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Analysing future change in the EU's energy innovation system

Yeong Jae Kim[a,b,*], Charlie Wilson[b,c,d]

[a] RFF-CMCC European Institute on Economics and the Environment (EIEE), Via Bergognone 34, 20144, Milano, Italy
[b] Tyndall Centre for Climate Change Research, University of East Anglia, UK
[c] School of Environmental Sciences, University of East Anglia, Norwich, NR4 7TJ, UK
[d] International Institute for Applied Systems Analysis, Schlossplatz 1, A-2361, Laxenburg, Austria

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ABSTRACT

We develop a novel approach for quantitatively analysing future storylines of change by combining econometric analysis and Monte Carlo simulation for four different storylines of change in the EU's energy innovation system. We explore impacts on three key innovation outcomes: patenting (innovation), co-invention (collaboration), and technology cost reduction (diffusion). We find that diverse mixes of policy instruments stimulate collaborative innovation activity. We find that both RD&D expenditure and trade imports support knowledge generation and exchange, and that these relationships are largely robust to future uncertainty. Conversely, we find that policy durability and stability are only weakly linked to innovation outcomes, suggesting that adaptive policy responding to rapidly changing innovation environments should play an important part of the EU's energy future.

1. Introduction

The European Commission has stated "*the ambition to achieve … a fundamental transformation of Europe's energy system*" [1]. This transformation requires solutions and policies informed by systemic analysis of energy innovation. As the Organisation for Economic Co-operation and Development (OECD) explains: "*Parts of the system … cannot be assumed to be effective in delivering their prescribed functions …. The root of the failure is usually assumed to be the inability or unwillingness to coordinate. Responsibility or agency for this failure is distributed throughout the system rather than resting with a particular set of stakeholders*" [2]. A systemic perspective on innovation emphasises the influence that wider social, institutional, and economic processes have on innovation outcomes.

In 2008 the Strategic Energy Technology (SET) Plan was launched to provide strategic planning and coordination of energy research & innovation activities within the European Union (EU). The SET Plan was designed to support EU policy objectives on climate change, energy efficiency, and renewable energy, as well as energy security, energy union, growth, jobs, and global competitiveness [1,3]. The SET Plan was implemented through a range of activities including European Industrial Initiatives for technologies with near-term market impact (to 2020), and longer-term research actions to 2050.

In 2015 the Commission proposed a revised SET Plan that was more targeted, and that used a whole systems approach to ensure better integration across sectors and technologies [1]. The revised Integrated SET Plan set out four priority areas (renewable energy and storage, smart systems and consumers, energy efficiency, sustainable transport) and two additional areas (carbon capture and storage, nuclear power). These six priority areas correspond to discrete technology fields or clusters of inter-related technologies.

The future of complex systems like the EU's energy innovation system is unknown. Scenarios provide a way of exploring and better understanding salient uncertainties. Scenario analysis is a widely-applied technique for systematically varying a small number of critical uncertainties to explore how they may affect future outcomes. Scenario analysis assesses potential risks, informs decision making, identifies strategies robust to uncertainty, and tests linkages from near-term actions to long-term outcomes. For the EU's energy innovation system, important branching points include the extent of decentralisation (or centralisation) and the extent of cooperation (or fragmentation). How these drivers of change play out in the future will shape the decisions and activities of innovation actors, from technology developers and investors to the European Commission and national regulators. Future uncertainties will therefore impact innovation system processes and resulting outcomes, from codified outputs (e.g., numbers of patents) to knowledge exchange (e.g., patent co-inventions) and technology performance (e.g., learning rates).

Future uncertainties can be analysed both deterministically (e.g., using narrative storylines to vary drivers of change) and stochastically

* Corresponding author. RFF-CMCC European Institute on Economics and the Environment (EIEE), Via Bergognone 34, 20144, Milano, Italy.
E-mail addresses: yeongjae.kim@eiee.org (Y.J. Kim), Charlie.wilson@uea.ac.uk (C. Wilson).

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(e.g., using probability distributions to characterise future performance of influential variables). Monte Carlo simulation is a commonly-used tool for stochastic uncertainty analysis [4,5]. Probability distributions are assigned to key uncertain variables (based on historical data or expert judgement), and then propagated through explanatory models which determine uncertain outcomes.

In this paper we develop a novel approach for understanding future innovation outcomes by combining empirical analysis of innovation system processes with scenario analysis and Monte Carlo simulation of future uncertainty. We show how this approach can be applied to map narrative storylines onto quantitative analysis of innovation system performance into the future. We distinguish and combine two streams of analysis: narrative and empirical.

In an initial narrative stream, we interpret storylines of future change in terms of how specific innovation system processes and resulting innovation outcomes are affected. We use four storylines to explore a possibility space defined by 2 orthogonal axes: extent of decentralisation and extent of pan-EU cooperation.

In a subsequent empirical stream, we estimate quantitative relationships between innovation system processes and innovation outcomes using econometric models, and then vary key uncertain future parameters using Monte Carlo simulation to project innovation outcomes. The outcome variables in both the empirical analysis and the Monte Carlo simulation are patents, co-invention and technology costs. These are proxy measures of innovation or knowledge generation and codification (patents), knowledge exchange and actor interaction (co-invention), and market deployment and learning (technology costs).

The rest of this paper is structured as follows. First, we describe a framework characterising key processes in the energy innovation system. We construct standardized indicators for measuring these processes, and collect data for each of the six technology fields or 'priority areas' of the EU's SET Plan across the full set of indicators. Second, in the narrative stream of analysis, we describe four broad storylines of future change in the EU energy innovation system which explore critical uncertainties. We then identify specific innovation system processes which may be either strengthened or weakened under each storyline. Third, in the empirical stream of analysis, we estimate baseline econometric models describing relationships between innovation system processes and innovation outcomes observed historically. We then simulate how future uncertainties affect the econometric models. Finally, we combine the simulation results with the narrative storylines to generate both quantitative and qualitative insights about the EU's future energy innovation system.

2. Background

Fig. 1 illustrates a heuristic framework of the energy technology innovation system (ETIS) which is explained and evidenced in detail in: [6–8]. The innovation system comprises: (1) a technology lifecycle from research and development (R&D) through to diffusion; (2) four dimensions describing the enabling conditions for successful innovation outcomes; (3) specific processes associated with each of these dimensions.

The four dimensions of the ETIS framework are: knowledge, resources, actors & institutions, and adoption & use. First, knowledge generation, spillovers and learning are engines of innovation [9–12]. However, knowledge generation can be depreciated due to staff turnover, business volatility or technological obsolescence [6]. Second, resources mobilised to support innovation activity emphasise public policy and the specific portfolio of instruments used [8,13]. Third, the actors & institutions dimension characterises the participation and interaction of diverse innovation actors including private firms, government organisations and civil society [14–16]. Fourth, the adoption & use dimension points to the importance of consumer uptake and market demand for innovation outcomes [17].

Table 1 (leftmost column) shows the main innovation system processes corresponding to each of the four dimensions: knowledge, resources, actors and institutions, and adoption and use (Fig. 1). Each of these processes can be measured by indicators which are generalisable across technologies [18]. A standardized set of quantitative indicators enables cross-technology analysis. Table 1 (rightmost columns) shows the set of indicators used including the main data source.

We collected data characterising innovation system processes across the six technology fields prioritised in the EU's SET Plan: renewable energy, smart grid, energy efficiency, sustainable transport, carbon capture and storage, and nuclear power [19]. Time series data from 2001 to 2015 were collected at the EU level for all the indicators in each of these six technology fields.

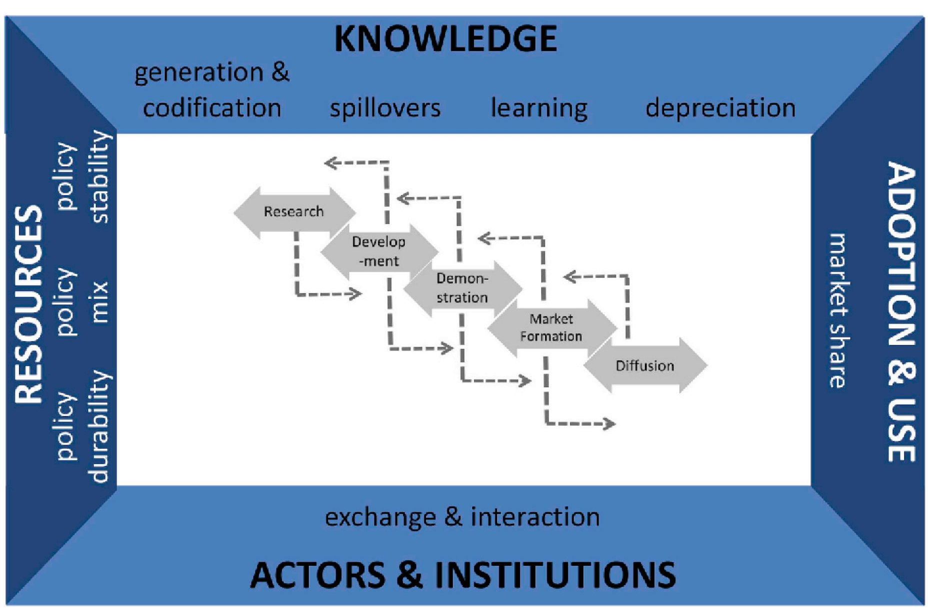

Fig. 1. The energy technology innovation system (ETIS) framework in simplified form, adapted from: [6].

Table 1
Technology-specific indicators of innovation system processes in the ETIS framework.

Innovation system processes	Technology-specific indicators	Main data source[a]
KNOWLEDGE		
Generation & Codification	Public energy research development & demonstration (RD&D) expenditure	1
	Number of patents	2
Spillover	Energy technology imports (international trade)	3
Learning	Technology costs	4
Depreciation	Stability in public energy RD&D expenditure	1
RESOURCES		
Policy Durability	Durability of policy instruments (cumulative years in place)	5
Policy Mix (or Diversity)	Diversity of policy instruments (innovation, regulatory, market-based, and strategic - including targets, roadmaps, and action plans)	5
Policy Stability	Stability of policy instruments (frequency of revisions, amendments or cancellations)	5
ACTORS & INSTITUTIONS		
Exchange & Interaction	Patent co-inventions	2
ADOPTION & USE		
Market Share	Actual market size as % of potential market size	4

[a] Main data sources for six technology fields in the EU: 1 – International Energy Agency (IEA) energy RD&D statistics; 2 – United States Patent and Trademark Office (USPTO) PatentsViews database; 3 – Eurostat EU trade statistics; 4 – Secondary data from peer-reviewed studies; 5 – IEA 'Addressing Climate Change' policy database.

3. Methodology

3.1. Narrative stream I: developing storylines of future change

Future change in the EU energy system is unknown, but can be usefully characterised by scenarios and translated into quantitative pathways by simulation modelling. Four storylines of change were developed as part of a broader project on 'Navigating the Roadmap for Clean, Secure and Efficient Energy Innovation' in the EU (www.set-nav.eu). A 2 × 2 typology was used to combine two main dimensions of uncertainty into four storylines spanning a wide possibility space. Fig. 2 (left panel) shows the scenario typology which varies two critical uncertainties: the extent of decentralisation (x-axis); and the extent of European cooperation (y-axis). The poles of each axis can therefore be characterised as: decentralisation vs. path dependency (x-axis); and cooperation vs. entrenchment (y-axis).

Path dependency describes the shaping and constraining of future development trajectories by accumulated historical precedent. The energy system is strongly path dependent as it is large, complex, has many interdependencies, and is characterised by long-lived infrastructure with slow turnover rates [20]. Through the 20th century, technical and economic returns to scale have given rise to a strongly centralised energy system in both physical terms (e.g., GW-scale power plants distant from end users) and in economic terms (e.g., national or regional monopoly utilities) [21–23]. However, there is an increasingly strong technological and business case for decentralisation, underwritten by systemic forces of change ranging from market liberalisation, environmental standards and policies, technological innovation in renewables and storage, continued end-use efficiency improvements, and the convergence of information technologies and digital control systems with energy infrastructure and hardware [24,25]. This is already creating major challenges for incumbent energy companies whose business models and balance sheets are linked to centralised assets [26,27].[1] By enabling smaller increments of capital investment, smaller-scale technologies from shale gas to solar Photovoltaics (PV) have opened up markets to the destabilising force of new entrants [28]. This tension between path dependency and decentralisation is a major uncertainty for the future development of the EU energy system, affecting technological innovation and deployment, policy and regulatory environments, business strategies and investments, and social acceptance and engagement.

The second critical uncertainty is the more familiar and more existential question for the EU of ever-closer union, and specifically in this context, ever-closer cooperation and integration in energy markets, policies, and infrastructures. The European Commission's communication in 2015 on the Energy Union Package opens with: "Our vision is of an integrated continent-wide energy system where energy flows freely across borders, based on competition and the best possible use of resources, and with effective regulation of energy markets at EU level where necessary" [1]. To enact this vision, the communication argues: "We have to move away from a fragmented system characterised by uncoordinated national policies, market barriers and energy-isolated areas." In the current political climate of Brexit, national populism, and external threats to political and social cohesion within the EU, it is uncertain whether the Commission's vision for a cooperative and integrative energy system will be achieved. A future in which national interests become increasingly entrenched, and member states exploit comparative advantages as well as local resources while prioritising their own energy interests, remains a possible alternative.

These two dimensions of uncertainty shown in the left panel of Fig. 2 combine to create a possibility space which can be explored by the four contrasting storylines shown in the right panel of Fig. 2. Working clockwise, the four storylines are:

- ***Diversification*** = decentralisation + cooperation
- ***Directed Vision*** = path dependency + cooperation
- ***National Champions*** = path dependency + entrenchment
- ***Localisation*** = decentralisation + entrenchment

3.2. Narrative stream II: mapping storylines onto innovation system processes

Fig. 3 summarises the headline features of each of these four storylines and their corresponding impacts on possible development

[1] The IEA's recent energy investment outlook summarises the uncertain future for centralised utilities: "*Decentralised solar PV, battery storage and charging EVs blur the distinction between consumers and producers, while demand-side response programs have the potential to provide flexibility in balancing supply and demand in real time at a lower cost than utility-owned generating capacity. In addition, digitalisation is opening up opportunities for new entrants to the supply of energy services and is changing the interaction of consumers with the electricity system …. Regulatory frameworks will need to adapt to these models providing the appropriate arrangements to allow them to contribute to the overall efficiency and decarbonisation of the energy system. The implications of all these changes for future investment are still very unclear*" *(p178 [82], World Energy Investment. International Energy Agency, Paris, France).*

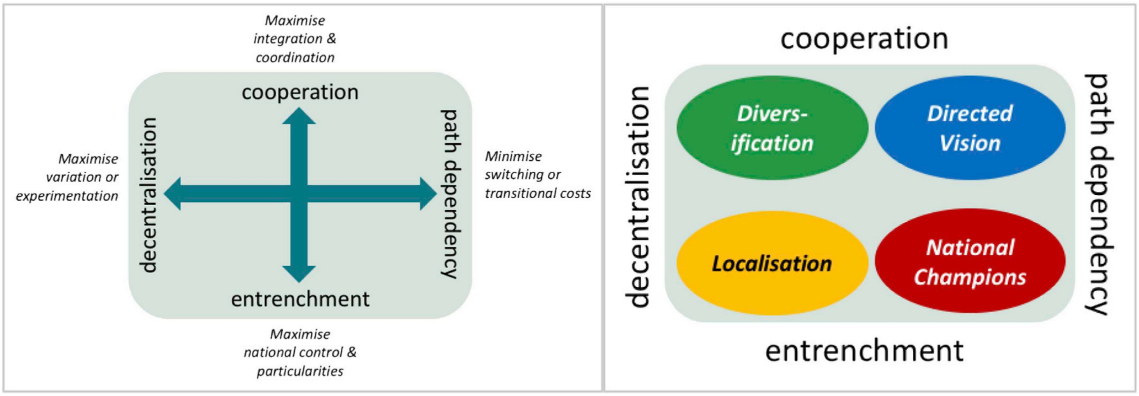

Fig. 2. A possibility space for EU energy futures. Left panel shows a 2 × 2 scenario typology varying two critical uncertainties; right panel represents four storylines spanning the possibility space.

pathways for the EU's energy system. These short descriptions emphasise only the most salient features that help distinguish the storylines from one another. As an example, digitalisation is explicitly noted in the *Diversification* and *Localisation* storylines, but this does not mean it is not also important in the futures depicted by the *Directed Vision* and *National Champions* storylines. It simply means that digitalisation is not one of the stand-out features of these storylines which distinguish them from the others.

The ***Diversification*** storyline describes a decentralising trajectory for the EU energy system in the context of cross-border cooperation and integration (Fig. 3, top left). This signals the entry of new, heterogeneous actors, challenging the dominance of centralised asset-owners and incumbent service-providers. Open digital platforms become essential for coordinating the activity of this diversified energy economy, facilitated by regulatory experimentation and opening. The *Diversification* storyline describes a diverse set of new actors becoming involved in energy innovation throughout the EU, particularly from the digital and tech sectors. This storyline places emphasis on strong, collaborative exchange and interaction between these actors, enabled by open digital platforms. However, diversification and experimentation also means that innovation policy frameworks become less stable and durable.

The effects of the *Diversification* storyline on energy innovation in the EU can be captured by changes in specific quantitative indicators of innovation system processes (shown here in *italics*):

1. *Patent co-invention (intra-EU)* is strengthened as more diverse innovation actors interact and collaborate.
2. *Diversity of policy instruments* is strengthened as policy frameworks open up to support new innovations in multiple ways.
3. *Durability of policy instruments* is weakened as existing policy frameworks are revised to support experimentation and regulatory opening.
4. *Stability of policy instruments* is weakened as an emphasis on policy experimentation and learning leads to revisions and improvements.

The ***Directed Vision*** storyline describes a path-dependent trajectory for the EU energy system which is directed by the Commission's vision set out above for an ever-closer energy union (Fig. 3, top right). The EU together with large stakeholders with the capacity to operate at an EU level are guided by strong and shared expectations for future goals and the directions of travel required to meet these goals. This broad buy-in becomes enshrined in stable policy frameworks which are coordinated between member states to ensure a consistent European-wide playing field. The *Directed Vision* storyline places emphasis on strong, clear and

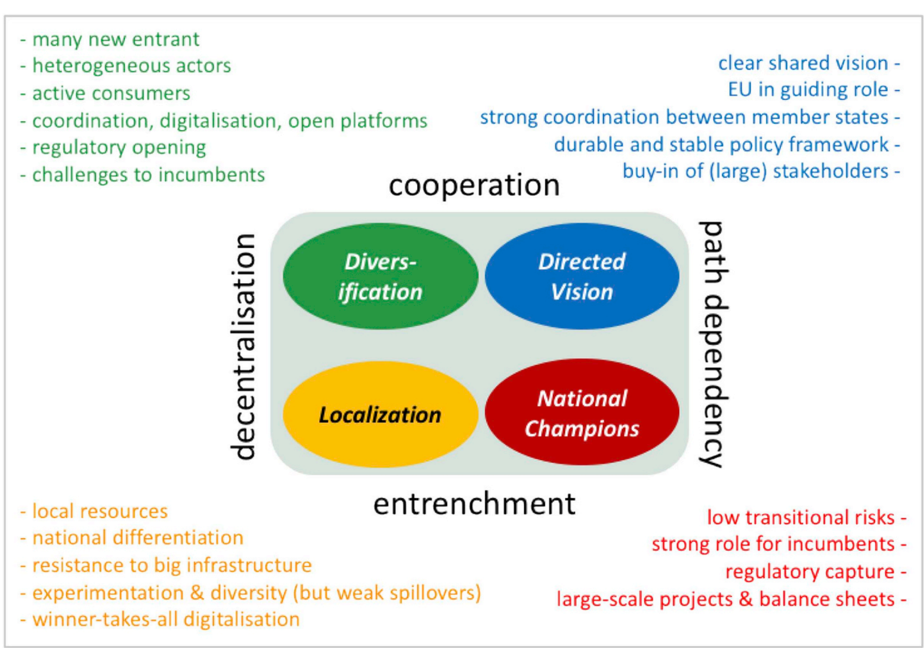

Fig. 3. Headline features of four storylines of the EU's future energy system.

stable expectations shared by both public and private actors. However, the centralising pan-European leadership also means that only large stakeholders have the capacity to remain directly involved with SET Plan activities so innovation actors become more homogeneous.

The effects of the *Directed Vision* storyline on the innovation system for energy technologies in the EU are captured by changes in specific quantitative indicators of innovation system processes (shown here in *italics*):

1. *Public energy R&D expenditure* and *demonstration budgets* are strengthened in line with strong central coordination and prioritisation of energy innovation as an EU policy area.
2. *Durability of policy instruments* is strengthened under clear and stable expectations for the direction of future change.
3. *Diversity of policy instruments* is weakened as the Commission's vision for an ever-closer energy union is implemented through a preferred set of instruments including roadmaps, targets, and strategic plans.

The ***National Champions*** storyline describes a path-dependent EU in which historical incumbency and national interests grow in influence (Fig. 3, bottom right). This continuity in development minimises transitional risks and costs, at least in the near-term. Incumbent firms and organisations, including current or former national monopolies, play a leading role particularly in the design, finance, construction and operation of large-scale energy infrastructure. The *National Champions* storyline describes member states supporting their distinct comparative advantages through innovation and industrial policy. This storyline places emphasis on strong and stable innovation policy frameworks, even if at the national rather than EU level. However, the influence of national champions including in the traditional energy industries also mean regulatory capture by incumbent fossil-fuel companies dampening support for strategic development of alternatives.

The effects of the *National Champions* storyline on energy innovation in the EU are captured by changes in specific quantitative indicators of innovation system processes (shown here in *italics*):

1. *Stability in energy RD&D expenditure* is strengthened as member states commit resources to build long-term competitive advantage in selected innovation fields.
2. *Durability of policy instruments* is strengthened as member states align policy frameworks with long-term national priorities.
3. *Stability of policy instruments* is strengthened to ensure consistent support and enabling conditions for dominant national firms.
4. *Energy technology imports* are weakened as member states support their comparative advantage through innovation and industrial policy.

The ***Localisation*** storyline describes how the decentralising forces emerging in the EU start to chip away more forcefully at the centralised infrastructures, firms, and regulatory environments, but with marked national and local variation (Fig. 3, bottom left). Member states seek to maximise their use of locally-available resources, giving rise to differentiated energy strategies and policy frameworks across the EU. Resistance to pan-European infrastructure and integration projects opens up space for smaller-scale experimentation and diversity. Digitalisation becomes essential for supporting coordination and effective system management, but with an emphasis on national competitive advantage in the returns to scale of a single dominant platform. The *Localisation* storyline describes increasingly differentiated energy strategies across the cities, regions and countries of the EU. This storyline places emphasis on high levels of innovation investments (R&D expenditure) at multiple scales in pursuit of locally-resilient energy developments. However, the proliferation of local actors and innovation activities also means that knowledge exchange and collaborations weaken due to coordination difficulties and mismatches of scale.

The effects of the *Localisation* storyline on the innovation system for energy technologies in the EU are captured by changes in specific quantitative indicators of innovation system processes (shown here in *italics*):

1. *Public energy RD&D expenditure* and *demonstration budgets* are strengthened as cities and regions look to build knowledge stocks for successfully exploiting local resources.
2. *Energy technology imports* are strengthened as locally-focused innovation strategies focus only on key growth areas, relying on active trade to supply other areas.
3. *Diversity of policy instruments* is strengthened as national and local innovation policy frameworks are tailored to suit specific innovation environments throughout the EU.
4. *Patent co-invention (intra-EU)* is weakened as innovation activity becomes increasingly differentiated and localised.

3.3. Empirical stream I: estimating baseline econometric models

The ETIS framework shown in Fig. 1 describes a complex, dynamic system constituted by diverse processes. It is not possible to express ETIS functioning as a single causal model. However, specific linkages among subsets of relationships can be hypothesized and tested based on available literature.

Here we estimate empirically the influence of selected innovation system processes on three distinct innovation outcomes: patents (as a measure of knowledge generation and codification); co-inventions (as a measure of knowledge exchange and actor interaction); and technology cost (as a measure of deployment experience and user uptake). Equations (1)–(3) show the baseline econometric models. Each model hypothesises the effect of specific innovation system processes measured by the ETIS indicators shown in Table 1. The one exception is market share (in the adoption & use dimension of the ETIS framework) which is strongly dependent on a range of market, institutional and infrastructural conditions exogenous to innovation systems.

We set up the econometric models by drawing on the literature as follows. In the first model, we hypothesise that generated and codified knowledge, proxied by the number of patents, is affected by: (1) lagged RD&D expenditure [29–31] and stock of knowledge [9]; (2) stability in RD&D expenditure [32]; (3) exchange and interaction between heterogeneous actors [14–16]; and (4) policy instruments which are both durable [33,34] and stable [35,36]. Based on the literature, we expect the signs of the independent variable coefficients in equation (1) to be positive.

In the second model, we hypothesise that knowledge exchange and actor interaction, proxied by patent co-inventions, is affected by: (1) lagged RD&D expenditure, (2) stability in RD&D expenditure, (3) durable and diverse policy instruments [8,13,37,38] and (4) international knowledge spillovers [39]. Based on the literature (see also previous paragraph), we expect the signs of the independent variable coefficients in equation (2) to be positive.

In the third model, we hypothesise that cost of technology, which is related to learning-by-doing and market deployment, is affected by: (1) cumulative capacity as a measure of experience [40–44]; (2) cumulative RD&D expenditure [45–48]; (3) durable and diverse policy instruments; (4) international knowledge spillovers through trade. Based on the literature (see also previous paragraphs), we expect the signs of the independent variable coefficients in equation (3) to be negative.

The three baseline econometric models are

$$\begin{aligned} Patents = {} & \beta_1 + \beta_2 \times RDD_{t-1} + \beta_3 \times RDD_{stability} + \beta_4 \times Coinvention \\ & + \beta_5 \times Stock\_Patent + \beta_6 \times Policy_{durability} + \beta_7 \times Policy_{stability} \\ & + \gamma_i + \varepsilon_{i,t} \end{aligned} \tag{1}$$

Table 2
Indicators of innovation system processes which are strengthened or weakened in four storylines of future change in the EU energy system.

Innovation system processes	ETIS indicators (and variables in panel regression)	Diversification	Directed Vision	National Champions	Localisation
KNOWLEDGE					
Generation	Public energy RD&D expenditure		strengthened		strengthened
	Number of patents[a]				
Spillover	Energy technology imports			weakened	strengthened
Learning	Technology costs[a]				
Depreciation	Stability in public energy RD&D expenditure			strengthened	
RESOURCES					
Policy Durability	Durability of policy instruments	weakened	strengthened	strengthened	
Policy Diversity	Diversity of policy instruments	strengthened	weakened		strengthened
Policy Stability	Stability of policy instruments	weakened		strengthened	
ACTORS & INSTITUTIONS					
Exchange & Interaction	Patent co-inventions[a]	strengthened			weakened

[a] These are outcome (dependent) variables and so are not directly affected by a storyline assumption. However, patent co-inventions also are an explanatory (independent) variable in equation (1).

$$Coinvention = \beta_1 + \beta_2 \times RDD_{t-1} + \beta_3 \times RDD_{stability} + \beta_4 \times Policy_{durability} + \beta_5 \times Policy_{diversity} + \beta_6 \times Trade + \gamma_i + \varepsilon_{i,t} \quad (2)$$

$$Cost\ of\ technology = \beta_1 + \beta_2 \times Capacity_{cumulative} + \beta_3 \times RDD_{cumulative} + \beta_4 \times Policy_{durability} + \beta_5 \times Policy_{diversity} + \beta_6 \times Trade + \gamma_i + \alpha_t + \varepsilon_{i,t} \quad (3)$$

where Patents is the number of patents, RDD_{t-1} is one-year lagged RD&D expenditure, $RDD_{stability}$ is the stability in RD&D expenditure (measured as the inverse of volatility), *Coinvention* is the number of patent co-inventions, *Stock_Patent* is the cumulative stock of patents, $Policy_{durability}$ is the durability of policy (measured as the cumulative length of policies in place), $Policy_{stability}$ is the stability of policy (measured as the cumulative length of policies in place divided by the total number of times policies have been changed), $Policy_{diversity}$ is the diversity of policy instruments (measured by Shannon's diversity index across three types of policy instrument - innovation, market and regulatory), *Trade* is the total import value of energy technologies, $Capacity_{cumulative}$ is the cumulative installed capacity, $RDD_{cumulative}$ is the cumulative RD&D expenditure, γ_i is a technology fixed effect, α_t is a time fixed effect, and ε is residuals. A detailed explanation of how each indicator is constructed is provided in Appendix A2.

To estimate equations (1) and (2), we use Poisson models with robust standard errors as the dependent variable is count data. The conditional fixed effects negative binomial estimator should be avoided because it is not a true fixed-effects estimator [49,50]. We use the Poisson fixed-effects estimator based on the method in Ref. [51]. Poisson models estimated by pseudo-maximum likelihood as is the case in Stata are perfectly capable of dealing with both under and overdispersion [52]. To estimate equation (3), we use an ordinary least square model with robust standard errors as the dependent variable is a continuous variable and non-count data.

Equations (1)–(3) are generalisable hypotheses linking innovation system processes to specific innovation outcomes. For the analysis in this paper, we estimate the coefficients for equations (1)–(3) using historical data describing each variable across the six technology fields of the EU's SET Plan. Each variable corresponds to a technology-specific ETIS indicator shown in Table 1, and quantified for the EU: patents are those filed by innovators from an EU country; co-inventions are patents filed by innovators from at least two different EU countries; policy durability, diversity, and stability are based on policy instruments at both EU member state level and EU level; and so on. A detailed explanation of how the data used for each variable is provided in Appendix A2.

Table 3
Stochastic components of innovation system processes.

Innovation System Processes	Random Variable	Interval
Strengthened	$X_i \sim N(\mu, \sigma^2)$	X ε (1,2)
Weakened		X ε (0,1)

3.4. Empirical stream II: introducing stochastic components into the baseline econometric models

To use the baseline econometric models for exploring future uncertainty, we draw on the narrative stream of analysis described above. As shown in Table 2, each storyline of the future EU energy system can be interpreted as having both positive and negative effects on certain innovation system processes. Some innovation system processes are strengthened, others are weakened. (Note that market share as an indicator of the adoption & use dimension of the ETIS framework is not included in our storyline analysis as it is affected by a large number of conditions exogenous to the energy innovation system).

We assign probability distributions to the coefficients for each of the variables in the baseline econometric models affected by future uncertainty. Specifically, we use truncated standard normal distributions which cut off both tails (Table 3). This is a first-order approximation of how to incorporate future uncertainty into the econometric models as a result of the strengthening or weakening of innovation system processes in each of the four storylines.

We then use Monte Carlo simulations to introduce these uncertainties into the baseline econometric models. We generate 10 000 random draws from the probability distributions and rerun the models for each draw. We then compare the Monte Carlo simulation results with the baseline econometric model results to see whether the effects of strengthened or weakened coefficients (independent variables) has impacted innovation outcomes (dependent variables).

Our overall approach therefore combines changes in innovation system processes from the storylines (Table 2) with empirical estimations (equations (1)–(3)) to characterise the resulting effect of each storyline on innovation outcomes.

4. Results

4.1. Baseline econometric models

Table 4 shows the estimation results on the effect of innovation system processes on three key innovation outcomes historically in the EU: (1) the number of patents, (2) patent co-inventions, and (3) cost of

Table 4
Baseline models of innovation system outcomes.

Variables	(1)	(2)	(3)
	Poisson (Quasi-ML) with robust SE: Number of patents, 2001–2013, 6 technologies[a]	Poisson (Quasi-ML) with robust SE: Co-inventions, 2001–2013, 6 technologies[a]	OLS regression: Cost of technology, 2011–2015, 3 technologies[a]
$RDD_{(t-1)}$	0.001***	0.002***	
	(0.000)	(0.000)	
RDD stability	−0.033**	−0.011	
	(0.015)	(0.014)	
Co-invention	0.000**		
	(0.000)		
Cum_patent	0.000***		
	(0.000)		
Policy durability	−0.007	−0.009	−0.008
	(0.007)	(0.012)	(0.014)
Policy stability	−0.266***		
	(0.048)		
Policy diversity		0.077	0.573
		(0.177)	(0.768)
Trade imports		0.000***	−0.000
		(0.000)	(0.000)
Cum_capacity			−0.000**
			(0.000)
Cum_RDD			−0.000**
			(0.000)
Time FE	NO	NO	YES
Tech FE	YES	YES	YES
- renewables	2.74	3.29	- (base)
- smart grid	1.62	2.33	n/a
- energy efficiency	3.35	4.23	−9.01
- sustainable transport	2.65	3.81	−5.12
- carbon capture & storage	0.98	1.78	n/a
- nuclear power	- (base)	- (base)	n/a
Pseudo R square (models 1 & 2), R square (model 3)	0.971	0.957	1.000

Robust standard errors (SE) in parentheses, ***$p < 0.01$, **$p < 0.0$

[a] Patent and co-invention models span 2001–2013 due to patent data truncation issues with more recent data; cost of technology model covers 2011–2015 and only applies to three technology fields (renewable energy, energy efficiency, electric vehicles) due to data availability.

technology. Applied to future EU energy innovation, the baseline econometric models represent a business-as-usual scenario in which historical relationships remain consistent. For data reasons, historical data for the patents and co-inventions models covered the period 2001–2013, and for the cost of technology model, 2011–2015 (see Appendix A2 for details).

In the first column of Table 4 corresponding to equation (1), we confirm the positive and significant effect of RD&D expenditure, co-invention and knowledge stock on the number of patents. However, we find three unexpected results relating to RD&D stability, policy durability and policy stability. First, the negative and significant effect of RD&D stability on the number of patents can be explained by the global financial crisis which negatively affected RD&D expenditure in all countries midway through the study period.[2] Consequently RD&D stability follows a skewed U-shaped curve. One interpretation is that RD&D volatility due to the financial crisis did not adversely affect patent applications due to the credible and strong EU commitments to low-carbon technologies (e.g., SET Plan, 20-20-20 Directive and EU Emissions Trading System). Second, the negative effect of policy durability on the number of patents is contrary to expectations but is not statistically significant. Third, the negative and significant effect of policy stability on the number of patents is associated with a downward trend in policy stability over the period 2000–2015. This is largely explained by more frequent revisions, updates or amendments to policy instruments in the period 2010- onwards. One interpretation of the regression result could be that the effect of policy instability on patenting will be time-lagged and so only become evident in more recent data. An alternative interpretation is that policies were being revised in a way which strengthened incentives for innovators (the stringency of policies is not captured in the indicators and is an important area for further research).

In the second column of Table 4 corresponding to equation (2), we confirm the positive and significant effect of RD&D expenditure and trade imports on patent co-inventions. We also find a positive but non-significant effect of policy diversity. However, we find two unexpected results relating to RD&D stability and policy durability which both have negative although non-significant coefficients (see previous paragraph for possible explanations).

In the third column of Table 4 corresponding to equation (3), we confirm the negative and significant effect of cumulate deployment and cumulative RD&D expenditure on cost of technology. This is consistent with a two-factor learning curve. We also find negative but non-significant effects of policy durability and trade imports on cost of technology. The one unexpected result is the positive but non-significant effect of policy diversity. One interpretation is that sustained learning is more dependent on a stable set of market-pull instruments signalling clear payoffs to innovators, and that an emphasis on policy diversity across different types may undermine this relationship.

To check the robustness of the models, we tested longer RDD time lags in line with [53,54] and found no material impact on the regression results (see Appendix Table A4). We included one-year, two-year and three-year time lags for RD&D spending gradually in models (1) and (2) and found the one-year time lag is only statistically significant. As this exercise further reduces data availability, we consider thee-year time lags as a sensitivity analysis.

Year fixed effects are used in model (3) to reduce selection bias, but not in models (1) and (2) due to non-convergence issues. Technology fixed effects are used in all three models to reduce selection bias.

[2] https://www.oecd.org/sti/sti-outlook-2012-chapter-1-innovation-in-the-crisis-and-beyond.pdf.

Technology fixed effects eliminate time-invariant confounding factors allowing the estimation of the independent variables' effect on the dependent variable using only within-unit variation (i.e., within each technology field). In other words, the econometric estimation is intentionally non-technology specific and so generalisable across technology fields. Coefficients for the technology fixed effect can be interpreted as follows: the higher the fixed effect coefficient for a given technology, the weaker the baseline effect (and vice versa).

Coefficients for the technology fixed effects are shown in Table 4. For models (1) and (2), the coefficient for energy efficiency is the highest among five technology fields (relative to nuclear power which is the base indicator with an implicit coefficient of zero). Our interpretation is that the more mature the technology field, the weaker the baseline effects as cumulative causation (path dependence) makes innovation outcomes less dependent on the full set of innovation system processes [55]. As energy efficiency is arguably the most mature technology field in the EU SET Plan, its coefficient for the technology fixed effect is the highest, and the significant relationships between independent variables and dependent variables in the baseline model weakens. Conversely, the coefficient is lowest for carbon capture and storage which is arguably the least mature technology field and so sees a stronger baseline effect. Technology fixed effects in model (3) should be interpreted with more caution as only three technologies are included (with renewable energy as the base indicator which is therefore dropped). Direct comparisons between models are also not possible due to differences in time periods analysed.

4.2. Monte Carlo simulations

Table 5 summarises the findings of the Monte Carlo simulation mean estimation results on the number of patents, co-inventions and cost of technology. We focus on changes in significance from the baseline estimation results to the Monte Carlo simulation results as these changes indicate the impact of storyline uncertainty on innovation outcomes (relative to a continuation of historical innovation system performance). In Table 5, coefficients which change in significance are shown in bold, with changes from non-significant to significant also shown in grey highlight. Full details of the estimation results are provided in Appendix A1. In Table 5 we also show changes in the size of coefficients, with 'similar' denoting the same coefficient to three decimal places, and 'strengthened' and 'weakened' denoting an increase or a decrease respectively in the size of coefficients.

5. Discussion

The final integrative step is to interpret how the strengthened or weakened innovation system processes in each of the four storylines impact innovation outcomes. We focus on coefficients whose significance changes (from non-significant to significant or vice versa) in the Monte Carlo simulation models relative to the baseline econometric models. These changes are shown in bold text in Table 5 and represent how uncertainties in the storyline may affect future energy innovation in the EU.

In the *Diversification* storyline we assume (as inputs to the Monte Carlo simulations) that patent co-invention and policy diversity are strengthened but that policy durability and policy stability are weakened (Table 2). This changes the significance of coefficients in the baseline models in three ways: the effect of co-invention and policy stability on patents becomes non-significant, and the effect of policy diversity on co-invention becomes significant (Table 5).

First, the positive effect of policy diversity on co-invention becomes significant in the Monte Carlo simulation. This would be consistent with a diverse mix of policy instruments being more likely to influence heterogeneous actors in the EU's energy innovation system. This interpretation is in line with literature that finds policy mixes which are mutually reinforcing can stimulate collaboration among innovation actors [56,57] and also attract new actors into innovation networks [58].

Second, co-invention has a positive and significant effect on the number of patents in the deterministic model which becomes insignificant in the stochastic model. This would be consistent with stronger co-invention substituting for rather than adding to single inventor patents. In other words, patenting activity would be diverted from innovators within a single EU country (classified here as single inventor patents) to innovators collaborating between EU countries (classified here as co-invention). Consequently, stronger co-invention changes the type of patenting activity but not the overall output or total number of patents. This interpretation suggests that for the more heterogeneous innovation actors in the *Diversification* storyline, there would be a trade-off between within-country innovation and between-country collaboration.

Third, the negative and significant effect of policy stability on the number of patents becomes non-significant in the stochastic model. Weaker policy stability in the *Diversification* storyline (i.e., more frequent revisions or amendments to existing instruments) does not negatively affect patent output. The unexpected negative effect of policy stability on patents in the baseline model (with more patents in less stable policy environments) is therefore removed as policy stability becomes less pronounced. This would be consistent with revisions, amendments or cancellations of insufficiently stringent policies which provide only limited incentives for innovation activity.

Overall, we can interpret the impact of uncertainties on future EU energy innovation in the *Diversification* storyline as follows: a mix of policy instruments positively affects collaboration among diverse innovation actors, but this does not affect the aggregate knowledge stock measured by patents.

In the *Directed Vision* storyline we assume (as inputs to the Monte Carlo simulations) that RD&D expenditure and policy durability are strengthened but that policy diversity is weakened (Table 2). This changes the significance of coefficients in the baseline models in two ways: the effect of RD&D on co-inventions and of cumulative RD&D on technology costs become non-significant (Table 5).

First, the positive and significant effect of RD&D expenditure on co-invention becomes non-significant in the Monte Carlo simulation. Possible interpretations are that there would be diminishing returns in the role of RD&D expenditures for stimulating collaboration among innovation actors, or that increased RD&D expenditures would be concentrated in large incumbents who would have less need to collaborate with new actors. Another interpretation is that strengthened RD&D would reinforce localised innovation capabilities [59] but would not incentivize inter-country collaboration across the EU.

Second, the negative and significant effect of RD&D expenditure on the cost of technology becomes non-significant in the Monte Carlo simulation. Cumulative RD&D drops out of the two-factor learning curve specification of the baseline model shown in equation (3) such that increasing RD&D spending would not translate into a reduction in the cost of technology. This would be consistent with additional RD&D funding being prioritised for selected technologies so that a generalised effect applicable to the full technology portfolio would not be detectable.

Overall, we can interpret the impact of uncertainties on future EU energy innovation in the *Directed Vision* storyline as follows: strengthened public RD&D investments in line with EU strategic goals do not induce further collaboration among innovation actors and also fails to stimulate additional cost reductions across the SET Plan portfolio as a whole.

In the *National Champions* storyline we assume (as inputs to the Monte Carlo simulations) that RD&D stability, policy durability, and policy stability are strengthened but that knowledge spillovers through trade imports are weakened (Table 2). This changes the significance of coefficients in the baseline models in three ways: the effects of RD&D stability and policy stability on number of patents become non-significant, as does the effect of trade imports on co-inventions (Table 5).

Table 5
Monte Carlo simulation results in four storylines (relative to baseline estimations). Note: bold text with grey highlight denotes 'has changed to become significant'; bold text without highlight denotes 'has changed to become non-significant'.

Relative to baseline estimations	***Diversification***	***Directed Vision***	***National Champions***	***Localisation***
Monte Carlo simulation effects on: **(1) Number of patents**	**Strengthened co-invention -> similar positive effect, but becomes *non-significant*** Weakened policy durability -> *weakened* negative effect **Weakened policy stability -> *strengthened* negative effect but becomes *non-significant***	Strengthened RD&D -> similar positive effect Strengthened policy durability -> similar negative effect	**Strengthened RD&D stability -> similar negative effect but becomes *non-significant*** Strengthened policy durability -> *weakened* negative effect **Strengthened policy stability -> *weakened* negative effect but becomes *non-significant***	**Strengthened RD&D -> similar positive effect but becomes *non-significant*** Weakened co-invention -> similar positive effect
Monte Carlo simulation effects on: **(2) Co-inventions**	**Strengthened policy diversity -> *strengthened* positive effect which becomes *significant*** Weakened policy durability -> similar negative effect	**Strengthened RD&D -> similar positive effect which becomes *non-significant*** Strengthened policy durability -> similar negative effect Weakened policy diversity -> *weakened* positive effect	Strengthened RD&D stability -> similar negative effect Strengthened policy durability -> similar negative effect **Weakened trade imports -> similar positive effect but becomes *non-significant***	**Strengthened RD&D -> similar positive effect but becomes *non-significant*** **Strengthened policy diversity -> weakened positive effect which becomes *significant*** **Strengthened trade imports -> similar positive effect but becomes *non-significant***
Monte Carlo simulation effects on:	Weakened policy durability -> *strengthened* negative effect	**Strengthened RD&D -> similar negative effect but becomes *non-significant***	Weakened trade imports -> similar negative effect	**Strengthened RD&D -> similar negative effect but becomes *non-significant***
(3) Cost of technology	Strengthened policy diversity -> *weakened* positive effect	Strengthened policy durability -> similar negative effect Weakened policy diversity -> *weakened* positive effect	Strengthened policy durability -> similar negative effect	Strengthened trade imports -> similar negative effect Strengthened policy diversity -> *weakened* positive effect

First, the negative and significant effects of stability in both RD&D spending and policy instruments on the number of patents become non-significant in the stochastic analysis. As a result the Monte Carlo simulation aligns more closely with prior expectations than the baseline model which found that stability in both push (RD&D) and pull (policy) support for innovation had the perverse effect of weakening innovation activity. This finding was very much contrary to the literature [60,61]. Although this contrariness is removed in the Monte Carlo simulation, strengthened RD&D and more stable policies would still not result in an increased knowledge stock from patenting. One interpretation is that innovation and industrial policies in the *National Champions* storyline would support already mature technology fields with relatively lower levels of patenting activity.

Second, the positive and significant effect of imports on co-invention becomes non-significant. This means that declining volumes of energy technology imports would no longer increase collaboration in patenting, which is contrary to literature on the benefits of trade for collaborative activity [39]. One interpretation is that large incumbents in the *National Champions* storyline would have fewer incentives to collaborate on innovation activities with other countries.

Overall, we can interpret the impact of uncertainties on future EU energy innovation in the *National Champions* storyline as follows: strengthened RD&D expenditure and policy stability fail to stimulate additional knowledge generation in mature technology fields, with large incumbents also being less incentivised to pursue collaborative innovation externally.

In the *Localisation* storyline we assume (as inputs to the Monte Carlo simulations) that RD&D expenditure, imports, and policy diversity are strengthened but that patent co-inventions are weakened (Table 2). This changes the significance of coefficients in the baseline models in five ways: the effects of RD&D expenditure on number of patents, on co-invention and on cost of technology become non-significant, and the effect of imports on co-inventions also becomes non-significant, but the effect of policy diversity on co-inventions becomes significant (Table 5).

First, the positive and non-significant effect of policy diversity on co-invention becomes significant. A similar effect was observed in the *Diversification* storyline. One interpretation is that policy experimentation would respond to the heterogeneous needs of established and new entrant innovation actors and so would stimulate collaborative activity.

Second, the positive and significant effect of RD&D spending on the number of patents, on co-invention and on cost of technology become non-significant. These are unexpected results because there is generally a positive relationship between RD&D spending and knowledge generation. One interpretation is that innovators in a localised EU would have diminished innovation capabilities so additional public RD&D investments would no longer impact knowledge stocks. For example, future innovators in the *Diversification* storyline would be interested in exploiting locally available resources for smaller-scale projects rather than investing in intellectual property and collaborative activity.

Third, the positive and significant effect of energy technology imports on co-inventions becomes non-significant. One interpretation is that imported manufactures would be needed to supplement local capacities, but for deployment rather than for fostering collaborative innovation.

Overall, we can interpret the impact of uncertainties on future EU energy innovation in the *Localisation* storyline as follows: greater investment in RD&D expenditure does not feed into increase knowledge generation activities, but a more diverse policy mix does support collaborative patenting activity.

To summarise the results in general terms across the storylines, the Monte Carlo simulations used for stochastic analysis of future energy innovation produce very cautious and mixed results. Many of the significant effects in the baseline models (estimated on historical data) become non-significant in the stochastic analysis. We consider three possible explanations.

First, stochastic effects (strengthened or weakened) are estimated on historical values of the independent variables., but with the independent variable in each model unchanged. As a result, the deterministic and stochastic effects can cancel each other and so have no overall net effect on the independent variables (number of patents, co-inventions and cost of technology). In other words, we are not using Montel Carlo simulation to forecast future innovation outcomes. Rather we explore what would happen if we changed a set of assumptions about key innovation system processes in future storylines.

Second, future uncertainties relating to decentralisation and co-operation in the EU energy system impact multiple innovation system processes which have offsetting effects on innovation outcomes. This is an inescapable result of the complex system dynamics of an innovation system which resist singular causal hypotheses. In the context of the future SET Plan, there were few systematic differences between storylines in the 2 × 2 possibility space explored (Fig. 2). This implies there is no single preferred or optimal storyline of future change in the EU energy innovation system.

Third, the baseline models are not robust in the sense that relatively small changes in specific independent variables can cause the main effects (in line with the literature) to be weakened or reversed. One example is that policy stability had a significant negative effect on numbers of patents in the historical estimations, but this became non-significant in all four storylines whether policy stability was strengthened, weakened, or unaffected. An even clearer example is with the cost of technology model which has the form of a two-factor learning curve in the historical estimations, with negative and significant effects for cumulative capacity and cumulative RD&D as expected. In the stochastic analysis of all four storylines, these two main effects become non-significant regardless of whether RD&D is strengthened or left unaffected. The cost of technology models are inherently weaker due to due to the limited time series (2011–2015) across only three technologies.

These interpretations - complex causality and weak baseline models - are closely inter-related: the difficulty of capturing innovation system functioning in parsimonious regressions using proxy variables for hard-to-observe innovation system processes means that resulting model fits are weak. This is further exacerbated by our use of panel data across six technology fields in an attempt to generate portfolio-level insights (rather than insights specific to any given SET Plan technology with characteristic maturity, innovation needs, market structure, and so on).

6. Policy implications

Strengthening policy diversity benefits patent co-inventions as a measure of collaborative activity and actor interaction. This is observed particularly in the *Diversification* and *Localisation* storylines which we assume to be characterised by greater policy diversity as a response to new entrants and more heterogeneous actors. Collaboration among new entrants builds coalitions of interest and advocacy which help overcome resistance from incumbents. Exchange and interaction among producers and between producers and users also generate essential tacit knowledge alongside the codified knowledge from RD&D activities [62–64]. This insight on policy diversity, heterogeneous actors, and collaborative innovation activity reflects the complexity of the energy innovation system which cautions against singular, top-down, directed, concentrated innovation systems. An implication for the future SET

Plan is therefore to continue emphasising a strong collaborative approach by engaging industry, small and medium-sized enterprises, research institutes, policymakers, and other innovation actors in between-country activities.

The other policy variables in our analysis - durability and stability - had no systematic effect. We found policy durability had non-significant effects on patents, co-inventions, and cost of technology in the baseline models and in all four storylines. We also found policy stability had an unexpected negative and significant effect on numbers of patents, although this became insignificant in all four storylines. Counter to expectations, we cautiously infer that policy durability and stability are only weakly linked to innovation outcomes, suggesting the importance of adaptive policy responding to rapidly changing innovation environments in the future SET Plan.

In line with expectations, we did find that RD&D expenditure positively affects knowledge generation and codification (patents), knowledge exchange and actor interaction (co-inventions), and technology performance (cost reductions). These positive effects in the baseline models hold in all four storylines although became non-significant. Maintaining and strengthening RD&D with supportive innovation policy environments should be an integral feature of the future SET Plan.

Finally, with indirect relevance to innovation policy and the SET Plan, in the baseline estimations we found that imports of energy technologies positively and significantly affect co-inventions. Trade enables the EU to access global knowledge stocks with standardized, non-localised characteristics such as solar PV panels or electric vehicles. Given the importance of such technologies for decarbonisation objectives, maintaining and strengthening trade relationships is also an important supporting condition for the future SET Plan.

7. Conclusions

This paper develops and applies a novel approach for analysing storylines of future change from an innovation systems perspective. The stepwise approach combines econometric analysis of historical innovation system performance with a stochastic simulation of future performance based on an interpretation of how specific innovation-system processes are impacted under different future storylines. Although applied here to energy innovation in the EU, the approach is generalisable to any scenario analyses combining future narratives with quantitative analysis based on econometric relationships.

Our empirical analysis of patent, co-invention and cost of technology as innovation outcomes under the EU's SET Plan finds broadly expected results but with some exceptions. Numbers of patents are positively affected by RD&D and co-inventions, but are negatively affected by RD&D stability and policy stability. Co-inventions are positively affected by RD&D and trade imports. Cost of technology is negatively affected (i.e., cost reductions) by cumulative capacity and RD&D.

Translating future storylines for the EU's innovation system into the strengthening or weakening of specific innovation system processes, we find that many of these significant effects observed historically fall away. We interpret this to mean that the innovation system is complex, so that the impact of one process on an outcome variable of interest may be offset by the impact of another in way which are hard to isolate. However we do find that diverse mixes of policy instruments stimulate collaborative innovation activity measured by co-inventions between different EU countries. This is particularly important in a decentralising future which emphasises localised experimentation and a democratisation of energy innovation away from large incumbents. We also find that both RD&D expenditure and trade imports support knowledge generation and exchange, and that these relationships are largely robust to future uncertainty.

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Appendix A1

Tables A1a and A1b show the full estimation results for number of patents as an innovation outcome variable. Table A1a shows summarises the signs and significance of coefficients in the both the baseline and stochastic analyses. The left columns show results of the baseline econometric model estimated on 2001–2013 data across 6 technology fields in the EU SET Plan. The right columns show independent variables (IVs) strengthened or weakened in narrative storylines, and the signs and significance of the Monte Carlo simulation model results. Table A1b provides the full results of the Monte Carlo simulation models.

Table A1a
Baseline & Stochastic Analysis of Number of Patents (2001–2013, 6 technology fields).

DV = number of patents	Baseline econometric model		Stochastic analysis in future storylines			
IVs	Expected sign	EU SET Plan 2001–2013	Diversification	Directed Vision	National Champions	Localisation
RD&D expenditure	+	+ ***	+ ns	strengthened + **	+ ns	strengthened + ns
RD&D stability	+	- **	- ns	- ns	strengthened - ns	- ns
patent co-inventions	+	+ **	strengthened + ns	+ **	+ ns	weakened + **
cumulative patents	+	+ ***	+ ns	+ **	+ ns	+ ns
policy durability	+	- ns	weakened - ns	strengthened - ns	strengthened - ns	- ns
policy stability	+	- ***	weakened - ns	- ns	strengthened - ns	- ns

IVs not used = cumulative capacity, cumulative RD&D, trade imports, policy diversity.
+ positive sign, - negative sign, ***p < 0.01, **p < 0.05.

Table A1b
Monte Carlo Mean Estimation Results: Number of patents (2001–2013, 6 technology fields).

Independent Variables (IVs)	Diversification	Directed Vision	National Champions	Localisation
RDD(t-1)	0.001	0.001**	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
RDD stability	−0.033	−0.034	−0.033	−0.033
	(0.029)	(0.031)	(0.021)	(0.031)
Co-invention	0.000	0.000**	0.000	0.000**
	(0.000)	(0.001)	(0.001)	(0.001)
Cum_patent	0.000	0.000**	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Policy durability	−0.006	−0.007	−0.006	−0.006
	(0.024)	(0.020)	(0.020)	(0.020)
Policy stability	−0.267	−0.266	−0.264	−0.261
	(0.483)	(0.260)	(0.185)	(0.260)

Robust standard errors in parentheses ***p < 0.01, **p < 0.05.

Tables A2a and A2b show the full estimation results for patent co-inventions as an innovation outcome variable. Table A2a shows summarises the signs and significance of coefficients in the both the baseline and stochastic analyses. The left columns show results of the baseline econometric model estimated on 2001–2013 data across 6 technology fields in the EU SET Plan. The right columns show independent variables (IVs) strengthened or weakened in narrative storylines, and the signs and significance of the Monte Carlo simulation model results. Table A2b provides the full results of the Monte Carlo simulation models.

Table A2a
Baseline & Stochastic Analysis of Patent Co-Inventions (2001–2013, 6 technology fields).

DV = patent co-inventions	Baseline econometric model		Stochastic analysis in future storylines			
IVs	Expected sign	EU SET Plan 2001–2013	Diversification	Directed Vision	National Champions	Localisation
RD&D expenditure	+	$+^{***}$	$+^{ns}$	strengthened $+^{ns}$	$+^{ns}$	strengthened $+^{ns}$
RD&D stability	+	$-^{ns}$	$-^{ns}$	$-^{ns}$	strengthened $-^{ns}$	$-^{ns}$
trade imports	+	$+^{***}$	$+^{ns}$	$+^{ns}$	weakened $+^{ns}$	strengthened $+^{ns}$
policy durability	+	$-^{ns}$	weakened $-^{ns}$	strengthened $-^{ns}$	strengthened $-^{ns}$	$-^{ns}$
policy diversity	+	$+^{ns}$	strengthened $+^{**}$	weakened +	$+^{**}$	strengthened $+^{**}$

IVs not used = cumulative capacity, cumulative RD&D, cumulative patents, co-inventions, policy stability.
+positive sign, - negative sign, ***p < 0.01, **p < 0.05.

Table A2b
Monte Carlo Mean Estimation Results: Co-inventions (2001–2013, 6 technology fields).

Independent Variables (IVs)	Diversification	Directed Vision	National Champions	Localisation
RDD(t-1)	0.002	0.002	0.002	0.002
	(0.001)	(0.001)	(0.001)	(0.001)
RDD stability	−0.011	−0.011	−0.011	−0.011
	(0.028)	(0.028)	(0.019)	(0.029)
Policy durability	−0.009	−0.009	−0.009	−0.009
	(0.024)	(0.019)	(0.020)	(0.040)
Policy diversity	0.078**	0.066	0.070**	0.076**
	(0.322)	(0.453)	(0.589)	(0.336)
Trade	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)

Robust standard errors in parentheses***p < 0.01, **p < 0.05.

Tables A3a and A3b show the full estimation results for cost of technology as an innovation outcome variable. Table A3a shows summarises the signs and significance of coefficients in the both the baseline and stochastic analyses. The left columns show results of the baseline econometric model estimated on 2011–2015 data across 3 technology fields in the EU SET Plan. The right columns show independent variables (IVs) strengthened or weakened in narrative storylines, and the signs and significance of the Monte Carlo simulation model results. Table A3b provides the full results of the Monte Carlo simulation models.

Table A3a
Baseline & Stochastic Analysis of Cost of Technology (2011–2015, 3 technology fields).

DV = cost of technology	Baseline econometric model		Stochastic analysis in future storylines			
IVs	Expected sign	EU SET Plan 2011–2015	Diversification	Directed Vision	National Champions	Localisation
cumulative capacity	–	- **	- ^{ns}	- ^{ns}	- ^{ns}	- ^{ns}
cumulative RD&D	–	- **	- ^{ns}	strengthened - ^{ns}	- ^{ns}	strengthened- ^{ns}
trade imports	–	- ^{ns}	+ ^{ns}	- ^{ns}	weakened + ^{ns}	strengthened - ^{ns}
policy durability	–	- ^{ns}	weakened - ^{ns}	strengthened - ^{ns}	strengthened - ^{ns}	- ^{ns}
policy diversity	–	+ ^{ns}	strengthened + ^{ns}	weakened + ^{ns}	+ ^{ns}	strengthend + ^{ns}

IVs not used = RD&D expenditure, RD&D stability, cumulative patents, co-inventions, policy stability.
+ positive sign, - negative sign, ***p < 0.01, **p < 0.05.

Table A3b
Monte Carlo Mean Estimation Results: Cost of Technology (2011–2015, 3 technology fields).

Independent Variables (IVs)	Diversification	Directed Vision	National Champions	Localisation
Cum_Capacity	−0.000	−0.000	−0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Cum_RD&D	−0.000	−0.000	−0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Policy Durability	−0.009	−0.008	−0.008	−0.009
	(0.047)	(0.043)	(0.044)	(0.045)
Policy Diversity	0.568	0.570	0.606	0.487
	(1.169)	(1.134)	(9.836)	(9.565)
Trade	0.000	−0.000	0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)

Robust standard errors in parentheses***p < 0.01, **p < 0.05.

Table A4
Robustness checks.

Variables	(1)	(2)	(3)	(4)
	Poisson (Quasi-ML) with robust SE: Number of patents 2001–2013 6 technologies†	Poisson (Quasi-ML) with robust SE: Number of patents 2001–2013 6 technologies†	Poisson (Quasi-ML) with robust SE: Co-inventions 2001–2013 6 technologies†	Poisson (Quasi-ML) with robust SE: Co-inventions 2001–2013 6 technologies†
RDD(t-1)	0.001***	0.001***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
RDD(t-2)	0.000	−0.000	−0.000*	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)
RDD(t-3)		−0.000		−0.000
		(0.000)		(0.000)
RDD stability	−0.031**	−0.027	−0.008	−0.003
	(0.015)	(0.018)	(0.016)	(0.014)
Co-invention	0.000*	0.000*		
	(0.000)	(0.000)		
Cum_patent	0.000***	0.000***		
	(0.000)	(0.000)		
Policy durability	−0.008	−0.011	−0.009	−0.010
	(0.007)	(0.007)	(0.012)	(0.012)
Policy stability	−0.265***	−0.264***		
	(0.049)	(0.064)		
Policy diversity			0.050	0.020
			(0.197)	(0.197)
Trade imports			0.000***	0.000***
			(0.000)	(0.000)
Year FE	NO	NO	NO	NO
Tech FE	YES	YES	YES	YES

Robust standard errors (SE) in parentheses, ***p < 0.01, **p < 0.0† Patent and co-invention models span 2001–2013 due to patent data truncation issues with more recent data; cost of technology model covers 2011–2015 and only applies to three technology fields (renewable energy, energy efficiency, electric vehicles) due to data availability.

Appendix A2

This section explains how we construct each indicator.

Public energy RD&D expenditure. RD&D is the most readily available measure of knowledge generation. We used public energy RD&D expenditure including demonstration budgets from the International Energy Agency (IEA) RD&D database.

Number of patents. We counted the number of relevant patent applications in 2015 using Cooperative Patent Classifications (CPCs) from the U.S. Patent and Trademark Office (USPTO)[3] [65].

Knowledge stock. A technological knowledge stock reflects the cumulative technological knowledge that a country possesses at a given point in time [66,67].

$$K_{nt} = (1 - \delta)_{n(t\text{-}1)} + R_{n(t\text{-}x)}$$

where *Knt* is the knowledge stock in country n during time period t. Moreover, δ is the annual depreciation rate of the knowledge stock ($0 \le \delta \le 1$), K*n*0 represents each country's initial national knowledge stock, R*n*0 is the number of a technology patent counts in the first year available, and x is the number of years (lag) it takes before new patents add to the knowledge stock (J [68]. Typically, the time lag is assumed to be three years. Note that we assume discount factor of 15% [69,70].

Energy technology imports. We used imports of related goods and Extra-EU collaboration in patenting as a measure of knowledge spillover into the EU energy innovation system. We obtained data on the total import of energy technologies from EU trade data since 1988 by Harmonised System (HS)6.[4] We used the HS codes to attribute the import data to the different SET-Plan priority areas [71,72].

Technology costs. Learning describes cost reductions and performance improvements as a function of cumulative experience. Learning rates are a simple measure of the % reduction in cost per doubling of cumulative capacity or production. We sourced learning rates per technology from existing literature [47,73,74].

Stability in public energy RD&D expenditure. Knowledge depreciates more rapidly in stop-go environments associated with staff turnover and investment volatility. We calculated the volatility of energy RD&D expenditure based on earlier work on market volatility [75] applied using a method from the economics of energy innovation [32,76]. For the comparability of other indicators, we used the inverse of the coefficient of variation so that lower volatility results in a higher score on the indicator:

$$PV_{i,t} = \frac{1}{Coefficient\ of\ Variation_{i,t}} = \frac{1}{Policy\ Volatility_{i,t}} = \frac{\frac{1}{5}\sum_{k=0}^{4} RD\&D_{i,t-k}}{\sqrt{\frac{1}{5}\sum_{k=0}^{4}\left[RD\&D_{i,t-k} - \left(\frac{1}{5}\sum_{k=0}^{4} RD\&D_{i,t-k}\right)\right]^2}} \tag{A1}$$

with i as a country, t as a year, and k = 0–4 (lagged year).

Policy Durability. The policy durability indicators are based on the cumulative length of policies in place in a particular technology field in each year, defined as:

$$Durability_{2015,s,p} = \frac{\sum_{i=1}^{n}(2015_{s,p} - Startyear_{i,s,p})}{n_{s,p}} \tag{A3}$$

with i as one policy instrument ($i = 1, \ldots, n$), *startyear* as a year of policy introduction, p as types of policy instrument (p = innovation, market-based and regulatory) and s as SET-Plan priority area ($s = 1, \ldots, 6$).

Policy Diversity. The policy diversity indicator measures whether different types of policy instrument are well-balanced within each of the six SET-Plan priority areas [77,78]. Building on the energy literature [79,80], we used a statistical measure of diversity applied to the types of policy instruments, i.e., Shannon's diversity index H (sometimes Shannon–Weiner or Shannon–Wiener index):

$$H_s = -\sum_i p_i \ln p_i \tag{A4}$$

with p_i as share of a type of policy instrument in the SET-Plan priority area. The higher the value of H, the more diverse the mix of policy instruments.

Policy Stability. As an aggregate measure of policy stability, we divided the cumulative duration of all policy instruments by the total number of times policies had been changed, also using data from the IEA's Addressing Climate Change Database. Higher scores on the indicator denote fewer changes to policy instruments overall and so greater stability:

$$Stability_s = \frac{\sum_{i=1}^{n}(2015_{s,p} - Startyear_{i,s,p})}{n_{s,p} \times No.\ of\ revisions} \tag{A5}$$

with i as one policy instrument ($i = 1, \ldots, n$), *startyear* as a year of policy introduction and s as SET-Plan priority area ($s = 1, \ldots, 6$).

Patent co-inventions. We identified Intra-EU collaboration as 1 if any inventors (authors) from EU countries who collaborated with EU countries, otherwise 0. On a side note, we considered a single inventor or author as a 0.

Cost of technology. We calculated the cost of technology from below sources.

- **Renewable energy:** Total installed cost (2015 Euros/MW) (Source: https://www.irena.org/-/media/Files/IRENA/Agency/Publication/2018/Jan/IRENA_2017_Power_Costs_2018.pd)
- **Energy efficiency (appliance)** (Source: Euromonitor Passport data(Total number of appliances and average unit retail price))
- **Sustainable transport**: Average price of electric vehicles: 32 500 Euros
  (Source: http://www.theicct.org/sites/default/files/publications/ICCT_EU-pocketbook_2015.pdf)

[3] USPTO's PatentsView database: http://www.patentsview.org/web/#viz/relationships.

[4] https://data.europa.eu/euodp/en/data/dataset/PApkoFg8zsTS5CyokPyQ.

Cumulative capacity. We calculated the cumulative capacity since 2000 (where data is available).

- **Renewable energy**: installed capacity (MW)
  Infrastructure - electricity - annual data (MW)
  Source: http://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=nrg_113a&lang=en
  onshore wind (Source: https://www.eia.gov/electricity/generatorcosts)
  solar PV actual installed capacity(peak) (Source: https://www.eurobserv-er.org/photovoltaic-barometer-2016)
  Cumulative and annual offshore wind installations (Source: https://windeurope.org/wp-content/uploads/files/about-wind/statistics/WindEurope-Annual-Offshore-Statistics-2016.pdf)
  Solar thermal and concentrated solar power barometer (Source: https://www.eurobserv-er.org/solar-thermal-and-concentrated-solar-power-barometer-2016/)
  Goethermal (Source: https://www.worldenergy.org/wp-content/uploads/2017/03/WEResources_Geothermal_2016.pdf)
  Ocean (Source: https://setis.ec.europa.eu/sites/default/files/reports/ocean_energy_report_2016.pdf)
- **Energy efficiency (appliance):** number of homes with A+++ rated appliances (#)
  A weighted average of A+++ rated appliance sales including refrigerators, washing machines, and tumbler drier are based on 2014 data (Source: http://www.topten.eu/uploads/File/WhiteGoods_in_Europe_June15.pdf)
- **Sustainable transport**: number of electric vehicles (#)
  Electric vehicles in Europe (Source: European Environment Agency)

Scope of data search to match SET Plan priority areas

Data corresponding to each of the six priority areas of the SET Plan were identified either by searching databases using classifications (e.g., patents) or by allocating database-defined categories to priority areas (e.g., RD&D investments in IEA database). Wherever possible, the scope or breadth of data corresponding to each priority area was kept consistent across all the indicators (Table A5). The aim was to maximise consistency of scope across indicators to ensure comparability.

Table A5
Matching of Scope of Data for ETIS Indicators to SET Plan Priority Areas. Text in italics shows main deviations from SET Plan Priority Areas.

		SET Plan priority area	Target Scope of Data for ETIS indicators
1	RE	Renewable energy & system integration	all renewable energy (exc. fuels) (exc. stationary storage)
2	SG	Smart technologies & grid	all grid and power systems (inc. stationary storage) (exc. smart homes)
3	EE	Energy efficiency in buildings & industry	all energy efficiency in buildings and industry
4	ST	Sustainable transport (EVs, renewable fuels)	all alternative fuels and vehicles (inc. mobile storage) (inc. all H2)
5	CCS	Carbon capture + storage or use	all carbon capture (from large point sources), storage & use
6	NP	Nuclear power	all nuclear fission and fusion (inc. safety)

Some inconsistencies were unavoidable due to differences in database structure or in the database-defined categories. In these cases, it was not possible to match the scope of the SET Plan priority area to the scope of the data for all indicators. As a result, a 'lowest-common denominator' approach to defining the scope of data was adopted to ensure consistency across all indicators. The main resulting mismatches between scope of data and scope of SET Plan priority areas were:

- SG (Smart Grid) data over-estimates activity as includes all 'non-smart' grid and power systems, but under-estimates activity as doesn't include smart technologies & homes as consumer products;
- ST (Sustainable Transport) over-estimates activity as includes all H2 as fuel which may be for stationary applications and/or non-renewable;
- NP (Nuclear Power) over-estimates activity as includes all nuclear-related activity (not limited to safety).

Based on the target scope of data for all ETIS indicators defined in Table A5, specific sets of search terms and/or category allocations were used for the different databases used for each indicator. The resulting scopes of data are summarised in Table A6, with the main inconsistencies shown in italics. The remainder of this appendix includes additional details on data-collection methods. Table A7 shows the category of the IEA public RD&D expenditure and SET-Plan priority areas respectively. Table A8 includes IPC classes to identify SET-Plan priority patents. Table A9 shows harmonised system (HS) codes of low carbon goods.

Table A6
Scope of Data Collected for ETIS Indicators on each SET Plan Priority Area. Text in italics shows main inconsistencies (see table footnotes for details).

	Target Scope (see Table A5)	knowledge generation	knowledge codification	knowledge codification	knowledge spillover
		IEA RD&D $	Web of Science publications	Patent CPC	Harmonised System (HS codes
RE	all renewable energy: solar, wind, geo, wave, marine, ocean, hydro, bioenergy (exc. fuels) (exc. storage)	Solar, wind, geo, ocean, hydro, other renewable sources (exc. Fuels, biofuels, storage)	solar thermal, solar PV, wind, geothermal, ocean, hydro, bio energy (exc. Fuels, biofuels, storage)	solar thermal, solar PV, wind, geothermal, marine, hydro, integration technologies (exc. fuels) (exc. storage)	Solar thermal, solar PV, wind, bioenergy, ocean, wave, marine, geothermal, hydro (exc. fuels) (exc. storage)

(*continued on next page*)

Table A6 (*continued*)

	Target Scope (see Table A5)	knowledge generation	knowledge codification	knowledge codification	knowledge spillover
		IEA RD&D $	Web of Science publications	Patent CPC	Harmonised System (HS codes
SG	all grid and power systems (inc. stationary storage, exc. smart homes)	all grid and power systems (inc. storage, exc. vehicle storage)	all grid and power systems, smart technologies and grids (inc. storage, exc. vehicle storage)	all grid and power systems, smart grids (inc. storage, exc. vehicle storage)	electricity meters, smart grids (inc. storage exc. vehicle storage)
EE	all energy efficiency in buildings and industry	energy efficiency (buildings, industry)	energy efficiency (buildings, industry)	energy efficiency (buildings, industry)	thermostats, heat exchangers, insulation, lighting, EE in heavy industry 1
ST	all alternative fuels and vehicles (inc. mobile storage) (inc. all H2)	EV, mobile (vehicle) storage, H2, fuel cells, biofuel	biofuels, EVs, FCVs H2, vehicle storage	biofuels, EVs, FCVs, H2, hybrid vehicle, vehicle storage, charging stations and enabling technologies	EVs, energy storage(mobile), biofuels, batteries 2
CCS	all carbon capture (from large point sources), storage & use	all carbon capture (from anthropogenic point sources)	all carbon capture and storage	all carbon capture and storage	CCS surveying equipment 3
NP	all nuclear fission and fusion (inc. safety)	all nuclear fission and fusion, and other generic nuclear	all nuclear fission and fusion (inc. safety)	all nuclear fission and fusion	nuclear reactors 4

1 under-estimates activity as includes only specific subsets of energy efficiency in buildings & industry.
2 under-estimates activity as excludes H2 and other alternative fuels than biofuels and EVs.
3 strongly under-estimates activity as includes only a specific type of CCS equipment (for surveying).
4 under-estimates activity as includes only reactors and not componentry or balance of plants.

Table A7
IEA public RD&D expenditure (Total RD&D in Million Euro (2015 prices and exch. rates))

Category	Sub-category	SET-Plan areas
GROUP 1: ENERGY EFFICIENCY		
11	Industry	3
12	Res. and comm. buildings, appliances and equipment	3
13	Transport	
1311	Vehicle batteries/storage technologies	4
1312	Advanced power elecs, motors, EV/HEV/FCV sys	4
1314	Electric vehicle infrastructure	4
1315	Fuel for on-road vehicles (excl. hydrogen)	4
14	Other energy efficiency	
19	Unallocated energy efficiency	
GROUP 2: FOSSIL FUELS		
21	Oil and gas	
22	Coal	
23	CO2 capture and storage	5
29	Unallocated fossil fuels	
GROUP 3: RENEWABLE ENERGY SOURCES		
31	Solar energy	1
32	Wind energy	1
33	Ocean energy	1
34	Biofuels (incl. liquids, solids and biogases)	4
35	Geothermal energy	1
36	Hydroelectricity	1
37	Other renewable energy sources	1
39	Unallocated renewable energy sources	1
GROUP 4: NUCLEAR		
41	Nuclear fission	6
42	Nuclear fusion	6
49	Unallocated nuclear	6
GROUP 5: HYDROGEN AND FUEL CELLS		
51	Hydrogen	
511	Hydrogen production	
512	Hydrogen storage	4
513	Hydrogen transport and distribution	
514	Other infrastructure and systems	
515	Hydrogen end-uses	
519	Unallocated hydrogen	
52	Fuel cells	4
59	Unallocated hydrogen and fuel cells	4

(*continued on next page*)

Table A7 (*continued*)

Category	Sub-category	SET-Plan areas
GROUP 6: OTHER POWER AND STORAGE TECHNOLOGIES		
61	Electric power conversion	
611	Power generation technologies	
612	Power generation supporting technologies	2
613	Other electricity power generation	
619	Unallocated electric power generation	
62	Electricity transmission and distribution	2
63	Energy storage	2
631	Electrical storage	
632	Thermal energy storage	
639	Unallocated energy storage	
69	Unallocated other power and storage techs.	2
GROUP 7: OTHER CROSS-CUTTING TECHS/RESEARCH		
71	Energy system analysis	2
72	Basic energy research not allocated	
73	Other	
GROUP 8: Unallocated		

Table A8
Knowledge Codification: Patents.

Technologies	CPC	SET-Plan
4.1. Renewable energy generation	Y02E10	1
- wind energy		
- Solar thermal energy		
- Solar PV energy		
- Solar thermal-PV hybrids		
- Geothermal energy		
- Marine energy		
- Hydro energy		
7.1. Integration of renewable energy sources in buildings	Y02B10	1
- Photovoltaic [PV]: Roof systems for PV cells; PV hubs		
- Solar thermal: Evacuated solar collectors; Air conditioning or refrigeration systems		
- Wind power		
- Geothermal heat-pumps		
- Hydropower in dwellings		
- Use of biomass for heating		
- Hybrid systems; Uninterruptible or back-up power supplies integrating renewable energies		
4.5. Technologies for an efficient electrical power generation, transmission or distribution	Y02E40	2
4.5.1. Superconducting electric elements or equipment		
Flexible AC transmission systems [FACTS]		
Active power filtering [APF]		
Reactive power compensation		
Arrangements for reducing harmonics		
Arrangements for eliminating or reducing asymmetry in polyphase networks		
Smart grids		
4.6.4. Smart grids in the energy sector	Y02E60/70	2
4.7. Other energy conversion or management systems reducing GHG emissions	Y02E70	2
4.6.1.2. Capacitors	Y02E60/13	2
- Ultracapacitors, supercapacitors, double-layer capacitors		
4.6.1.3. Thermal storage	Y02E60/14	2
- Sensible heat storage, Latent heat storage, Cold storage		
4.6.1.4. Pressurised fluid storage	Y02E60/15	2
4.6.1.5. Mechanical storage	Y02E60/16	2
- Mechanical energy storage, e.g. flywheels		
4.6.1.6. Pumped storage	Y02E60/17	2
7.2. Energy efficiency in buildings	Y02B20, Y02B30, Y02B40, Y02B50, Y02B60, Y02B70	3
7.3. Architectural or constructional elements improving the thermal performance of buildings	Y02B80	3
7.4. Enabling technologies in buildings	Y02B90	3
Enabling technologies or technologies with a potential or indirect contribution to GHG emissions mitigation:		
- Applications of fuel cells in buildings		
- Cogeneration of electricity with other electric generators		
- Emergency, uninterruptible or back-up power supplies integrating fuel cells		
- Cogeneration or combined heat and power generation, e.g. for domestic hot water		
- Fuel cells specially adapted to portable applications, e.g. mobile phone, laptop		
- Systems integrating technologies related to power network operation and ICT mediating in the improvement of the carbon footprint of the management of residential or tertiary loads, i.e. smart grids as enabling technology in buildings sector (e.g.		

(*continued on next page*)

Table A8 (*continued*)

Technologies	CPC	SET-Plan
related to uninterruptible power supply systems, remote reading systems, etc.)		
4.3.1. Technologies for improved output efficiency (Combined heat and power, combined cycles, etc.)	Y02E20/12	3
Heat utilisation in combustion or incineration of waste	Y02E20/14	
Combined heat and power generation [CHP]	Y02E20/16	
Combined cycle power plant [CCPP], or combined cycle gas turbine [CCGT]	Y02E20/18	
Integrated gasification combined cycle [IGCC]		
4.3.2. Technologies for improved input efficiency (Efficient combustion or heat usage)	Y02E20/30-366	3
- Direct CO2 mitigation: Use of synair, i.e. a mixture of recycled CO2 and pure O2; Use of reactants before or during combustion; Segregation from fumes, including use of reactants downstream from combustion or deep cooling; Controls of combustion specifically inferring on CO2 emissions		
- Indirect CO2 mitigation, i.e. by acting on non CO2 directly related matters of the process, e.g. more efficient use of fuels: Cold flame; Oxyfuel combustion; Unmixed combustion; Air pre-heating		
- Heat recovery other than air pre-heating: at fumes level, at burner level		
4.2.1. Biofuels	Y02E50/10	4
- CHP turbines for biofeed; Gas turbines for biofeed		
- Bio-diesel		
- Bio-pyrolysis; Torrefaction of biomass		
- Cellulosic bio-ethanol; Grain bio-ethanol; Bio-alcohols produced by other means than fermentation		
4.6.1.1. Batteries	Y02E60/12	4
- Lithium-ion batteries		
- Alkaline secondary batteries, e.g. NiCd or NiMH		
- Lead-acid batteries		
- Hybrid cells		
4.6.2. Hydrogen technology	Y02E60/30-368	4
Hydrogen storage: Storage of liquefied, solidified, or compressed hydrogen in containers; Storage in caverns; Reversible uptake of hydrogen by an appropriate medium (e.g. carbon, metal, rare earth metal, metal alloy, organic compound)		
- Hydrogen distribution		
- Hydrogen production from non-carbon containing sources: by chemical reaction with metal hydrides, e.g. hydrolysis of metal borohydrides; by decomposition of inorganic compounds, e.g. splitting of water other than electrolysis, ammonia borane; by electrolysis of water; by photo-electrolysis		
4.6.3. Fuel cells	Y02E60/50-566	4
6.1.2. Hybrid vehicles	Y02T10/62	4
6.1.3. Electric vehicles	Y02T10/64–649, Y02T10/70–7094, Y02T10/72-7291	4
6.5. Enabling technologies in transport	Y02T90	4
- Electric vehicle charging		
- Application of fuel cell and hydrogen technology to transportation		
Combined cycle power plant [CCPP], or combined cycle gas turbine [CCGT] combined with carbon capture and storage [CCS]	Y02E20/185	5
5.1. CO2 capture and storage (CCS)	Y02C10	5
- Capture by biological separation		
- Capture by chemical separation		
- Capture by absorption		
- Capture by adsorption		
- Capture by membranes or diffusion		
- Capture by rectification and condensation		
- Subterranean or submarine CO2 storage		
4.4. Nuclear energy	Y02E30	6
- nuclear fusion reactors		
- nuclear fission reactors		

Source: [81].

Table A9
Description and harmonised system (HS) codes of low carbon goods

Technology class	HS code	Description	SET-Plan
Hydro energy	841011	Hydraulic turbines & water wheels,of a power not > 1 000 kW	1
	841012	Hydraulic turbines & water wheels,of a power > 1 000 kW but not > 10 000 kW	1
	841013	Hydraulic turbines & water wheels,of a power > 10 000 kW	1
	841090	Parts (incl. regulators) of the hydraulic turbines & water wheels of 8410.11–8410.13	1
Solar thermal	841919	Instantaneous/storage water heaters,non-electric (excl. of 8419.11)	1
Solar photovoltaic	854140	Photosensitive semiconductor devices, incl. photovoltaic cellswhether or not assembled in modules/made up into panels; light emitting diodes	1
Wind energy	850231	Wind-powered electric generating sets	1
	730820	Towers and lattice masts, of iron or steel	1

(*continued on next page*)

Table A9 (*continued*)

Technology class	HS code	Description	SET-Plan
Bioenergy	840290	Steam or other vapour generating boilers (other than central heating hot water boilers capable also of producing low pressure steam); super-heated water boilers. [Ca, J, NZ, K]	1
Bioenergy	840410	Auxiliary plant for use with boilers of heading 84.02 or 84.03 (for example, economisers, super-heaters, soot removers, gas recovers'); condensers for steam or other vapour power units	1
Bioenergy	850164	AC generators (alternator), of an output exceeding 750 kVA	1
Bioenergy, Ocean, wave, marine Geothermal e-nergy	850239	Biogas generator sets; Gas Generator Small hydro, ocean, geothermal and biomass gas turbine generating sets. [US]	1
Smart grids	902830	Electricity meters	2
Energy storage	850720	Lead-acid electric accumulators except for vehicles	2
Automatic regulating or controlling instruments, other. [Ca, J, NZ, K, Au, Ru, BD]	903289		2
Insulation	680610	Slag wool, rock wool & similar mineral wools(incl. intermixtures thereof), in bulk/sheets/rolls	3
	680690	Mixtures & articles of heat-insulating/sound-insulating /sound-absorbing mineral materials (excl. of 68.11/68.12/Ch.69)	3
	700800	Multiple-walled insulating units of glass	3
	701939	Webs, mattresses, boards &similar non-woven products of glass fibres	3
Heating	903210	Thermostats	3
Heating	841861	Compression-type refrigerating/freezing equip. whose condensers are heat exchangers, heat pumps other than air conditioning machines of heading 84.15	3
Heating	841950	Heat exchange units, whether/not electrically heated	3
Lighting	853931	Electric discharge lamps (excl. ultra-violet lamps),fluorescent, hot cathode	3
	853120	Indicator panels incorporating liquid crystal devices(chemically defined)/light emitting diodes (LED)	3
Energy efficiency in heavy industries	840410	Economizers, super-heaters, soot removers, gas recoverers and condensers for steam or other vapour power units	3
Energy storage	850710	Lead-acid electric accumulators (vehicle)	4
Energy storage	850730	Nickel-cadmium electric accumulators	4
Energy storage	850740	Nickel-iron electric accumulators	4
Energy storage	850780	Electric accumulators	4
Energy storage	850790	Parts of electric accumulators, including separators	4
Energy storage	853224	Fixed electrical capacitors, other than those of 8532.10,ceramic dielectric, multilayer	4
Biofuels	220720	Ethyl alcohol, other spirits (denatured)	4
	220710	Ethyl alcohol (alcoholic strength 80° or more)	4
Electric vehicles	870320	HEV, PHEV, biofuels, and etc.	4
Battery Electric vehicles	870390	BEVs	4
Carbon capture and storage	901580	Other surveying, hydrographic, oceanographic, hydrological, meteorological or geophysical instruments and appliances, excluding compasses,not elsewhere specified in 90.15	5
Nuclear energy	840110	Nuclear reactors	6
	840120	Machinery and apparatus forisotopic separation, and parts thereof	6
	840140	Parts of nuclear reactors	6

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