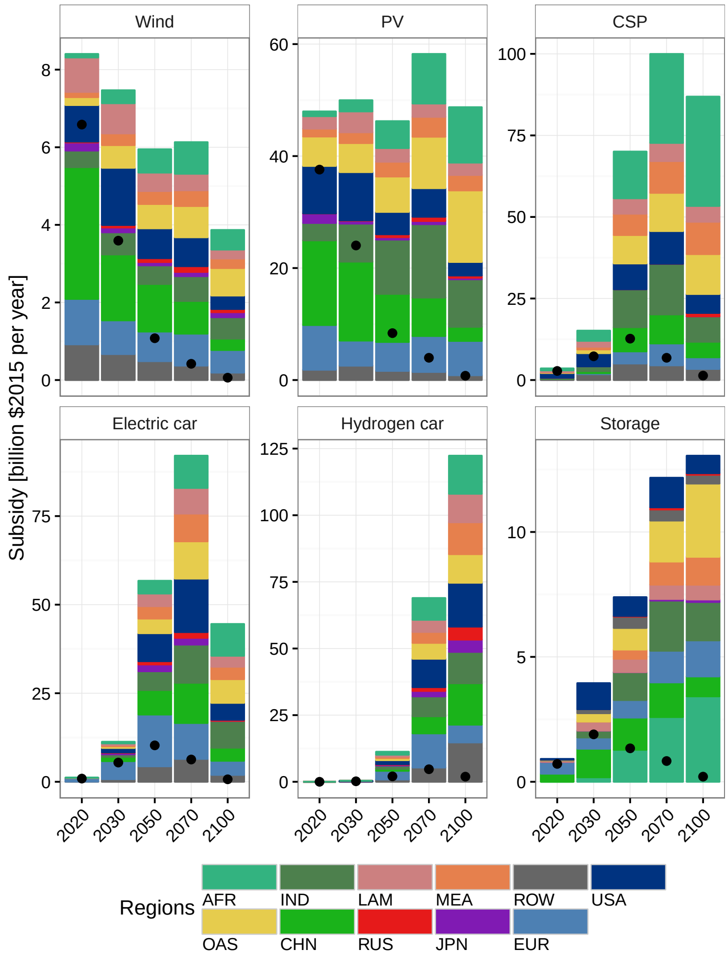

Figure 2: Optimal subsidy by region and technology. Stacked bars show regional distribution of the subsidy in constant value terms. Present values (in US$$_{2015}$) are indicated by black dots. Region code definitions are found in Section 2.1.

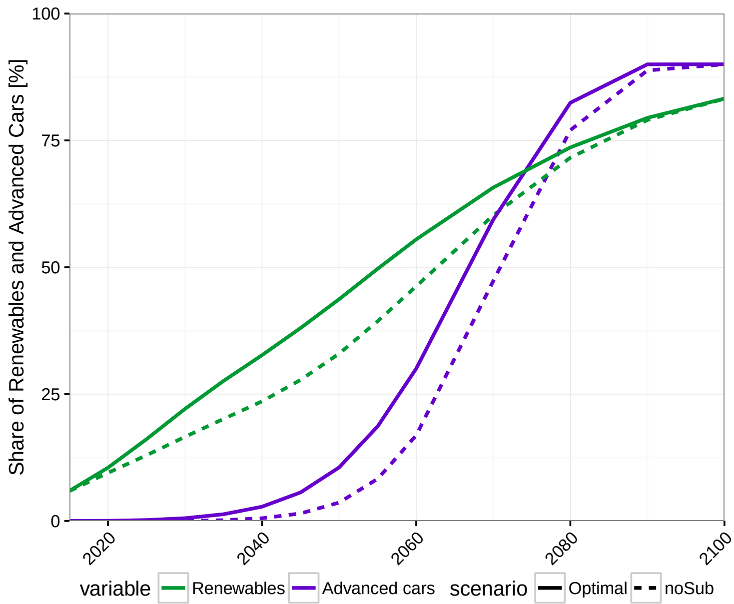

Figure 3: The low-carbon transformation accelerated by subsidies: The share of variable renewables in total electricity generation (green lines) and the share of non-fossil passenger vehicles in total vehicles (purple lines) is rising earlier in the Optimal (solid lines) than in the NoSub scenario (dotted lines).

List of Tables

Scenario	Description	Cost increase	Subsidies	Ratio subsidies/tax revenue	Tax level in 2020
NoSub	no subsidies, carbon tax from 2020 only	0.01 pp	0	0	33 US$/tCO2
Optimal	optimal mix of subsidies and tax from 2020	–	1.4 US$ trillion	6.2 %	31 US$/tCO2
LowTax	slightly too low tax from 2020, subsidies close the gap	0.08 pp	5.3 US$ trillion	26 %	28 US$/tCO2
DelayTaxNoSub	full tax from 2035 only, no subsidies	0.40 pp	0	0	7 US$/tCO2
DelayTaxHighSub	full tax from 2035, large subsidies before	0.31 pp	2.1 US$ trillion	8.2%	7 US$/tCO2

Table 1: Scenarios for climate stabilization at 2°C. Mitigation cost increases are in percentage points above the optimal (first-best) level of 1.62% of discounted consumption losses from 2015 to 2100. Cumulative values of subsidies and taxes are given in US$2015 net present value terms. Model results are highlighted over scenario assumptions in grey.