This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 727114

MONROE - Modelling and evaluating the socio-economic impacts of research and innovation with the suite of macro- and regional-economic models

D2.4.1: Working paper on modelling stochastic public R&I decisions including financial constraints

June 2018: Confidential only for members of the MONROE Consortium (including the Commission Services)

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 727114

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Document Details

Authors	I. Charalampidis, K. Fragkiadakis, L. Paroussos
Creation Date	28-06-2018
Date of Last Revision	
Version	1
Description	Draft final report

Version History

Version	Updated By	Date	Changes / Comments

Project Involvement

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1. Introduction

The aim of this report is to present the current status on public R&D modelling and suggest a methodology to endogenise public R&D decisions on clean energy technologies in the GEM-E3 model. The study focus on how the public sector currently spends its R&D budget on clean energy technologies, what is the learning potential for these technologies and how the public sector will make an optimal[1] selection regarding R&D budget allocation on clean energy technologies under uncertainty. Data on R&D budget and learning by research rates have been extracted from the EUROSTAT, OECD and IEA databases and the respective literature.

This report is structured in the following way: i) the next section provides a literature survey regarding public R&D and its determinants, ii) the third section provides a review on how public R&D is represented in CGE modelling, iii) the fourth section presents historical and current R&D spending in clean energy technologies and provides a review of learning by research rates, iv) the fifth section provide an overview of the state-of-the-art modelling of public R&D optimal allocation and v) the last section presents how the public R&D decision is modelled in GEM-E3.

2. The need for public R&D

Economic theory provides solid grounds for the need of public R&D investments on the basis of market failures (Arrow K., 1962 and Nelson R., 1959) and spillover effects (an overview can be found in Martin S. and Scott T.J. 1998). Market failures are associated to the specific nature of knowledge when treated as a traded commodity (indivisibility, inappropriability, uncertainty) and lead to a suboptimal level of investments in R&D in the absence of public expenditures, as the private benefit from conducting R&D is much lower than the social rate of return. An example of market failures is provided by Tirole (2001) and is described as the "appropriability" effect; the

[1] Optimal refers to maximizing consumers welfare

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social surplus exceeds the private surplus when perfect price discrimination is not possible.

The most essential bottlenecks that hinder private R&D investments from reaching the social optimal level are well summarized in the European Commission's report "The Economic Rationale for public R&I funding and its impacts" (2017) and include: i) uncertainty and social, technological and market risks, ii) high investment costs are often accompanied by high fixed costs and the benefits result several years after the successful completion of an R&D project, iii) difficulties associated to the nature of the R&D process (e.g. non-excludability etc.), iv) funding constraints and v) the existence of spillover effects that reduce R&D intensity. Hal et al. (2010) associates social returns with the presence of spillovers and identifies four sources of spillovers: i) from research conducted by other firms in the sector, ii) from research conducted by firms which belong to another industry, iii) by public research, and iv) by research conducted outside the country.

The case of market failures in the energy sector and in clean energy technologies has been studied among others by Jaffe et al. (2005) which stress the role of public policies when the coexistence of two market failures, one associated to environmental pollution and one associated to innovation, lead to a rate of investments in clean energy technologies lower than the social optimum; the same point is summarized in a note of Stavins (2011), where he stresses out the importance for public sector interventions to support clean energy R&D along with the imposition of a carbon tax to achieve the transition towards a carbon-free economy. The importance of public policy for the promotion of clean energy technologies in the presence deals with the role of clean energy policies in the presence of market failures and barriers has been also analyzes by Brown (2001).

Apart from spillover effects and market failures another concept that provides useful insights on the role of public and non-profit institutions in the R&D and innovation process is that of "basic knowledge". Nelson (1959) distinguishes research activities into "basic research" which results from scientific activities and "applied-science research" which is more closely tied to the solution of practical problems. The former is necessary for the latter; in reality firms do not have incentives to undertake such huge R&D programs whose outcome is uncertain and the market benefits cannot be a priori quantified. Thus, he concludes that the social return on knowledge is higher than its market valuation and economy is underinvesting compared to what is socially optimal.

Finally, R&D is linked to the "knowledge absorptive capacity" or "ability to replicate" of a country, an attribute closely related to the notion of "tacit" knowledge (David P. 1992, Bravo-Ortega and Marin, 2011), which refers to the ability to assimilate technological advances made abroad. It is also known as the "second face" of R&D, the first one being innovation, and its importance on the convergence of total factor productivity in industries across countries has been verified by a number of studies (e.g. Griffith R. et al. 2001).

Market failures, spillovers, endogenous economic growth, all set the theoretical background which highlights the necessity of the government to get actively involved in R&D. Besides direct funding of R&D activities there is a set of available policies that country's implement to foster private R&D investments in order to fill this "R&D investment gap". These measures aim at lowering the financial cost of conducting R&D or to reduce the risk associated to the uncertainties of R&D output. The set of alternative policies include:

- Subsidies (i.e. to employ R&D personnel)
- Tax credits
- Cooperation of public R&D researchers with the private sector
- Project grants
- Project loans

But "do public R&D (expenditures or policy measures) complement or substitute private R&D investments?". Paul et al. (2000) review the main body of econometric evidence for the past 35 years and find no clear-cut answer as there doesn't exist a homogeneous approach of the subject by the reviewing studies. Similarly Quevedo (2004) concludes that there is an ambiguity regarding the net effect (complementarity vs. substitution) when performing a meta-analysis of econometric evidence on the relationship between public

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R&D subsidies and private R&D programs. Studies with similar conclusions and policy recommendation on this subject include Zuniga-Vicente et al. (2014), Becker (2015), Coccia (2011). On the other hand Cohen et al. (2002) finds a positive impact of public R&D in most U.S. industries although the effect is not uniformal.

The role of basic knowledge as a source of complementarities between public and private R&D investments has been described in Guellec and Pottelsberghe de la Potterie (2000) as the leverage effect: the basic knowledge increases the return on R&D thus firms are willing to invest more on R&D. In other words it can be defined as the amount of private sector funding that wouldn't have occurred if the public sector R&D expenditures had not been realized (Department for Business, Innovation & Skills, 2015). Other sources include the creation of the necessary pool of high-educated labour force through public education which is then employed in the private sector, infratechnology etc. Nevertheless the relationship between private and public R&D is not characterized only by complementarities but also by substitutabilities. These include possible crowd-out effects of private investments stemming either from the increased demand for R&D services (e.g. through wage increases of the R&D personnel), the financing of projects that would have been either way undertaken by the private sector etc.A country's public R&D strategy is mostly determined in accordance to its national development targets. In most cases the set of targets and measures implemented are the outcome of consultations between the public institutions and the private sector: The policy targets are defined according to each country's competitive advantage, future challenges that may be associated to social and environmental risks, the ability to cope with global challenges etc.

The OECD recognizes the effect of megatrends in formulating R&D expenditures (OECD, 2016). Megatrends are considered as "*large-scale social, economic, political, environmental or technological changes that are slow to form but which, once they have taken root, exercise a profound and lasting influence on many if not most human activities, processes and perceptions*" (OECD, 2016). Some of the most important trends included in the report are:

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- Demography; for example the projected increase of the share of aged people to total population is expected to affect the mix and the characteristics of products and services in the economy
- Natural resources and energy; for example technology improvements may help the efficient use of natural resources, improve productivity of agricultural sector to sustain food security, development of energy storage options
- Climate change and environment; for example energy technology innovation for mitigation of climate change, the development of a "circular economy" etc.
- Globalization

These megatrends define a frame, a kind of guidelines, for the development of National strategies. Nevertheless, effective R&D policies should take into account social and economic challenges and dynamics that are specific to each country. Thus, a tailor-made innovation plans are needed to ensure the maximum benefits from R&D investments. Most of the National Innovation strategies stress the importance of innovation in ensuring competitiveness in global markets.

In our study we focus on how a megatrend and in particular the climate change mitigation policies affect the public R&D decision on energy technologies.

3. Modelling public R&D: a survey

The inclusion of R&D in applied models to capture the effects of knowledge-induced technical change and to examine the repercussions of policies which promote R&D on the competitiveness has been a relatively recent development.

The representation of R&D in CGE models has been intensified by studies focusing on climate change and the impact of environmental policies which target the abatement of CO2 emissions on the economy in the early 90s. In early studies most models assessed the cost of climate change action, but it was obvious to the researchers that a more holistic approach needed to be

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considered. Thus, scientists began to investigate the benefits stemming from the success of R&D projects which were investigating ways to decouple economic activity from fossil fuels. The success of these programs was linked to technological progress. Among the first ones to address this issue with the use of computable general equilibrium models were Goulder and Schneider (1999) and Diao et al. (1999). An overview of the treatment of endogenous growth mechanisms in economic models for the assessment of environmental policies can be found in Loschel (2002). In this paper Loschel sketches the main modelling methods for including in economic models investments in R&D, spillover effects, technological learning and also presents alternative approaches to endogenous technical change (e.g. econometric estimations). Arrow et al. (2009) summarize, in a short note, the direct and indirect role of the government regarding the promotion of R&D in clean technologies as a response to climate change mitigation efforts and provide some policy recommendations.

The analysis of direct public R&D expenditures, in contrast to other R&D supporting policies (i.e. subsidies) has only drawn limited attention and only a small part of studies in the literature (using numerical models) is to this subject. The main body of the literature is concentrated in the indirect channel through which the government can affect the level of R&D expenditures in the economy. Recently, general equilibrium models with endogenous R&D have been applied in a number of country-specific studies to assess the impact of growth policies. Gosh (2007) examines the impact of alternative policies on economic growth of Canada with the use of a CGE with capital varieties. He assumes that there exists one R&D sector which produces blueprints which are then turned to new varieties. The model accounts also for spillover effects and Gosh (2007) considers the following policies which aim to promote R&D: i) direct R&D subsidies, ii) subsidies to the users of R&D and iii) trade liberalization which enhances the effect of R&D spillovers. He concludes that the first option has the greatest impact on the Canadian economy.

Bor et al. (2010) use a CGE model, the SciBud-CGE, to examine the role of public R&D investments in promoting growth and the interaction of private and public investments for Taiwan; R&D is introduced as a primary factor of

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production along with land, labor and non-R&D capital. Furthermore R&D capital is decomposed into private R&D capital and public R&D using a Constant Elasticity of Substitution (CES) function. They find a positive effect of public R&D on GDP in the short and medium term which the output of increased exports in high-tech industries; they also underline the need of traditional primary industries (e.g. agriculture, food industry) to adjust towards more technology intensive production structure (i.e. their R&D input is found to be quite small) as they may record losses due to the transformation of the economy by the high-tech industries.

Wang et al. (2009) apply a CGE model, the TDGE_CHN, which treats technological growth endogenously to examine the role of technical change in formulating GHG mitigation targets and commitments for China. In their analysis knowledge is considered as a production factor, treated as a form of capital, with the stock of knowledge accumulating according to investment decisions. The benefits stemming from knowledge accumulation are spread across the sectors of the economy as knowledge is considered a "public good". They examine the effect of public subsidies as an incentive to boost R&D on the marginal abatement cost curves for various emission reduction targets, and they find an alleviation in the cost of abatement across all scenarios.

In another study from Křístková (2012) a CGE model is employed to assess i) the impact of knowledge stock accumulation to the projected growth, ii) the efficiency of R&D investments compared to physical investments and iii) the impact of a potential increase of EU-policy based R&D investments on the macroeconomic behavior and structural changes for the Czech Republic. Similarly to the previous studies knowledge is introduced in the model both as a production factor and as an investment choice (in a two-stage process). The allocation of total investments between physical capital and intangible assets in made according to the constrained maximization of a bank's utility function (assumed to be of a Cobb-Douglas form). At the next step allocation of investment choices calculated in the first step to production sectors follows the Tobin's Q. The study compares the output of two models (one with and one without R&D) and finds only a marginal impact (on average) of the inclusion of the R&D mechanism on growth (0.12%) which can be attributed

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also to the relatively small share of knowledge in the economy-wide value added at the benchmark point. The inclusion of the R&D mechanism allows to better capture the structural changes in the economy where it is expected that for developed countries the tertiary and quaternary sector will increase relative to the primary and secondary sectors. Finally, she also compare different rates of investment in R&D expenditures (changing the share parameters in the CD function of total investment) to examine the impact of increasing expenditures in R&D compared to investments in physical capital and finds a negative relationship between GDP growth and R&D shares (an inverse U-shaped curve).

A single country CGE for South Korea with endogenous R&D is developed by Hong et al. (2014) to evaluate the performance of an enhanced model over a standard CGE model for the period 1995 to 2010. R&D enters the model both as a production factor (knowledge capital) and as an investment good. R&D is distinguished into two categories: public and private. Public R&D which is financed by government expenditures is assumed to create and expand the stock of "basic knowledge" within the economy, hence all sectors rip the benefits of knowledge increase. Private R&D on the other hand is sector specific and increases the total factor productivity (TFP) of the sector undertaking investments in R&D. The accumulation process for both private and public R&D shares the same formulation with the accumulation process of physical capital (same equation used to describe the "law of motion" but with different depreciation rates). Allocation of investments follows the Tobin's Q logic. Spillover effects between public and private knowledge are included in the model. These spillovers decrease the share of value added per unit of output and are a function of the public R&D stock and of private R&D stock (excl. the stock of knowledge created within the industry which is a production factor). They find that the enhanced model fits better in cases with high TFP growth.

Buonanno et al. (2003) compare three version of the ETC-RICE model to study the properties of endogenous technical change making a distinction between environmental-related technical change and technical change in general: i) a model with endogenous technical change and exogenous environmental

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technical change, ii) a model where both concepts of technical change are endogenous and iii) a model which accounts for spillover effects. The optimal R&D effort is chosen by a central planner and the stock of accumulated knowledge is a factor entering the production function of the model. They find that endogenous environmental technical change reduce the effect of abatement costs and that spillover effects decrease R&D efforts due to the presence of free-riding incentives, hence increasing the cost of abatement.

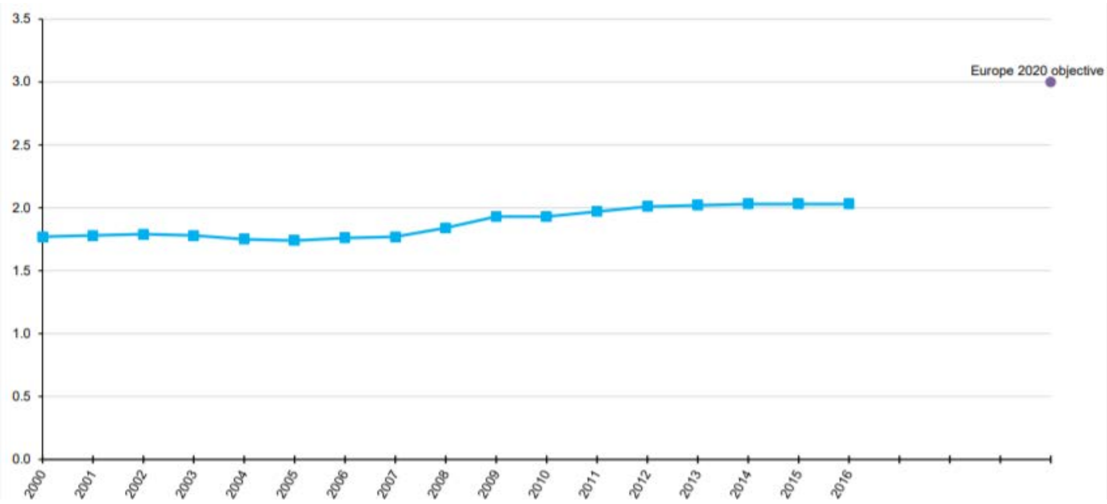
Popp (2004) modifies the DICE model to include technical change (ENTICE model) and evaluates the impact of two policy options (an optimal policy and a restrictive policy) using two models; the one with exogenous and the one with endogenous technical change. He finds that when removing market failures and the private rate of return to R&D is equalized to the social rate of return the model yields a welfare gain of 16.7%. Another interesting finding is that research in the energy field crowds-out research in other fields limiting the gains stemming from the former.

Bosetti et al. (2009) use the WITCH model to calculate optimal investment pathways and the combination of technical change to achieve a stabilization in the CO2 concentration at the levels of 550ppm or 450ppm. They stress the need for increased public R&D expenditures and policies which promote R&D for the development of new cleaner technologies in order to reduce the costs of climate change mitigation. Finally, Gu et Wang (2018) use a climate-economy integrated assessment model to examine the impact of different R&D expenditures on the carbon emissions and climate change mitigation costs.

4. EU R&D expenditures

The R&D intensity of the EU is increasing over the last decade moving from 1.76% in 2006 to 2.03% in 2016. In absolute terms this amounts to a total €300 billion spent on Research & Development (R&D) in 2016. Despite the increase of the intensity EU falls short as compared either to its competitors' countries like South Korea (4.23%), Japan (3.29%), USA (2.79%) and China (2.07%) or to its 2020 R&D target.

Figure 1: R&D Intensity in the EU



Source: EC, EUROSTAT, Newsrelease 2017

R&D Expenditures in energy

In the EU the Public R&D intensity and the R&D public budget in energy has remained relatively stable during the last decade (Figure 2).

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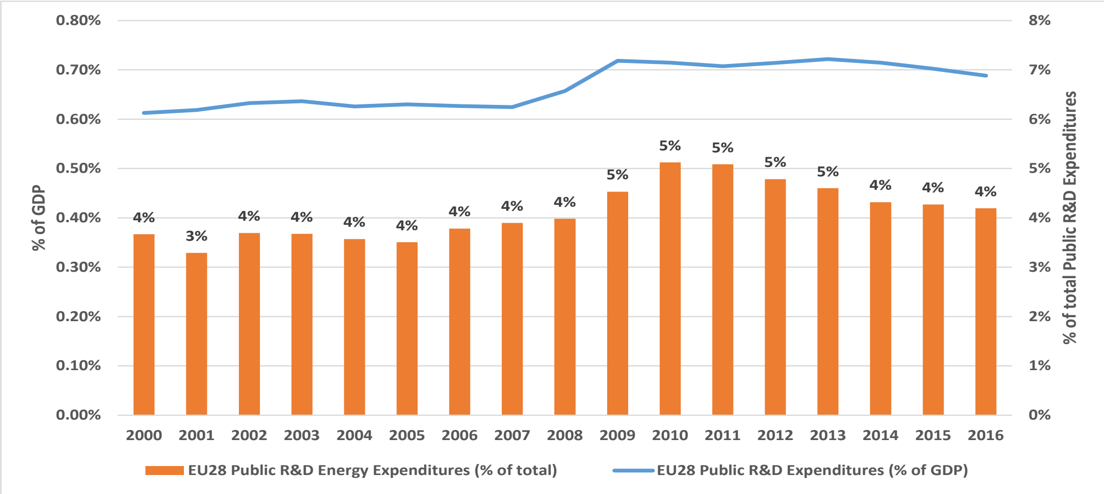
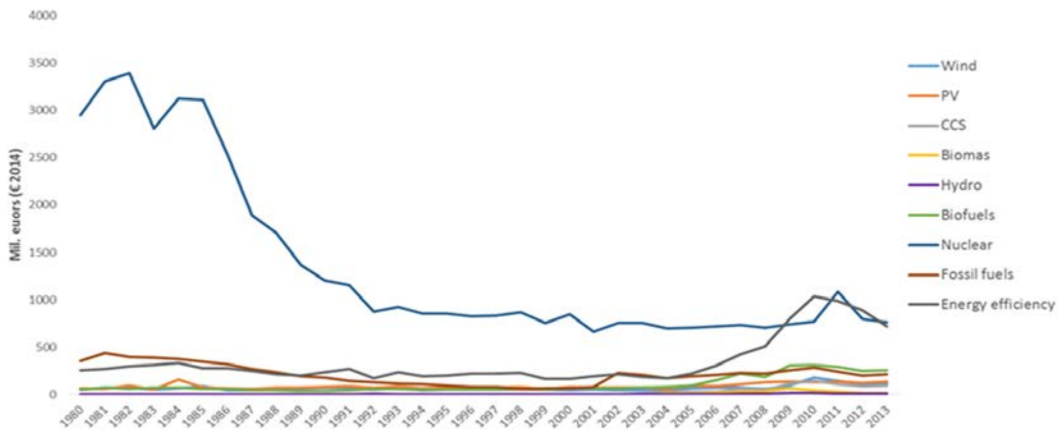
Figure 2: EU28 Public R&D expenditures



Source: IEA Energy R&D statistics and EUROSTAT

However, the allocation of R&D expenditure over the technologies has changed considerably (Figure 3) with a clear trend towards clean energy technologies. This is also reflected in the number of patents generated by each technology (Figure 4).

Figure 3: R&D expenditure by energy technology



Source: IEA Energy R&D statistics

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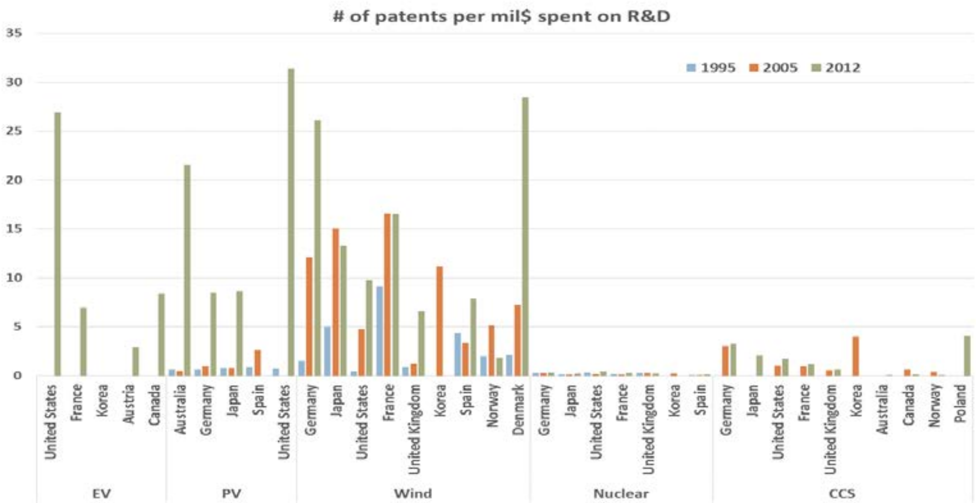
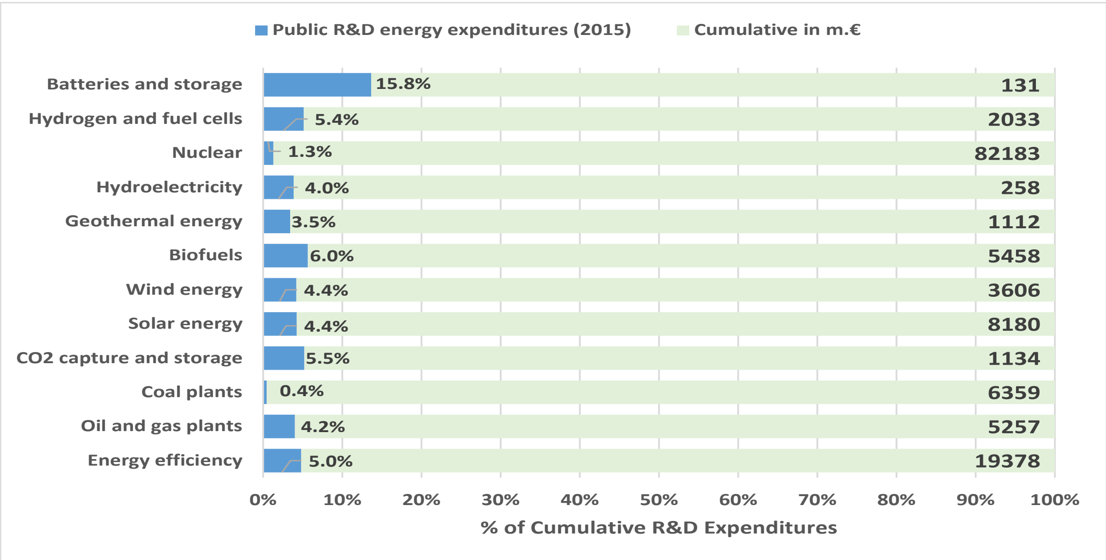
Figure 4: Number of patents and R&D expenditure



Source: IEA Energy R&D statistics

Figure 5 presents the EU28 cumulative public R&D energy expenditures and the EU28 public R&D energy expenditures at 2015 over the technologies.

Figure 5: EU28 Public R&D energy expenditures over the technologies



Source: IEA Energy R&D statistics

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Financing R&D expenditures

The relationship between economic growth and R&D expenditures has been investigated thoroughly in the literature but mainly for the case of private R&D. Recently, Pellens et al. (2018) looked into the of economic cycles on R&D developments and they found that on average that R&D expenditures are ruled by a pro-cyclical relationship. At the country level this depends greatly on the position of the country in the innovation ladder. For example in countries that can be characterized as followers in the innovation process R&D investments are counter-cyclical, while this is not the case for pioneers of the technological race.

They also stress the importance of public financing as a key factor affecting R&D budget. They find that 1% "an increase in the surplus to GDP ratio (or a reduction in the deficit to GDP ratio) by 1 percentage point, stimulates government budget appropriations or outlays for R&D (GBAORD) by 0.6 to 0.8 percent in the short-run. But governments face a trade-off when using an increase in budget surplus for additional spending. Alternatively, they could have used it to repay debts. Increasing government debt levels on the contrary have led to reductions in public R&D spending in the period under consideration. High levels of debt exert a strong pressure to consolidate public budgets so that spending for R&D is likely to be cut as well. The pressure to reduce public debt levels is currently observed in most European countries so that R&D budgets are likely to contribute to fiscal consolidation in the future. Table 2 provides the latest figures regarding the sources of financing for R&D in the energy sector. Data suggests that the contribution of the private sector in R&D spending for clean energy technologies is null or relatively small for most European Countries.

Return on R&D

The estimation of social and private rates of return on R&D has been a subject of extensive research in the literature. The social rates of return are usually found to be larger than the private rates (Mansfield et al 1977); this result

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strengthens the argument for public intervention to reach the optimal level of R&D investments. The value of the estimates differ across studies, for example in Georghiou (2015) social rates of return is found to be 20% and 50% while some macro-econometric studies estimate a net benefit of 10%-20% (for more details see the report of European Commission; 2017). In overall it can be said that the estimation depends on the methodological approach adopted by the researchers conducting the study as well as on a number of assumptions and indicator choices. Ugur et al. (2016) in their meta-regression analysis refer three main constraints of the primary studies they examine regarding the measurement of productivity and R&D returns: i) "true productivity" vs "revenue productivity", ii) the presence of lags between the R&D and the realization of productivity gains and iii) the restrictive assumptions that need to be imposed in order to compare social rate of returns at the industry level with private rates of return from firm data (constant returns to scale plus that all firms within the industry face common factor prices).

Hal et al. (2010) in their extensive review of the literature on the rates of return to R&D presents the high uncertainty on the private and social rate of return. The private rate of return estimated by different studies lie in the interval of 10% to 75%. Regarding the social rates of return they identify two main estimation approaches: the first one is based on case studies of specific R&D projects and the second one to the econometric estimation of the relationship between R&D and productivity. Findings using the first approach yields estimates of the social rate of return on the order of 25%-270%, while findings using the second approach provide estimates on the order of 0%-100% depending on the set-up of the study.

In a subsequent study Corderi and Linn (2011) estimate the social rate of return to R&D for three energy-related manufacturing industries (coal, petroleum and nuclear) in OECD countries using data from the OECD STAN database. Their findings suggest that countries that are considered as technological pioneers (e.g. US, UK) tend to have lower returns to R&D and that the rates of return in related countries are of similar order. Their estimates vary from 3.4% for the UK up to 26.1% for Italy while they suggest that their results are also in line with cluster-effect of R&D and they find

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similar values for i) Italy and Germany, ii) Japan and Korea and iii) Belgium, Netherlands, Sweden and Finland. In the same spirit Novoa and Lawell (2016) estimate the lower bounds of social returns for coal, petroleum products and nuclear fuels manufacturing considering intra-industry spillovers only within national borders. In order to capture the spillovers they use as measures productivity at the industry level and R&D intensity. Furthermore, they claim that their study differs from the studies of Corderi and Linn (2011) and of Inglesi-Lotz (2017) which overestimate social returns in that it uses a more-appropriate methodology for measuring productivity by adopting the EU KLEMS database. Their findings suggest that the social return to energy R&D might be a U-shaped function as they find positive and statistically significant values only for France (11.9%), which has a high level of value added in energy industries, and for Finland (5.1%) and the Netherlands (which have low levels of value added). Finally with respect to the clean-energy industries the US Office of Energy Efficiency and Renewable Energy reports an annual rate of return of more than 27% and an undiscounted benefit-to-cost ratio of 33 to 1. Inglesi-Lotz (2017) estimates the social rate of return for various energy technologies in order to identify which one is the most suitable for R&D investments using data from the G7 countries. She finds that R&D investments in technologies for Energy Efficiency and Nuclear yields the highest rate of return in overall in contrast to the R&D investments in fossil fuels. She also points out the differences between social benefits across countries which implies that there is no universal rule for R&D investments but rather country-specific policies to attain the optimal benefit level.

Ugur et al. (2016) stress the importance of the imposed assumptions, regarding constant returns to scale and uniform price of production factors, for the observed differences between private and social rates of return to R&D. In fact when these assumptions are relaxed then the private rates of return are very close to the inter-industry social rates of returns, as the industry-level estimates "may capture both spillover-effects and shifts in aggregate industry productivity caused by different combinations of firms with different firm-specific factor prices". Another interesting finding is that publicly-funded

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R&D conducted by private firms is associated with lower returns compared to both private and social returns.

Table 1: Social rates of return

Year	Authors	Country	Sectors	Estimated Social rate of return
2011	Corderi D., Linn S. C.-Y.	OECD	Coal, petroleum and nuclear manufacturing	3.4% - 26.1% (depending on the country)
2017	Inglesi-Lotz R.	Canada, France, Germany, Italy, Japan, United Kingdom, United States	Energy efficiency, fossil fuels, renewable energy, nuclear, other cross-cutting technologies	Postitive and statistically significant mainly for energy efficieny and nuclear (0.93%-5.6%), mixed results for renewables
2001	Griffith et al.	Canada, Denmark, Finland, France, Germany, Italy, Japan, Netherlands, Norway, Sweden, United Kingdom, United States	Whole economy	43.2% - 95.2% (depending on the country)
2015	Georghiou	Literature review		12%-100%
2007	Sveikauskas	Literature review		65%

Uncertainty in R&D

The very nature of R&D is uncertain; there are several factors affecting the evolution and in the end the conclusion of a research. As Baretto (2001) points out technology is linked to the social and economic context in which it is created. The evolution process is dynamic and a two-way relationship as technology affects and is both affected by the context in which it develops. It depends on a number of factors such as i) the opportunities for innovation, ii) the incentives that are provided to the agents to carry out innovation and their

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ability to cope with innovation and iii) the mechanisms, institutional and organizational, that facilitate the innovation process. On route to technological innovation three milestones can be identified: invention, innovation and diffusion. At each of these stages uncertainty regarding the outcome is present and can be attributed, among others, to i) the diversity of solutions to a given problem, ii) information regarding the technology and iii) unknown future technologies (Baretto, 2001). Another cause of uncertainty which exerts negative pressure on R&D investments is that of irreversibility; costs are project specific and cannot be couped if the program is not successful (Atanassov et al., 2015; Grabowski, 1968; Dixit and Pindyck, 1994).

In the fields of energy and environment R&D investments are an essential step for the transition and, in the end, the transformation of the current system towards a zero-emitting economy in response to the emerging challenges posed by climate change, depletion of natural resource, volatility of fossil fuel prices etc. The ability to cope with these challenges is closely related to innovation; that is the development of cleaner technologies for power generation that come at reasonable cost, the development of new products/materials to support energy savings (e.g. insulation materials) and new energy efficient methods of production. In order to develop a highly effective strategy plan and to intensify R&D efforts, both the public and the private sector, need to incorporate in their decision-making process the issue of uncertainty.

A well-established empirical concept describing potential cost reductions associated to the introduction and the diffusion of a new technology (or even a new production method) is that of the experience or learning curve (Wright, 1936). In its general form it describes the cost reductions resulting from a doubling of the productive capacity (or merely production). Although in the beginning the experience/learning curve formulation was used to explain cost reductions from learning-by-doing (LBD) effects, later on this idea was developed in order to incorporate learning-by-research (LBR) and gave rise to the 2-factor learning curve (2FLC).

But even in this empirical approach there is room for uncertainties. There is no robust evidence that the future cost of technologies will remain along the path projected (Rubin et al. 2015) due to the uncertainties related to this measure (see Mauleón 2016; Neij 2003a; Nemet, 2006; Nordhaus, 2014; Holmes, 2010) for different reasons such as lack of data, irrelevant data, etc. Depending on the data available the learning rates vary a lot. Furthermore, there are various approaches to characterize historical learning rates but there is no certainty that the spotted historical trend will persist, all the more so when the future context will be different. Finally it is important to exclude the others factors that could contribute to the effects of reducing prices (Wiesenthal et al. 2012). Nordhaus (2014) showed bias in the use of learning parameters and how it could direct towards the wrong technologies because it is generally overestimated.

5. Allocation of R&D spending

Uncertainties regarding the evolution of future costs of clean energy technologies and the outcome of R&D programs made clear that applied modelling tools need to adapt to capture the complex dynamics of innovation. By introducing of uncertainty and by applying portfolio optimization techniques in order to maximize the benefits from allocating a given R&D budget models attempt to deal with unforeseen future events and to provide useful insights for the dynamics of technology progress and policy recommendations.

In a recent paper Way R. et al. (2017) deal with the problem of how to allocate a given R&D budget between competing energy technologies by applying a modern optimal portfolio technique (Markowitz). The differences between a financial portfolio and a technological portfolio that requires to adjust the original formulation of the problem are presented in Table 2.

Table 2: Financial vs. Technological portfolio

	Financial portfolio	Technological portfolio
Shares	Negative shares are allowed due to short-selling	Only positive shares are allowed

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Returns	Financial products returns on assets are purely stochastic	Technology options with the use of experience curves have deterministic returns
Objective	Maximize the return with given variance	Minimize the cost with given variance
Dimension	A multivariate model is needed. Returns are highly correlated	A univariate model is needed. Returns are uncorrelated

Using a simple model they attempt to address the trade-off between investing in one technology to spur progress vs investing in a number of alternative to hedge against failure. They use experience curves to describe the relationship between investment and technology costs; also they use a mean variance objective function to understand the role and the effects of risk aversion. Uncertainty is introduced in the model by assuming a white noise on the log-first-difference of the learning curve equation. They find that optimal investment depends on risk-aversion, initial conditions (relative technology maturity and initial cost), progress characteristics (mean progress rate and uncertainty of future shocks) and market size. However, this optimization technique poses the limitation that the learning rates of each technology are close to zero; which limits its application on relatively mature power generation technologies.

Gritsevskyi and Nakic-Henovic (2000) introduce a three dimension uncertainty in the MESSAGE model: i) for the future costs of all technologies, ii) for the learning rates of new technologies and finally iii) for the energy extraction and production costs. Uncertainty regarding the cost reductions of new technologies enters the model thought the experience/learning curve where it is assumed that the progress ratio (i.e. the learning rate) is a random variable with known probability distribution. The costs are defined by conditional probabilities that result from the realization of a specific value of the progress rate using a log-normal distribution. They conclude that it is better for R&D expenditures to be distributed across "related" technologies

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and better not to focus on one technology and also that in terms of diversification it is more beneficial to be spread across technologies that have the potential to create technology clusters.

Blanford (2009) applied a two-step method to measure the benefits stemming from alternative R&D programs. At the first stage the potential research outcomes are valuated in market terms and at the second stage he assesses the relationship between investments and potential outcomes. For the first stage the MERGE model is used to calculate the welfare in a variety of technology-specific scenarios; this welfare is considered as the outcome of various R&D programs. Then results are fed to a simple model which related investments with a probability distribution. In this module the optimal portfolio is calculated. He concludes that diversification in the optimal portfolio mix depends on three forces : i) decreasing returns which favor a diversified portfolio due to the decreased marginal benefit from increased investments to a certain technology option, ii) uncertainty which leads to a diversified set of choices from the social planner ,who seeks to maximize the return irrespectively of the variance, as a response to uncertainties regarding future policies and iii) heterogeneity of applications, which when examining carbon-free technologies means that decarbonization can be achieved by combinations of carbon-free technologies due to their wide application in various sectors.

A similar two-step methodology is also used by Marangoni et al. (2017) to address the issue of uncertainty in technological change associated to R&D efforts with the use of the WITCH model. They apply Approximate Dynamic Programming through multiple runs of WITCH to for computing the value function, experts' elicitation data to quantify uncertainties in order to determine the optimal R&D portfolio. In their study four technologies associated to clean energy supply are considered: i) solar technologies and the associated electricity cost, ii) liquid biofuels and the associated cost of production, iii) batteries for LDV and iv) biomass and the associated electricity cost. Uncertainty regarding the realization of effectiveness of R&D investments is captured by introducing a stochastic term for the learning rates. For this purpose, they have used data from the ICARUS project to estimate

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probabilistic distributions of future costs. The optimal portfolio is determined by taking into account trade-offs between pushing towards the lower end of the distribution, achieving the maximum potential cost reductions and the amount of money that you have to spend today on R&D. The formulation of the problem is intertemporal; R&D budget is allocated between different alternative options for the period 2010-2030 while the realization of cost reductions due to R&D efforts is taking place in the period after 2030 and up to 2050. Furthermore it is assumed that energy R&D investments crowds-out other R&D investments, and that the former have a social rate of return which is four (4) times higher with respect to the latter (i.e. each dollar spend on public energy R&D corresponds to four dollars of private consumption or investments). They examine two cases: a "Certain equivalent" and a "Stochastic" case. In the latter learning rates are drawn from the Weibull distribution while in the first case learning rates are deterministic and equal to the mean value of the stochastic distribution Their findings suggest a break in historical terms in terms of overall optimal R&D investments as their model suggests an increase in optimal R&D investments and in terms of the mix of alternatives technologies as batteries dominate the optimal portfolio of investments.

Bistline (2016) investigates optimal portfolio decision under uncertainty in climate policy and gas prices. Success of R&D programs can modelled in three possible ways according to the author: i) as increasing probability of achieving a specific cost level or level of technical change, ii) as a reduction of the time needed to achieve a certain cost or technical target and finally iii) to adjust distributions related to cost or technical performance. This paper adds in the analysis of uncertainty the dimension of market diffusion of a technology: the success of R&D programs depends on the economic and political context in which it takes place. A "here-and-now" approach is adopted which assumes that future possible conditions are unknown when the R&D decision is taken. Bistline identifies three factors that determine the value of success of R&D programs:

1. Interactions between uncertainties
2. Form of distribution

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3. Changes in technology characteristics due to R&D programs
4. His model uses exogenous innovation production functions to compare the benefits and costs of projects, mapping R&D investments to probabilities success.

Finally the issue of uncertainty in R&D investments for clean energy technologies has been addressed in Wang et al. (2018) in a case study for China. Using the GCAM model they determine the optimal portfolio which minimizes the social cost related to the abatement of GHG emissions. . Innovation is modelled as the impact on marginal abatement costs (MAC), the cost of reducing emissions by an additional ton. The main findings of this study can be summarized below:

1. Different climate damage risks do not affect the optimal R&D technology investment decision
2. The optimal technology R&D portfolio varied under different opportunity cost scenarios
3. Synergistic R&D strategies for different technologies are conducive to enhancing the level of CO2 abatement as well as for reducing the total social cost of abatement

Addressing Uncertainty

In this section we present the mathematical formulation adopted, in the referenced literature of Section 5, to treat uncertainty with respect to technical change and optimal portfolio decisions. The most common way of introducing stochasticity in the problem of allocating a given R&D budget between alternative technology options is through the learning rate parameter of the experience/learning curve.

Optimal Clean Energy R&D Investments under Uncertainty (Marangoni et al. 2017)

The relationship between costs and accumulated knowledge is described by the following equation

$$C\big(I,\lambda(\omega)\big) = C_f + C_0 \cdot \left(\frac{K(I)}{K_0}\right)^{-\lambda(\omega)}$$

where

K: is the stock of knowledge that depends on R&D investments
I: are R&D investments
C: is the technology cost
C_f: is the technology floor cost
λ: is the learning rate which depends on the realization ω

To find the optimal clean energy mix, they determine which investments during a first period T1 will induce a cost effective solution in the post-period T2 by maximization the following utility function:

$$U_T(I,\lambda) = U_{T1}(\lambda) + E[U_{T2}(I,\lambda)]$$

where

$$U_{T1}(I) = \sum_{t\in T1} u_t(Q_t(I))$$

$$U_{T2}(I,\lambda) = \sum_{t\in T2} u_t\Big(Q_t\big(C(I,\lambda)\big)\Big) = V(C(I,\lambda))$$

The method is developed in different steps. First, they derive the uncertain learning rates λs from the future cost distributions created in the ICARUS Project. This project had gathered expert elicitations for different scenario s: 0%, 50% and 100% increase of R&D budget. And by inverting the Cost function above, they obtain N samples for λs from which they take the mean of λs across all Scenarios s. Finally they use the Weibull distribution to identify the uncertain learning rates that fit the given cost distribution In the second step, they transform the above optimization problem by using an Approximate dynamic programming (ADP) method and Hermite Interpolation to approximate the Value function V(C(I,λ)), with the use of the WITCH model.

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Wright meets Markowitz: How standard portfolio theory changes when assets are technologies following experience curves (Way R. et al., 2017):

The experience/learning curve is described by the following equation:

$$c_1 = c_0 \cdot \left(\frac{z_0}{z_0+q}\right)^{\alpha} \cdot e^{\eta}$$

where

c_1: cost of the technology at time t=1

z_0: is the production (or capacity) at time t= 0

q: is the production choice

a: learning exponent

η: noise

The distribution of future costs depends on: i) the state at t=0, ii) the exponent in the learning curve, iii) the production choice and iv) the white noise. A normal distribution is assumed for the shock and thus, based on this assumption the costs are log-normally distributed. The expected value of the cost and the variance are given by the following equations:

$$E[c_1] = c_0 \cdot \left(\frac{z_0}{z_0+q}\right)^{\alpha} \cdot e^{\sigma^2/2}$$

$$Var[c_1] = c_0{}^2 \cdot \left(\frac{z_0}{z_0+q}\right)^{2\alpha} \cdot (e^{\sigma^2} - 1) \cdot e^{\sigma^2}$$

The optimization problem for two technologies that are perfect substitutes now can be described as:

$$\min_{q^A} f(q^A) = E[V(q^A)] + \lambda \cdot Var[q^A]$$

$$s.t. \qquad K = q^A + q^B$$

$$q^A \in [0, K]$$

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where $V(q^A)$ is the total cost of technologies and is determined as $V(q^A) = \sum_{i=A,B} c^i \cdot q^i$ and the objective function becomes:

$$f(q^A) \approx \sum_{i=A,B} c_0^i e^{(\sigma^{2i})/2} + \lambda(c_0^i)^2 (e^{(\sigma^i)^2} - 1)\, e^{(\sigma^i)^2} (q^i)^2$$

where learning rates play no longer a role as previously mentioned: the Markowitz model is a no-learning limit of a technology portfolio.

R&D investment strategy for climate change (Blanford G.J., 2009)

The model has as decision variable the R&D program. The net benefit (NB) from investing to a program id defined as:

$$NB = f(a) \cdot EV - a$$

A risk neutral decision maker would then chooses a for which the marginal NB equals zero. The function $f(a)$ stands for the probability of success of a specific program and is called the innovation production function. It is determined as:

$$f(a_i) = \rho_i \cdot \left(1 - e^{-\frac{a_i}{\beta_i}}\right)$$

Taking the marginal probability a wide variety of assumptions regarding R&D productivity can be modelled. The ρ denotes the probability of success of the R&D program while β stands for the difficulty of investments (or the intensity of investments needed). For each technology case three (3) values for ρ and β are examined. The marginal probability is given by:

$$f'(a_i) = \frac{\rho_i}{\beta_i} \cdot e^{-\frac{a_i}{\beta_i}}$$

The optimal investments are given by the intersection of the marginal probability curve and a threshold value that is defined over the discounted expected value.

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The optimal research and development portfolio of low-carbon energy technologies: A study of China (Wang K. et al. 2018)

In this study a two-stage process is used to solve the problem of minimizing the social cost of GHG abatement through optimal R&D investments. The technologies included in the optimal R&D portfolio are nuclear, solar PV and CCS. Hydro technology is not included in the available for investments technology option as it is considered being in a mature stage and R&D investments in this technology have only a marginal impact to cost reductions. Also wind and biomass are not included in the study due to the lack of data for China. Each of the 3 technology options are further subdivided into 3 projects, thus a total of 9 projects are included in the model. The two-stage decision process includes the following steps:

1. The optimal R&D portfolio is chosen. Then random variables associated to each R&D project are realized
2. The decision regarding the intensity of abatement effort is made.

The objective function minimized is the expected cost related to climate change; that is the abatement cost plus the climate damage cost:

$$E_{a,h,Z}(min_{\mu}[C(\mu;a,h)+D(\mu;Z)])$$

μ: represents the degree of abatement and lies between 0 and 1
α: stands for the pivoting effect on the marginal cost of abatement associated to technological change
h: stands for the shifting effect on the marginal cost of abatement associated to technological change
There are 3 levels of funding considered (low, medium, high) and two possible outcomes for each investment project: failure or success. For example the probability of success of a specific project with high funding while no success in any other program is achieved is determined as:

$$\Pr = p_{133,1} \cdot \prod_{(i,j,k)\neq(C,3,3)} p_{ijk,0}$$

i: stands for the technology (Nuclear, Solar PV, and CCS)

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j: denotes the specific project associated to each technology (1,2,3)
k: denotes the investment effort (1 = low, 2 = medium, 3 = high)
Another important assumption of the modelling methodology is that only the best technology project will be realized. In other words if all projects associated to a single technology succeed only the more cost-efficient will be implemented in the model. Thus we have:

$$a_i(x) = \max_{j,k}(x_{ijk} \cdot a_{ijk,l})$$

x_{ijk}: is a binary variable that takes values 0 = if there is not an investment project at the funding level 1 = if there exists an investment project.
Two models are considered in this paper: A Budget constraint model (BCM) and an Overall Optimal model (OOM). The portfolio choice in the former problem is:

$$\min_x \left(E_{a,h,Z}\left(min_\mu [C(\mu; a, h) + D(\mu; Z)] \right) \right)$$

With constraints:

$$\beta \cdot \sum_i \sum_j \sum_k f_{ijk} \cdot x_{ijk} \leq B$$

$$\sum_K x_{ijk} \leq 1$$

f_{ijk}: is the level of investment
β*:* is the opportunity cost
The portfolio choice in the latter case becomes part of the objective function and we have:

$$\min_x \left(\sum_i \sum_j \sum_k f_{ijk} \cdot x_{ijk} + E_{a,h,Z}\left(min_\mu [C(\mu; a, h) + D(\mu; Z)] \right) \right)$$

$$\sum_K x_{ijk} \leq 1$$

x_{ijk} is the first stage decision variable which denotes the investment project.

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Energy technology R&D portfolio management: Modeling uncertain returns and market diffusion (Bistline J.E., 2016)

The objective is to maximize the expected net benefit = expected discounted value under a number of technological, policy and economical scenarios:

$$\max_{a} E\left[V\left(\tilde{\theta}, \tilde{\omega}\right)\right] - \sum_{i=1}^{n} a_i$$

$$\sum_{i=1}^{n} a_i \leq B\,, a_i \geq 0$$

α: R&D allocation vector

$V(\theta, \omega)$: is the value function which depends on the success of the program (θ) and on market outcome (ω). There are two possible distributions for θ i) the Baseline distribution if the program fails ii) the enhanced R&D distribution if the program succeeds. Then the first term of the objective function can be written as:

$$E\left[V\left(\tilde{\theta}, \tilde{\omega}\right)\right] = \sum_{\theta \in \boldsymbol{\theta}} \boldsymbol{p}(a;\theta) \cdot E[V(\theta, \tilde{\omega})]$$

The expected value of the success of a program is defined as:

$$E[V^{*}(\theta, \tilde{\omega})] = \min_{x} E_{\omega} f(x; \theta_0, \omega) - \min_{x} E_{\omega} f(x; \theta, \omega)$$

For a single program the probability of success is defined by the following equation (the f.o.c):

$$\frac{\partial p}{\partial a} = \frac{1 + \lambda_{\beta}}{E[V(\theta', \tilde{\omega})]}$$

For more than one technologies, if they are independent the portfolio optimization reduces to the single technology case. If there exists dependencies then the probability function is defined. A system of simultaneous equation is determined since the valuation of R&D success depends on the outcomes of other programs. The system equates the success probability of marginal investments across all technologies.

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6. Public R&D in GEM-E3

Public R&D expenditures are assumed to increase the global stock of knowledge by sector. The accumulation of the stock of knowledge regards the stock of "basic knowledge" worldwide and is treated as a public good: it is a non-excludable, non-rival good. Firms take advantage of technological progress achieved through public funding and gain competitiveness advantages.

The stock of knowledge accumulates according to the following function:

$$KDE_{j,t} = KDE_{j,t-1} \cdot (1 - \delta_{kde}) + \sum_{r} RDI_{j,r,t}$$

where r: region, j: sector, t: time, δ_{kde}: the depreciation of the stock of knowledge, KDE: the cumulative stock of knowledge and RDI the R&D public expenditures.

The cumulative stock of knowledge interacts with the unit cost of production of clean energy technologies via a total factor productivity by assuming a learning curve, where the total factor productivity is the output of learning-by research:

$$UC_{j,r,t} = f\left(UC_{i,r,t}, tfp_{j,r,t}\right)$$

$$tfp_{j,r,t} = \left(\frac{KDE_{j,t}}{KDE_{j,0}}\right)^{\lambda(\omega)}, \lambda(\omega) = -\frac{log\left(1-LR(\omega)\right)}{\log(2)}, PR = 2^{-\lambda(\omega)}$$

where tfp: the total factor productivity, UC the unit cost of production, $\lambda(\omega)$ is the elasticity that captures the percentage reduction in costs associated with an increase in learning measured as cumulative knowledge, $LR(\omega)$ is the uncertain learning by research rate, and PR the progress ratio which is the amount that costs reduce to after a doubling of cumulative knowledge.

The learning by research rates used in the GEM-E3 model by energy category are presented Table 3. In order to account for the high uncertainty regarding the exact value of the learning rate in each technology a number of sensitivity runs are performed. In each sensitivity run, the learning by research value, per energy category, is drawn from a normal distribution with mean value equal to the learning rates as reported in the literature and standard deviation equal the 1/3 of the mean. Technologies that are considered mature like hydroelectricity and nuclear have low learning by research rates and standard deviations.

Table 3: Learning rates (mean value and variance)

	Mean	Variance
Energy efficiency	6.0%	0.040%
Oil and gas plants	10.0%	0.111%
Coal plants	8.3%	0.077%
CO2 capture and storage	12.0%	0.160%
Solar energy	12.0%	0.160%
Wind energy	16.5%	0.303%
Biofuels	11.0%	0.134%
Geothermal energy	9.0%	0.090%
Hydroelectricity	1.4%	0.002%
Nuclear	1.0%	0.001%
Hydrogen and fuel cells	11.0%	0.134%
Batteries and storage	16.0%	0.284%

Sources: Kittner, N et al. (2017), Rubin, E. S. et al. (2015) and Samadi, S. (2018).

As an example, the empirical distribution of the learning rates for the solar energy technology is presented in Figure 6. Depending on the number of sensitivities a number of cases are selected (usually 50).

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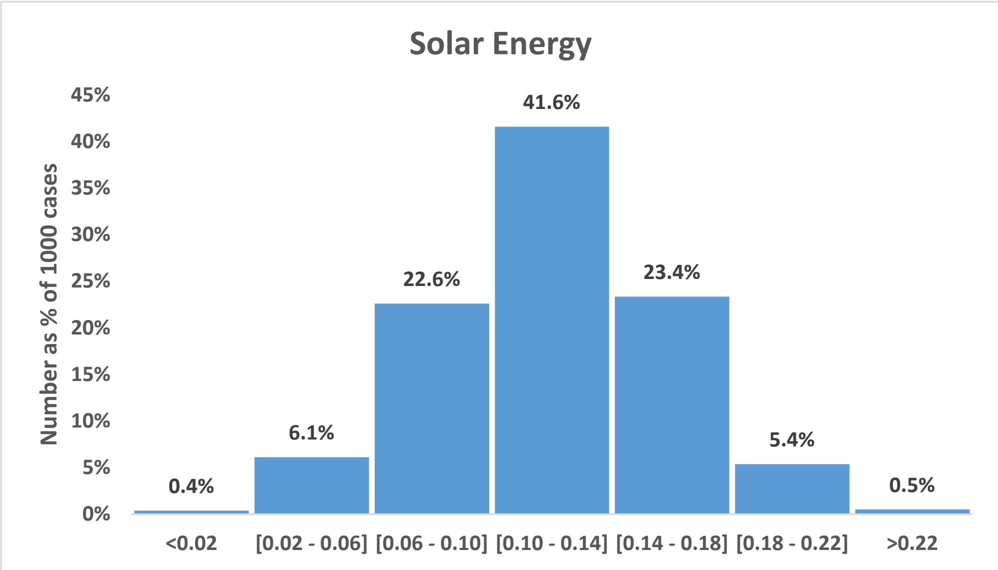
Figure 6: Empirical distribution of the learning rates used in the model for the solar energy technology



In the GEM-E3 model the optimal allocation of R&D expenditure on the different technologies takes into account the impact of R&D by technology on the economy's GDP. Since the model is recursive dynamic the optimal amount of investment in each type of energy expenditures is derived by applying an iterative approximation of Dynamic Programming (two steps process).

In the first step, public R&D expenditures per type of energy expenditure are set according to historical data. This allocation is used as an initial point for each period simulated.

In the second step, an iterative algorithm is used to approximate the optimal allocation of R&D expenditures which maximizes GDP. In each period, based on the learning rates, the model calculates (endogenously) the shares per type of R&D energy expenditures with sequential iterations until the maximum GDP is achieved. The present value of GDP is used as a metric of optimality:

$$\max_{j=1\ to\ N} \langle GDP_j, GDP_{Initial} \rangle$$

where

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$$GDP_j = \sum_t \left(1 + i1_{r,t}\right)^{-t} \cdot GDP_{j,r,t}$$

i1: Discounting growth rate

N: total number of iterations

r: region

t: time

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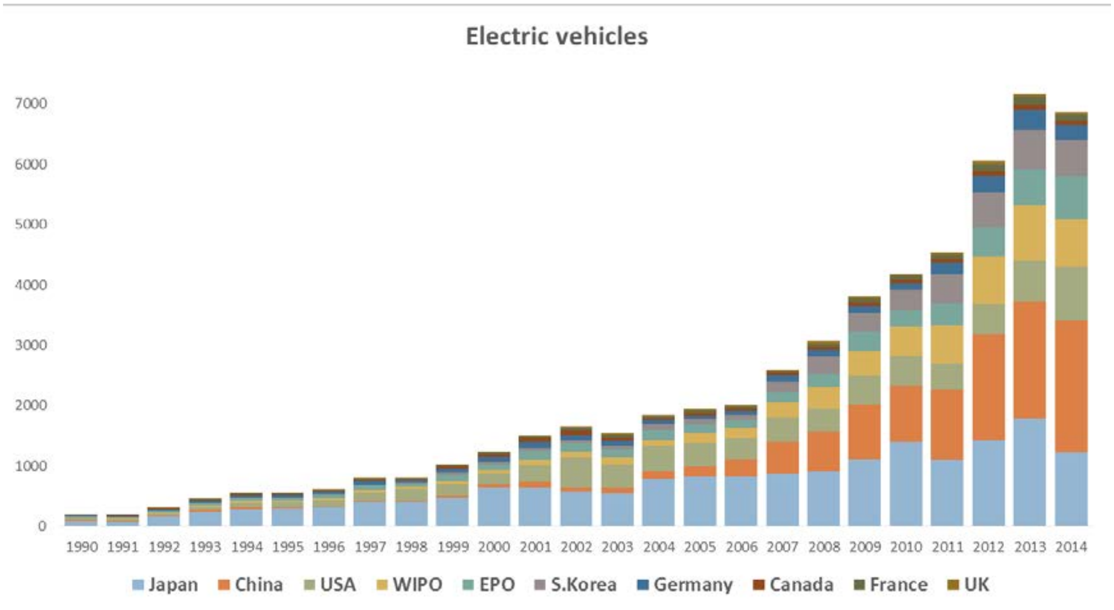
ANNEX



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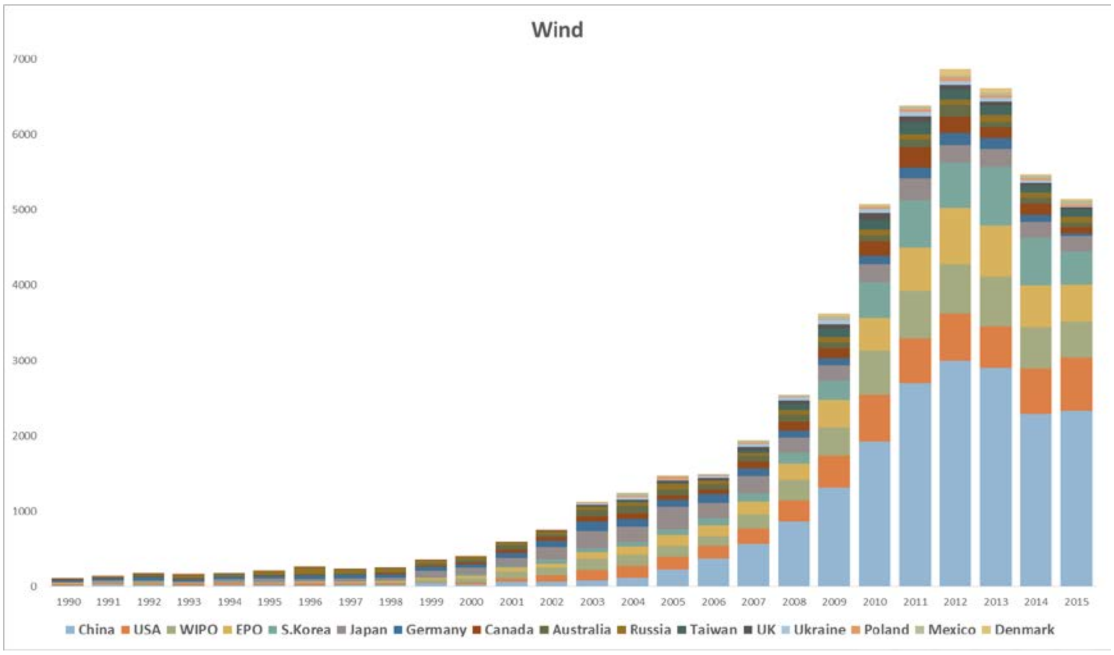

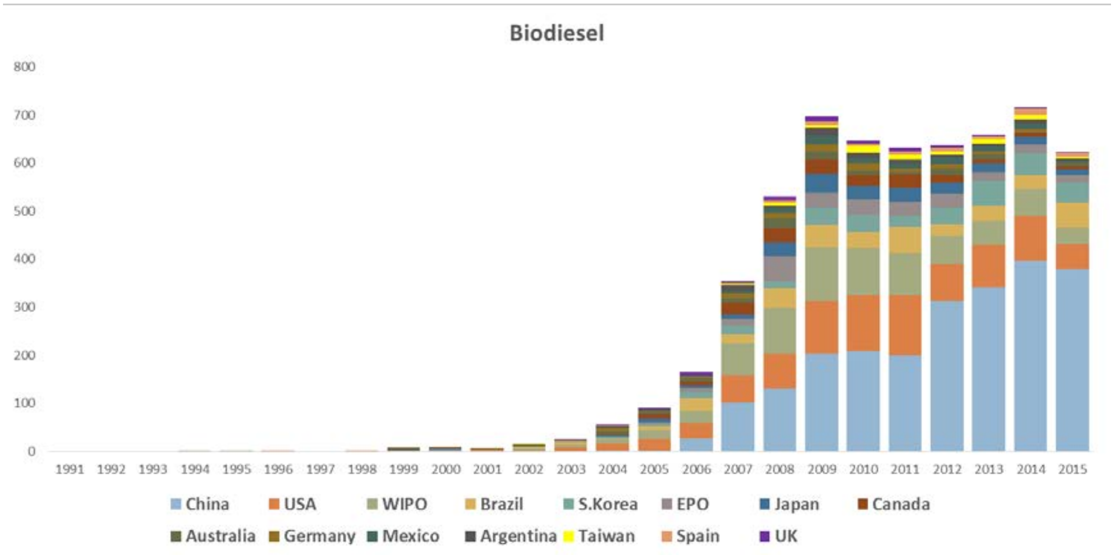

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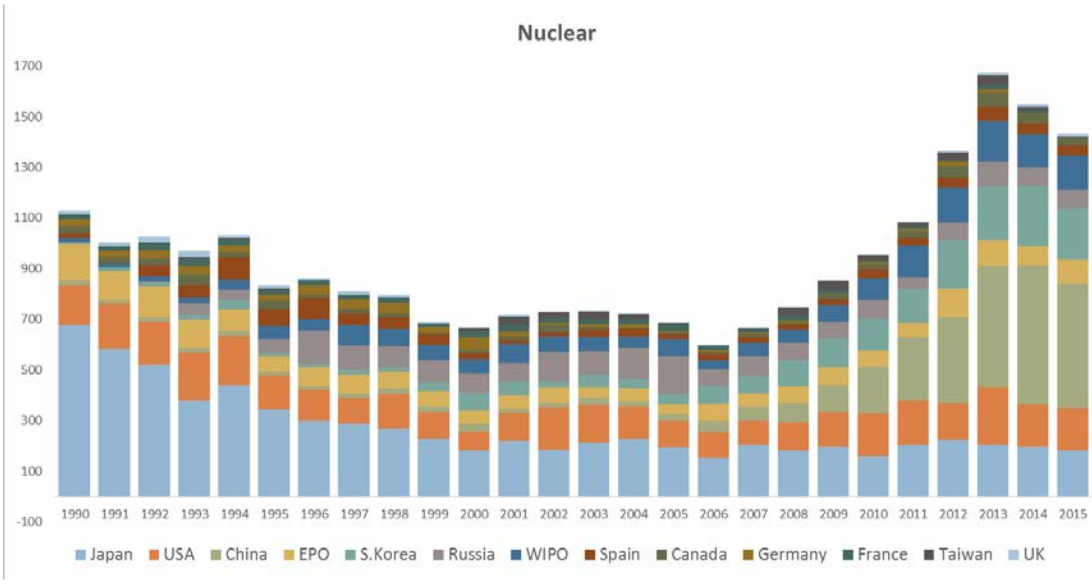

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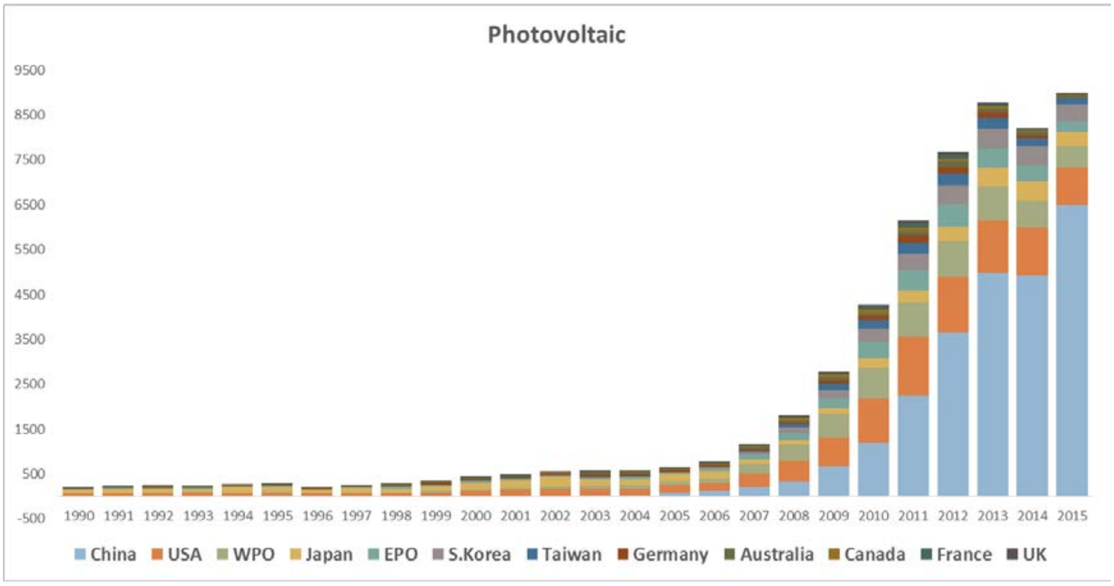

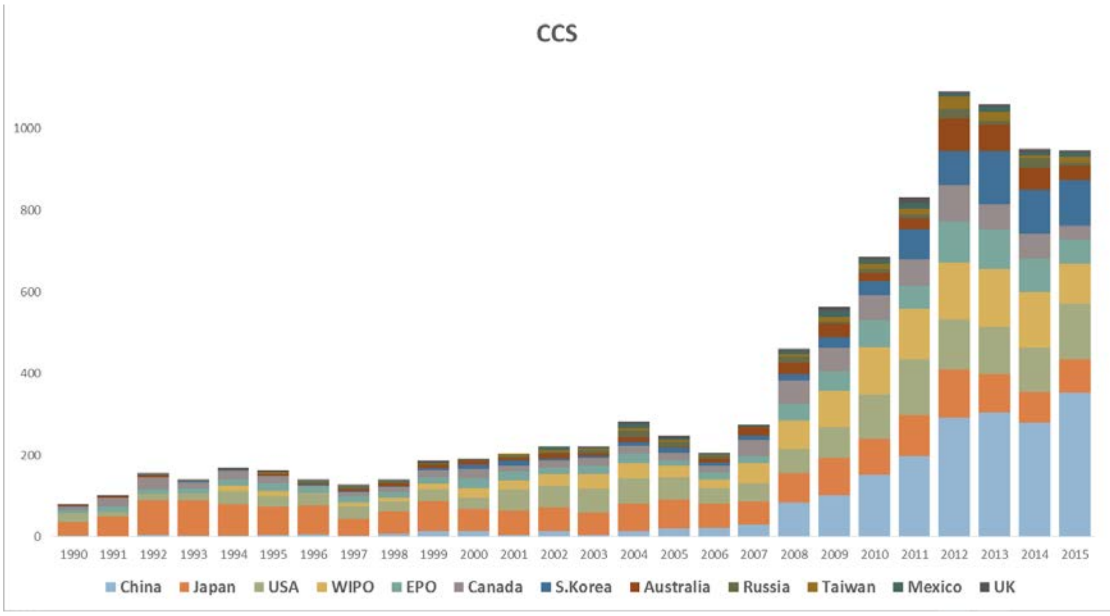

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