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Beyond innovation and deployment: Modeling the impact of technology-push and demand-pull policies in Germany's solar policy mix

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1. Introduction

Societal challenges—from climate change and resource depletion to local pollution—call for a sustainability transition that decouples economic growth from negative consequences for natural ecosystems (Markard et al., 2012). Thus, policymakers in many countries have introduced policies to speed up the transition, steer economic activities onto more sustainable pathways, and reduce greenhouse gas emissions (Roelfsema et al., 2020). These interventions are usually not limited to a single policy instrument but include several instruments as part of a policy mix (Flanagan et al., 2011; Ossenbrink et al., 2019; Rogge and Reichardt, 2016). Specifically, policy mixes often combine technology-push and demand-pull instruments to foster innovation and the deployment of more sustainable technologies (Peters et al., 2012; Rennings, 2000). Technology-push instruments seek to enhance the supply of clean technologies by reducing the private cost of their development through, for example, public expenditure on research and development (R&D) (Nemet, 2009). Demand-pull measures, on the other hand, foster technological change by stimulating the demand for novel technologies through, for example, economic incentives (Peters et al., 2012). By combining technology-push and demand-pull instruments, governments aim to strike a balance between both approaches that would help them realize their objectives (Costantini et al., 2017).

Historical experiences have demonstrated the importance of both technology-push and demand-pull instruments for steering sociotechnical change; however, two important gaps remain in the literature (Costantini et al., 2015; Rogge and Schleich, 2018). First, while in practice policymakers and analysts pay attention to multiple policy goals, the literature on policy mixes has so far been concentrated on innovation and deployment outcomes (Costantini et al., 2017; Hille et al., 2020; Johnstone et al., 2009; Wiebe and Lutz, 2016; Wiesenthal et al., 2012). When designing and implementing policy mixes, policymakers usually pursue multiple objectives in addition to technological change, such as creating jobs, reducing CO2 emissions, or making the country a climate or technological leader. For example, when

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introducing a feed-in tariff (FIT) for solar photovoltaics (PV), German policymakers stated that their solar policy mix aimed not only to foster innovation but also to create jobs, encourage the establishment of new firms, and increase exports in a promising high-tech industry, among other goals (Hoppmann et al., 2014). Over time, the FIT produced such an acceleration of PV deployment that its influence was soon felt well beyond Germany’s borders. Germany’s FIT significantly contributed to reductions in global PV prices by spurring innovation and deployment and leading many other countries to adopt FIT policies (Buchholz et al., 2019; Nuñez-Jimenez et al., 2020a). At the same time, though, Germany’s PV industry struggled to compete with foreign manufacturers, and most of the jobs it created were eventually lost (BSW-Solar, 2020).

Germany’s historical experience illustrates the importance of considering goals beyond innovation and deployment and how to combine technology-push and demand-pull policies to achieve them. Recently, some researchers have investigated the impact of demand-pull instruments on industry development and knowledge spillovers (Hansen et al., 2019; Hoppmann et al., 2013; Zhang et al., 2016). However, there is lack of systematic analysis regarding how the combination of technology-push and demand-pull instruments in one policy mix influences multiple policy objectives at the same time.

A second gap in the literature is a weak quantitative understanding of the effects of the interactions between technology-push and demand-pull policy mix outcomes. This gap stems from the limitations of the methods used in most quantitative studies that address these questions. For instance, the linear regression analyses of historical policy mixes can identify whether the interactions between policy instruments create effects that are greater than the sum of their individual effects (Guerzoni and Raiteri, 2015). However, linear regression analyses are not well equipped for studying the non-linear and dynamic interactions between policy instruments expected in large, complex sociotechnical systems (STSs) (Flanagan et al., 2011). Although recent modeling studies have started to close this gap, they have remained highly aggregated (Corradini et al., 2018), focused only on innovation and niches (Falcone et al., 2019; Ghazinoory et al., 2019), or omitted key aspects that influence policy mix outcomes, such as knowledge spillovers and international trade (Herrmann and Savin, 2017).

To address these shortcomings, we apply a modeling approach to systematically investigate how different emphases on technology-push and demand-pull instruments influence sociotechnical change. An agent-based model (ABM) of the STS for PV in Germany was developed to investigate whether a small shift toward technology-push of Germany’s demand-pull-oriented policy mix could have led to better outcomes (Frondel et al., 2010). First, four policy mix scenarios that differ with respect to their emphasis on technology-push and demand-pull are analyzed in detail. Subsequently, the effects of the interactions between technology-push and demand-pull instruments on key policy objectives, such as technology deployment, policy cost, and job creation, are systematically studied by simulating 45 different variations. The ABM is empirically validated using the abundant data on the evolution of the STS for PV in Germany. While the ABM is a simplification of complex real-world processes, it is able to represent the decision-making of PV adopters, supply chain dynamics, induced technological change, knowledge spillovers, and international trade.

Our study makes three contributions to the literature. First, the results show that a narrow focus by academic researchers on innovation and deployment outcomes could lead to recommendations for the design of policy mixes that may compromise crucial dimensions of sociotechnical change. Previous quantitative studies have focused on the impact of the balance of the instrument mix on innovation (Costantini et al., 2017) or deployment (Albrecht et al., 2015), leading to a search for an optimal balance that maximizes one objective—often deployment—while minimizing policy costs or CO2 emissions (Corradini et al., 2018; Herrmann and Savin, 2017). Our study shows that policy mixes with different emphases on technology-push and demand-pull could achieve similar deployment and emissions savings at comparable policy costs but with starkly different consequences in terms of jobs and international trade.

Second, our results demonstrate the need to pay more attention to how policy mixes influence the entire STS they target—including the parts of the STS outside the borders of the country adopting the policy mix—in order to fully capture the effect of technology-push and demand-pull instruments. Policy mix studies have predominantly analyzed the interactions between policy instruments by focusing on the consistency of the policy instruments with the policy strategy, objectives, and other instruments (del Río and Cerdà, 2017; Rogge and Reichardt, 2016) using national borders as the analysis boundaries (Edmondson et al., 2020; Herrmann and Savin, 2017; Rogge and Schleich, 2018). This article shows that the interactions between technology-push and demand-pull instruments, both domestically and abroad, are key to understanding the outcomes of policy mixes.

Third, this paper proposes agent-based modeling as a useful methodology for investigating and evaluating policy mixes. Previous studies have primarily relied on historical data (Costantini et al., 2017; Guerzoni and Raiteri, 2015; Rogge and Schleich, 2018) and case studies (Edmondson et al., 2020; Gomel and Rogge, 2020; Hansen et al., 2019). This paper adds to recent efforts to complement and overcome the limitations of more traditional methods (Caprioli et al., 2020; Herrmann and Savin, 2017; van der Veen and Brouillat, 2015).

The rest of the paper is structured as follows: The theoretical background is provided in Section 2. The ABM and research setting are described in Section 3. The results of our model simulations and their implications are discussed in Sections 4 and 5, respectively. Finally, the conclusion of this study is provided in Section 6.

2. Theoretical background

2.1. Policy mixes for sustainability transitions

A core concern in the literature on sustainability transitions has been how societies can foster changes in STSs to steer economic systems onto more sustainable pathways (Markard et al., 2012). The networks of actors, institutions, material artifacts, and knowledge that configure STSs are difficult to change (Geels, 2004), and historical experiences have shown that public policies can be essential for expediting their transformation (Horbach et al., 2012; Mowery et al., 2010). Scholars in both the neoclassical and evolutionary traditions acknowledge that policies are essential drivers for sustainability because they can help to address market, system, and institutional failures (Jaffe et al., 2005; Weber and Rohracher, 2012) as well as break out of path dependencies and lock-ins (Kivimaa and Kern, 2016; Null and Kemp, 2009).

Given their importance, it is not surprising that many studies have investigated which policies are best suited to fostering sociotechnical change. Early studies focused on testing and comparing the effects of different policy instruments, mainly on innovation and deployment outcomes (Jaffe et al., 2002; Jänicke and Lindemann, 2010). A core debate has emerged about the merits of technology-push versus demand-pull policies as two key types of instruments for inducing sociotechnical change (Nemet, 2009; Peters et al., 2012; Remmings, 2000). Technology-push instruments aim to foster sociotechnical change by reducing the private costs of R&D (Nemet, 2009). Typical technology-push measures include public R&D funding, tax reductions for R&D investments, and financial support for pilot projects. Demand-pull instruments, however, aim to stimulate sociotechnical change by encouraging demand for technologies (Edler and Georghiou, 2007). Demand-pull measures typically include subsidies or tax credits for end consumers, standard-setting instruments (e.g., performance standards), information campaigns, and public procurement programs.

Although studies have shown that both technology-push and demand-pull instruments are important for spurring sociotechnical change (Cantner et al., 2016; Costantini et al., 2017; Rogge and Reichardt, 2016), the debate on how to combine them is still ongoing.
Technology-push instruments have long been demonstrated to enhance firms’ innovative activity (Klaassen et al., 2005), but a strong reliance on push measures, even if they make a country a technological leader, does not necessarily lead to more deployment (Hansen et al., 2019). In contrast, demand-pull instruments have been found to effectively accelerate the diffusion of new technologies (Cantner et al., 2016), but often with considerable policy costs while part of the benefits of accelerated deployment, such as industry development, may spill over to other regions (Hansen et al., 2019; Hoppmann et al., 2013; Zhang et al., 2016).

The idea that different policy instruments have distinct influences on sociotechnical change and that they complement one another in the pursuit of multiple objectives has motivated policymakers to combine instruments into policy mixes (Rogge et al., 2017; Schmidt and Sewerin, 2019). Policy mixes combine strategies that set long-term objectives and interacting instruments characterized by type, purpose, and design features that try to achieve those objectives (Rogge and Reichardt, 2016). Two components are essential to policy mixes. One is the coexistence of multiple policy objectives that might pose trade-offs in selecting what instruments to include in a policy mix (Flanagan et al., 2011). The other is interaction between policy instruments, which requires the consideration of the instruments’ joint influence in addition to their individual effects, when designing a policy mix (Sorrell et al., 2003).

Although policy mixes are gaining increased attention, important questions about these two components remain underexplored. Among them, this paper focuses on: 1) How should policy mixes be designed to deal with multiple (potentially conflicting) objectives? 2) How do different emphases on technology-push and demand-pull instruments influence the interactions between them and, thus, the outcomes of the policy mix?

2.2. Designing policy mixes for multiple objectives

The literature on policy mixes stresses that a single policy mix often encompasses many policy objectives (Howlett and Rayner, 2013; Kern and Howlett, 2009) whose consistency, credibility, and coherence influence its outcomes (Reichardt and Rogge, 2016; Rogge and Schleich, 2018). The German Renewable Energy Sources Act 2000, for example, lists the reduction of carbon emissions, improvement of technologies, and creation of industries and jobs as its main objectives (German Parliament, 2000).

Despite acknowledging the diversity of policy mix objectives, scholars have mostly focused only on few goals, typically around innovation and deployment (Cantner et al., 2016; Costantini et al., 2017; Johnstone et al., 2009; Wiebe and Lutz, 2016). There has been a recent trend toward expanding the policy goals considered to include ambitions such as industry development (Gomel and Rogge, 2020), economic growth (Edmondson et al., 2019, 2020), or leaving behind polluting technologies (Kivimaa and Kern, 2016). However, this trend has not yet extended to empirical studies that remain overwhelmingly focused on one goal, most commonly, innovation (Choi, 2018; Costantini et al., 2017; Ghatinnoory et al., 2019; Hille et al., 2020; Pielis et al., 2020).

Analyzing policy mixes by considering only innovation and deployment objectives can present a simplistic view of the policy mix effectiveness and overlook the trade-offs between goals that working with a broader set of objectives could reveal. Policymakers face many trade-offs when designing policy mixes, for instance, between fostering new technologies, which require nurturing technological niches, and short-term reductions in CO₂ emissions, which require the rapid expansion of the use of available technologies (Corradi et al., 2018; Herrmann and Savin, 2017). A narrow approach to policy objectives by academia researchers could motivate attempts to find optimal or “unambiguously ‘good’ mixes” that prioritize one single objective at the expense of other goals (Flanagan et al., 2011). Therefore, more studies are needed to investigate quantitatively the impact of alternative policy mix configurations on multiple policy objectives, such as reducing CO₂ emissions, using public funds efficiently, and creating jobs (Parris and Kates, 2003; Rogge and Reichardt, 2016).

2.3. Balancing the emphasis of a policy mix to benefit from instrument interactions

In addition to not considering multiple policy goals, most empirical studies often consider the interactions between a policy mix’s instruments only in a limited way. The concept of policy mix explicitly recognizes that the effect of one policy instrument is modified by the simultaneous presence of other instruments (Nauwelaers, 2009), often in path-dependent, dynamic ways that are hard to predict (Flanagan et al., 2011). Attention to interactions initially gained ground in the environmental policy literature (del Río, 2007; Gunningham and Sinclair, 1999; Sorrell et al., 2003). Since then, the focus of studies on innovation and sustainability transitions has gradually been shifted from the effects of individual instruments to the joint influence of several instruments as part of a policy mix (Kern et al., 2019). In this context, researchers have predominantly considered the interactions between instruments based on the consistency of the policy instruments with the policy mix’s strategy, objectives, and other instruments (Rogge and Reichardt, 2016; Rogge and Schleich, 2018), with some exceptions (Schmidt and Sewerin, 2019).

Yet two aspects remain relatively understudied: (1) the path-dependent nature of interactions, and (2) the influence of minor changes in the instrument design features. How instruments interact depends on their individual characteristics and the context in which they are applied (Gunningham and Grabsky, 1998). In this way, path-dependent, sociotechnical changes triggered by a policy mix could alter how policy instruments interact with one another, even if the policy mix itself remains unchanged. In addition, because of cumulative effects, small differences in the instrument design can lead to major consequences over time (Flanagan et al., 2011; Kemp and Pontoglio, 2011).

Previous studies have overlooked these considerations in part because of the limitations of ex-post evaluations using qualitative methods (del Río, 2010; del Río and Cerdá, 2017) and regression analyses of historical data (Albrecht et al., 2015; Guerzoni and Raiteri, 2015; Nemet, 2009; Rogge and Schleich, 2018). Recent attempts to explore policy mixes through modeling have contributed to overcoming those limitations but have thus far remained highly aggregated (Corradi et al., 2018), focused only on innovation goals (Falcone et al., 2019; Ghatinnoory et al., 2019), or excluded relevant aspects for the outcomes of a policy mix, such as knowledge spillovers and international trade (Herrmann and Savin, 2017).

Therefore, there is lack of sufficient research on how considering multiple policy objectives and interactions between policy instruments could influence what policy mix formulations are most desirable. Addressing this gap is crucial for advancing the literature on policy mixes and providing better informed recommendations to policymakers. Not knowing how a policy mix will influence its various objectives obfuscates the presence of trade-offs and synergies between the multiple dimensions of sociotechnical change. In addition, the oversimplification of the interactions between policy instruments can create misleading expectations about and assessments of the outcomes of policy mixes. For

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1 This applies to interactions between instruments as well as other elements and characteristics of policy mixes. For instance, the (perception of the) credibility of a policy mix can increase over time just because it remains in place without significant modifications (Gomel and Rogge, 2020; Rogge and Schleich, 2018). In this case, the policy mix has not changed but the context in which it exists has. Therefore, the influence between policy mix characteristics and technological change in the framework proposed by Rogge and Reichardt (2016) could be regarded as bidirectional.
all these reasons, in this paper, we investigate how different emphases on technology-push and demand-pull instruments within a policy mix influence sociotechnical change.

3. Method

3.1. Research approach and setting

To investigate how different emphases on technology-push and demand-pull instruments in a policy mix influence sociotechnical change, we used agent-based modeling and applied it to the STS for PV in Germany. ABMs are used in many disciplines, such as ecology (Grimm and Railsback, 2005), ecosystem management (Janssen, 2002), and economics (Dosi et al., 2018). They are built on the idea that to represent the emergent dynamics of complex STSs, a simulation model needs to integrate the behaviors and interactions of individual actors. ABMs have been used extensively to investigate innovation diffusion (Zhang and Vorobeychik, 2019) and, recently, climate and energy policy (Castro et al., 2020; Lamperti et al., 2019). The ABM in this manuscript follows the principles and methods of “history-friendly” models (Malerba et al., 1999; Capone et al., 2019) and bridges the gap between the studies that used ABMs to research innovation (Dosi et al., 2018) and deployment policies (Rai and Robinson, 2015; Nunez-Jimenez et al., 2020a).

We selected PV as a technology due to its vital role in decarbonizing the electricity sector. PV has been subject to considerable policy support in the past, and it shares key features with emerging technologies such as electricity storage (for example, mass production, modularity, and strong learning effects) (Kütner et al., 2017). We chose Germany as the geographical setting because it has been very effective in supporting PV adoption (IEA-PVPS, 2019a). Germany’s strong emphasis on demand-pull measures, such as FITs, underpinned the rapid deployment of PV in the country. However, the high associated costs of the FIT for PV led to a controversial debate about the balance between push and pull instruments in Germany’s policy mix and whether a stronger technology-push would have helped to attain the policy mix’s multiple objectives in a more cost-efficient manner.

Using the ABM, we first evaluated four policy mixes with distinct emphases on either technology-push or demand-pull and then analyzed 45 variations to explore the impact of minor emphasis changes on key policy objectives. Based on their salience during the policy process, deployment, policy costs, employment, trade, and technology costs were considered as the main policy objectives and therefore used as variables to assess the German policy mix for PV (Hoppmann et al., 2014). The ABM was coded in NetLogo, simulated in Python using the pyNetLogo package (Jaxa-Rozen and Kwakkel, 2018), and then analyzed with Python. Simulations were run in a computing cluster, requiring 15 clock hours on average for 45 policy mixes and 10 cores with at least 8 GB of memory each. The rest of this section provides a summary of the model.

The Supplementary Information (SI) includes a detailed description of the model.

3.2. Model overview and purpose

The aim of the model was to represent the historical STS of PV in Germany (i.e., domestic region) and its interaction with the global PV market (i.e., foreign region) to analyze the effects of different support levels for technology-push and demand-pull instruments in Germany’s policy mix (see Fig. 1). This model was built upon a previous version that focused only on the decision-making of PV adopters (Nunez-Jimenez et al., 2020a, 2020b).

Since the purpose of this study is to simulate the impact of the policy mix on sociotechnical change, the main input parameters are the levels of support for technology-push and demand-pull instruments in relation to their historical levels (see Section 4 of SI). On the demand-pull side, the policy input proportionally modifies the historical FIT in Germany, whereas on the technology-push side, the model increases or reduces the historical public R&D spending on PV within Germany. These two measures are representative of the categories of demand-pull and technology-push policy instruments, and both played a major role in the evolution of PV’s STS in Germany (Hansen et al., 2019; Johnstone et al., 2009; Lipp, 2007).

The model’s main outputs monitor sociotechnical change through variables that reflect the most prominent policy objectives of Germany’s renewable energy policy mix: deployment, as installed PV capacity and consequent emission savings; employment in the German PV industry; technological progress, approximated by the reduction in PV prices; and the total cost of policy measures to evaluate the efficiency of different policy mixes.

3.2.1. Entities, state variables, and scales

There are three types of entities in the model: observer, adopters, and suppliers. The observer is a system-level entity that updates the model’s global variables. The adopters are individual, heterogeneous agents that represent the population of potential adopters in Germany who decide whether to invest in a PV system. There are three categories of adopters: residential, commercial, and industrial, and utility-scale characterized
by installation sizes that range from small rooftop systems to large, ground-mounted installations (Table 1). Each agent’s key attributes, such as environmental awareness, PV size, or discount rate, were assigned to them using statistical distributions that allow the representation of randomness and uncertainty in the real world. For simplicity, the behavior of foreign adopters was represented in an aggregated form at the system level. Finally, supply agents were economic actors in the PV supply chain represented by four agents, one per industry segment and region (e.g., one PV module manufacturer and one installer in the domestic region and their counterparts in the foreign region). A detailed description of the state variables for each entity is provided in Section 1.1.3 of the SI.

To simulate the model within a reasonable time given the available computing resources, the agent population was scaled down by a factor of 1:1000 (i.e., one residential agent in the model represented 1000 homeowners in reality). The total population of artificial agents in the model was 20,829 adopter agents in Germany and four producer agents—two per region. The model was geographically explicit for adopter agents who were distributed across Germany in geographical patches of 10 × 10 km based on the density of buildings in each German state. Meanwhile, supply agents had a country-wide presence. Simulations were run in batches and statistically analyzed to account for the stochastic nature of some model inputs. In the simulations, monthly time steps between January 1991 and December 2016 were used, and the period up to December 1999 was used to initialize the model variables. The temporal scope of the analysis spanned 2000–2016. After 2016, the FIT for smaller systems continued; however, auctions, whose simulation fell beyond the scope of this analysis, replaced the FIT for utility-scale installations.

3.3.2. Adoption decision-making (2)

When the global variables are up to date, the adopter agents go through the adoption decision-making process. A potential adopter goes through two steps. Step 1: The agent determines whether it will develop the idea to install PV based on the combined influence of its environmental awareness, peer effects, available information, and perceived profitability of PV. Step 2: Agents that develop the idea conduct an economic evaluation and adopt PV if the investment’s net present value is positive. A small share of highly environmentally aware agents (around 1%, based on the environmental awareness threshold set during the model’s calibration) skip the economic evaluation and adopt right away, representing early adopters. During the second step, the adopter agents choose between a PV system with domestic (i.e., German) or foreign PV modules based on a net present value comparison. Agents apply a higher discount rate to PV systems with imported PV modules to represent a perceived risk of lower performance or inferior reliability of imported equipment (Binz and Anadon, 2018; Mangelsdorf, 2012). If domestic PV modules are preferred but are not available in the domestic installer’s stock, the adopter buys foreign PV modules as long as the installation’s net present value remains positive; otherwise, it postpones the decision. In the foreign region, demand for domestic (i.e., German) PV modules is modeled by an aggregated function based on historical exports, whereas demand for foreign PV modules follows the historical deployment of PV.

3.3.3. Supply chain dynamics

After the simulation of the demand for PV modules, the supply agents represent the supply chain dynamics in five steps through processes 3–7.

3.3.3.1. Technology supply (3). First, the domestic and foreign installer agents buy PV modules from domestic and foreign PV module manufacturers, assuming that the next month’s demand will follow the demand in the current month. For domestic installers, the demand for domestic and foreign PV modules also depends on their remaining stock, while foreign installers buy PV modules according only to the demand they experience. Subsequently, PV module manufacturers try to satisfy the demand from installers. However, domestic PV module manufacturers can only sell as many PV modules to installers as they have in stock, with a preference for domestic clients. Meanwhile, foreign PV module manufacturers can sell as many PV modules as installers demand given their much larger production capacity. Finally, domestic PV module manufacturers set their production targets for the next time step. To determine the production level, they consider their remaining stock of PV modules, production capacity, and expected demand.

3.3.3.2. Cross-regional trade (4). Cross-regional trade in PV modules is represented through transactions between domestic and foreign installer agents and their PV module manufacturer counterparts. The imports of PV modules into Germany are determined by the demand for foreign PV modules from adopter agents. Meanwhile, foreign demand for German PV modules is modeled by an aggregated function that increases (or decreases) the historical demand for exports in direct proportion to the difference between the simulated and historical prices of German PV modules (see Section 1.3.3 of SI).

3.3.3.3. Employment (5). After the conclusion of the purchases and sales of PV modules, the supply agents in the domestic region adjust their workforce. For simplicity, foreign supply agents operate without employees. Domestic installers estimate how many workers will be required for the next month by considering the average demand during the previous six months, and they adjust their workforce based on the
labor productivity of their workers, which is a calibration parameter. Similarly, domestic PV module producers determine the workforce required to operate their manufacturing facilities based on the number of PV modules they aim to produce and the labor productivity of their employees. For both supply agents, changes in the workforce from one time step to the next (i.e., one month) are limited to keep the model's volatility within realistic boundaries.

### Technological learning (6)

The last step in the model's monthly loop is updating technology prices. PV system prices comprise PV module and non-module prices (Schaeffer et al., 2004), which evolve following two-factor and one-factor experience curves, respectively. Non-module prices account for all elements required to install PV systems other than PV modules (for example, inverters, and installation). The domestic installer agent sets non-module prices based on production costs and their mark-up. Production costs for non-module elements follow a one-factor experience curve that captures the learning-by-doing of domestic installers based on their cumulative installations. The experience curve parameters were derived (see Section 14 of SI) from historical data (Bundesnetzagentur, 2017; IEA-PVPS, 2017). For simplicity, non-module prices are considered only in the domestic region.

Similarly, domestic PV module prices depend on production costs and the manufacturer's profit margin. The production costs of foreign PV modules are assumed to already include the foreign manufacturer's profit margin. The model simulates the evolution of PV module production costs in the two regions (domestically and abroad) using two separate two-factor experience curves (Kobos et al., 2006; Qiu and Anadon, 2012; Zheng and Kammen, 2014). While individual technology changes are stochastic in nature, two-factor experience curves can represent the aggregate influence of the manufacturers' cumulative experience through learning-by-doing and of the cumulative knowledge from innovation efforts through learning-by-researching. Both were key drivers of cost reductions in PV modules throughout the simulated

### Table 1

<table>
<thead>
<tr>
<th>Region</th>
<th>Category</th>
<th>Population(^a)</th>
<th>System size [kWp](^c)</th>
<th>Self-consumption [% solar generation](^d)</th>
<th>Electricity price</th>
<th>Discount rate(^e)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Domestic (Germany)</td>
<td>Residential</td>
<td>16,891,049(^‡)</td>
<td>0–10</td>
<td>30(^%)</td>
<td>Historical rates(^g)</td>
<td>Historical rates(^h)</td>
</tr>
<tr>
<td></td>
<td>Commercial and industrial</td>
<td>3,853,103(^‡)</td>
<td>10–40</td>
<td>20(^%)</td>
<td>Historical rates(^g)</td>
<td>Historical rates(^h)</td>
</tr>
<tr>
<td></td>
<td>Utility-scale</td>
<td>85,086(^‡)</td>
<td>40–10,000</td>
<td>40(^%)</td>
<td>Historical rates(^g)</td>
<td>Historical rates(^h)</td>
</tr>
</tbody>
</table>

\(^a\) Average number of households and firms over several years to account for population changes during the simulation years.

\(^b\) See 5 in SI.

\(^c\) Fraction of electricity generated from the solar PV system consumed by the adopter.

\(^d\) The historical lending rate for each agent adopter type is added to the individual discount rate for each agent.


\(^f\) Rate randomly assigned from a truncated normal distribution between 0 and 1, with the above mean based on historical values in Germany and an assumed standard deviation of 0.05 (Fraunhofer, 2017).

\(^g\) See 6 in SI.

\(^h\) See 7 in SI.
The knowledge created within a region through public and private R&D expenditures accumulates into a knowledge stock after 36 months, representing the average time required for R&D activities to translate into cost reductions (Barreto and Kypreos, 2004; Kobos et al., 2006). As knowledge gradually becomes obsolete, knowledge stocks depreciate by 10% annually (Kobos et al., 2006). The model accounts for international spillovers by considering the flows of knowledge developed from public R&D investments between the simulated regions. International spillovers take time to become part of the other region’s knowledge stock, and their impact is modulated by a proportionality constant. Both parameters were estimated (see Section 14 of SI) from historical data (Huo and Zhang, 2012; Huo and Zhang, 2013; IEA-PVPS, 2019a, 2019b).

3.3.3.5. **Manufacturing capacity (7).** At the end of each year, domestic PV module manufacturers decide whether to increase or reduce their manufacturing capacity. They compare the total demand for domestic PV modules over the year with their current manufacturing capacity and decide to add capacity equal to the sales they missed out on over the previous year (that is, when their available stock was not sufficient to meet the demand from installers). Conversely, if they have overcapacity, they scale it back to serve the same demand as in the past year. In both cases, the PV module manufacturers slightly overbuild their capacity so that they can absorb demand fluctuations, corresponding to the behavior observed in the industry (IEA-PVPS, 2017; see Section 12 of SI). The speed of the build-up and scale-back of the manufacturing capacity is constrained to avoid excessive model volatility (see Section 1.3.3 of SI). Foreign PV module manufacturers are assumed to always have sufficient capacity to meet high demands owing to their much larger scale compared to the German PV industry.

### 3.4. Model calibration and validation

The model was validated by ensuring that its outputs are a good representation of real-world observations of the historical evolution of PV in Germany during the studied period. Four historical patterns—PV deployment (IEA-PVPS, 2019a), employment (O’Sullivan et al., 2019; BSW-Solar, 2020), PV prices (IEA-PVPS, 2019a), and imports (Eurostat, 2020)—were used between January 2000 and December 2016. Nine parameters were used to calibrate the model (see Table 2) in three steps: (1) calibration of adoption decision-making, (2) calibration of the supply chain, and (3) joint calibration of adoption and supply chain parameters. After an initial exploration based on pattern-oriented modeling, the parameters were selected by minimizing the distance between the historical and simulated time series (see Section 2 of SI).

The stochastic nature of some model inputs required statistical analysis to calibrate the model and a simulation batch size that is a representative sample of the model’s behavior. Based on early simulations and previous studies that used the same method (Nunez-Jimenez et al., 2020a, 2020b), we opted for 50 simulation-run batches. A total of 798 combinations, accounting for almost 40,000 simulation runs, were analyzed. Table 2 presents the calibrated parameters, and Fig. 3 shows the temporal evolution of the calibration patterns that are adequately reproduced by the model.

### 3.5. Scenario and push-pull balance analysis

Investigating how different emphases on technology-push and demand-pull measures influence the policy mix’s outcomes required us to systematically vary the level of support for each instrument. To do so, the historical government expenditure on solar R&D in Germany was used as the reference for the technology-push instrument and the historical level of the solar FIT for the demand-pull instrument (Johnstone et al., 2010). We only considered policy mixes that increase support for technology-push and/or reduce support for demand-pull because of Germany’s historical policy mix strong emphasis on demand-pull measures (Koseoglu et al., 2013; Zheng and Kammen, 2014).

First, the analysis focused on four clearly distinct scenarios that represent alternative push-pull balances in Germany’s policy mix for PV (see Table 3). (1) “PULL FOCUS” replicates the historical policy mix in Germany, (2) “PUSH INCREASE” increases the German government’s monthly expenditure on R&D by 125% while maintaining the FIT at historical levels, (3) “PULL REDUCTION” maintains public R&D spending at historical levels and reduces the FIT by 20%, and (4) “PUSH FOCUS” simultaneously increases public R&D expenditure by 125% and reduces the FIT by 20%. The changes in the support levels for the technology-push and demand-pull instruments were chosen such that the cumulative PV deployment at the end of the PULL FOCUS and PUSH FOCUS simulation scenarios was approximately the same in order to facilitate comparisons between the scenario results.

In the second part of our analysis, we investigated a set of 45 small variations of emphases on technology-push and demand-pull in Germany’s policy mix for PV, with values ranging between the historical value (i.e., 1) and three times that value (i.e., 3) for public R&D expenditures, and between the historical FIT level (i.e., 1) and a reduction of 40% (i.e., 0.6). The number of variations enabled the systematic exploration of counterfactual scenarios.

### 4. Results

In this section, we first present the results for the PULL FOCUS [historical policy], PULL REDUCTION, PUSH INCREASE, and PUSH FOCUS (see Section 4.1). We then explore 45 variations in the emphases on technology-push and demand-pull in Germany’s policy mix for PV (see Section 4.2). Finally, we discuss the sensitivity analyses (see Section 4.3).

#### 4.1. Scenario results

Fig. 4 shows the evolution of (A) cumulative installed capacity, (B) policy costs, (C) employment in the PV industry, (D) cumulative PV module net exports, (E) German PV module prices, and (F) foreign PV module prices (see Section 3 of SI for detailed figures). The PULL FOCUS scenario achieved approximately 40 Gwp of cumulative capacity at a policy cost of almost €98 billion. Reducing the level of support for
demand-pull without increasing it for technology-push (i.e., PULL REDUCTION) significantly reduced policy costs (−60%), PV deployment (−35%), and emission savings (−56%) compared to PULL FOCUS (not in figure; see Section 3 of SI). An opposite trend occurred in the PUSH INCREASE scenario. By increasing the level of support for technology-push without reducing it for demand-pull, PV deployment rose much earlier and was 40% higher and led to a more than doubling of emission savings, compared to the PULL FOCUS scenario, as well as to an explosion in policy costs (+87%). The PUSH FOCUS scenario, with its increased technology-push and reduced demand-pull, resulted in a slightly earlier take-off of PV deployment that otherwise followed a remarkably similar pattern and reached the same cumulative PV deployment as the PULL FOCUS scenario—as intended. Policy costs were reduced by 9% while emission savings increased 18%.

The evolution of cumulative PV module net exports (4D), however, was very different across scenarios. The increased public R&D expenditures and earlier market uptake in the PUSH FOCUS scenario gave the German PV industry a competitive advantage that translated into a positive balance between exports and imports, which was only surpassed in the PUSH INCREASE scenario. In scenarios with historical technology-push levels (i.e., PULL FOCUS and PULL REDUCTION), fewer exports and more imports resulted in negative trade balances.

German PV module prices (4E) revealed the distinct impacts of technology-push and demand-pull instruments on cost-reduction drivers. Initially, innovation was the main driver of cost reductions. The higher public R&D spending in the PUSH INCREASE and PUSH FOCUS scenarios since 1991 enhanced learning-by-researching and explains the lower German PV module prices in 2000 compared to the prices in the PULL FOCUS and PULL REDUCTION scenarios. When PV deployment gained momentum after 2008, learning-by-doing became the main cost-reduction driver while the influence of higher public R&D spending decreased, as revealed by the narrower gap in German PV module prices between scenarios with different technology-push but similar deployment levels (for example, PULL FOCUS vs. PUSH FOCUS). Foreign PV module prices (4F) evolved similarly in all scenarios, mainly due to the larger role of deployment in the evolution of PV module prices outside Germany and the decreasing influence of the German market on global PV deployment over time.

Since two of the analyzed scenarios (PULL FOCUS and PUSH FOCUS) resulted in similar PV deployment and policy costs but vastly different employment evolutions, we explored the changes in employment in more detail. Fig. 5 shows the annual PV module manufacturer and installer jobs, and cumulative job months in all four scenarios (see Section 3 of SI for detailed figures).

The cumulative number of job months in the PUSH FOCUS scenario was almost 2.5 times higher than that in the PULL FOCUS scenario. This enormous difference was driven mainly by the need for PV module manufacturers to hire more workers to meet higher domestic and foreign demands and, to a lesser degree, by the creation of more installer jobs. Both installer and manufacturing jobs showed a boom-and-bust pattern in all scenarios because the domestic market was rapidly exploited, and the FIT sharply reduced after 2012 (see Section 5 of SI). In the historical-policy PULL FOCUS scenario, annual changes in employment levels were smaller than those in the two scenarios with increased technology-push, but employment remained at significantly lower levels and the share of PV module manufacturing jobs was much lower. This trend was
even more pronounced in the PULL REDUCTION scenario, where weaker support for PV adoption was not counteracted by increased public R&D spending, thereby delaying the onset of domestic demand and preventing the emergence of a German PV industry.

Therefore, the level of support for technology-push and demand-pull measures influences not only the pattern of job creation and total number of jobs but also their type (i.e., manufacturers vs. installers). The comparison of the historical PULL FOCUS scenario with the PUSH FOCUS scenario revealed that neither (domestic) PV deployment nor policy costs are decisive in terms of job creation. Rather, the interactions between the policy instruments determine the number and type of jobs created.

4.2. Balancing the emphasis on technology-push and demand-pull

The above results reveal the hard-to-predict impacts of the interactions between technology-push and demand-pull instruments on sociotechnical change. In this section, we explore this complex interplay
by investigating 45 different policy mixes in which the level of support for technology-push varies from one to three times its historical level and, for demand-pull, from one to 0.6 its historical level.

Fig. 6 shows the relationship of deployment and employment with policy costs for the different combinations of push-pull support levels. Larger bubbles indicate stronger demand-pull, whereas yellower bubbles indicate stronger technology-push.

A strong demand-pull is critical to achieving high deployment, as shown by the growing bubbles toward the top of Fig. 6 (top). The influence of technology-push on deployment is smaller, as shown by the yellow bubbles throughout Fig. 6 (top). Importantly, all the median values (black circles) are roughly within the Pareto frontier, which suggests that it would have been impossible to increase PV deployment and decrease policy costs at the same time by exclusively changing the support for technology-push and demand-pull in Germany's historical policy mix. In addition, the concave curve formed by the bubbles in Fig. 6 (top) shows that each additional billion EUR of policy costs triggers increasingly fewer PV installations.

The color code indicates the level of support for technology-push up to three times the historical level, and the bubble sizes are proportional to the level of support for demand-pull, which is 60–100% of the historical level. The black circles indicate the median results for each policy-mix variation.

Although technology-push influences employment more than deployment, the relationship is not as simple as that between demand-pull and deployment. Far fewer median outcomes are located along the Pareto frontier for employment than for deployment, and those that do tend to be policy mixes with strong technology-push (i.e., yellow bubbles). Therefore, from an employment perspective, there are combinations of technology-push and demand-pull support levels that are always preferable to others because they create more jobs and have lower policy costs, and those dominant combinations tend to be policy mixes with a strong emphasis on technology-push.

Employment gains from increasing the emphasis on technology-push

Fig. 5. Development of PV module producer and installer jobs in the four scenarios in the German solar PV industry. The bars represent the number of PV module manufacturer and installer jobs in that year. The dotted lines represent the cumulative number of job months.

Fig. 6. Deployment (top) and employment (bottom) in relation to the total policy costs of 50 simulation runs for 45 policy mixes, with different emphases between technology-push and demand-pull instruments.
revealed by the closeness of the isolines between the red and green triangles in Fig. 7). More importantly, the results identify a configuration boundary where minor changes in either the level of technology-push or demand-pull can result in large shifts in policy outcomes (as revealed by the closeness of the isolines between the red and green triangles in Fig. 7).

Within the configuration boundary, minor adjustments to public R&D expenditures or the FIT can lead to drastically different deployment and employment outcomes. For example, policy mix A in the incumbent configuration region (the red triangle in Fig. 7) achieved a PV deployment of 22.2 GWp and 3.2 million job months, whereas policy mix B, which has only a slightly higher public R&D spending and FIT but is located within the configuration boundary (the corridor between the triangles in Fig. 7), achieved a PV deployment of 35.9 GWp and 9.8 million job months. This confirms that the outcomes of policy mixes with different emphases on technology-push and demand-pull instruments depend not only on the balance between push–pull measures but also on the absolute level of support for each instrument.4

In addition, the results corroborate the fundamental role of demand-pull instruments in triggering large-scale deployment, particularly in policy mixes with lower technology-push levels (see the relatively flat red isolines in the bottom-left corner of Fig. 7), while job creation is more clearly a function of both demand-pull and technology-push.

4.3. Sensitivity analyses

To evaluate how simulation outputs may change depending on the value of the key model parameters and assumptions, several sensitivity analyses (SAs) were conducted:

- **SA1** – Decreasing discount rate for imported PV modules: In this SA, as German consumers become less concerned about the reliability of imported PV modules, the discount rate gradually decreases to zero. This results in 10–25% higher PV deployment and imports and a switch from manufacturing to installer jobs unless the emphasis on technology-push is stronger than in the historical policy, which allows German PV modules to remain competitive. The implications of the scenario results remain largely unchanged.

- **SA2** – Larger and faster knowledge spillover from Germany to the rest of the world: Technology transfer (e.g., via equipment sales) could enlarge and accelerate knowledge spillovers (Zhang and Gallagher, 2016). Considering a much larger and faster spillover from Germany to the rest of the world increases PV deployment and PV module imports. However, the outcomes in scenarios with increased technology-push are similar to the reference case, even though more public R&D spending in Germany spills over to foreign competitors and brings forward the reduction in foreign PV module prices by several months. Although the differences between scenarios become smaller, their implications remain the same.

- **SA3** – Variable profit margins for German PV module manufacturers: In this SA, manufacturers can adjust their profit margins if PV module production costs decrease owing to stronger technology-push or if foreign competition becomes more intense. As expected, variable profit margins reduce the differences between scenarios by, for example, increasing the number of jobs in scenarios with historical technology-push levels through smaller profit margins to fend off foreign competitors and by reducing job creation in scenarios with increased technology-push as domestic firms set higher mark-ups to benefit from lower production costs. Although the differences between scenarios are smaller, they persist, suggesting that the implications of the scenarios remain qualitatively the same.

- **SA4** – Delayed increase in technology-push emphasis: The main drivers of cost reductions change throughout the development stages of a technology (Kavlak et al., 2018). Therefore, policy mix outcomes may vary, depending not only on the level of support for demand-pull and technology-push but also on the timing of changes to those levels of support. Simulations of a delayed increase in technology-push emphasis confirm the main results and implications of the scenarios, even though its impacts on jobs and trade significantly reduce.

Further details on these analyses can be found in the SI.

5. Discussion

5.1. Implications for the literature and policymakers

This paper provides important contributions to the literature on policy mixes and has relevant implications for policymakers.

First, we show that important dimensions of sociotechnical change could be compromised if policy mixes are assessed only on innovation and diffusion outcomes. How a policy mix is evaluated can significantly influence its design (Cerradini et al., 2018). For example, when considering only deployment and policy costs, there is little difference between the simulation results of Germany’s historical policy mix for PV (i.e., PULL FOCUS scenario) and a policy mix with slightly less emphasis on demand-pull and a stronger support for technology-push (i.e., PUSH...
technology-push is always better when considering jobs and trade. A slight reduction (i.e., 20% lower FIT) would lead to more jobs and PV modules exports. However, this does not suggest that a policy mix reliant only on technology-push is always better when considering jobs and trade. Germany's historical policy mix had such a strong emphasis on demand-pull that a slight reduction (i.e., 20% lower FIT) would have still maintained a staunch support for PV adoption. On median terms, for each €1 of public funds spent in the PULL FOCUS scenario, €0.98 went to the FIT and €0.02 to public R&D, whereas in the PUSH FOCUS scenario, €0.96 went to the FIT and €0.04 to public R&D. Further decreasing the level of demand-pull, even if the emphasis on technology-push tripled, would lead to worse PV deployment and job outcomes (as seen in Fig. 7). Therefore, demand-pull and technology-push instruments play unique roles and are not substitutes for or superior to each other.

Second, the results of the 45 systematic variations of the historical policy mix reveal that the detailed design features of policy instruments can have a major influence on the interactions between policy instruments. Even small variations in the level of support for technology-push or demand-pull (e.g., a 10% change in the historical annual public R&D funds or in the FIT) can produce radically different policy mix outcomes. This finding is well aligned with previous calls to carefully consider instrument-design features (Kemp and Pontoglio, 2011) and sheds light on the dynamic, path-dependent nature of interactions, and the disproportionate influence that design features exert on them.

Minor differences in instrument design build up to large consequences over time because their impact is cumulative and the responses from actors in the STS are neither linear nor constant. For example, a reduction of the FIT (i.e., demand-pull) limits the possibility of domestic producers to reduce technology costs through learning-by-doing because of a smaller domestic market and constrains learning-by-researching because private R&D would be scaled down due to lower sales. Over time, this facilitates the entry of foreign competitors and increases the likelihood of imports becoming dominant. With more imports, the sales of domestic producers reduce even further, creating a self-reinforcing loop that undermines the development of a competitive domestic industry. Such a prominent role of foreign producers and consumers in explaining the different evolution of PV’s STS when the policy instrument designs are changed highlights the limitation of using national borders as boundaries for the analysis of policy mixes.

Our results show that increasing technology-push through higher public R&D spending before imports become dominant could enhance the competitiveness of domestic manufacturers and thus contribute to a larger domestic industry. Boosting public R&D expenditures for PV when the first FIT was introduced in 1991 would have improved the performance and costs of German PV modules to the point that foreign competitors would have had a much harder time entering the German market. In this context, investments in R&D go beyond basic research and not only help increase knowledge production but also enhance the capacity of renewable energy firms to absorb knowledge (Hoppmann, 2021, 2016). The simulated interactions between technology-push and demand-pull instruments are in line with the previous literature (Wiebe and Lutz, 2016; Wiesenthal et al., 2012) and confirm the relevance of design features, such as the level of support, for understanding the outcomes of policy mixes (Schmidt and Sewerin, 2019).

Policy timing is an important consideration in adequately interpreting these results. All simulations follow the historical development of Germany's policy mix for PV, including fluctuations in annual public R&D expenditures and changes to the FIT (see Section 5 of SI). Therefore, increased technology-push and reduced demand-pull always cover the entire simulated period from 1991 to 2016. Altering the emphasis on technology-push or demand-pull in a policy mix at different times than those simulated would lead to different outcomes, among other reasons because the main drivers of technology cost reductions change depending on the development stage of the STS it addresses, as confirmed by SA4.

Two implications for policymakers can be derived from these findings. On the one hand, the cost–benefit analyses of policy mixes could be quite different depending on whether the policy mix will bring the STS close to a configuration boundary. By exploring 45 policy mixes with different emphases on technology-push and demand-pull, this study revealed the existence of STS configuration boundaries. Around these boundaries, minor changes in policy inputs can result in drastically different policy outcomes, while far from them, large changes in policy

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**Fig. 7. Policy outcomes landscape for combinations of push and pull policy inputs.** The red values next to the grey crosses indicate the median deployment (in GWp) and the red isolines represent regions where different emphases on technology-push and demand-pull lead to the same employment, with increments of 5 GWp between the lines from 15 to 55 GWp. The blue isolines represent regions where different emphases on technology-push and demand-pull achieve the same employment, with increments of 2 million job months between the lines from 2 to 14 million job months. The positions of the isolines were linearly extrapolated from the median results for the 45 simulated variations. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)
inputs have minor impacts. Therefore, claims about the effectiveness and cost efficiency of individual technology-push and demand-pull measures need to be interpreted within the context of the targeted STS and are difficult to generalize.

On the other hand, the simulation outputs revealed the limits of how much balancing the policy mix’s emphasis on technology-push and demand-pull instruments alone could influence the evolution of the targeted STS. Compared to the outcomes of Germany’s historical policy mix for PV, our results show that adjusting the support for technology-push and demand-pull could have simultaneously increased jobs and reduced policy costs. However, none of the 45 policy mix variations was able to increase PV deployment and reduce policy costs at the same time. This study is among the first attempts to ascertain the boundaries of the debate around technology-push and demand-pull instruments, and it calls for caution when asserting that weaker policy support for technology deployment could have reduced policy costs and increased diffusion at the same time as long as a stronger emphasis was placed on innovation policies (Frondel et al., 2010; Wiesenthal et al., 2012).

Third, this study proposes agent-based modeling as a useful methodology for researching policy mixes. Previous policy mix studies have relied mainly on econometric analyses of historical data (Costantini et al., 2017; Guerzoni and Raiteri, 2015; Rogge and Schleich, 2018) and case studies (Edmondson et al., 2020; Gomel and Rogge, 2020; Hansen et al., 2019). Agent-based modeling is emerging as a relevant methodology for investigating policy mixes that can complement other methods and help overcome some of their limitations (Caprioli et al., 2020; Herrmann and Savin, 2017; van der Vooren and Brouillat, 2015). This study contributes to this by (a) showing how a “history-friendly” ABM can reveal the trade-offs between key policy objectives in the design of policy mixes, (b) demonstrating that ABMs can simultaneously consider macro and micro phenomena that determine the outcomes of policy mixes (e.g., from technology adoption to international competition), and (c) illustrating the effect of path-dependent interactions between policy instruments that are difficult to capture with other methods. These contributions open interesting paths for future research on policy mixes including exploratory modeling using “history-friendly” ABMs, as illustrated by the results in Section 4.2.

Finally, this study demonstrates the usefulness of modeling as a support tool for better policy decision-making. Although a modeling exercise similar to that in this manuscript was technically impossible at the time of the approval of Germany’s Electricity Feed-in Act in 1991, future policy mixes could benefit from the use of modeling analyses to inform their designs.

5.2. Limitations and future research

This study has limitations that open new avenues for future research. First, the number of goals analyzed was limited by the scope of the model. A broader set of goals, such as the 17 Sustainable Development Goals of the United Nations (Mulugetta et al., 2019), may reveal the impacts on sustainability dimensions not captured in this analysis. Second, decision-making by manufacturing firms had to be strongly simplified to reduce the overall complexity of the model. Further research that includes a more detailed representation of the behavior of firms—particularly regarding pricing and capacity expansion decisions—is needed. Third, in our model, technology cost reductions in PV modules and knowledge spillovers are represented by two-factor experience curves. Although these are useful, this modeling approach has limitations, including uncertainty about time lags and international spillovers. Increasing the level of detail of the representation of both innovation processes and international spillovers would help overcome constraints on how to account for the inherently stochastic nature of innovation and how to simulate spillover mechanisms such as production equipment sales and personnel hires. Fourth, the highly modular, mass-produced character of PV modules, as well as the high learning rates in this industry, challenge the transferability of our results to more complex, integrated, and customized technologies (Malhotta and Schmidt, 2020). Fifth, limiting scenario variations to changes in the level of support of technology-push and demand-pull instruments prevented us from exploring the impact of changing other design features. Alternative modifications to the instrument designs might have been able to move the Pareto frontier, thus improving policy outcomes without increasing costs, for example, through responsive designs to adjust the level of support in response to the evolution of sociotechnical change (Núñez-Jimenez et al., 2020a). Finally, in this study, the selection, design, and time of introduction of the policy instruments were determined by the historical case. As the literature suggests, different instruments may be better suited to specific phases of technological change (Sagar and van der Zwaan, 2006; Sorrell et al., 2003), and changes in other design features could alter the instrument’s efficiency (Núñez-Jimenez et al., 2020b). Investigating variations along these dimensions is a prominent issue that could be explored in future research.

6. Conclusion

In this study, we analyzed how the emphasis on technology-push and demand-pull instruments in policy mixes influences sociotechnical change. To explore this question, we developed an ABM of a socio-technical system for PV in Germany. The model was used to simulate 45 variations in the level of support for technology-push and demand-pull measures, in the form of public R&D funds and feed-in tariff, respectively, of the historical policy mix between 2000 and 2016. The results showed that the level of support for technology-push and demand-pull influences the interaction of these instruments and their joint effect on the diverse outcomes of sociotechnical change. These findings raise important questions about how to design suitable policy mixes for accelerating the transition toward more sustainable energy systems while providing relevant implications for scholars and policymakers. By expanding the scope of previous studies and highlighting the usefulness of “history-friendly,” empirically grounded, agent-based modeling in theory and practice, this manuscript contributes to the literature on policy mixes and opens avenues for future work.

CRediT authorship contribution statement

ANJ stands for Alejandro Núñez-Jimenez
CK stand for Christof Knoeri
JH stands for Joern Hoppmann
VH stands for Volker H. Hoffmann

ANJ, CK, JH, and VH: conceptualization, writing of the original draft and review and editing. ANJ and CK: methodology and software. ANJ: data curation, validation, formal analysis and visualization. VH: supervision and funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

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