The effects of local interventions on global technological change through spillovers

A modeling framework and application to the road-freight sector

Journal Article

Author(s):
Noll, Bessie; Steffen, Bjarne; Schmidt, Tobias

Publication date:
2023-10-17

Permanent link:
https://doi.org/10.3929/ethz-b-000636160

Originally published in:
Proceedings of the National Academy of Sciences of the United States of America 120(42), https://doi.org/10.1073/pnas.2215684120

Funding acknowledgement:
847585 - RESPONSE - to society and policy needs through plant, food and energy sciences (EC)

PNAS RESEARCH ARTICLE | SUSTAINABILITY SCIENCE OPEN ACCESS

The effects of local interventions on global technological change through spillovers: A modeling framework and application to the road-freight sector

Bessie Noll[a,1], Bjarne Steffen[b,c], and Tobias S. Schmidt[a,c,1]

Edited by Amanda Giang, The University of British Columbia Institute for Resources, Environment and Sustainability, Vancouver, Canada; received September 15, 2022; accepted May 31, 2023 by Editorial Board Member William C. Clark

To address global sustainability challenges, (public) policy interventions are needed to induce or accelerate technological change. While most policy interventions occur on the local level, their innovation effects can spill over to other jurisdictions, potentially having global impact. These spillovers can increase or reduce the incentive for interventions. Lacking to date are computational models that capture these spillover dynamics. Here, we devise a conceptual and methodological approach to quantify ex ante the effects of local demand-side interventions on global competition between incumbent and novel technologies. We introduce two factors that moderate global spillovers—relative size of selection environments and relative innovation potential of competing technologies. Our approach incorporates both factors in a techno-economic discrete choice model that evaluates technology competition over time through endogenized technological learning. We apply this modeling framework to the case of road freight. Different demand-pull interventions and shocks are modeled to assess spillover effects. In the case of road freight, electric vehicles experience growth in most application segments but can still be accelerated substantially through public policy intervention—spillovers occur if strong public interventions are introduced in large regions or in multiple combined regions under club policy interventions. These findings are discussed in the context of club policy interventions and a modeled geopolitical shock in China. A full sensitivity analysis of model input parameters and intervention or shock dynamics reveals high model robustness. Finally, we discuss the implications of the road-freight case study as it might inform the progress of other niche technologies in transitioning sectors.

innovation spillovers | technology diffusion | road freight | electric vehicles | trucks

Significance

Redirection and acceleration of technological change through policy intervention is essential for addressing climate change and other sustainability challenges. We offer frameworks to conceptualize and model ex ante how local interventions can induce global technical change through innovation spillovers. Spillovers are a two-way street as they can increase the rationale for governments to intervene, thereby creating first-mover advantages for national industry; or reduce incentives, as spillovers reduce costs for other nations, thereby creating a free-rider problem. As such, it is particularly important to understand the extent of spillovers. We present a system-dynamics model that quantifies spillover effects and apply it to the road-freight sector. The developed model is generalizable and thus can also be applied to sustainability transitions in other sectors.

Society faces global environmental sustainability challenges that require sweeping institutional, behavioral, but, in particular, technological change (TC) at the global level. The importance of policy interventions in accelerating TC has been widely recognized (1). Interventions can increase the diffusion of "clean" but immature technologies into the market, thereby inducing innovation, accelerating cost reductions and thus facilitating competitiveness (2–6). Indeed, many sustainability challenges are global, though only few historical examples of meaningful global-level interventions exist (7–10). Most public interventions occur on the local, typically national level. Spillovers between jurisdictions can occur when incentives for a novel technology in one region positively (or negatively) influence the same technology's deployment in other regions, thereby inducing further learning. Many of these spillovers occur through exports, which is a key motivating factor for local policy intervention—for some technologies, a home market can enable experience that creates industry entry barriers and in turn, sustained competitive advantage outside of the home market (11, 12). Conversely, the tendency for nonintervening nations to "free-ride" without contribution is pervasive and difficult to overcome (13), particularly for standardized technologies (14). Lacking to date are models that conceptualize and quantify ex ante the scale of such global spillover effects, which is highly relevant for designing policies that induce TC to address global challenges.

Hitherto, broadly, three groups of models are primarily used to forecast TC: techno-economic projection models, economic equilibrium models including integrated assessment models (IAMs), and other heterodox adoption diffusion models such as system-dynamics models or agent-based models. Techno-economic projection models while dynamic and often global in scope with regional disaggregation do not consistently endogenize technological learning and rarely incorporate innovation spillover effects (15–18). A second cohort of models, IAMs or other economic equilibrium models used to project technology pathways, has more recently endogenized technological improvements of energy technologies (e.g., solar PV plants) through learning curves where past global deployment

This paper is part of a Special Feature on Modeling Dynamic Systems for Sustainable Development. The collection of all PNAS Special Features in the Sustainability Science portal is available here: https://www.pnas.org/sustainability-science.

The authors declare no competing interest.

This article is a PNAS Direct Submission. A.G. is a guest editor invited by the Editorial Board.

[1]To whom correspondence may be addressed. Email: bessie.noll@gess.ethz.ch or tobiasschmidt@ethz.ch.

This article contains supporting information online at https://www.pnas.org/lookup/suppl/doi:10.1073/pnas.2215684120/-/DCSupplemental.

Published October 9, 2023.

affects future technology cost (19–23). While IAMs may include resolution in different countries or world regions, technology costs are typically global parameters, following a global learning curve. Examining "local" intervention spillover effects in IAMs is therefore difficult. Finally, more heterodox technology adoption diffusion models are typically characterized by high case-specific technological detail, endogenized TC, and representative behavioral realism (24–29). Yet, few are truly global models that can capture jurisdictional spillovers. *SI Appendix*, Tables S25–S27 provide an overview of select models for each group.

In addition, a growing literature of model development papers seeks to improve the representation of some aspects of technology forecast modeling in further detail. In particular, illustrating the effects of cooperative ("club") interventions on TC and spillovers has become more prominent in recent studies (30, 31). Representing innovation spillovers is crucial in these newer studies, though mechanisms for modeling spillovers are varied. One common approach is exogenous spillover determination via spillover matrices or spillover weights estimated from patent citations or other historical data (30, 32, 33). Besides their novel insights, such static formulations are not able to project the competition between novel technologies in markets that are transformed radically, as is the case for low-carbon energy transitions. Spillovers are often either regionally constrained or not disaggregated at all. Policy interventions that limit spillovers (e.g., through national-level content requirements or import tariffs) have also been recently examined in studies that contextualize green industrial policy (34–37).

To address these modeling gaps and add to the literature on improved representation of innovation spillovers, we devise a framework and methodological approach to quantifying the effects of local demand-side interventions on global competition between incumbent and novel technologies. We emphasize the interactive nature of jurisdictions in the framework through which we can endogenize global transitions in more geographical detail through innovation spillovers. Besides incomplete spillovers due to local customization, two factors are introduced that moderate global spillovers—relative size of selection environment, and relative innovation potential of competing technologies. Our modeling approach incorporates these factors in a techno-economic discrete choice model that evaluates technology competition over time through endogenized technological learning and intervention scenarios with a high level of technological granularity.

We apply this framework to the case of decarbonizing road freight, a sector which contributes to just under half of global road-based transport carbon emissions and is particularly troubling for low-income communities often situated near local air pollution hotspots (1, 38). Though low-carbon (and less air-polluting) alternative technologies for road freight have emerged, uncertainty remains around which technologies to transition to, how fast, and in which specific applications (39). We model the road-freight transition to zero-emission alternatives, such as battery electric or fuel cell electric vehicles, by simulating competition between incumbent and niche technologies to project market shares of new vehicles sold globally through 2035. Different demand-pull interventions in select or combined jurisdictions are modeled, to assess global spillover effects. We stress that the model is primarily a conceptual advancement and therefore most useful for application and showcasing of the framework to specific case studies in transitioning sustainability sectors.

The results show that spillovers can be substantial and depend largely upon the relative market size of the intervening jurisdiction(s) as well as the relative "starting position" (i.e., initial deployment) and relative experience rates of competing technologies. In the case of road freight, electric vehicles (EV) experience growth in light- and medium-duty application segments absent intervention, reaching ~60% global market share of new vehicles sold by 2035. However, EV growth in all application segments, especially for heavy-duty segments, can be further accelerated through policy intervention and spillovers. Spillovers occur if strong policies are introduced in large markets such as China and the European Union (EU). Cooperative interventions in policy clubs can enhance spillover effects if clubs represent large markets. Private-sector interventions based on corporate fleet commitments display minimal effects and appear rather insignificant. An isolation of China from the rest of the world shows the importance of free exchange of goods and knowledge for global transition dynamics. We discuss insights from the road-freight case study and derive implications for other niche technologies competing in transitioning sectors. Finally, we conclude with a contextualization of the modeling contribution and a discussion of potential limitations and users.

Frameworks

Conceptual Framework. First, we propose a conceptual framework for understanding the effects of a national policy intervention on global innovation toward greater sustainability. We do this by estimating innovation spillovers from a local intervention in a select jurisdiction to the global level (Fig. 1 illustrates the fundamental process). Sustainability transitions typically involve the initial emergence and eventual mass adoption of "clean" technologies in a given market (niche), though the transformational path is largely unknown a priori (40–42). Capturing dynamic technology competition that integrates path dependency and increasing returns to scale is therefore central to understanding transitional outcomes (43–45). In this framework, we define two competing technologies: a niche "clean" technology (Fig. 1, in orange) and an incumbent "dirty" technology (Fig. 1, in blue). We also define the selection environment as the jurisdiction within which technology competition occurs. Dynamic selection of competing technologies in jurisdiction *Jp* gives baseline deployment projections measured in market shares. As a result of a local intervention in jurisdiction *Jp* (Fig. 1, red star), deployment of the niche technology is accelerated *globally* (Fig. 1, red market shares). Importantly here, we distinguish increased niche technology deployment in the intervening jurisdiction (*Jp*) from increased deployment in all other jurisdictions (*World – Jp*). The local intervention induces innovation directly in the intervening jurisdiction but also indirectly in other jurisdictions through innovation spillovers. Effectively, accelerated deployment is enabled through global cost reductions and increased competitiveness of the niche technology.

Besides incomplete spillovers (see below), two factors moderate these spillovers—the relative size of selection environment and the relative innovation potential of competing technologies. We utilize an outcome metric, deployment, to quantify the diffusion of innovation ex ante (refs. 17 and 46–48 and *SI Appendix*, Table S28). Complex "clean" technologies gain experience and improve with each additional unit of deployment (43–45). Accordingly, the relative size of the selection environment in which the intervention occurs is crucial—the larger the relative market size (i.e., the size of the markets within which technologies compete in different jurisdictions), the greater the relative deployment potential and subsequent spillover potential Eq. **1**.

$$\Delta s = \frac{S_{J_p}}{S_{World-J_p}}, \qquad [1]$$

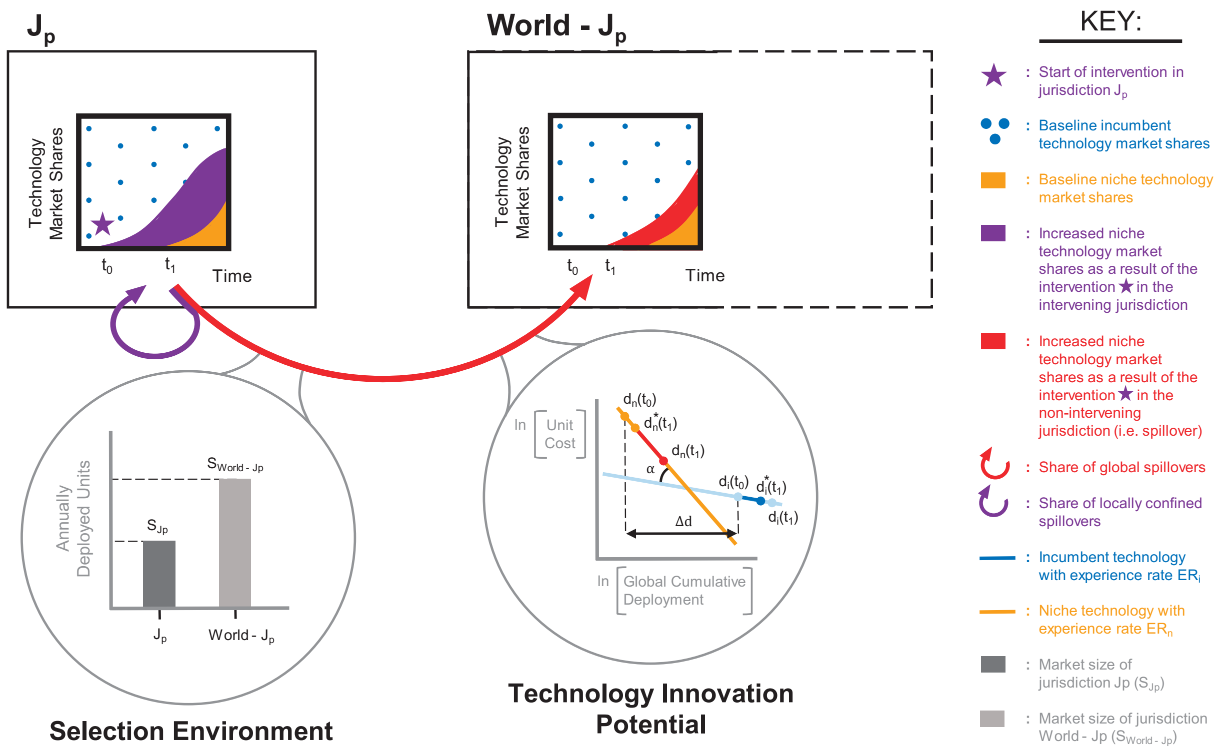

Fig. 1. Schematic of the conceptual framework.

Spillovers are also moderated by the relative technology innovation potential. Cost is a primary driver of technology competition. In this framework, component-based experience curves are used to model cost dynamics, which have been established as a prominent approach to projecting future costs of niche technologies particularly for methods that endogenize technological learning (26, 48–51). In Fig. 1, we illustrate two experience curves, one for the incumbent and one for the niche technology, to define two relative innovation potential variables—the relative starting position or starting deployment Δd Eq. **2** and the relative steepness of experience curves $\tan(\alpha)$ for the incumbent and niche technologies Eq. **3**.

$$\Delta d = d_i\left(t_0\right) - d_n\left(t_0\right), \qquad [2]$$

$$\tan\alpha = \frac{m_i - m_n}{1 - m_i m_n}; \qquad [3]$$
$$\text{where } m_i = \frac{\ln[1 - ER_i]}{\ln[2]}, \quad m_n = \frac{\ln[1 - ER_n]}{\ln[2]},$$

In a selection environment where a niche technology is "catching-up" to the incumbent technology, spillovers can induce innovation by accelerating cost reductions. Deployment, however, rather depends on cost competitiveness and is therefore a function of both the relative starting position and relative steepness of the two competing technologies, which is in part determined by a technology's design complexity (14).

Incomplete spillovers are also considered in the framework to emphasize the effects of local and global learning on technology innovation (52, 53). Standardized technologies that are globally produced and traded have very little local learning and are therefore best predicted by global, aggregate market trends than by country-specific context factors (e.g., solar PV modules). For such technologies, the framework assumes complete spillovers from the intervening jurisdiction to all other jurisdictions (Fig. 1, red spillovers arrow). For highly customized technologies requiring context-specific local learning (e.g., building envelope retrofits), knowledge spillovers do not completely propagate (Fig. 1, purple incomplete spillover arrow). We contend spillover completeness to be a function of the need for customization, i.e., the extent to which technologies need to be adapted to their use environments (14).

The interplay between technology competition dynamics and global innovation spillovers are key for estimating the speed of global sustainability transitions under various intervention scenarios. While the factors described in Eqs. **1**–**3** allow us to conceptually describe expected differences in deployment depending on the market sizes and technology innovation potentials (see *Materials and Methods* for an application to our case), evidence-based policy advice requires a quantitative evaluation of potential interventions, as discussed next.

Modeling Framework. We operationalize the above-described framework in a system-dynamics techno-economic model that simulates technology competition over time and analyzes the effects of global innovation spillovers on clean technology deployment. Our parsimonious approach [as compared to other conventional system-dynamics approaches (54–56)] prioritizes greater generalizability of the case study but remains empirically grounded. Fundamentally, the model is well suited to capture technology competition dynamics, incorporate global spillover effects, and project innovation diffusion for sustainability transitions. For more details on the model selection, please refer to *SI Appendix*, Text 2.

We build on previous models that examine technology competition, endogenous feedback dynamics, or both (26, 57–59). Crucially, we endogenize innovation by way of component-based experience curves. By doing so, we derive a technology's future cost from its previous deployment (60) and establish a model architecture that empirically quantifies innovation feedback and global spillover effects. The basic model architecture follows an iterative procedure over a specified time period. In each time step, selection of competing technologies, incumbent and niche, is modeled within defined jurisdictions through a discrete choice Monte Carlo simulation of bounded rational investors. The selection decision is solely based on the operational lifetime cost of the technology (i.e., total cost of ownership) as well as a switching cost, which we model as an additional cost barrier defined by an investor's propensity to switch to a niche technology away from the incumbent (e.g., driven by a perceived technology risk). Selection and subsequent deployment of a technology leads to gained experience and increasing returns to scale, thereby reducing component costs, but also diminishing switching costs in the future. Lifetime and switching cost dynamics in subsequent iteration steps are thus derived from a technology's previous deployment; however, lifetime costs depend on previous global deployment and switching cost on previous local deployment. For each time step, technology market shares of new units deployed are dynamically projected in a baseline scenario, absent any intervention. Then, a local policy intervention in a select jurisdiction is introduced, and baseline market shares are disrupted—not only in the intervening jurisdiction but as well in other jurisdictions through spillovers. Importantly, the model treats policy exogenously with respect to spillovers. Assuming no trade barriers, increased deployment in the intervening jurisdiction (*Jp*) results in lower technology costs in all other jurisdictions in future time steps. Innovation spillovers, quantified as disrupted market shares, may be increased or decreased outside of the intervening jurisdiction, for example, in *World – Jp* (Fig. 1).

Case Study

The proposed framework is applied to the case of commercial road freight. In 2019, road transport accounted for roughly 70% of global transport sector green-house-gas (GHG) emissions, and nearly 15% of global total GHG emissions for which road freight, in particular, plays a large contributing role (1). Fossil fuel–based road freight creates other environmental and social problems (61). Especially troubling are the severe health impacts of local air pollution hotspots that often disproportionally affect low-income communities situated near major highways, in inner cities, or along congested freight corridors (62). Though frequently discussed as a difficult-to-abate sector, sustainable niche alternatives have emerged: battery electric vehicles (BEV) and hydrogen-powered fuel cell electric vehicles (FCEV). These alternative technologies are relatively complex in design and manufacturing and therefore gain tremendously from learning-by-doing and using feedback effects (63). Furthermore, the incumbent and clean technologies competing in this sector are globally traded products, making the sector well suited for questions pertaining to intervention spillovers. Consequently, we assume complete spillovers as incumbent and BEV and FCEV are largely standardized products with high global learning.

As the road-freight transition is still in the formative phase (64), our case selection allows for a forward-looking analysis of a sustainability transition that exhibits multiple competing technologies and relies heavily on interventions, innovation spillovers, and global knowledge flows. At the same time, the transitional outcome for road freight is still uncertain, which has great consequences for local burdened communities as well as for global climate change and thus society at large. We recognize that climate action, in this case, interventions that enable the uptake of zero- or low-emission road-freight vehicles, is not equivalent to sustainable development. Note, however, that many cobenefits to climate action-driven interventions exist in the sector.

Our case study-specific results—market share projections of competing road-freight vehicle technologies—are of value for actors in the space, though we recognize that numerical outcomes of data-heavy models are necessarily also a function of choices made on input parameters. Though concerted effort was put into input parameter data collection, in the results section, we emphasize rather the primary contribution of the analysis: the assessment of the effects of national policies on global TC and the quantification of innovation spillovers.

Complications. For the selected case study, additional complications are introduced to the framework. First, for the case of road freight, we model not two (niche vs incumbent) but four technologies: two incumbent, internal combustion engine vehicles that run on diesel and natural gas (ICE-D and ICE-NG), and two niche technologies, BEV and FCEV. Each competing technology has a different innovation potential, both in terms of experience curve steepness [cf. Eq. **3**, $\tan(\alpha)$] and relative initial cumulative deployment (Eq. **2**, Δd). Second, we model not two but five regions representing the global geographies with the most road-freight ton-kilometers traveled—China, the European Union (EU), the United States, India, and Brazil, as well as a Rest of World region (65). Third, we define application segments divided along the weight and range dimensions for which light- (LDV), medium- (MDV), and heavy-duty vehicles (HDV) each travel in urban, regional, and long-haul distances (39). Dynamic technology competition is therefore modeled between four technologies, in six regions, and nine application segments, on an annual time step resolution over a fifteen-year time-period from 2020 through 2035. Fourth, switching costs in the road-freight market are considered to consist of two factors, reflecting both behavioral elements (e.g., cognitive bias toward established technology due to habits) and institutional elements (e.g., ease of maintenance and refueling). In sum, the model projects technology market shares of new vehicle sales in a business as usual (BAU) baseline scenario and for intervention scenarios on top of the baseline. Our modeled BAU scenario is very similar to a "current policies" scenario; however, existing CAPEX subsidies are not included.

Spillovers can occur across regions and application segments. This is because we assume complete spillovers for all technology components (e.g., battery modules). As an example, BEV deployment in the LDV-Urban segment in China can, in theory, spill over to the HDV-LongHaul segment in the United States.

Policy Interventions. Intervention, particularly public policy intervention, is often required to correct market or system failures such as negative or positive externalities, or innovation system failures (66, 67). For emerging or novel technologies seeking to break decades of technology dominance, interventions that target deployment are essential not only for innovation but also for diffusion and adoption of a new technology (68–70). Here, we model, exogenously, hypothetical interventions to demonstrate the potential to accelerate sustainability transitions through global innovation spillovers. We focus on demand-pull interventions (44). Though scholars widely agree that both demand-pull and technology-push interventions spur technical change and spillovers (69), it is also acknowledged that local (domestic) innovators are unlikely to benefit substantially from foreign technology-push funding as compared to foreign demand-pull policies (71, 72). Furthermore, demand-pull interventions are typically market-based instruments that target deployment and thus align better with our framework's measure of innovative output. To offer a final case-specific argumentation, sustainable niche road-freight technologies have largely surpassed the research and development phase where technology-push interventions are more relevant (73).

Three public interventions are modeled. First, a technology-neutral carbon tax for the road-freight sector is modeled, based on the well-to-wheel emission intensity of the vehicle technology. Fuels, including electricity, are taxed based on their carbon content. For hydrogen, we assume strictly "green" hydrogen from electrolysis, with an assumed emissions factor of zero. Carbon tax scenarios are oriented at the ambition level of existing policies (e.g., in the case of the United States, a low tax scenario is based on the carbon price in California in 2020, and high tax scenario is based on the low-carbon fuel standard credit price in 2020). Second, we model a road toll exemption for zero-emission vehicles, particularly effective in regions with high tolls (39). Third, we model a technology-specific CAPEX subsidy—a common policy option to advance adoption of niche road vehicle technologies (74). This subsidy cuts the initial cost differential between a zero-emission vehicle (ZEV) and the baseline vehicle by 25%. In some scenarios, we also combine these interventions. We present three additional interventions to better understand spillover dynamics: a cooperative intervention (i.e., a policy club), a geopolitical shock restricting the free trade of technology, and a private sector intervention (corporate commitments from multinationals that own large truck fleets). For the geopolitical shock, analyzing a restriction of free technology trade allows for an understanding of the potential negative effects of regional isolation on spillovers. The private intervention is motivated by the fact that interventions from nonstate actors, complimentary to national policies, can sometimes have meaningful impact on global issues (75). In *SI Appendix*, we also model and assess a toll-exemption and CAPEX subsidy for just one specific technology (FCEV) in the EU.

Each intervention is modeled in select region(s). We begin the public interventions in 2023 though the modeling period starts in 2020. Only the private intervention is modeled in multiple regions as the multinational corporate vehicles committed in the EV100 initiative operate globally.

Results

In Fig. 2*A*, we show the results of the business as usual (BAU) baseline scenario absent intervention. All modeled regions as well as an additional "Global" aggregate are shown in the columns. For simplicity, we combine the range application segments and show only differentiated weight segments, though the full application matrix results are included in *SI Appendix*, Figs. S4–S9. A few observations are highlighted. First, the transition from dirty incumbent vehicles such as ICE-D (Fig. 2*A*, in brown) or ICE-NG (Fig. 2*A*, in yellow) to clean niche vehicles such as BEV (Fig. 2*A*, in blue) advances in the LDV and MDV segments in certain regions, though not in the HDV segments. Globally, BEVs reach nearly 60% market share of new vehicles sold in the LDV and MDV segments with some regions such as China and the EU surpassing 70% in the MDV segment. In the HDV segments, ZEV market shares remain below 10% globally. This result stresses the importance of intervention for heavy-duty road-freight decarbonization. Second, regional projection outcomes differ starkly. Transition speeds and shapes as well as selected technologies follow different trends in different regions—China and the EU feature the fastest ZEV adoption rates, whereas India and Brazil lag behind with high penetration rates of ICE-NG and ICE-D respectively. Finally, electrification of the road-freight sector almost exclusively develops with BEVs. Only in the HDV segment of the

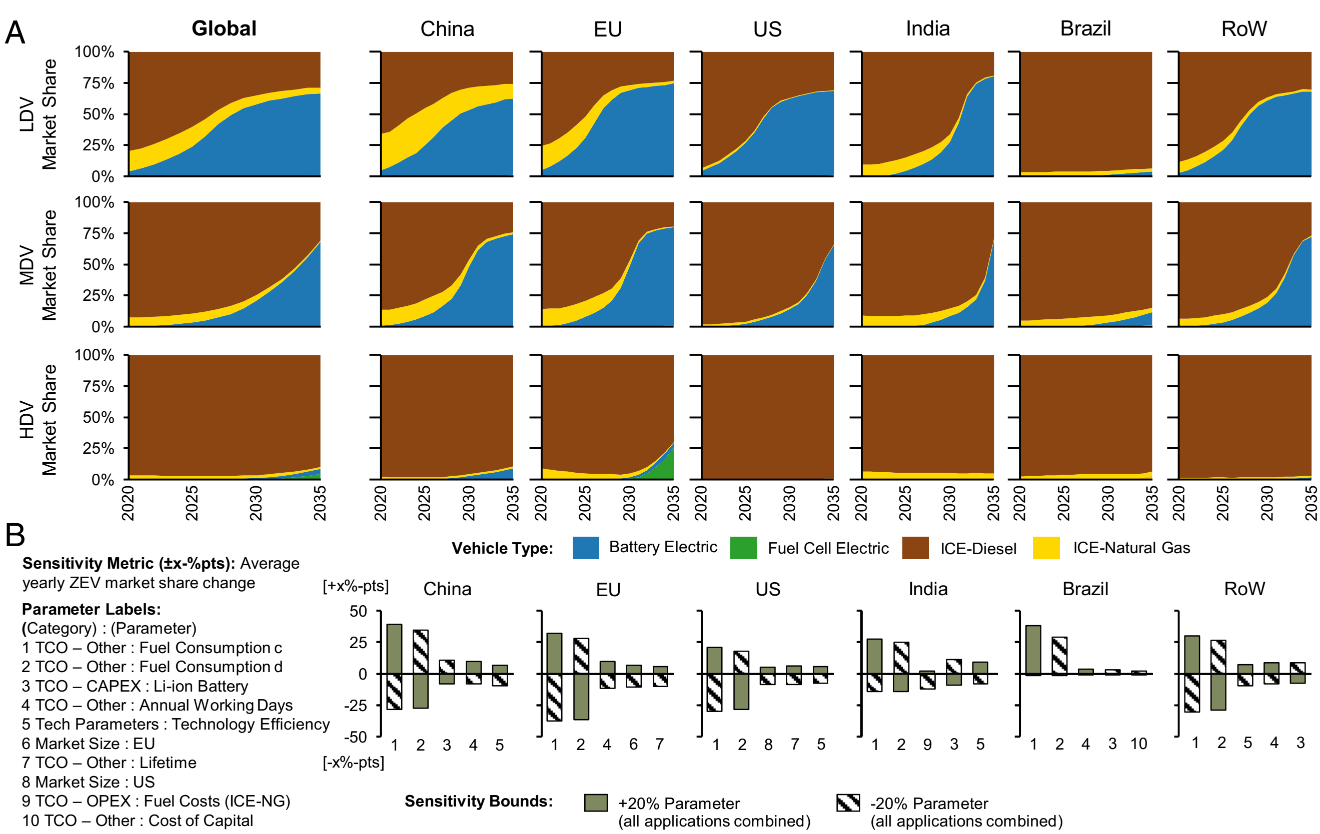

Fig. 2. (*A*) Baseline market share projection results of new road-freight vehicles sold in each modeled region and application segment from 2020 through 2035. For readability, we show only the combined weight segments (LDV, MDV, and HDV). Regions are ordered from left to right in decreasing market size order. The *y* axis shows market shares of newly sold vehicles (%), and the *x* axis shows years modeled. Four technologies compete for market shares in each segment and each region—a battery electric vehicle (BEV) in blue, fuel cell electric vehicle (FCEV) in green, internal combustion engine that runs on diesel (ICE-D) in brown, and one that runs on natural gas (ICE-NG) in yellow. The "Global" region on the left is the aggregate of the six modeled regions to the right. In the business as usual baseline result, no intervention is implemented. (*B*) Sensitivity analysis tornado chart for the top five most sensitive parameters in each region for all application segments combined. The sensitivity metric measures the average yearly ZEV market share change (%-pts) given a +/−20% change in parameter. Parameter labels correspond to the same naming convention as in *SI Appendix*, Table S2.

EU do FCEVs gain minimal market shares after 2030 (we further discuss FCEV's role in *SI Appendix*).

Note that the BAU market share projections in Fig. 2*A* do display technological learning feedbacks and innovation spillovers, just not as the result of an intervention in a specific region. Fig. 2*B* shows the BAU ZEV market share sensitivities to model parameter changes of ±20%. The top five most sensitive parameters are shown in each region for all applications combined. These results are part of a comprehensive sensitivity analysis performed in two parts to assess the robustness of our model—one to test model parameter sensitivities and one to test intervention or shock sensitivities (*Materials and Methods*). Overall, we find the BAU market share results to be robust to reasonable parameter changes (±20%), though Fig. 2*B* highlights, in particular, the high market share sensitivity to fuel efficiency and technology efficiency parameter changes across regions and applications. This supports earlier findings on the influence of OPEX or other energy consumption-related parameters on commercial vehicle TCO (39). Baring the two fuel efficiency parameters, remaining parameter sensitivities show no more than 5 to 10% changes in the average yearly ZEV market shares across regions and for combined applications.

Overall, the BAU results indicate a high apparent need for intervention, especially in the heavy-duty segments where ICE-D vehicles continue to dominate. Given this baseline outlook, in the following, we analyze whether local interventions can accelerate the global low-carbon road-freight transition.

Public Policy Interventions in the United States. Fig. 3 displays the results of three public interventions. A technology-neutral US-wide carbon tax on all transport fuels (high and low scenario), a CAPEX subsidy for ZEVs, and a policy mix. In Fig. 3, the *y* axis now shows ZEV market shares. The gray area thus indicates baseline ZEV shares from the BAU scenario in Fig. 2. Both carbon tax interventions and the policy mix increase these baseline shares in all segments. The CAPEX subsidy increases ZEV shares in the LDV and MDV segments but not in the HDV segments. On the left, we see the effects of the carbon tax intervention in the US—ZEV deployment is accelerated in all application segments, though much more for the LDV and MDV segments than for the HDV segment. For instance, by 2030, ZEV market shares in the MDV and LDV segments rise from 11 to 76% and 60 to 74%, respectively, due to the high carbon tax, even more with the mixed policy. On the right, we see the global spillover effects, or lack thereof, of local interventions in the United States—generally in all segments, spillover effects are minimal. This is largely due to a relatively small US market size. Even with substantial modification of sensitive parameters such as fuel consumption (±20%), global spillover effects remain minor. Most additionally deployed ZEVs as a result of the carbon tax interventions are in the MDV segment, for which the vehicle market is comparatively much smaller than LDV and HDV. Market size is thus underscored as a crucial moderating factor for innovation spillovers.

Public Policy Interventions in China. With the largest road-freight market, greatest number of road-based ton-kilometers traveled, and thus highest transport-related carbon emissions profile in the world, the rationale to decarbonize domestic movement of commercial goods is clear. China is heavily prioritizing the electrification of their transport sector at large (76). Considerable global spillovers may be expected as a result of increased niche technology deployment in a large market such as China. In Fig. 4, we model four different policy interventions in China and show the effects on the Chinese market as well as the resulting spillovers to other regions. We model a CAPEX subsidy for ZEVs (Fig. 4, in blue), a toll exemption for ZEVs (Fig. 4, in pink), a technology-neutral carbon tax on transport fuels (Fig. 4, in green), and an intervention mix that combines all three public policies (Fig. 4, in black dotted). The results not only show significantly accelerated and increased local deployment of ZEVs but also increased global deployment where spillovers are abundant. For example, local ZEV

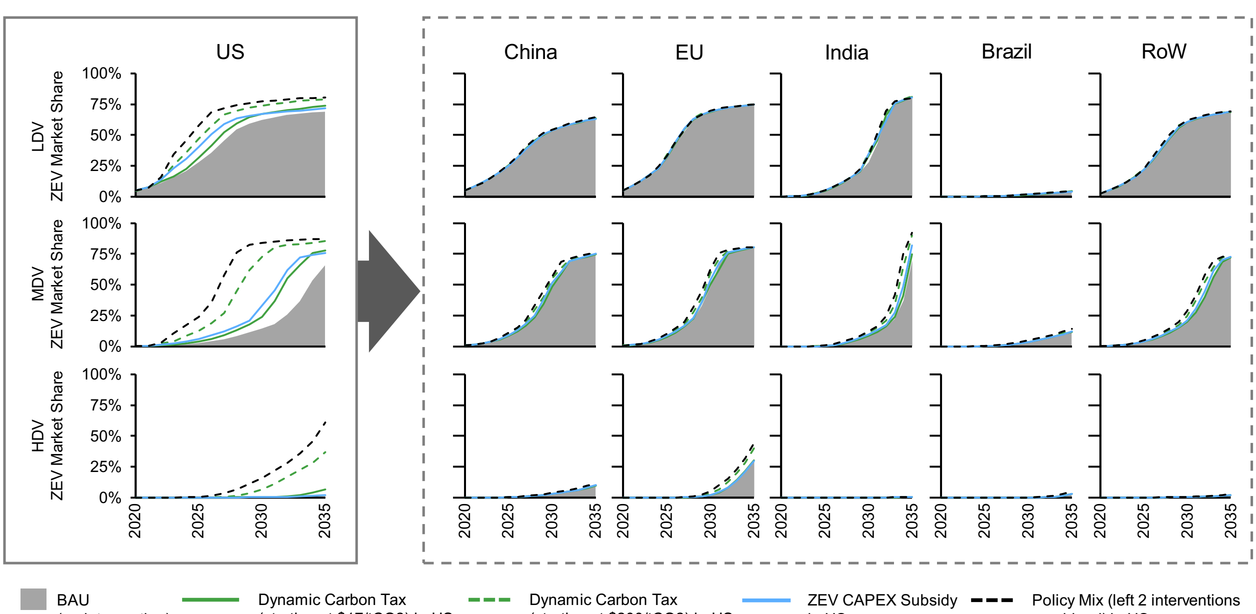

Fig. 3. ZEV market share results of public interventions in the United States. Increased ZEV market shares in the United States on the left are a direct result of local interventions. Increased ZEV market shares in all other regions to the right are an indirect result of spillovers. The carbon tax applies to all vehicle technologies and is based on well-to-wheel emissions, that is, the carbon emissions from the fuel extraction, production, and transport combined with the carbon emissions from the technology during on-road use. The region-specific carbon intensity of the electricity grid is also dynamically accounted for. We model the CAPEX subsidy (in light blue) in the United States as 25% of the difference between the ZEV CAPEX and the ICE-D vehicle CAPEX in each respective segment and region. The policy mix (in dotted black) combines the high dynamic carbon tax and the CAPEX subsidy. All interventions are introduced starting in the year 2023.

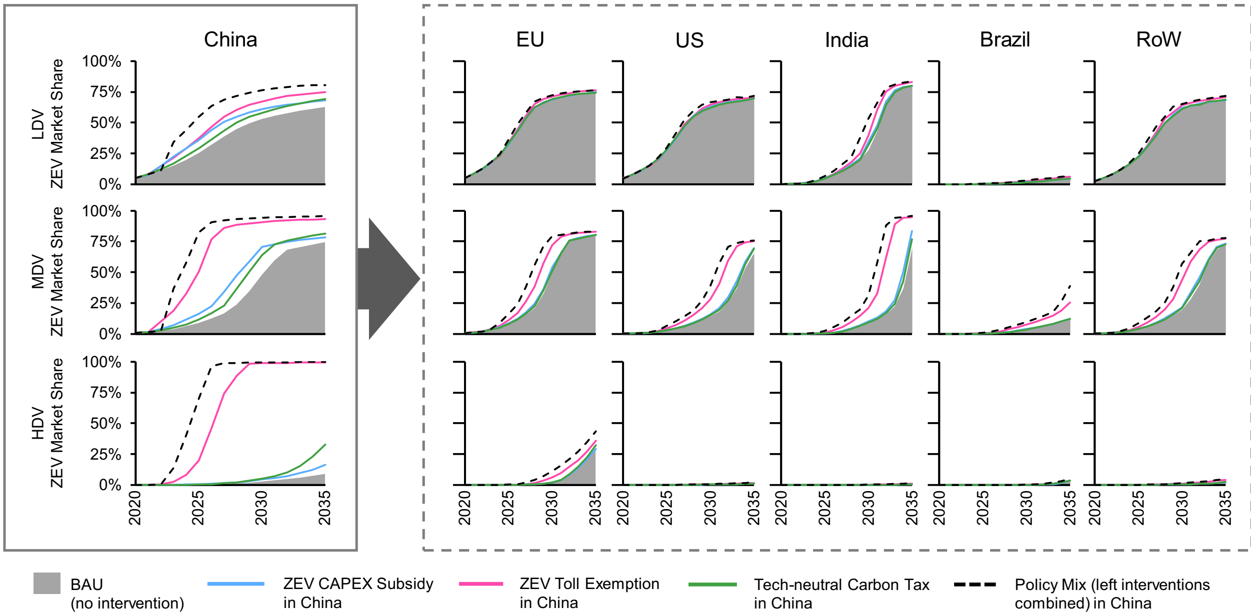

Fig. 4. ZEV market share results of four public policy interventions in China. Increased ZEV market shares in China on the left are a direct result of local interventions. Increased ZEV market shares in all other regions to the right are an indirect result of spillovers. A CAPEX subsidy for ZEVs is shown in light blue. We model the subsidy as 25% of the difference between the ZEV CAPEX and the ICE-D vehicle CAPEX in each respective segment and region. A toll exemption for ZEVs is shown in pink. Tolls in China are quite expensive with charges of 0.36 USD/km, 0.14 USD/km, and 0.068 USD/km for the HDV, MDV, and LDV segments, respectively. These charges are 264%, 141%, and 92% higher than the average tolls of all other regions in the HDV, MDV, and LDV segments (see Dataset S1 for toll data). A technology-neutral carbon tax is shown in green. Here, we model a different dynamic cost of carbon as compared to the US interventions in Fig. 3 (*SI Appendix*, Fig. S10). A policy mix is shown as a dashed black line. This intervention combines all three previously described interventions—the CAPEX subsidy, the ZEV toll exemption, and the carbon tax. All interventions are introduced starting in the year 2023.

deployment in the MDV and HDV segments in China would increase from 15 to 85% and from <1 to 58% in 2027 as a result of the ZEV toll exemption policy. Spillover effects in other regions are largest in the MDV segments, for example, in the United States or India, with a 42% and 68% ZEV deployment increase in 2033 as a result of the ZEV toll exemption policy in China.

Noticeable as well is the relative intensity of each modeled intervention. In China, road tolls are expensive (see Fig. 4 caption and *SI Appendix*, Fig. S59 for direct budgetary implications of all modeled interventions in China). Accordingly, a ZEV road toll exemption greatly increases niche technology competitiveness for which tolls are a key determinant. This is particularly the case for the HDV segment where vehicle kilometers traveled are high and distance-based taxes thus pivotal. Comparatively, the CAPEX subsidy and carbon tax interventions prove not as effective in enabling additional ZEV deployment in China, while the policy mix intervention, a combination of the three, appears most effective. The policy mix and toll exemption interventions increase average ZEV deployment market shares in China across segments by 40% and 25%, respectively, as compared to 8% and 5% market share increases from the CAPEX subsidy and carbon tax interventions. As has been shown empirically in other cases (77), we also observe that the policy mix intervention can be less than the sum of each individual intervention. This is the case both in China and the United States.

Furthermore, we find that the intensity of local intervention also implies the intensity of observed global spillovers. The ZEV toll exemption and policy mix interventions in China accordingly induce the greatest spillover effects in other regions. In the LDV segments, spillovers are greatest for regions that exhibit lower baseline ZEV diffusion rates such as in India. In the EU and the United States, for example, higher baseline ZEV market shares in the LDV segment suppose a limit beyond which spillovers induced by interventions in China do not breach. The MDV segments display the greatest spillover effects, where lower but positively trending initial ZEV deployment levels are substantially accelerated as a result of interventions in China. In the HDV segments however, other than in the EU, minimal spillovers are observed, despite strong local intervention effects. Furthermore, for spillovers that are observed in this segment, deployment is almost exclusively BEV with little to no FCEV adoption. We suppose two reasons for these findings. First, in the HDV segment, despite observable CAPEX reductions from spillovers, BEV deployment spillovers are missing because the switching cost barrier is not overcome. Second, the deployment of BEV over FCEV points especially to the innovation potential of competing technologies—a high relative experience curve angle, α, between the niche BEV technology and incumbent ICE-D technology—leads to higher BEV cost reductions and thus increased competitiveness.

Further Interventions and Shocks. We analyze the effects of three further interventions: policy club public interventions in the EU, the United States, and China, a geopolitical shock in China, and a private intervention. Fig. 5 shows the effects of these interventions or shock via the average yearly ZEV market share change for the intervention or shock as compared to no intervention or shock. Note that Fig. 5 shows both the within-region intervention effect and the spillover effect (see color-coded legend). The policy club interventions (Fig. 5*A*), for which we model a CAPEX subsidy, show negligible spillovers for the EU and US club. Only when China joins the policy club does the model project nonnegligible spillovers to nonclub regions, a finding in line with a prominent study analyzing climate clubs and spillovers in international climate policy (13). Advancing ZEV market shares by 5 y is actually quite substantial given the timeline of the required transition, particularly in developing economies such as India. Our analysis examining spillover effects under select model parameter sensitivities shows a 7 to 15% change in the spillover metric for the club policy interventions depending on the region, application

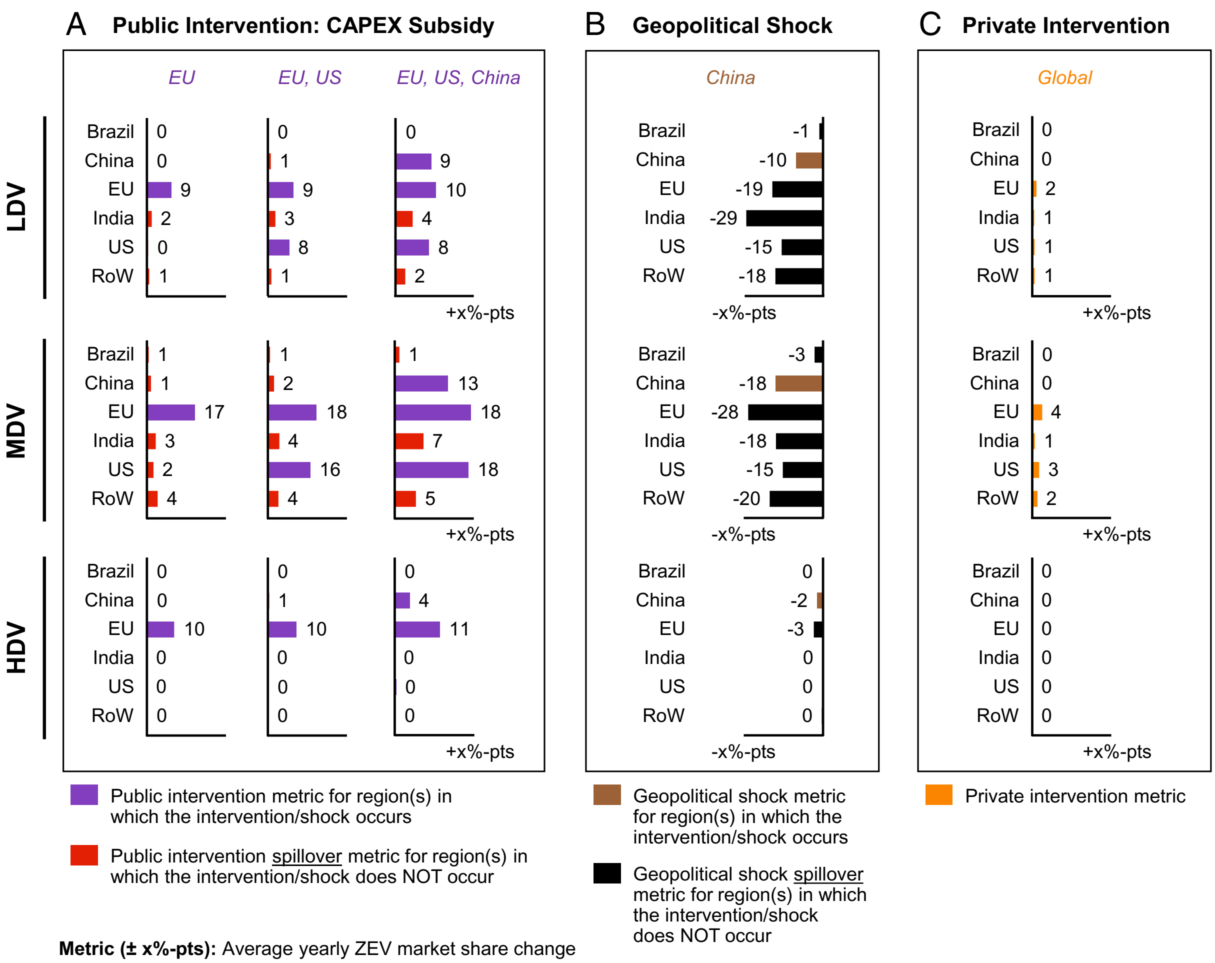

Fig. 5. Model spillovers under different interventions or shocks. For three intervention groups, we show the average yearly zero-emission vehicle (ZEV) market share change as a result of the intervention as compared to the BAU scenario. In (*A*) a club policy CAPEX Subsidy is implemented in the EU on the left, in the EU and the United States in the middle, and in the EU, the United States, and China on the right. The purple bars indicate regions in which the intervention occurs, and the red bars indicate regions in which the intervention does not occur, which is effectively the spillover. In (*B*) the geopolitical shock is implemented in China. The brown bars indicate regions in which the intervention occurs, and the black bars indicate regions in which the intervention does not occur, which is again the spillover effect. In (*C*) a global private intervention based on the EV100 multination corporate fleet commitments is implemented, though only in the LDV and MDV segments. Additional deployment in any given country stems from the direct local effect of the private intervention as well as the spillovers that the private intervention induces.

segment, and sensitive parameter (*SI Appendix*, Figs. S29–S58). For the geopolitical shock cutting off China, the model projects strong negative spillovers (Fig. 5*B*). In this scenario, the transition to low-carbon road-freight vehicles would be tremendously slowed in China but even more so in other regions. In the LDV segment, India, in particular, would loose on average 29 market share %-points yearly. The EU is similarly penalized in the MDV segment, though the HDV segment is largely unaffected due to minimal initial ZEV shares in the BAU scenario. Spillover effects of a private intervention (Fig. 5*C*) based on EV100 multinational corporate fleet commitments appear slim. Despite including larger multinationals, the overall corporate commitments are too small to make a difference. Even under a high EV100 private intervention scenario (3× the base commitments, results shown in *SI Appendix*, Fig. S2), limited deployment spillover is apparent. Spillover effect sensitivities are >3% for the private intervention and >12% for the geopolitical shock across regions, applications, and select parameter sensitivities (again see *SI Appendix*, Figs. S29–S58).

Discussion

We begin the discussion with generalized insights into the role of spillovers for global technical change. Spillovers can accelerate transitions, but they are not a given. According to our modeling results, the size of the spillover effects very much depends on the intervening jurisdiction, intervention type, strength and timing, and competition dynamics of niche and incumbent technologies. Framing this complex interplay of elements is central to modeling TC. We stress here again the usefulness of the two conceptual factors, relative size of selection environment and relative innovation potential of competing technologies, for understanding spillover moderation. For niche technologies competing in a selection environment with relatively high experience rates and a "head-start" in terms of cumulative deployment, global innovation spillovers can be the decisive push needed to overcome lingering cost barriers and accelerate adoption. The magnitude of spillovers depends as well on the relative market size, or rather the local deployment potential of the intervening jurisdiction vis-à-vis the overall global potential. Under strong intervention scenarios, jurisdictions of large relative market size can have profound impacts on niche technology deployment globally through spillovers. We recognize these guiding factors to be generalizable and thus applicable to broader sustainability transition case studies. Incomplete spillovers are another important factor to consider and depend principally upon a technology's need for customization, a largely technology-inherent characteristic. The incomplete spillover concept emphasizes the importance of differentiating local vs. global technological learning in technology projection models.

Spillovers are a two-way street. On the one hand, spillovers can expand the benefits of stringent national policy, but they can also reduce the incentive for intervention. Export potential is often a key motivator for national policy—establishing a strong home market can in turn generate positive local feedback effects such as job creation, technology development, economic growth, and further increased policy ambition (18, 52). In rare cases, exportation of policy itself can also be a policy goal as was the case for the German Energiewende, which, upon enactment, sought policy imitation in other jurisdictions to bolster collective climate change mitigation action (78). Other examples of adopting local policy to create global spillovers include the European hydrogen strategy (79) or Britain's attempt to expert their healthcare policy (80). Foreign jurisdictions may choose to expand their own local policies, or they may choose to "free-ride", an unavoidable consequence of spillovers. Accordingly, national industrial policy aims may trigger protectionist trade barriers thus limiting the extent to which nonintervening nations can benefit or "free-ride" from spillovers. Club policies offer a potential remedy to the competition-skewed two-way street (13). Cooperative intervention scenarios, particularly ones that include multiple regions, not only expand the reach of global spillovers but also balance policy costs and herald positive signaling effects for industry players, manufacturers, as well as consumers. Interestingly, our results indicate that competition scenarios can be much more damaging than cooperative scenarios are benefiting (see the geopolitical shock modeled in China).

From the road-freight case study results, we understand foremost the importance of public intervention for clean technology deployment. We project that heavy-duty trucks will continue to run on fossil fuels absent strong public policy intervention. Spillovers as a key accelerator of niche technology deployment in the sector should not be overlooked. Particularly striking is the meager effect of private interventions on the road-freight transition (see Fig. 5), which not only questions popularized "collaborative" initiatives from private corporate companies but also puts pressure on public institutions to increase support for clean technologies, either independently or as a policy club. A comment on policy cost is thus relevant at this point. As an example, take an effective but rather costly public intervention, the road toll exemption. In certain regions, say China and the EU, this policy has major consequences for transport budgets and public revenue streams. Despite the policy's positive overall effect on ZEV uptake, a phase-out or cap on toll exemptions may be necessary (see *SI Appendix*, Figs. S59–S61 for direct budgetary implications of all modeled interventions). Generally, policy cost is not only a function of market size but also of the region-specific calibration level and relative innovation potential of competing technologies. It is also dependent on the extent to which national cooperation exists (i.e., presence of policy clubs). We also learn from the road-freight case that overcoming switching costs ("soft-costs"), or more broadly institutional and behavioral barriers, is crucial for niche technology deployment and that competition dynamics between niche technologies is as important for understanding market development as competition between niche and incumbent technologies. In particular, the switching cost qualitative adoption factor parameter proved influential in the sensitivity analysis across most regions, largely in the MDV segment. Given the importance of relative market size for induced spillovers, we find that the road-freight sector could benefit from joint policy action or collaboration between regions, which could further increase spillovers. This could also address potential first-mover disadvantages due to spillovers (72). Additionally, the case-specific model results indicate that governments should not solely rely on spillovers if a swift transition is desired. Local intervention is needed in many (large) regions for accelerated adoption of ZEVs. The robustness of our model results as shown in the sensitivity analysis only further emphasizes the relevance of these discussed policy implications.

Though our results suggest that public policy intervention is much more effective than private interventions in enabling niche tech deployment, public policy is in fact shaped by private interests and technology advocacy. The local (national) industry position, toward novel technologies is thus highly relevant. Rising market shares of a novel tech (induced through spillovers) could trigger positive feedback and thus policy activity in other jurisdictions (i.e., in the case of PV) but also backlash or negative feedback from incumbent market players. In the case of road freight, industry interests do not only refer to the vehicle producers (which only produce in few regions in the world) but also from the users (trucking companies), which represent a major workforce in many countries.

Turning now to the modeling framework, we discuss scope, contributions, and limitations and contextualize our case-specific model with existing ones. In principle, our model is of generalizable nature and can be applied to any field where technologies compete for markets and where policy intervention is conceivable. The approach is particularly helpful in sectors where learning by doing and using is important. The main contribution is the assessment of the effects of national policies on global TC and the quantification of endogenized innovation spillovers ex ante. The model also serves as a cost benchmarking tool for technologies not yet in the market, which is of interest for researchers and modelers but also for investors. That is, how cheap must a technology become to stand a chance in the market? From the sensitivity analyses, for example, we learn that the lithium-ion battery cost is an influential parameter for projected ZEV deployment—continued cost decreases for this technology are extremely important. We stress, however, that these kinds of models cannot be used for completely novel technologies where experience rates are unavailable or cannot be calculated based on empirical observations. For these technologies, other models (and policies) are needed. Additionally, the model is primarily suitable for technologies that are highly standardized and for which we would expect high international deployment spillovers. International spillovers and thus our framework are less relevant for technologies with high degrees of customization (such as biomass power or building envelopes), whose learning is highly locally confined. An ex post analysis—replaying history and alternative histories (81)—is also conceivable. Remodeling technological competition and international spillovers would require a very good understanding of the case and (potentially) large amounts of historical data on technologies and interventions. For actors in the transitioning road-freight case, the simulated market share projections themselves are of value. Compared to larger integrated assessment models or general equilibrium models that mostly rely on elasticities and exogenous innovation, our model opens the black box of technology and therefore requires a structural understanding of the sector and its technologies. As with all structurally and technologically rich models, input data can be a limiting factor. In order to adapt the model to other sectors, detailed region-specific factors such as fuel prices, policies, and the composition of the sector would need tailoring. Computational efficiency is also rather limiting, particularly for understanding parameter sensitivities, given the high number of model parameters. Another limitation is that the model cannot directly address questions of equity for sustainability transitions. Indirectly, the model can inform policy design to accelerate clean technology deployment, which in the case of road freight can have dramatic health benefits for the broader public but also particularly for individuals residing near highways who are highly exposed to vehicle exhaust.

Ultimately, the model helps to inform policy making, primarily for national policy-makers but also for potential policy collaboration (i.e., club policies). It can inform private actors as well, for example, from multinational corporate initiatives (such as EV100) or investors and industrial companies considering which technologies to invest in, when, and how. Of course, the politics of policy intervention cannot be understated. The prevailing literature suggests that the presence of international spillovers strongly affects the political will for intervention and that foreign innovation diffusion is in fact a disincentive for policy-derived domestic market creation (72, 82). Again, we return to the two-way street argument. National policy-making is often motivated by national industrial policy aims and thus may favor interventions that support domestic firms. From a sustainability transitions perspective, however, innovation spillovers that accelerate global technical change are fundamental and should be explored fully. Shocks that decelerate global technical change are also highly relevant and should rather be avoided. Spillovers may also often be incomplete, thus further increasing the importance of local or even regional cooperative intervention. For policy users, the model can inform the choice of region, where to intervene, and the timing for desired outputs. It also provides insights into the technology—which technologies to support and how much, which support mechanisms are most effective or perhaps ineffective, or which may lead to lock-in.

Materials and Methods

Model architecture. We project market diffusion dynamics of competing technologies and capture innovation spillovers in multiple regions using the following core structural elements: a detailed technology-rich representation and segmentation of the road-freight sector; a comprehensive metric for evaluating cost competitiveness that identifies key parametric differences between competing technologies–for road freight, the total cost of ownership (TCO) is employed; a technology selection mechanism that simulates investor (i.e., fleet owner or truck owner-operator) purchase decisions based on technology cost as well as switching cost; a dynamic assessment of cost progression using experience curves to derive a technology's future cost from its previous deployment. See Fig. 6 for the iterative modeling procedure.

Model Dimensions and Parameters. Four model dimensions are constructed to accurately characterize and project market shares of the commercial road-freight sector as in ref. 39–technology, application, region, and time. Four technologies (ICE-D, ICE-NG, BEV, and FCEV) compete in nine total application segments (LDV/MDV/HDV-Urban/Regional/LongHaul) and six regions (Brazil, China, EU, India, the United States, and Rest of World) in each model year (2020 to 2035). A more detailed overview of each dimension is included in *SI Appendix*.

A total of 77 model parameters are defined and calibrated to inform the core technology selection process of the model. Many of these parameters have region- and application-specific dependencies and are differentiated as such. These differences are important to highlight and relevant for understanding the parametric nuances of the model (please see *SI Appendix* for these details). All parameters are included in *SI Appendix*, Table S2, where we detail which parameters are calibrated from literature and which are assumed as well as which parameters are dynamic or static and which are stochastically or deterministically modeled in the Monte Carlo simulation. Error bounds for stochastic parameters were determined through literature review and data collection and reflect our best estimate for parameter uncertainty.

Total Cost of Ownership. The TCO is a comparative cost metric of road-freight vehicles widely employed by transport modelers and fleet owners alike (83). Here, we evaluate the TCO for specific technologies in specific applications and regions. We follow the TCO methodology from Noll et al. (39)

$$TCO_{t,a,r} = \frac{\left(CAPEX_{t,a,r} - SUB_{t,a,r} + SC_{t,a,r} - \frac{SV_{t,a}}{(1+i_r)^N}\right)\cdot CRF + \frac{1}{N_{a,r}}\sum_{n=1}^{N}\frac{OPEX_{t,a,r}}{(1+i_r)^n}}{AKT_{a,r}}, \quad [4]$$

where *TCO* is the total cost of ownership per kilometer (USD/km), *CAPEX* is the capital expenditure or initial purchase cost of the vehicle (USD), *SUB* is the subsidy on the vehicle CAPEX (USD), *SV* is the scrappage value, *OPEX* is the operating expenditure or annual operating cost (USD), *N* is the lifetime of the vehicle (years), and *AKT* is the annual kilometers traveled (km). For the discounting terms, *CRF* is the capital recovery factor $= (i(1+i)^N)/((1+i)^N - 1)$, and i is the discount rate. Subscripts *t*, *a*, and *r* refer to the technology, application, and region dimensions, respectively. *SC* is the switching cost (USD) and is described in more detail below. For more methodological detail on each TCO parameter, see *SI Appendix*, Text 2.

Switching Cost. Supplementary to the TCO, we model a switching cost representative of potential "soft" barriers to adoption new technologies face upon market entry (84). The switching cost is based on a percentage of the incumbent vehicle

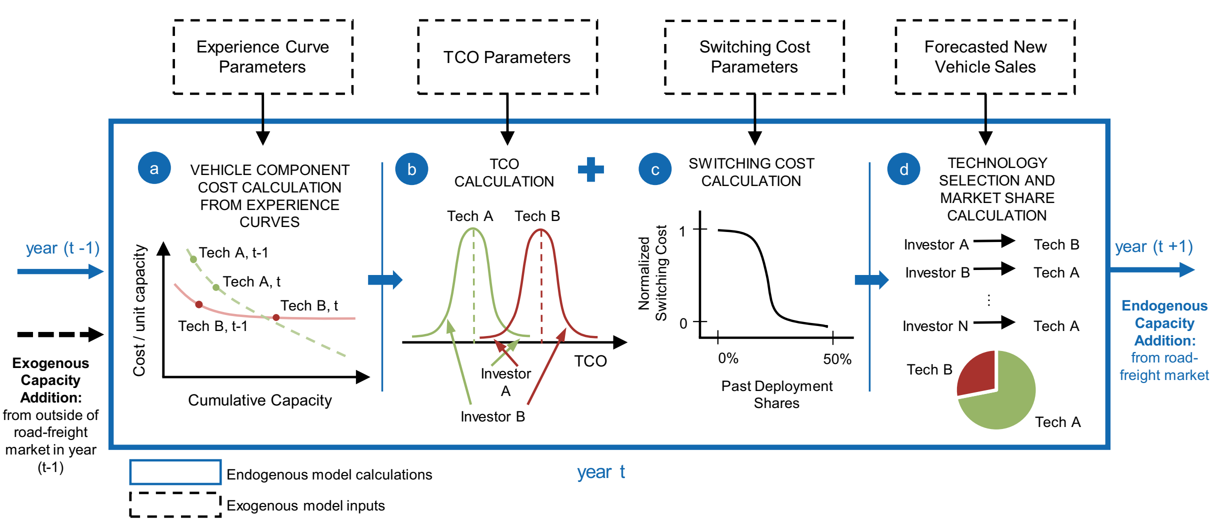

Fig. 6. Schematic of the iterative modeling procedure. Here, we visualize the iterative modeling procedure. In each time step, technologies compete in representative application segments and regions. Independent investors are simulated in a probabilistic Monte Carlo discrete choice selection mechanism. The selection decision (*d*) is based on the least "cost" technology available—derived based on the TCO (*b*), a "hard-cost" metric, and the switching cost (*c*), a developed "soft-cost" metric. Aggregated investor selections generate technology market shares. These shares when multiplied by forecasted deployment, both endogenous and exogenous, derive new technology component costs from the experience curves (*a*). New costs are then used in the TCO calculation and investor selection simulation in the subsequent time step. See *SI Appendix*, Text 2 for a more detailed description of the iterative procedure.

CAPEX (i.e., the ICE-D vehicle cost). The percentage is determined by multiplying two adoption factors (%): a qualitative and historical factor.

The qualitative adoption factor consists of two qualitative elements—a behavioral element and an institutional element—that define an investor's propensity to switch to a new technology away from the incumbent (45). Each modeled technology is rated based on the applicability and influence of an element on an investor's switching inertia. The applicability is modeled in the form of a percentage markup (as compared to the incumbent technology which we assume to have a 0% markup absent behavioral or institutional cost barriers) for a given technology in a given application and region. A 10% markup is applied if a behavioral or institutional element is partially applicable, and a 20% markup is applied if fully applicable.

The historical adoption factor is based on past deployment of each competing technology in each application and region. We use an inverted S-curve functional form to model the historical adoption factor which represents a technology's adoption progression as a function of historical deployment.

We base the switching cost calibration and implementation primarily on two sources from the literature (23, 84). See *SI Appendix*, Text 2 for more detail on the switching cost methodology.

Experience Curves. We construct experience curves for seven vehicle technology components—lithium-ion battery pack, hydrogen tank, diesel tank, natural gas tank, electric drive system, fuel cell system, and internal combustion engine powertrain. We also model three integration factor components—one each for the BEV, FCEV, and ICE-NG technologies.

Experience curves are derived from Wrights law (85) which connects historic product prices to cumulative deployed capacities. Component-based experience curves have previously been established in the literature for energy storage technologies (26, 49). Here, component-based experience curves are split according to the energy storage, powertrain, and integration factor for a specific technology. The cost equation for each component based experience curve is as follows:

$$Cost_t^{component,i}(X_t^{component,i}) = Cost_0^{component,i}(X_0^{component,i}) \times \left(\frac{X_t^{component,i}}{X_0^{component,i}}\right)^{-b}, \quad [5]$$

where $Cost_t^{component,i}(X_t^{component,i})$ is the cost of component i in year t as a function of $X_t^{component,i}$, the cumulative deployed capacity of component i in year t. $Cost_0^{component,i}$ and $X_0^{component,i}$ are the initial cost and cumulative deployed capacity of component i in the base year. For the integration factor experience curve equation, cost is replaced by an integration factor. The positive learning parameter b is derived from experience rates taken from the literature for each experience component as in Eq. **6**. The experience rate ER is defined as the fixed percentage cost reduction of a product for every doubling of cumulative installed capacity (60).

$$ER = 1 - 2^b, \quad [6]$$

With the inclusion of component-based experience curves, technological progress in the model assumes a global experience for all technology components, except for the vehicle chassis for which we do not assume experiential learning. See *SI Appendix*, Text 2 for more detail on experience curve model implementation.

Simulations. The simulation runs annually from 2020 to 2035. It employs a Monte Carlo discrete choice method, simulating investor technology selection via repeated outputs with stochastic input distributions. The model runs 10,000 simulations of each technology across segments and regions over the period.

Data and Sources. Effort was devoted to compiling a case-specific dataset for this model. Inputs are primarily from the literature, public reports, news articles, open-source datasets, and expert interviews for missing or uncertain data. All data are described and included in *SI Appendix* or Datasets.

Sensitivity Analysis and Robustness Checks. To test model robustness, we perform two distinct sensitivity analyses to analyze model parameter sensitivity and deployment spillover sensitivity. In Sensitivity Analysis 1, we look first at model parameter sensitivities by examining the average yearly ZEV market share change from the BAU scenario, with no intervention or shock, when each parameter is adjusted individually by ±20%. We justify this error bound for parameter sensitivity through both the literature (86–89) and our inclusion of uncertainty bounds for most model parameters in the Monte Carlo analysis. However, for four model parameters crucial for BEV cost competitiveness, we include an extended sensitivity analysis with a ±30% parameter change (*SI Appendix*, Figs. S17–S22). The results and procedure of Sensitivity Analysis 1 are discussed in detail in *SI Appendix*, Text 3 and are visualized in *SI Appendix*, Figs. S11–S16 for the top twenty most sensitive parameters in each region (six total figures). In Sensitivity Analysis 2, we then look at deployment spillover sensitivities by examining the average yearly ZEV market share change under all modeled intervention(s) and shock(s) in intervening and nonintervening regions. We do this first with no model parameter change and next by again changing (±20%) select parameters from Sensitivity Analysis 1. The results and procedure of Sensitivity Analysis 2 are discussed in detail in *SI Appendix*, Text 3 and are visualized in *SI Appendix*, Figs. S23–S58 for the top five most sensitive parameters from Sensitivity Analysis 1 in each region (36 total figures).

We devise a sensitivity metric used in both sensitivity analyses to assess outcomes: the average yearly change in ZEV market shares.

$$Avg\ Yearly\ \Delta\ ZEV\ Market\ Shares_{a,r} = \frac{\sum_{p=0}^{P} ZEV\ Market\ Share_{a,r}^{p,\,sensitivity\_run} - ZEV\ Market\ Share_{a,r}^{p,\,base\_run}}{P}, \quad [7]$$

where a is the application, r is the region, p is the time interval in years, and P is the period over which the sensitivity metric is being evaluated. Here, we sum the difference in ZEV market shares for the *sensitivity_run* and ZEV market shares for the *base_run* in each year p and divide by the total period P. Note that the period P, *sensitivity_run* and *base_run* vary depending on the sensitivity analysis performed. See *SI Appendix*, Text 3 for further detail.

Data, Materials, and Software Availability. Python model used to perform the analysis of this study has been deposited in Github (https://github.com/benoll/SD-Model--Road-Freight) (90).

ACKNOWLEDGMENTS. This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Marie Sklodowska-Curie grant agreement No. 847585 as well as from the Swiss State Secretariat for Education, Research and Innovation as part of the Horizon Europe Project PRISMA.

Author affiliations: [a]Energy and Technology Policy Group, Swiss Federal Institute of Technology, ETH Zurich, Zurich 8092, Switzerland; [b]Climate Finance and Policy Group, Swiss Federal Institute of Technology, ETH Zurich, Zurich 8092, Switzerland; and [c]Institute of Science, Technology and Policy, Swiss Federal Institute of Technology, ETH Zurich, Zurich 8092, Switzerland

Author contributions: B.N., B.S., and T.S.S. designed research; B.N. performed research; B.N. contributed new reagents/analytic tools; B.N. analyzed data; B.S. and T.S.S. secured funding; and B.N., B.S., and T.S.S. wrote the paper.

1. IPCC, 2022: Summary for Policymakers, "Contribution of Working Group III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change" in *Climate Change 2022: Mitigation of Climate Change*, P. R. Shukla, *et al.*, Eds. (Cambridge University Press, Cambridge, UK and New York, NY, USA, 2022), pp. 1–53.
2. P. del Río González, The empirical analysis of the determinants for environmental technological change: A research agenda. *Ecol. Econ.* **68**, 861–878 (2009).
3. G. F. Nemet, *How Solar Energy Became Cheap: A Model for Low-Carbon Innovation* (Routledge, 2019).
4. D. Jacobs, Policy invention as evolutionary tinkering and codification: The emergence of feed-in tariffs for renewable electricity. *Env. Polit.* **23**, 755–773 (2014).
5. A. Grubler, C. Wilson, *Energy Technology Innovation: Learning from Historical Successes and Failures* (Cambridge University Press, Cambridge, 2013).
6. R. P. M. Kemp, Environmental policy and technical change: A comparison of the technological impact of policy instruments. *Environ. Conserv.* **25**, 317 (1997).
7. UNEP, Montreal protocol on substances that deplete the ozone layer: Final act (1987). https://ozone.unep.org/treaties/montreal-protocol. Accessed 8 September 2022.
8. UNEP, Minamata convention on mercury - Text and annexes (2019). https://minamataconvention.org/en/resources/minamata-convention-mercury-text-and-annexes. Accessed 8 September 2022.
9. CITES, Convention on international trade in endangered species of wild fauna and flora (1973). https://cites.org/eng/disc/text.php. Accessed 8 September 2022.

10. UNEP, Stockholm convention on persistent organic pollutants (POPS) - Text and annexes. (2019). https://chm.pops.int/Home/tabid/2121/Default.aspx. Accessed 8 September 2022.
11. T. S. Schmidt, J. Huenteler, Anticipating industry localization effects of clean technology deployment policies in developing countries. *Glob. Environ. Chang.* **38**, 8–20 (2016).
12. K. Surana, C. Doblinger, L. D. Anadon, N. Hultman, Effects of technology complexity on the emergence and evolution of wind industry manufacturing locations along global value chains. *Nat. Energy* **510**, 811–821 (2020).
13. W. Nordhaus, Climate clubs: Overcoming free-riding in international climate policy. *Am. Econ. Rev.* **105**, 1339–1370 (2015).
14. A. Malhotra, T. S. Schmidt, Accelerating low-carbon innovation. *Joule* **4**, 2259–2267 (2020).
15. S. Paltsev, A. Ghandi, J. Morris, H. Chen, Global electrification of light-duty vehicles: Impacts of economics and climate policy. *Econ. Energy Environ. Policy* **11**, 2160–5890 (2022).
16. E. Mulholland, J. Teter, P. Cazzola, Z. McDonald, B. P. Ó. Gallachóir, The long haul towards decarbonizing road freight – A global assessment to 2050. *Appl. Energy* **216**, 678–693 (2018).
17. C. Facanha, K. Blumberg, J. Miller, Global transportation energy and climate roadmap (ICCT, 2012). https://theicct.org/publication/global-transportation-energy-and-climate-roadmap/. Accessed 12 May 2022.
18. T. Matsuo, Fostering grid-connected solar energy in emerging markets: The role of learning spillovers. *Energy Res. Soc. Sci.* **57**, 101227 (2019).
19. D. H. Lee, S. Y. Park, J. C. Hong, S. J. Choi, J. W. Kim, Analysis of the energy and environmental effects of green car deployment by an integrating energy system model with a forecasting model. *Appl. Energy* **103**, 306–316 (2013).
20. V. Ramanathan, Y. Xu, A. Versaci, Modelling human–natural systems interactions with implications for twenty-first-century warming. *Nat. Sustain.* **53**, 263–271 (2021).
21. M. Harmsen *et al.*, Integrated assessment model diagnostics: Key indicators and model evolution. *Environ. Res. Lett.* **16**, 054046 (2021).
22. O. Y. Edelenbosch *et al.*, Decomposing passenger transport futures: Comparing results of global integrated assessment models. *Transp. Res. Part D Transp. Environ.* **55**, 281–293 (2017).
23. D. L. McCollum *et al.*, Improving the behavioral realism of global integrated assessment models: An application to consumers' vehicle choices. *Transp. Res. Part D Transp. Environ.* **55**, 322–342 (2017).
24. R. R. Desai, E. Hittinger, E. Williams, Interaction of consumer heterogeneity and technological progress in the US electric vehicle market. *Energies* **15**, 4722 (2022).
25. G. Pasaoglu *et al.*, A system dynamics based market agent model simulating future powertrain technology transition: Scenarios in the EU light duty vehicle road transport sector. *Technol. Forecast. Soc. Change* **104**, 133–146 (2016).
26. M. Beuse, B. Steffen, T. S. Schmidt, Projecting the competition between energy-storage technologies in the electricity sector. *Joule* **4**, 2162–2184 (2020).
27. J. J. Gómez Vilchez, P. Jochem, Simulating vehicle fleet composition: A review of system dynamics models. *Renew. Sustain. Energy Rev.* **115**, 109367 (2019).
28. A. Nuñez-Jimenez, C. Knoeri, J. Hoppmann, V. H. Hoffmann, Beyond innovation and deployment: Modeling the impact of technology-push and demand-pull policies in Germany's solar policy mix. *Res. Policy* **51**, 104585 (2022).
29. A. Guerrero de la Peña *et al.*, "Modeling freight transportation as a system-of-systems to determine adoption of emerging vehicle technologies" in *International Conference on Transportation and Development,* American Society of Civil Engineers, Eds. (ASCE Library, 2019), pp. 156–169.
30. L. Paroussos *et al.*, Climate clubs and the macro-economic benefits of international cooperation on climate policy. *Nat. Clim. Chang.* **97**, 542–546 (2019).
31. R. Hanna, A. Abdulla, Y. Xu, D. G. Victor, Emergency deployment of direct air capture as a response to the climate crisis. *Nat. Commun.* **121**, 1–13 (2021).
32. L. Paroussos, F. Panagiotis, V. Zoi, F. Kostas, *A Technical Case Study on R&D and Technology Spillovers of Clean Energy Technologies* (European Commission, 2017), pp. 1–87.
33. W. Zhang, T. Zhang, H. Li, H. Zhang, Dynamic spillover capacity of R&D and digital investments in China's manufacturing industry under long-term technological progress based on the industry chain perspective. *Technol. Soc.* **71**, 102129 (2022).
34. J. P. Helveston, G. He, M. R. Davidson, Quantifying the cost savings of global solar photovoltaic supply chains. *Nature* **612**, 83–87 (2022).
35. M. R. Davidson, V. J. Karplus, J. I. Lewis, J. Nahm, A. Wang, Risks of decoupling from China on low-carbon technologies. *Science* **377**, 1266–1269 (2022).
36. J. Helveston, J. Nahm, China's key role in scaling low-carbon energy technologies. *Science* **366**, 794–796 (2019).
37. D. M. Hart, *The Impact of China's Production Surge on Innovation in the Global Solar Photovoltaics Industry* (ITIF, 2020).
38. W. F. Lamb *et al.*, A review of trends and drivers of greenhouse gas emissions by sector from 1990 to 2018. *Environ. Res. Lett.* **16**, 073005 (2021).
39. B. Noll, S. del Val, T. S. Schmidt, B. Steffen, Analyzing the competitiveness of low-carbon drive-technologies in road-freight: A total cost of ownership analysis in Europe. *Appl. Energy* **306**, 118079 (2022).
40. W. C. Clark, A. G. Harley, Sustainability science: Toward a synthesis. *Annu. Rev. Environ. Resour.* **45**, 331–386 (2020).
41. F. W. Geels, B. K. Sovacool, T. Schwanen, S. Sorrell, Sociotechnical transitions for deep decarbonization. *Science* **357**, 1242–1244 (2017).
42. L. Fuenfschilling, C. Binz, Global socio-technical regimes. *Res. Policy* **47**, 735–749 (2018).
43. W. B. Arthur, Competing technologies, increasing returns, and lock-in by historical events. *Econ. J.* **99**, 116 (1989).
44. T. S. Schmidt, B. Battke, D. Grosspietsch, V. H. Hoffmann, Do deployment policies pick technologies by (not) picking applications?—A simulation of investment decisions in technologies with multiple applications. *Res. Policy* **45**, 1965–1983 (2016).
45. K. C. Seto *et al.*, Carbon lock-in: Types, causes, and policy implications. *Annu. Rev. Environ. Resour.* **41**, 425–452 (2016).
46. A. Dechezleprêtre, E. Neumayer, R. Perkins, Environmental regulation and the cross-border diffusion of new technology: Evidence from automobile patents. *Res. Policy* **44**, 244–257 (2015).
47. F. Zhang, K. S. Gallagher, Innovation and technology transfer through global value chains: Evidence from China's PV industry. *Energy Policy* **94**, 191–203 (2016).
48. B. Nykvist, M. Nilsson, Rapidly falling costs of battery packs for electric vehicles. *Nat. Clim. Chang.* **5**, 329–332 (2015).
49. O. Schmidt, A. Hawkes, A. Gambhir, I. Staffell, The future cost of electrical energy storage based on experience rates. *Nat. Energy* **2**, 17110 (2017).
50. E. S. Rubin, I. M. L. Azevedo, P. Jaramillo, S. Yeh, A review of learning rates for electricity supply technologies. *Energy Policy* **86**, 198–218 (2015).
51. E. S. Rubin, J. E. Davison, H. J. Herzog, The cost of CO2 capture and storage. *Int. J. Greenh. Gas Control* **40**, 378–400 (2015).
52. J. Huenteler, C. Niebuhr, T. S. Schmidt, The effect of local and global learning on the cost of renewable energy in developing countries. *J. Clean. Prod.* **128**, 6–21 (2016).
53. K. Surana, C. Doblinger, L. D. Anadon, N. Hultman, Effects of technology complexity on the emergence and evolution of wind industry manufacturing locations along global value chains. *Nat. Energy* **510**, 811–821 (2020).
54. G. Papachristos, A system dynamics model of socio-technical regime transitions. *Environ. Innov. Soc. Transitions* **1**, 202–233 (2011).
55. T. Ansell, S. Cayzer, Limits to growth redux: A system dynamics model for assessing energy and climate change constraints to global growth. *Energy Policy* **120**, 514–525 (2018).
56. W. Fang *et al.*, Accessing on the sustainability of urban ecological-economic systems by means of a coupled emergy and system dynamics model: A case study of Beijing. *Energy Policy* **100**, 326–337 (2017).
57. B. Walrave, R. Raven, Modelling the dynamics of technological innovation systems. *Res. Policy* **45**, 1833–1844 (2016).
58. P. P. Saviotti, G. S. Mani, Competition, variety and technological evolution: A replicator dynamics model. *J. Evol. Econ.* **54**, 369–392 (1995).
59. G. Papachristos, E. Adamides, A retroductive systems-based methodology for socio-technical transitions research. *Technol. Forecast. Soc. Change* **108**, 1–14 (2016).
60. F. Ferioli, K. Schoots, B. C. C. van der Zwaan, Use and limitations of learning curves for energy technology policy: A component-learning hypothesis. *Energy Policy* **37**, 2525–2535 (2009).
61. G. Santos, H. Behrendt, L. Maconi, T. Shirvani, A. Teytelboym, Part I: Externalities and economic policies in road transport. *Res. Transp. Econ.* **28**, 2–45 (2010).
62. R. B. Gunier, A. Hertz, J. Von Behren, P. Reynolds, Traffic density in California: Socioeconomic and ethnic differences among potentially exposed children. *J. Expo. Sci. Environ. Epidemiol.* **133**, 240–246 (2003).
63. J. Huenteler, T. S. Schmidt, J. Ossenbrink, V. H. Hoffmann, Technology life-cycles in the energy sector - Technological characteristics and the role of deployment for innovation. *Technol. Forecast. Soc. Change* **104**, 102–121 (2016).
64. N. Bento, C. Wilson, Measuring the duration of formative phases for energy technologies. *Environ. Innov. Soc. Transitions* **21**, 95–112 (2016).
65. L. H. Kaack, P. Vaishnav, M. G. Morgan, I. L. Azevedo, S. Rai, Decarbonizing intraregional freight systems with a focus on modal shift. *Environ. Res. Lett.* **13**, 083001 (2018).
66. D. L. Weimer, A. R. Vining, Correcting market and government failures. *Policy Anal.*, 205–258 (2018).
67. A. Grubler, C. Wilson, "Policies for Energy Technology Innovation" in *Energy Technology Innovation: Learning from Historical Successes and Failures*, A. Grubler, C. Wilson, Eds. (Cambridge University Press, Cambridge, 2013), pp. 371–387.
68. N. Rosenberg, M. Stolpe, *Exploring the Black Box. Technology, Economics, and History* (Cambridge University Press, 1995).
69. J. Hoppmann, M. Peters, M. Schneider, V. H. Hoffmann, The two faces of market support - How deployment policies affect technological exploration and exploitation in the solar photovoltaic industry. *Res. Policy* **42**, 989–1003 (2013).
70. K. M. Weber, H. Rohracher, Legitimizing research, technology and innovation policies for transformative change: Combining insights from innovation systems and multi-level perspective in a comprehensive "failures" framework. *Res. Policy* **41**, 1037–1047 (2012).
71. A. B. Jaffe, M. Trajtenberg, R. Henderson, Geographic localization of knowledge spillovers as evidenced by patent citations. *Q. J. Econ.* **108**, 577–598 (1993).
72. M. Peters, M. Schneider, T. Griesshaber, V. H. Hoffmann, The impact of technology-push and demand-pull policies on technical change - Does the locus of policies matter? *Res. Policy* **41**, 1296–1308 (2012).
73. BNEF, *Electric Vehicle Outlook Report* (Bloomberg New Energy Finance, 2021).
74. J. Axsen, P. Plötz, M. Wolinetz, Crafting strong, integrated policy mixes for deep CO2 mitigation in road transport. *Nat. Clim. Chang.* **109**, 809–818 (2020).
75. T. Kuramochi *et al.*, Beyond national climate action: The impact of region, city, and business commitments on global greenhouse gas emissions. *Clim. Policy* **20**, 275–291 (2020).
76. IEA, Global EV Outlook 2021 Accelerating ambitions despite the pandemic. (2021). https://www.iea.org/reports/global-ev-outlook-2021. Accessed 15 June 2021.
77. C. Fischer, L. Preonas, Combining policies for renewable energy: Is the whole less than the sum of its parts? *Int. Rev. Environ. Resour. Econ.* **4**, 51–92 (2010).
78. F. Joas, M. Pahle, C. Flachsland, A. Joas, Which goals are driving the Energiewende? Making sense of the German Energy Transformation. *Energy Policy* **95**, 42–51 (2016).
79. S. van Renssen, The hydrogen solution? *Nat. Clim. Chang.* **109**, 799–801 (2020).
80. C. Holden, Exporting public–private partnerships in healthcare: Export strategy and policy transfer. *Policy Stud. J.* **30**, 313–332 (2009).
81. L. Haelg, M. Waelchli, T. S. Schmidt, Supporting energy technology deployment while avoiding unintended technological lock-in: A policy design perspective. *Environ. Res. Lett.* **13**, 104011 (2018).
82. Y. J. Kim, M. Brown, Impact of domestic energy-efficiency policies on foreign innovation: The case of lighting technologies. *Energy Policy* **128**, 539–552 (2019).
83. T. Buholtz *et al.*, Electrifying freight: Pathways to accelerating the transition (Electrification Coalition, 2020). https://electrificationcoalition.org/resource/electrifying-freight-pathways-to-accelerating-the-transition/. Accessed 13 November 2020.
84. P. Jenkins *et al.*, "White Paper building a beachhead: California's path to accelerating zero-emission commercial vehicles" (CALSTART, 2022). https://globaldrivetozero.org/publication/building-a-beachhead-californias-path-to-accelerating-zero-emission-vehicles/.
85. T. P. Wright, Factors affecting the cost of airplanes. *J. Aeronaut. Sci.* **3**, 122–128 (1936).
86. A. Saltelli *et al.*, Why so many published sensitivity analyses are false: A systematic review of sensitivity analysis practices. *Environ. Model. Softw.* **114**, 29–39 (2019).
87. L. Lanz, B. Noll, T. S. Schmidt, B. Steffen, Comparing the levelized cost of electric vehicle charging options in Europe. *Nat. Commun.* **13**, 5277 (2022).
88. E. Borgonovo, Tornado diagrams. *Int. Ser. Oper. Res. Manag. Sci.* **251**, 17–25 (2017).
89. S. A. El-Temtamy, T. S. Gendy, Economic evaluation and sensitivity analysis of some fuel oil upgrading processes. *Egypt. J. Pet.* **23**, 397–407 (2014).
90. B. Noll, SD Model – Road-Freight. Github. https://github.com/benoll/SD-Model--Road-Freight. Deposited 22 August 2023.