Directing Technological Change while Reducing the Risk of (not) Picking Winners: The Case of Renewable Energy

Nick Johnstone and Ivan Haščič

OECD Environment Directorate

29 November 2010

Abstract: There is increasing support for the use of policies to 'direct' technological change in a manner which reduces climate change. However, there is a widespread concern about the potential for policymakers to efficiently direct technological change in a welfare-improving manner. Indeed, by providing incentives for search, technology-neutral policies encourage potential innovators to identify and develop least-cost solutions to achieve given environmental objectives. In this paper empirical results are presented on the potential innovation benefits of supporting "local" general purpose technologies rather than specific generating technologies in the area of renewable energy. The study draws upon a rich database of patent applications, with data from 28 countries over three decades.

Keywords: environmental policy, climate change, technological innovation, patents, directed R&D

JEL Codes: Q42; Q54; Q55; Q58

Directing Technological Change while Reducing the Risk of (not) Picking Winners: The Case of Renewable Energy

Nick Johnstone and Ivan Haščič

1. Introduction

While there is little question that technological innovations are required to address the problem of climate change, there is a widespread concern about the potential for policymakers to efficiently 'direct' technological change in a welfare-improving manner by targeting specific technologies for support. Indeed, there is empirical evidence supporting the case for 'flexible' policy instruments which are technology-neutral (see Haščič et al. 2009). By providing incentives for 'search' technology-neutral policies encourage potential innovators to identify and develop least-cost solutions to achieve given environmental objectives. Moreover, they may also increase the potential for wide market diffusion of technologies developed (see Johnstone and Haščič 2011).

The case for technology-neutrality is strongest in the presence of information asymmetry (between the regulator and the regulated) and when there is potential for technology lock-in. The danger is that governments will 'pick technologies' which lock the economy into a trajectory which is unnecessarily costly. According to this framework, the 'ideal' policy instrument is one in which the externality is targeted directly and agents are given complete freedom to pursue the most efficient abatement strategy given their cost structures and technological capabilities.

However, in recent years closer attention has been paid to the need for 'directed' technological change in certain circumstances, particularly in the context of climate change mitigation. For instance, based on a model of endogenous technological change Acemoglu et al. (2009) find that under plausible assumptions, a policy mix which includes both a carbon tax and targeted R&D support for 'clean' R&D is likely to be more efficient than one which relies upon a carbon tax alone. This is consistent with the empirical results obtained by Bosetti et al. (2010) using the WITCH model, which finds that relying solely on a tax would be excessively costly.

However, neither paper discusses the difficulties associated with targeting R&D support. Nor do they provide evidence on how the targets of R&D support should be selected. In this paper we seek to identify a strategy whereby governments are able to 'direct' technological change in a manner which is relatively parsimonious with respect to information requirements and reduces the risk of lock-in. While the case of renewable energy is examined, the lessons learned are potentially applicable across a wide variety of areas.

The following section highlights the conflicting relationship between the nature of technology and directed technological change. This is illustrated by discussing the possible strategies in dealing with intermittency in renewable energy generation. The conceptual discussion is then followed by data analysis. An overview of recent trends in energy storage innovation is followed by a detailed discussion of the modelling strategy adopted in this paper and a description of the data and methodology used. Finally, the paper provides an interpretation of the empirical results and discusses their implications for policy.

2. Technology Neutrality and Directed Technological Change

There is a broad consensus that technological innovation will be required to address climate change. There is a 'dual' externality associated with environmental innovation. On the one hand, pollution is a negative externality (since elements of the assimilative capacity of the environment are public goods) while innovation is viewed as a positive externality (since elements of the information generated by innovation are public goods). Therefore, without public policies designed to overcome these market failures, firms pollute too much and innovate too little compared with the social optimum. Investments (and thus, innovation) in the development of 'green' technology are likely to be below the social optimum because, for such investments, the two markets failures are mutually reinforcing.

Economists have long argued that the necessary innovation is most efficiently induced through the use of policies which are flexible (or technology-neutral), giving potential innovators incentives to identify the optimal means of meeting the environmental objectives. (See Haščič et al. 2009 for recent empirical evidence.) For this reason, carbon taxes or tradable permit schemes (such as the European Union's Emissions Trading Scheme) are considered to be optimal instruments in terms of dynamic impacts.

However, in the absence of policies which internalize the positive externalities associated with innovation in general, 'environmental' innovation will remain sub-optimal. Intellectual property rights are one means by which this can be achieved. In addition, public investment in (or support for) basic research can increase returns on private investment in applied research. In this way, both the direction (through the change in relative prices associated with the use of the environment) and the rate (through the change in incentives for investment in innovation) of innovation are optimized.

However, it has been argued by some that more 'directed' support for specifically environmental innovation may also be required. For instance, Bosetti *et al.* (2010) argue that innovation market failures may be relatively more important in the area of climate change mitigation. They discuss issues such as appropriability problems (potential for intellectual property rights on key mitigation technologies to be restricted or abrogated), the lack of credibility of carbon pricing policies (since current governments may not be able to provide a credible commitment to future carbon pricing policies), or other more generic failures specific to the electricity sector (entry barriers associated with already installed infrastructure, learning-by-doing, etc.).

While the authors emphasise that it is unclear whether these problems necessarily warrant 'targeted' innovation support for 'climate mitigation' R&D, they do provide some results using the WITCH model which indicate that reliance on a pricing policy alone may impose excessive welfare costs. However, this result is due in large part to the benefits of international coordination of R&D efforts, rather than R&D *per se*.

In an endogenous model of technological change, Acemoglu et al. (2009) model the impacts of learning-by-doing more explicitly. In their case public R&D subsidies for 'clean' technologies will shift the economy onto a less damaging trajectory since the benefits of research efforts in one period are carried through to the next. Using a carbon tax both to reduce emissions in the short-run and to influence the path of innovation efforts in the longer run would lead to excessive distortions in the economy. For this reason, the joint application of a carbon tax with public R&D support for mitigation technologies would lower the cost of meeting climate change mitigation objectives relative to the application of a carbon tax on its own.

However, both these papers skate over some of the practical difficulties associated with targeting the R&D aspect of the policy mix. For instance, in the case of Acemoglu *et al.* (2009), which is a two-sector ('clean' and 'dirty') model, there is no indication of how to identify 'clean' sectors and technologies in a less abstract context. In the case of Bosetti *et al.* (2010), R&D is directed toward energy efficiency, renewable energy, and 'advanced' carbon-free technologies (e.g. CCS, advanced biofuels, and nuclear fusion).

While the level of detail is much greater, the hazards associated with designing and targeting support programmes is not discussed. Support programmes which are not completely technology-neutral must be targeted at specific technologies (or groups of technologies), and the implications of doing so need to be assessed. This imperative is not specific to climate change mitigation, and there is a long history in the economics literature on the hazards of introducing government policies which pick (or do not pick) winners.

However, as noted by David and Aghion (2008), there is almost no empirical evidence indicating whether governments are better or worse than firms at picking winners. Moreover, they point out that "one is less likely to notice the opportunities that may have been missed by pursuing a neutral policy strategy that increased aggregate R&D funding but spreading it over so many fields that economies of scale and critical mass fail to be achieved where they would do the greatest good" (ibid, page 24).

There are two related lessons which arise out of the literature which is sceptical with respect to the benefits of non-neutrality. Firstly, it is important to minimise information requirements in general for policymakers, and particularly cases of information asymmetry between the regulated community and the regulator. While allocating resources in the context of imperfect information about future returns of different technologies is a hazardous exercise, doing so when those who stand to benefit from the provision of support possess considerably more information about actual conditions and possible future trajectories than the government is particularly hazardous.

Secondly, it is important to minimise the risk of 'lock in' for technologies which ultimately prove to be more costly/less efficient than alternatives would have been. This is particularly important for technologies where network externalities exist. (Arthur 1994). Moreover, in addition to 'technology lock in' there may also be 'political lock-in', with the establishment of vested interests defending support for specific technologies long after the social returns on continued support have dwindled (Prado and Trebilcock 2009).

The usual proposed solutions to balance the benefits and risks associated with providing support for specific technologies is to favour basic research over applied research and, when providing support for applied research to ensure that the portfolio is sufficiently diverse to reduce risks. However, as argued by David and Aghion (2008), this may not suffice in order to shift technological trajectories in a more fundamental manner to meet pressing policy objectives.

In the following section we examine how this might be done in the context of innovation in renewable energy technologies, while taking into account the lessons learned on the risks associated with non-neutrality. In addition to the points made above, it will be argued that support for energy storage (rather than generation) has two key advantages: storage is a complement to a wide variety of generation technologies, reducing the need for perfect foresight on the part of the government; and, storage technology is relatively less mature than the main generation technologies, and thus the case for public support is stronger.

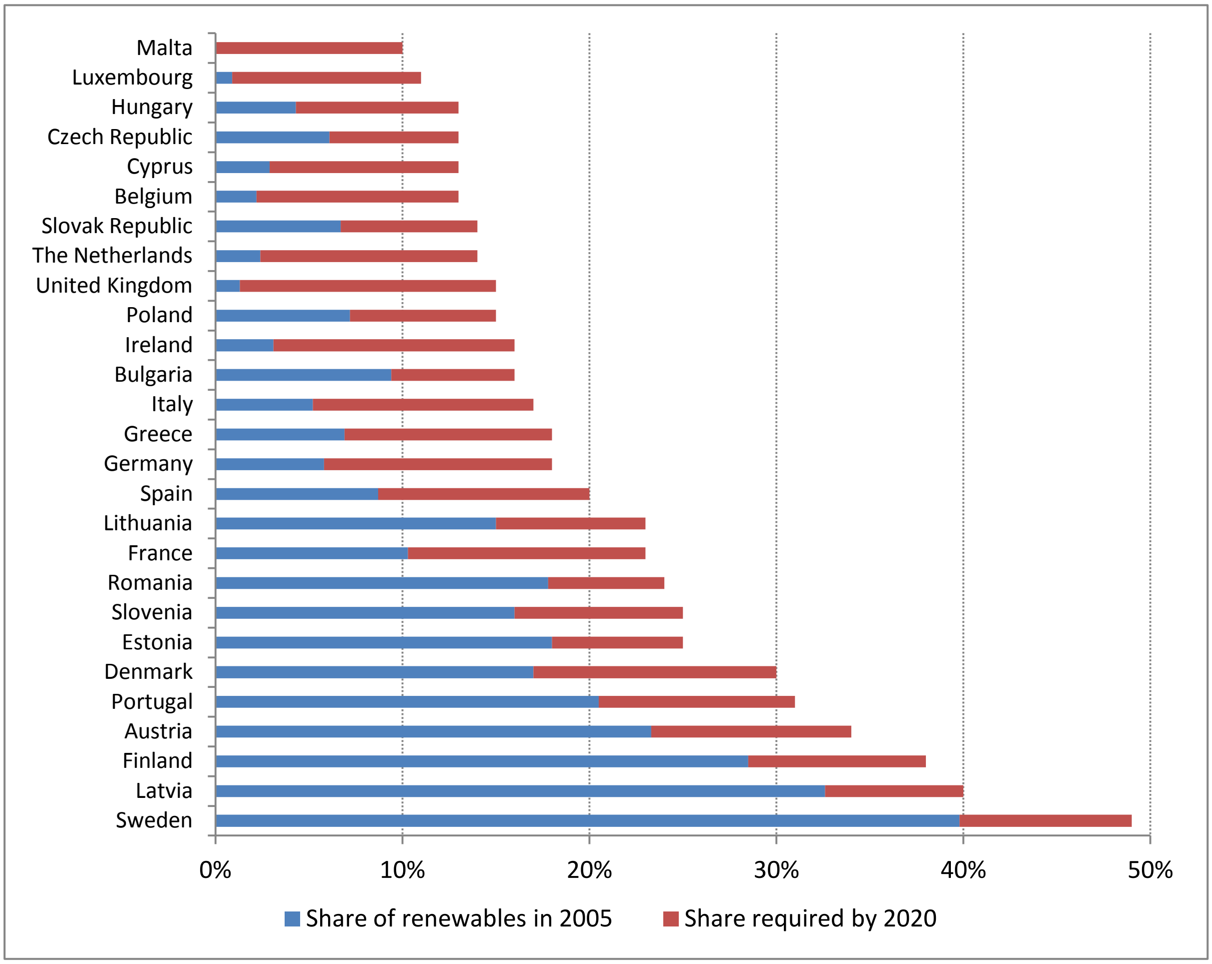
3. Intermittency and Storage in Renewable Energy Generation

A number of OECD (and other) governments have identified the increased penetration of renewable energy sources as a primary means of mitigating the emissions of greenhouse gases. Policy targets for renewable energy exist in at least 73 countries. Most national targets are for shares of renewable energy supply in total electricity production, typically 5-30%, but ranging all the way from 2 to 78% (REN21 2008).

For instance, the European Union Directive of 2008, which succeeds the one from 2001, requires member states to increase their shares of renewable energies to meet a 20% overall energy target by 2020. The Directive set a series of interim targets, known as 'indicative trajectories', in order to ensure steady progress towards the 2020 targets. EU countries are free to decide their own mix of renewables, allowing them to account for their different potentials, while Brussels reserves the right to enact infringement proceedings if states do not take appropriate measures towards their targets. Figure 1 gives the 2020 national targets for renewable use in EU as compared to the 2005 share of renewables in total energy supply.

Figure 1. Renewable Energy Targets in Europe

(Share in final energy by 2020 as compared to share of renewables in 2005)



Source: EurActiv (2010).

In order to meet such targets specific policies need to be introduced. By 2009, at least 64 countries had some type of policy to encourage renewable power generation (REN21 2008). Such government policies target different stages of the industrial process, ranging from the research and development (R&D), through the investment in physical capital (plants and equipment) up to the production and sale/consumption of energy.

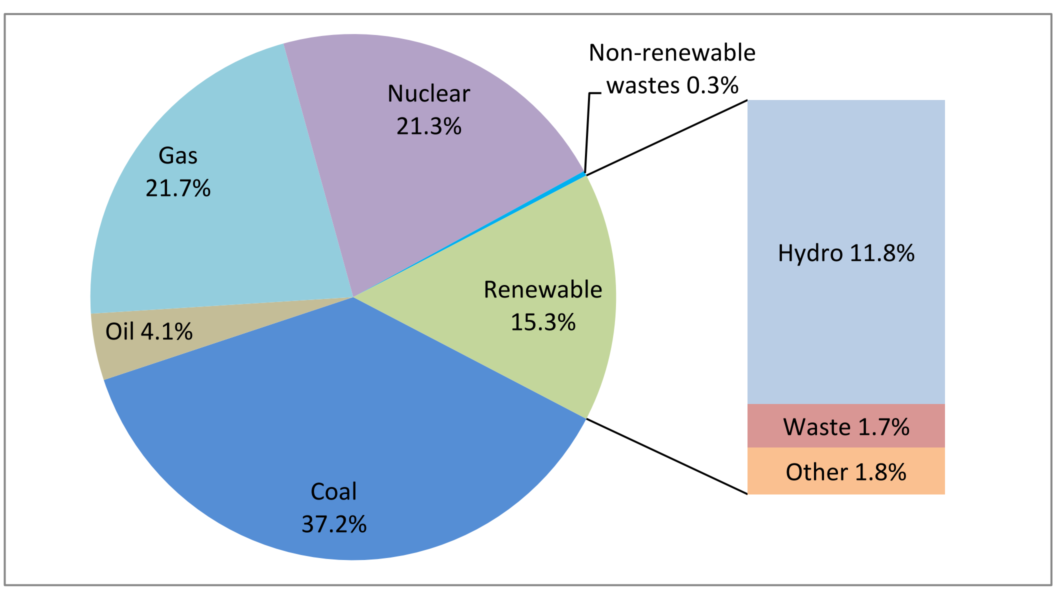
Based on data collected by the International Energy Agency (IEA), Figure 2 presents a chronology of the implementation different policy measures in IEA countries. Each point on the scatter plot represents the year in which a significant example of a particular type of policy instrument was first introduced in that particular country. Five different policy types are distinguished: investment incentives (e.g. risk guarantees, grants, low-interest loans); tax incentives (e.g. accelerated depreciation); tariff incentives (e.g. feed-in tariffs); voluntary programs; obligations (e.g. guaranteed markets, production quotas); and, tradable certificates. Significant changes have occurred in the public policy framework put in place to support renewable energy. Initially R&D programs were introduced in a number of countries. This was followed by investment incentives, and later, tax incentives and preferential tariffs. Next, voluntary programs were developed. More recently, quantitative obligations, and finally tradable certificates, have been applied.

Figure 2. Introduction of Renewable Energy Policies by Type

Source: IEA (2004), updated using IEA (2009a).

However, the penetration of renewable energy remains relatively low. Figure 3 gives the share of renewables in total electricity production amongst OECD countries for the year 2007, compared with the shares of the conventional energy sources. More than 80% of produced electricity comes from coal, natural gas and nuclear power plants, while renewable energy sources rank fourth. However, most of this comes from hydro.

Figure 3. Share of Renewables in OECD Electricity Production in 2007



Source: Electricity Information (IEA 2009b)

Cost is, of course, the main reason. Despite many policy initiatives, the cost of renewable electricity generation remains prohibitively expensive, although there are exceptions. However, a significant additional barrier to the increased penetration of renewable energy arises from the 'intermittent' nature of the electricity produced. While some sources are 'dispatchable' (e.g. hydro, geothermal, and biomass), wind, solar and wave/tide power are subject to varying weather and ecological conditions.[1]

Output from individual plants can vary on a scale of seconds to minutes, as well as over several hours. The extent to which the grid as a whole can accommodate such variations is a function of its capacity to adjust to supply and demand shocks (power system flexibility), and as the penetration of intermittent renewable sources increases the need for such capacity. Moreover, since those renewable which are the most promising sources of future increases in capacity (e.g. offshore wind, tidal/stream, barrages and lagoons, wave energy and solar photovoltaics) are intermittent in nature the need to be able to adjust output levels and sources on short notice is likely to rise (see Infield and Watson 2007; Sinden 2007).

In a sense, all plants have 'variable' output, insofar as there is some probability of a breakdown which puts the plant off-line for a period of time. Since power outages can impose significant economic costs, most regulators have a target "loss of load probability" (LOLP). For instance, in the United Kingdom this is set at 9 (i.e. 9 outages per century). This is met by building in a system margin, allowing the system to meet unexpected decreases in supply from some plants and/or unexpected increases in demand.

The introduction of intermittent renewable energy plants increases the required system margin in order to meet the target LOLP since they are able to contribute less to peak demand (Neuhoff 2005).[2] This can be measured as a capacity credit – i.e. the amount of electricity (expressed in terms of conventional thermal capacity) that can be served by intermittent plant without increasing the LOLP. For instance, while wind plants generally have a capacity factor in the region of 20% to 40% (relative to 80%-90% for conventional fossil fuel-fired plants) the capacity credit is less, reflecting the high variability of output through time. At 20% wind power penetration, Gross et al. (2007) estimate a capacity credit of 19%-26% for a plant with an average annual capacity factor of 35%. On the basis of a formula developed by Gross et al. (2007) this can be converted into a 'reliability cost'[3] of approximately £4/MWh, which can be considered as an 'externality cost' arising out of intermittency.

In the face of such vulnerability some governments have even sought to cap the penetration of intermittent renewable (see IEA 2008). Moreover, as penetration levels of intermittent renewables rise still further the ratio between capacity credit and capacity factor falls, reflecting increased vulnerability of the system. The extent to which the penetration of intermittent renewables increases LOLP is a function of the flexibility of the system. Flexibility can be introduced into the system in six ways:

[1] The IEA (2008) prefers the terms "firm" and "variable". Sinden (2007) uses the terms "dispatchable" and "non-dispatchable". The key factors are: what is the source of generating capacity; whether there is significant variation in the potential output of the source; and whether this variation is a consequence of exogenous factors beyond direct control (i.e. ecological conditions).

[2] However, there are some 'intermittent' variables which correlate with peak demand (e.g. solar photovoltaic and air conditioning). See Heal (2009) and Gross et al. (2007).

[3] The difference between the fixed cost of energy-equivalent thermal plant minus the fixed cost of thermal plant displaced by capacity credit of the intermittent plant.

Improved weather forecasting. Improved forecasting of meteorological and other ecological conditions (ocean wave activity, solar radiation, etc.) can help system operators efficiently balance the amount of dispatchable and different intermittent power sources in the grid (see e.g., IEA 2008; APS 2010).

Geographic dispersal of intermittent renewable energy plants. Since spatial dispersion will likely reduce the extent of correlation amongst the output of different plants, this will 'smooth' system-wide output (see e.g., Inage 2009).

Diversity in the portfolio of renewable energy sources. Since output variations between types of renewable is unlikely to be strongly correlated this will also smooth output (see e.g., Sinden 2007; Gross et al. 2007; Infield and Watson 2007).

Trade in electricity supply services. The reasoning is analogous to the point made above, but with imperfect grid connections between countries it is worth highlighting. Even within continental Europe there are significant lacunae (e.g. France↔Spain) (see Milborrow 2007; IEA 2008).[4]

Improvements in load management. The development of 'intelligent' grids allows for improved temporal balancing of demand and supply, and more flexible transfer between sources of supply (see e.g., IEA 2008; Duff and Green 2008).

Energy storage. Historically the primary back-ups (or reserves) have been fossil fuel plants which can come on-line relatively quickly. However, this can be costly and as a consequence pumped hydro plants are commonly used as a reserve source of energy. In recent years there have been significant innovations with respect to different types of battery storage of sufficient scale to serve as back-up for the grid (see e.g., Hall and Bain 2008; IEA 2005; IEA 2008).

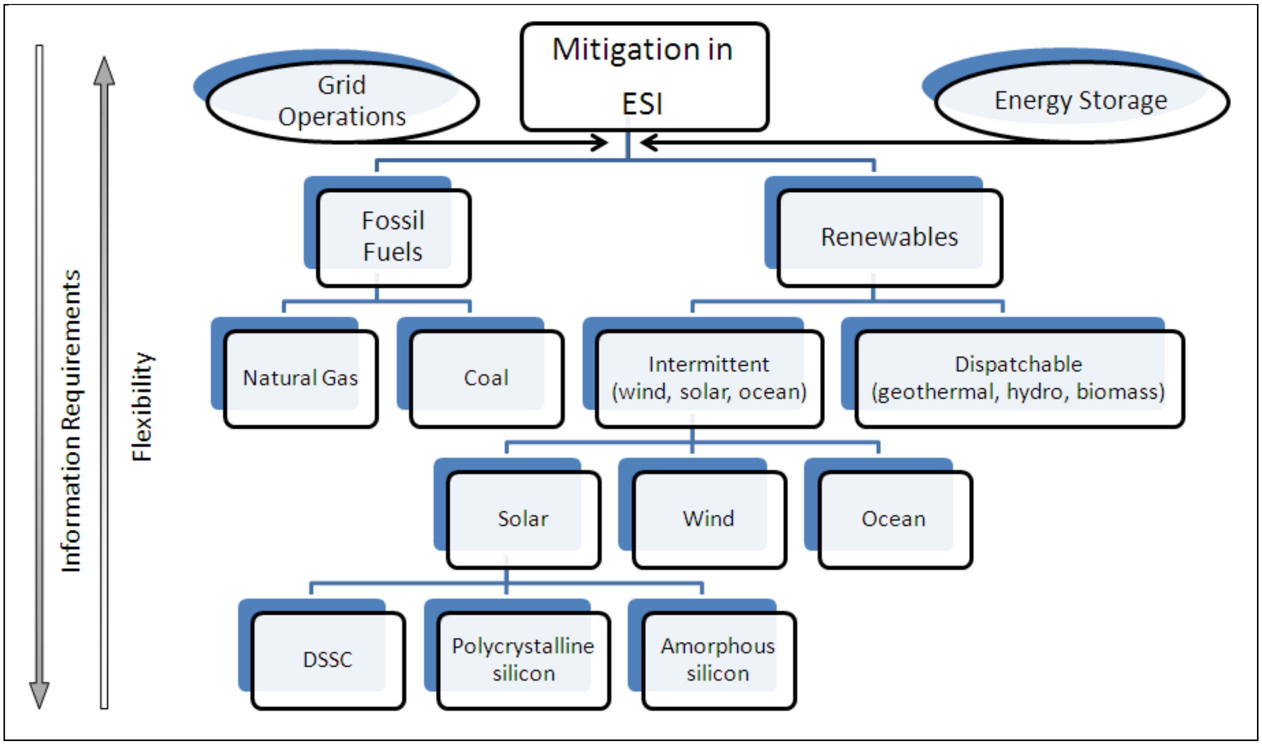
It is developments in load management and storage that is the primary focus of much on-going work, and this paper focuses on the case of innovation in storage. Inage (2009) and IEA (2005) highlight a number of different storage technologies (in addition to pumped hydro) which are 'efficient' at scales of 1MW and above. These include compressed air energy storage, superconducting magnetic energy storage, advanced lead acid batteries, lithium-ion batteries, and flow batteries. However, it remains the case that efficient energy storage is a significant constraint on the penetration of renewable energy sources in the market.

The increased availability of energy storage at reasonable cost is, therefore, one of the strategies which a government can pursue in order to increase penetration of renewables in the electricity supply industry. Publicly-supported innovation efforts which reduce cost of storage may be a cost-effective strategy to bring about reduced CO_2 emissions. However, resources devoted directly at the intermittent generating technologies (solar, wind, tide/ocean) may also be an equally cost-effective strategy.

[4] While 20% of Danish electricity is generated by wind, only 9% is consumed domestically with the balance exported to Norway and Sweden. Since the power exported to Norway and Sweden displaces power that is itself partly carbon neutral (e.g. hydro) the benefits in terms of carbon reduction may be limited (see CEPOS, Wind Energy: The Case of Denmark).

Based upon the discussion in Section 2 there are good reasons to believe that public research efforts targeted at storage are likely to be more cost-effective. Why? The information requirements (for governments) are more limited than would be the case in allocating public resources across different generating technologies. By targeting innovation 'upstream', flexibility is retained downstream. This point is represented in the schema presented below (Figure 4). In effect, energy storage technologies (and grid operations) can serve as an 'enabling' technology, allowing for increased power system flexibility. This increases the competitiveness of all intermittent renewable energy sources relative to dispatchable sources (renewable and other), without specifically favouring one intermittent source over another. It is a form of 'local' general purpose technology (GPT) within the basket of intermittent renewable energy sources.[5]

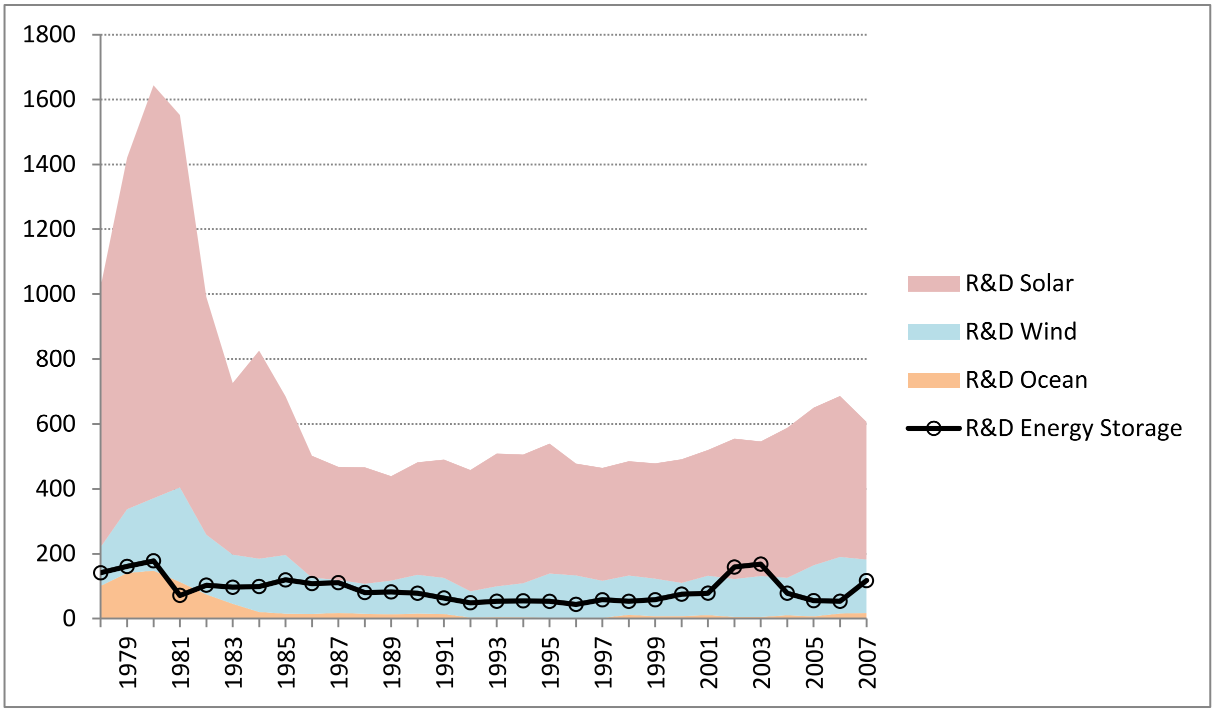
Figure 4. Flexibility and Policy Incidence



For these reasons, targeted support for innovation in storage technologies (rather than generating technologies) may avoid some of the potential pitfalls associated with public R&D subsidies. Moreover, redirecting support from generating technologies to storage technologies is likely to have a significant impact since the scale of public R&D going to storage technologies is exceedingly small relative to generating technologies. (See Figure 5)

[5] With 'locality' restricted to the basket of intermittent renewable energies. Such a strategy would favour intermittent over dispatchable renewable (e.g. hydro, geothermal) energy. Moreover, it would favour renewable energy in the electricity supply industry over other means of carbon abatement.

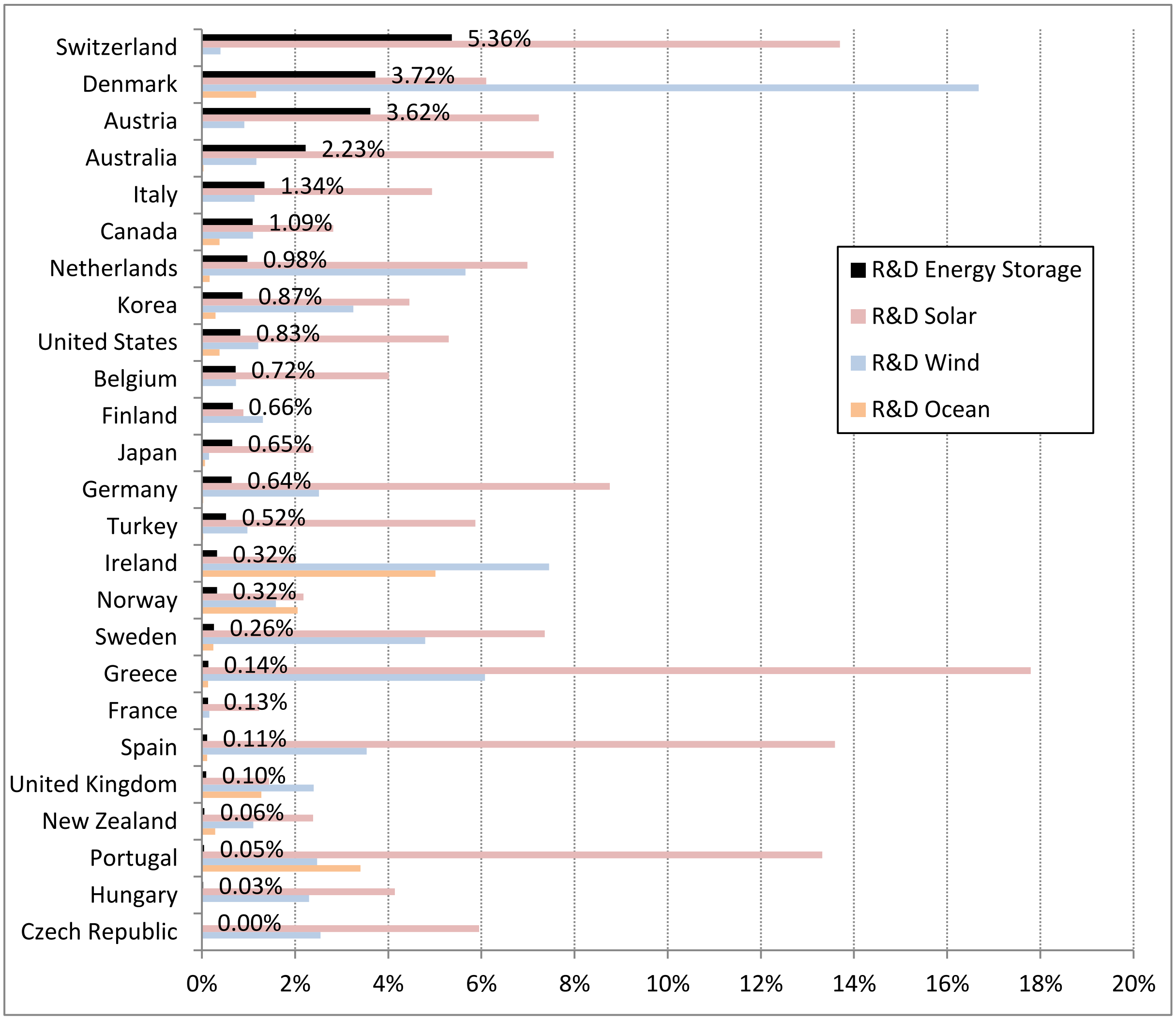
Figure 5. R&D on Energy Storage and Generation from Renewables (1978-2007)



Source: Energy Technology RD&D Budgets (IEA 2010).

The balance of expenditures for intermittent generating and storage technologies for different countries is presented in Figure 6, in which the countries are sorted in descending order of the % of total public energy R&D going toward storage technologies. Switzerland, Denmark and Austria target more than 3% of energy R&D at storage, while Japan, the United States and Germany all have less than 1%.

Figure 6. R&D on Energy Storage and Generation from Renewables (1978-2007)



Source: Energy Technology RD&D Budgets (IEA 2010).

However, it is important to emphasise that public support for R&D – whether on generating or storage technologies – is unlikely to suffice in the absence of policies which target the environmental externality more directly. A price on carbon is a necessary but not sufficient condition for the development of advanced carbon-saving technologies (Fischer et al. 2003).[6] As a consequence, it is hypothesised that the optimal strategy would be to provide targeted support for innovation in storage technologies (and load management) upstream, alongside downstream application of environmental policies which are neutral with respect to technology (i.e. carbon taxes).

4. Innovation in Energy Storage

Unlike the studies discussed in the introduction to this paper we are not able to test the more general hypothesis that the optimal mix of policy instruments involves a carbon tax (or tradable permit scheme) and targeted public support for research efforts. However, we can test whether the R&D arm of the policy mix – assuming that there should be such an arm – is best targeted at generating or storage technologies. We do so through the use of patent data, comparing the patent 'yields' when public support is targeted at storage on the one hand and generating technologies on the other hand. In both cases, the yield is measured in terms patents in the generating technologies (and not storage), with the assumption being that innovation in storage is a necessary complement to innovation in generating technologies.

As a measure of innovation in energy storage (and generating) technologies, patent counts have been developed. Patents are a set of exclusionary rights (territorial) granted by a state to a patentee for a fixed period of time (usually 20 years) in exchange for the disclosure of the details of a given invention. Patents are granted by national or regional patent offices on invention (devices, processes) that are judged to be new (not known before the application date of the patent), involving a non-obvious inventive step and that are considered useful or industrially applicable. The use of patent data as proxy for innovation has a long history in the field of innovation economics. Griliches (1990) argues that patents are imperfect but useful indicators of inventive activity. Their main limitation is linked to the facts that not all innovations are patented, not all patented innovations have the same economic value, and that propensity to patent may vary across countries and technological fields.

We use the selected IPC codes to extract patent data from the European Patent Office (EPO) World Patent Statistics Database, or PATSTAT (EPO 2010). PATSTAT is unique in that it contains data from more than 90 patent offices and on over 70 million patent documents. Patent documents are categorized using the international patent classification (IPC) and some national and regional classification systems, including the European classification scheme (ECLA). In addition to the basic bibliometric and legal data, the database also includes patent descriptions (abstracts) and citation data.

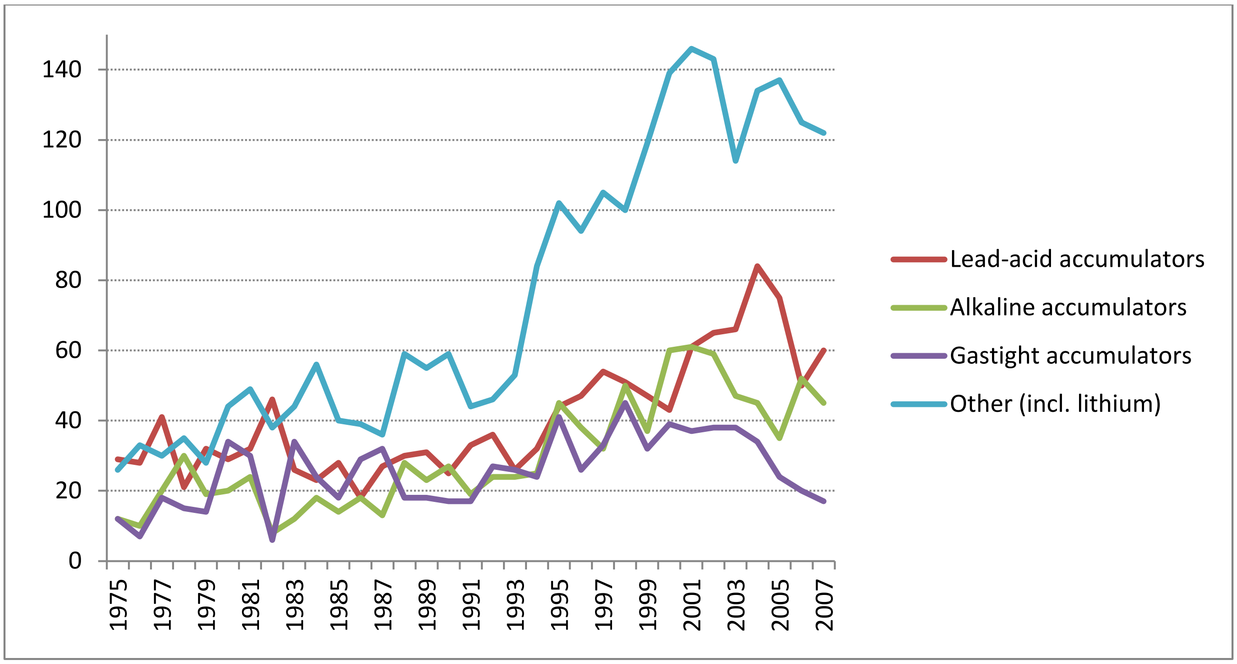
Data have been extracted on patent applications filed from 1975 to 2007 identified using the IPC code H01M10 (secondary cells) that covers inventions related to rechargeable batteries, including lead-acid accumulators (IPC: H01M10/06-18), alkaline accumulators (IPC: H01M10/24-32), gastight accumulators (IPC: H01M10/34) and other types of accumulators not provided for elsewhere (IPC: H01M10/36-40).

[6] It is interesting to note that a tax on carbon is not technology-neutral with respect to the underlying policy objective (mitigating climate change) if other greenhouse gases are not subject to equally stringent policy measures and there is a degree of substitutability between different greenhouse gases.

The rate of innovation in these different technologies has been very rapid in recent years. Figure 7 shows the number of patent applications (claimed priorities and singulars) for H01M10 deposited worldwide from 1975 to 2007. There has been almost a five-fold increase over the period.

Figure 7. Invention in Energy Storage

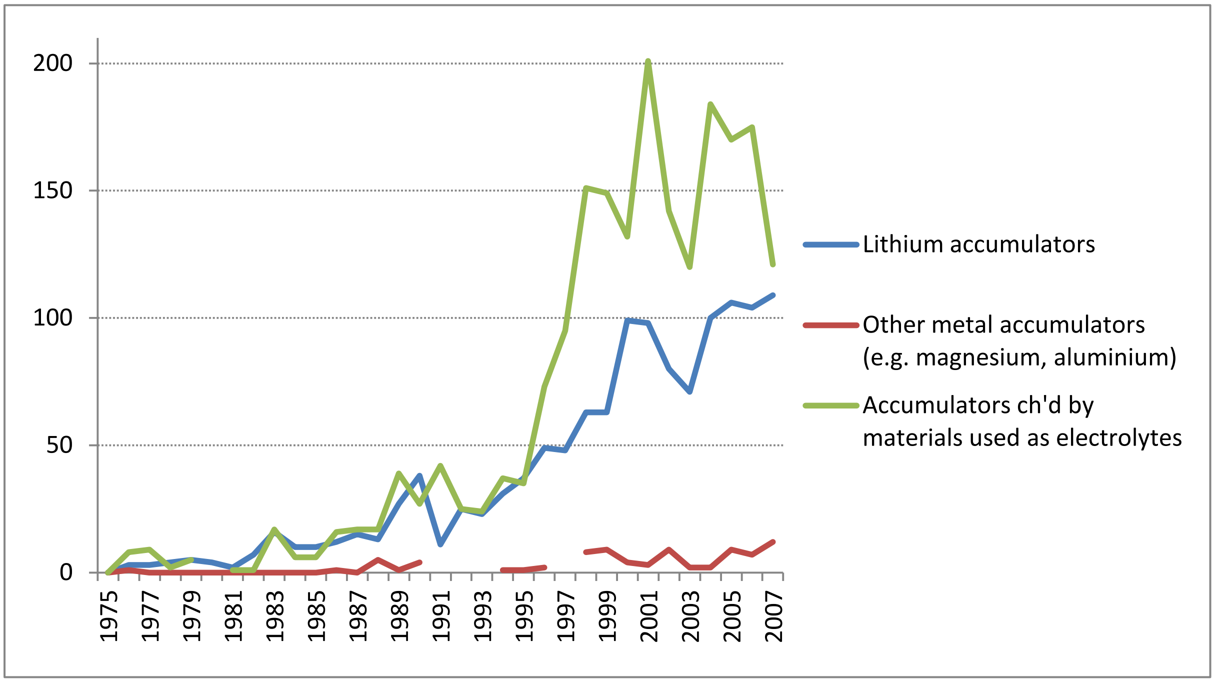
(CP and singular patent applications worldwide in selected electricity storage technologies)



Some of the most significant advances in battery technology, such as lithium accumulators, are classified as "other". However, the European classification (ECLA) provides greater detail within this category and Figure 8 presents the trends for lithium accumulators (ECLA: H01M10/052-0525), "other metal" accumulators (ECLA: H01M10/054), and accumulators "characterised by materials used as electrolytes" (ECLA: H01M10/056-0569).[7] There is little evidence of innovation in the first and third of these technologies until the early 1990s, at which point innovation in these fields takes off.

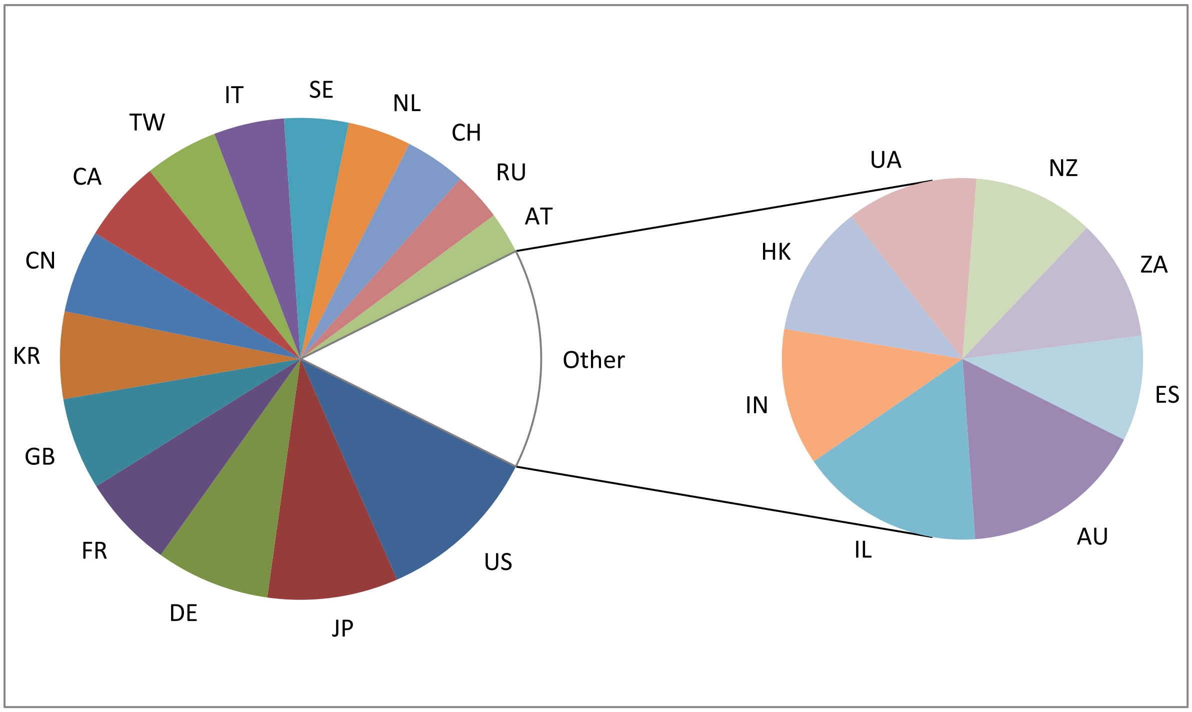
[7] The most recent (2010.01) release of the IPC scheme now integrates these former ECLA classes. However, this will only allow identifying these inventions in the IPC system in the future. For example, using the April 2010 version of PATSTAT, 98% of Li-batteries were still identified through ECLA.

Figure 8. Invention in Energy Storage
(CP and singular patent applications worldwide in selected electricity storage technologies)



The main inventor countries are presented in Figure 9 below. Half of all patent applications come from seven inventor countries: United States, Japan, Germany, France, Great Britain, Korea and China.

Figure 9. Invention in Energy Storage, 2000-2007
(Patent applications (claimed priorities and singulars) by inventor country in H01M10)



Note: The two-letter codes represent the following inventor countries: Austria (AT), Australia (AU), Canada (CA), Switzerland (CH), China (CN), Germany (DE), Spain (ES), France (FR), United Kingdom (GB), Hong Kong S.A.R. of China (HK), Israel (IL), India (IN), Italy (IT), Japan (JP), Korea (KR), Netherlands (NL), New Zealand (NZ), Russian Federation (RU), Sweden (SE), Taiwan Province of China (TW), Ukraine (UA), United States of America (US), South Africa (ZA) (*Source*: WIPO Standard ST.3 http://www.wipo.int/standards/en/pdf/03-03-01.pdf).

5. Modelling Strategy

Our principal hypothesis is that the benefits from targeting R&D at storage technologies are greater than when targeting generating technologies directly. Ideally, the benefits would be measured in terms of increased electricity generating capacity from renewable energy. However, in this preliminary analysis we focus on innovation benefits, reflected in patent yields. The hypothesis is tested through a two-stage econometric model, in which storage patents are estimated first. An energy storage knowledge stock is constructed based on the predicted values from the first stage. This variable is then used in second-stage estimation of patents in generating technologies.

Based on the discussion in Section 3, invention in energy storage is specified by means of the following equation:

$$PAT\_STORE_{it} = f\,(R\&D\_STORE_{it}\,,\ INTR\_PERC_{it}\,,\ INTR\_VAR_{it}\,,\ ELEC\_TRADE_{it}\,,\ PAT\_TOTAL_{it}\,,\ \omega_i\,,\ \varepsilon_{it}) \qquad [1]$$

where *i* indexes country and *t* indexes year. The dependent variable (*PAT_STORE*) represents the number of patent applications in the IPC H01M10 class, classified by inventor country[8] and priority year[9]. The variable represents the number of unique simple patent families worldwide because only claimed priorities and singular applications are counted, hence avoiding double-counting of inventions[10]. (The data source is as discussed above.)

As a control, a variable reflecting the propensity to invent and patent technologies in general (*PAT_TOTAL*)[11] is included as an explanatory variable. It is constructed in a manner analogous to the dependent variable (a count of patent families by inventor country and priority year) with the difference that all types of technologies (not only storage) are covered.[12] In the sample used for econometric analysis, storage patents represent on average only 0.16% of total patents. Nevertheless, in order to avoid any concern over possible endogeneity, regressions are estimated on the difference between the patent total and the dependent variable.

[8] 'Fractional' counts are generated in cases when inventors from multiple countries are listed.
[9] 'Priority date' indicates the earliest application date worldwide (within a given patent family).
[10] Using data on patent families, the following types of documents are distinguished: *Singular* is patent applied for at a single office, with no subsequent filings elsewhere (*i.e.* patent family size=1); *Claimed priority* (CP) is patent for which an application is filed at an additional office to that of the 'priority office"; these are inventions that have been applied for protection in multiple countries (patent family size>1); And finally, *duplicate* is the additional application (OECD 2009).
[11] Ideally, we would estimate the model using a two-stage procedure where total patenting activity is first estimated. This approach was followed in (Haščič *et al.* 2010) and it was found that results from the two-stage estimation were closely comparable with those from a reduced-form model.
[12] This is achieved by extracting data on all patent applications with an (any) IPC code assigned.

Public sector expenditure on R&D in energy storage (*R&D_STORE*) is included as an explanatory variable, expressed in million USD using 2008 prices and PPP. Assuming that such expenditures either result in patented innovations by the public sector, or contribute to patented innovations by the private sector the sign is expected to be positive. The data source is the IEA's *Energy Technology RD&D Budgets* (IEA 2010). The data covers government expenditures for RD&D on batteries, super-capacitors, superconducting magnetic, water heat storage, sensible/latent heat storage, photochemical storage, kinetic energy storage, and other means (excluding fuel cells).[13]

Trade in electricity services (*ELEC_TRADE*) is included as a percentage of electricity production. This variable is intended to capture the extent to which countries are able to compensate for intermittency by importing or exporting electricity services. The lower the level of trade, the greater are incentives for innovation in storage. The variable is constructed as the maximum of imports or exports over total generation. The source of the data is the IEA's *Electricity Information* (IEA 2009b).[14]

The percentage of 'intermittent' energy sources (wind, solar, ocean/tidal) in total electricity supply (*INTR_PERC*) is included to reflect the vulnerability to intermittency. The expected sign is positive. In addition, since the vulnerability to intermittency may be obviated through a more diverse portfolio of sources, a variable is constructed to reflect this variation. The variable (*INTR_VAR*) is constructed as the squared sum of the differences between the percentage dependence on each intermittent source and mean dependence for all intermittent sources. The source of the data is the IEA's *Renewables Information* (IEA 2009c).[15]

Finally, country fixed effects account for omitted country-variant effects that influence the dependent variable in a time-invariant manner. Most notably, this would capture the effect of geographical area, and thus potentially smoothing of intermittent sources. All the residual variation is captured by the error term.

In the second stage, a model of invention in energy generation is specified, broadly following Johnstone *et al.* (2010). The equation takes the form:

$$PAT\_GEN_{it} = f\,(KS\_STORE_{t} \, , ELEC\_PRICE_{it} \, , R\&D\_GEN_{it} \, , GEN\_POLICY_{it} \, , PAT\_TOTAL_{it} \, , \omega_{i} \, , \varepsilon_{it}) \qquad [2]$$

The variable *KS_STORE* is a measure of the stock of knowledge in storage technologies, based on the predicted values from the first-stage. It is constructed as a discounted stock of inventions patented by in-sample countries (global stock), using the perpetual inventory method and a 15% rate of decay (δ).[16] Knowledge stock in the initial year (t_0=1974) is calculated using the average growth rate of inventing activity during the period 1960-1974 ($\bar{g}$). This leaves a 5-year period for the KS to build up before the variable values are used in the second-stage regression. Our hypothesis is that the effect of this variable

[13] http://wds.iea.org/wds/pdf/documentation_RDD.pdf
[14] http://wds.iea.org/wds/pdf/doc_Electricity_2009.pdf
[15] http://wds.iea.org/WDS/tableviewer/document.aspx?FileId=1315
[16] This rate is consistent with others used in the R&D literature (e.g., Popp 2003; Popp et al. 2010). For example, discussing the literature on an appropriate lag structure for R&D capital, Griliches (1995) notes that previous studies suggest a structure peaking between 3 and 5 years. The rate of decay used in this paper provides a lag peaking after 3 years. We also estimated the models using the 5%, 10% and 20% decay rates, but results remain qualitatively robust.

should be greater for intermittent than for dispatchable sources. Formally, the variable is constructed as (for notational clarity, $PAT\_STORE_{it} = y_{i,t}$ and $KS\_STORE_{it} = K_{i,t}$):

$$K_t = \sum_i \hat{y}_{i,t} + (1-\delta)K_{t-1} \qquad [3]$$

$$\text{where} \quad K_0 = \frac{\sum_i \hat{y}_{i,0}}{\bar{g}+\delta} \quad \text{and} \quad \bar{g} = \frac{1}{N}\sum_i \sum_t \frac{\hat{y}_{i,t} - \hat{y}_{i,t-1}}{\hat{y}_{i,t-1}}$$

The renewable energy policy variable (*GEN_POLICY*) is based upon a database of public policies aimed at developing renewable energy sources compiled at the IEA and depicted in Figure 2 above. A composite policy dummy variable is constructed equal to one when any of the six policy types (excl. R&D) were in place and zero otherwise (see also Johnstone et al. 2010). In addition, a variable reflecting national public sector expenditures on energy technology R&D disaggregated by type of renewable energy is included (*R&D_GEN)*, expressed in million USD using 2008 prices and PPP. This is taken from the IEA's *Energy Technology Research and Development Budgets* (IEA 2010). The coefficients on both of these variables are expected to be positive.

We also include a variable reflecting the electricity price (*ELEC_PRICE*). Consistent with the "induced innovation" hypothesis, the commercial viability of renewable energy is dependent in large part upon its cost relative to substitute factor inputs. Since the costs of electricity production using renewable energy sources are generally greater than for fossil fuels, an increase in the *price of electricity* should increase incentives for innovation in the area of renewable energies. Moreover, since renewable sources represent a relatively small proportion of total electricity generation, we make the additional assumption that the price of electricity can be considered exogenous. Data on residential and industry end-user prices was obtained from IEA's *Energy Prices and Taxes Database* (IEA 2009d). The electricity price variable was constructed by weighting the prices for residential and industrial use by their respective consumption levels. It is expressed in USD using 2009 prices and PPP. The sign is expected to be positive for all sources.

And finally, as in the first-stage model, differences in the general propensity to patent between countries and over time are captured through the use of a variable which represents the total number of patent applications (simple patent families) filed across the whole spectrum of technological areas (*PAT_TOTAL*). This variable is intended to capture all of the more general economic factors which are likely to influence patenting activity (e.g. strength of intellectual property rights, administrative costs of applying for protection, business cycle, etc.), but which are not specific to generation technologies. The sign is expected to be positive. Similarly as above, only the difference between *PAT_TOTAL* and *PAT_GEN* is used in actual econometric estimation. Table 1 provides descriptive statistics for the dependent and explanatory variables included in the two panels.

Table 1. Descriptive Statistics for the Panel Dataset

Variable	N	Mean	Std.Dev. Overall	Std.Dev. Between	Std.Dev. Within	Min	Max
First-stage sample							
PAT_STORE	905	29.65	110.25	72.86	82.74	0	1023.75
R&D_STORE	905	3.18	11.26	7.29	8.63	0	149.72
INTR_PERC	905	0.46	1.75	0.93	1.47	0	19.24
INTR_VAR	905	2.14	16.14	7.64	14.20	0	246.66
ELEC_TRADE	905	0.23	0.70	0.64	0.26	0	6.24
PAT_TOTAL *(in '000s)*	905	9.6079	25.3747	20.4371	15.2281	0	209.5509
Second-stage sample							
PAT_GEN							
Wind	748	10.28	27.21	17.51	20.38	0	272.92
Solar	748	21.62	53.82	41.35	32.87	0	528.25
Ocean	748	2.80	7.46	4.46	5.89	0	77.50
All intermittent	748	34.70	84.00	61.73	54.91	0	876.67
Geothermal	748	0.91	2.85	1.65	2.28	0	35.00
Hydro	748	2.57	6.10	3.68	4.79	0	63.25
Biomass/Waste	748	3.88	8.26	6.09	5.38	0	67.50
All dispatchable	748	7.37	15.77	11.31	10.64	0	133.50
R&D_GEN							
Wind	748	5.42	13.34	9.96	8.55	0	160.64
Solar	748	20.33	64.06	43.33	45.88	0	880.19
Ocean	748	1.14	6.77	3.04	5.99	0	97.55
All intermittent	748	26.89	81.45	55.37	58.10	0	1116.11
Geothermal	748	5.85	25.48	15.55	19.76	0	338.30
Hydro	748	0.32	1.12	0.52	0.99	0	10.44
Biomass/Waste	748	7.62	17.67	14.38	9.68	0	200.70
All dispatchable	748	13.47	36.48	29.29	20.40	0	412.87
KS_STORE *(in '000s)*	748	10.9938	18.6764			0.7837	65.0194
ELEC_PRICE	748	0.0916	0.0387	0.0326	0.0227	0.0120	0.2362
GEN_POLICY	748	0.61	0.49	0.27	0.42	0	1
PAT_TOTAL *(in '000s)*	748	11.1724	27.5568	22.0108	15.6636	0	209.5509

Note: The estimation sample includes data 28 OECD countries (AT, AU, BE, CA, CH, CZ, DE, DK, ES, FI, FR, GB, GR, HU, IE, IT, JP, KR, LU, NL, NO, NZ, PL, PT, SE, SK, TR, US) for the period 1974-2007 (first sample) and 1978-2007 (second sample).

In both cases, our dependent variables represent the number of patent applications – patent counts. Count data models, such as the Poisson and negative binomial, have been suggested for estimating the number of occurrences of an event, or event counts (see e.g., Wooldridge 2002; Cameron and Trivedi 1998; Hausman, Hall and Griliches 1984; Maddala 1983:51). Formally, the Poisson model is derived by assuming that a random variable y is Poisson-distributed with the conditional density of y equal to $(y|\mathrm{x}) = \left(e^{-\theta}\theta^{y}\right)y!$, where θ = E[y|**x**]. The log of the mean θ is assumed to be a linear function of a vector of independent regressors x: lnθ = x'β, where β is a parameter vector. This specification ensures non-negativity of θ (Cameron and Trivedi 1998). However, the Poisson specification imposes a heavy restriction on the data – the equality of conditional mean and conditional variance, E[y|x] = V[y|x]=θ, referred to as the equidispersion property of the Poisson. Indeed, as with most empirical data, casual inspection of the sample mean and sample variance in Table 1 indicates that their conditional counterparts are likely to be different for both dependent variables, indicating over-dispersion. One way to account for over-dispersion is the negative binomial model suggested by Cameron and Trivedi (1998). They derive a negative binomial model from a Poisson-gamma mixture distribution (C&T: 100–102). In addition to y being conditionally Poisson-distributed, parameter θ is assumed to be the product of a deterministic term and a random term, $\theta = e^{\mathrm{x}'\beta+\varepsilon} = e^{\mathrm{x}'\beta} + e^{\varepsilon} = \mu\nu$. In other words, the unobserved error parameter (ν) introduces heterogeneity in the variance, and the intensity parameter (μ) is explained (in log) by a vector of explanatory variables (x). Therefore, by assuming a gamma distribution for v (mean 1, variance α) Cameron and Trivedi show that the marginal distribution of y is the negative binomial with the first two moments E[y|μ,α] = μ and V[y|μ,α] = $\mu+\alpha\mu^2$ (for the NB2 variance function, C&T:63). It follows that as $\alpha\rightarrow 0$ the NB model converges to the Poisson distribution with intensity μ. The dispersion parameter α is to be estimated.

Since there are a large number of zeros (37% in the first-stage sample), we also estimate the zero-inflated variant of the negative binomial model in which the count process and the binary process are modelled separately. In this case, the proportion of zeros φ is added to the probability distribution while reducing other frequencies by a corresponding amount with E[y] = $\mu(1–\varphi)$ and V[y] = $(1–\varphi)(\mu+ \varphi\mu^2)$. The proportion φ is parameterised by a logistic transformation of z'γ. The two parameter vectors β and γ are to be estimated (C&T:125-126).

Moreover, we also estimate a number of other count data models – including the (conditional) fixed-effects and random-effects negative binomial (Hausman et al. 1984), the zero-inflated Poisson model (Lambert 1992), and the fixed-effects Poisson quasi-ML (Wooldridge 2002) – and conduct tests to determine which model performs best. Maximum likelihood method is used to estimate the model parameters.[17]

6. Empirical Results

The results of the first-stage estimation are presented in Table 2. The total sample is 905 – an unbalanced sample with 28 countries and 34 years. A series of tests were conducted to determine which model performs best. Based on the 'link' test the negative binomial model performs better than the Poisson model (the dispersion parameter is significantly different from zero). This is also true of their zero-inflated variants, with the zero-inflated negative binomial model performing better than the zero-inflated Poisson model (the same conclusion is reached based on a likelihood-ratio test of alpha comparing the ZINB with the ZIP model). The Vuong (1989) test indicates a marginal preference (at the 8% level of significance) for the ZINB relative to the NB model. And finally, both the Akaike and the Bayesian information criterion (AIC, BIC) provide more robust evidence for the ZINB. Based on these tests, our preferred models are (1) and (2) and further only those results are discussed in detail.

---

[17] We use the zinb, nbreg, xtnbreg, zip, and xtpqml procedures in STATA.

Table 2. Estimated Coefficients of the First-Stage Equation

Dependent variable: *PAT_STORE_it*	Zero-inflated neg. binomial (ZINB)	Negative binomial (NB)	Conditional fixed-eff. NB	Random-effects NB	Zero-inflated Poisson (ZIP)	Conditional fixed-effects Poisson
	(1)	(2)	(3)	(4)	(5)	(6)
R&D exp. on energy storage	0.0125**	0.0143**	0.0048**	0.0049**	0.0053*	0.0054*
% intermittent sources	0.3960***	0.4315***	0.3711***	0.3736***	0.085	0.0906
Diversity in intermittent sources	-0.0353***	-0.0378***	-0.0358***	-0.0359***	-0.0068	-0.0069
Trade in electricity	0.257	0.2571	0.6864*	0.3976	3.9670**	3.8371
Total patents (in ‘000s)	0.0303***	0.0346***	0.0127***	0.0128***	0.0178***	0.0184*
Inflation model (logit)						
R&D exp. on energy storage	-8.571				-0.1821	
Trend	-0.2113***				-0.1182***	
Country dummies	Yes	Yes	-	-	Yes	-
Fixed effects	-	-	Yes	-	-	Yes
Random effects	-	-	-	Yes	-	-
Dispersion (alpha)	0.5716***	0.7044***	-	-	-	-
Number of observations (nonzero/zero)	905 (573/332)	905	905	905	905 (573/332)	905
Variance estimator	Robust	Robust	OIM	OIM	Robust	Robust
Wald chi-sq.	2844.09***	2868.54***	471.91***	484.83***	3959.95***	14285.3***
Log-(pseudo)likelihood	-2092.35	-2124.48	-2024.42	-2211.32	-6820.55	-7271.83
AIC	4258.70	4316.97	4060.85	4438.64	13713.09	14553.66
BIC	4436.59	4480.44	4089.70	4477.10	13886.18	14577.70

* p<0.05, ** p<0.01, *** p<0.001 based on robust standard errors where indicated. Intercepts are included in all models but are not reported here. The estimation sample includes data for 28 OECD countries and 34 years (1974-2007).

Note: The variance-covariance matrix estimator varies depending on the estimation procedure adopted: OIM = observed information matrix; Robust = variance estimator which is robust to some types of misspecification so long as the observations are independent (Source: Stata 11 Users Manual).

As expected public RD&D has a positive and significant impact. Based on the estimated elasticities (Table 3), a 10% increase in public sector R&D results in approximately 0.4%-0.5% increase in patents. Exposure to intermittent generation sources has the expected positive sign and is significant, with an elasticity at approximately 0.2. In addition, diversity in intermittent sources has the expected negative sign and is significant. The elasticity is approximately -0.08. Patenting overall is positive and significant, with an elasticity of approximately 0.3. And finally, the effect of trade is statistically insignificant.

Table 3. Estimated Elasticities

	Zero-inflated neg. binomial (ZINB)	Negative binomial (NB)	Conditional fixed-eff. NB	Random-effects NB	Zero-inflated Poisson (ZIP)	Conditional fixed-eff. Poisson
	(1)	(2)	(3)	(4)	(5)	(6)
R&D exp. on energy storage	0.0397	0.0454	0.1036	0.1580	0.0676	0.0153
% intermittent sources	0.1818	0.1981	1.1506	1.7408	0.0390	0.0371
Diversity in intermittent sources	-0.0755	-0.0809	-0.5176	-0.7804	-0.0146	-0.0132
Trade in electricity	0.0604	0.0604	1.0889	0.9480	0.9319	0.8035
Total patents	0.2907	0.3316	0.8201	1.2401	0.1703	0.1573

Note: Based on conditional marginal effects evaluated at sample means.

For the second-stage estimation of innovation in generating technologies, we report results using both the ZINB and NB models in Table 4 and 5 (in both cases, knowledge stock is constructed based on model 1 from Table 2).[18] The total sample is 748 – an unbalanced sample with 28 countries and 30 years. Again, a series of tests were conducted to determine the best-performing model. The evidence supports the NB model rather than the Poisson, and similarly with the ZINB is preferred to the ZIP. The Vuong test suggests indifference between the ZINB relative to the NB model. Similarly, evidence based on the AIC and BIC criteria is somewhat mixed. Based on these tests we report results of both the ZINB and NB models.

In the second stage separate models are estimated for three intermittent renewable energy sources (wind, solar, ocean) and – for purposes of comparison – three dispatchable sources (geothermal, hydro, biomass and waste). The results are presented in Table 4 (ZINB) and Table 5 (NB) below. The results are as expected with a few exceptions. The renewable energy policy variable is not significant in the wave/tide and geothermal ZINB models, and the R&D variable is not significant for hydro in either model.

In addition, the electricity price variable is negative and sometimes significant, contrary to our expectations. This finding might be explained by a number of factors. On the one hand, the electricity price might be endogenous, with innovation in renewable energy being of sufficient importance to affect electricity prices. On the other hand, there might be interactions between the policy variables and the electricity price that are not adequately reflected in the model. For instance, in the presence of quantity targets (such as renewable energy quotas) a rise in the price of electricity might actually reduce incentives for innovation. Further work is required to explore this possibility.

[18] We also estimate the same set of models when *KS_STORE* is based on model 2. Results remain qualitatively similar with the only differences being that *PRICE* is insignificant and *PAT_TOTAL* is significant for "Ocean" (model 9), and *RD_GEN* in the inflation model is significant for "Biomass-Waste" (model 13). With respect to results reported in Table 5, the only difference is that *PRICE* is insignificant for "Ocean" (model 17).

Table 4. Estimated Coefficients of the Second-Stage Equation (ZINB model)

Dependent variable: *PAT_GEN_it*	Wind	Solar	Ocean	All Intermittent	Geothermal	Hydro	Biomass & Waste	All dispatchable
	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Knowledge stock (in ‘000s)	0.0414***	0.0456***	0.0543***	0.0459***	0.0315***	0.0274***	0.0131***	0.0267***
Electricity price	-0.4814	-4.7272*	-5.6907*	-2.9618	-4.6082	-4.0173	2.5112	-0.7703
Total patents (in ‘000s)	0.0105***	0.0074***	0.0028	0.0091***	0.0039	0.0075***	0.0082***	0.0076***
Specific R&D exp.	0.0148***	0.0030***	0.0160***	0.0025***	0.0049***	0.0609	-0.0071***	0.0023***
Renewables policies	0.4499***	0.1904*	0.2302	0.3102***	0.1704	0.4740*	0.6315***	0.5672***
Inflation model (logit)								
Specific R&D exp.	-0.1396	-0.6857*	-1.0454*	-0.1194**	-0.4911	-2.2744	-18.0636*	-0.3634*
Trend	-0.1227***	-0.3619	-0.1073***	-0.1892***	-0.1560***	-0.063	-0.0006	-0.1856
Country dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dispersion (alpha)	0.4011***	0.3825***	0.3179***	0.3995***	0.4101*	0.5608**	0.3508***	0.3151***
Number of obs. (nonzero/zero)	748 (518/230)	748 (591/157)	748 (369/379)	748 (647/101)	748 (181/567)	748 (347/401)	748 (426/322)	748 (507/241)
Wald chi-sq.	8992.04***	3474.98***	4196.67***	3524.92***		733.97***	1429.47***	1940.60***
Log-(pseudo)likelihood	-1701.33	-1999.73	-1073.91	-2422.99	-546.51	-1085.31	-1207.47	-1550.24
AIC	3476.66	4073.45	2221.83	4919.99	1157.02	2244.63	2488.94	3174.49
BIC	3647.50	4244.30	2392.67	5090.83	1304.78	2415.47	2659.79	3345.33

* p<0.05, ** p<0.01, *** p<0.001 based on robust standard errors. Intercepts are included in all models but are not reported here. The estimation sample includes data for 28 OECD countries and 30 years (1978-2007).

Table 5. Estimated Coefficients of the Second-Stage Equation (NB model)

Dependent variable: *PAT_GEN_it*	Wind	Solar	Ocean	All intermittent	Geothermal	Hydro	Biomass & Waste	All dispatchable
	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)
Knowledge stock (in ‘000s)	0.0431***	0.0456***	0.0567***	0.0457***	0.0644***	0.0286***	0.0239***	0.0261***
Electricity price	-0.3342	-4.5604*	-5.8043*	-1.9907	-6.7569	-3.7443	1.7816	0.0225
Total patents (in ‘000s)	0.0132***	0.0081***	0.0035*	0.0097***	0.0035	0.0076***	0.0088***	0.0082***
Specific R&D exp.	0.0169***	0.0031***	0.0176***	0.0026***	0.0054***	0.0721	-0.0076***	0.0025***
Renewables policies	0.5629***	0.2248*	0.3116*	0.3327***	0.4160*	0.5508***	0.6170***	0.6560***
Country dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dispersion (alpha)	0.6101***	0.4001***	0.4173***	0.4386***	0.6211	0.6906**	0.3881***	0.3612***
Number of obs.	748	748	748	748	748	748	748	748
Wald chi-sq.	8434.0***	3571.4***	7995.3***	3593.1***	20655.5***	1058.4***	1495.5***	2125.6***
Log-(pseudo)likelihood	-1719.76	-2004.32	-1077.80	-2430.85	-553.98	-1086.65	-1209.59	-1558.66
AIC	3507.52	4076.64	2223.59	4929.69	1175.95	2241.29	2487.17	3185.33
BIC	3664.51	4233.63	2380.58	5086.69	1332.94	2398.28	2644.17	3342.32

* p<0.05, ** p<0.01, *** p<0.001 based on robust standard errors. Intercepts are included in all models but are not reported here. The estimation sample includes data for 28 OECD countries and 30 years (1978-2007).

In order to get an indication of the relative magnitude of the effects of the different variables Tables 6 and 7 present the elasticities for the two sets of models. Comparing the results for the "all intermittent" model and the "all dispatchable" model it can be seen that the effect of the energy storage knowledge stock variable is almost twice as large in the former case. Interestingly, the effect of renewable energy policy is smaller for intermittent sources.

Table 6. Estimated Elasticities (ZINB model)

	Wind	Solar	Ocean	All intermittent	Geoth.	Hydro	Biomass & Waste	All dispatchable
	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Knowledge stock	0.3011	0.3323	0.3955	0.3345	0.3459	0.1993	0.1438	0.1946
Electricity price	-0.0441	-0.4331	-0.5213	-0.2713	-0.4222	-0.3680	0.2301	-0.0706
Total patents	0.1169	0.0828	0.0309	0.1012	0.0435	0.0834	0.0918	0.0845
Specific R&D exp.	0.1237	0.0610	0.0616	0.0703	0.1875	0.0488	-0.0538	0.0338
Renewables policies	0.4499	0.1904	0.2302	0.3102	0.1459	0.4740	0.5358	0.5672

Note: Based on conditional marginal effects evaluated at sample means. In the case of the policy dummy, semi-elasticity is reported for a binary 0-1 change.

Table 7. Estimated Elasticities (NB model)

	Wind	Solar	Ocean	All intermittent	Geoth.	Hydro	Biomass & Waste	All dispatchable
	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)
Knowledge stock	0.3141	0.3317	0.4131	0.3328	0.4693	0.2083	0.1738	0.1898
Electricity price	-0.0306	-0.4178	-0.5317	-0.1824	-0.6190	-0.3430	0.1632	0.0021
Total patents	0.1479	0.0907	0.0392	0.1078	0.0391	0.0847	0.0986	0.0914
Specific R&D exp.	0.0917	0.0629	0.0201	0.0692	0.0316	0.0232	-0.0581	0.0343
Renewables policies	0.5629	0.2248	0.3116	0.3327	0.4160	0.5508	0.6170	0.6560

Note: Based on conditional marginal effects evaluated at sample means. In the case of the policy dummy, semi-elasticity is reported for a binary 0-1 change.

In Table 8 we present elasticities for the energy storage knowledge stock variable using different models. The results are consistent, particularly with respect to the relative magnitudes of for intermittent and dispatchable sources.

Table 8. Summary of Estimated Elasticities w.r.t. Knowledge Stock

	Wind	Solar	Ocean	All intermittent	Geoth.	Hydro	Biomass & Waste	All dispatchable
I. Zero-inflated neg.bin. (ZINB)	0.3011	0.3323	0.3955	0.3345	0.3459	0.1993	0.1438	0.1946
II. Negative binomial (NB)	0.3141	0.3317	0.4131	0.3328	0.4693	0.2083	0.1738	0.1898
III. Zero-inflated Poisson (ZIP)	0.3268	0.2752	0.3899	0.3146	0.3707	0.1795	0.1932	0.2213
IV. Conditional fixed-effects NB				0.4698				0.2347
V. Random-effects NB				0.4690				0.2331
Average (I-III)	0.3140	0.3131	0.3995	0.3273	0.3953	0.1957	0.1703	0.2019
Average (I-V)				0.3841				0.2147

What do these results mean for our hypothesis concerning the targeting of R&D? Simulations were run in which a 10% increase in public R&D expenditures was disbursed, with the 'return' (or yield) measures in terms of the increase in intermittent generating technology patents. The expenditure increase was allocated according to three different scenarios:

- Risk minimisation – Allocating the increase to energy storage technologies, i.e. our hypothesised strategy;
- Business-as-usual – Allocating the increase to intermittent generating technologies in a manner proportional to actual portfolio of expenditures by country and by year;
- Perfect information – Allocating the increase to intermittent generating technologies according to which yielded the highest return (patents per dollar) by country and by year.[19]

The funds are allocated over a 20-year period (1981-2000) in the middle of our sample period. The results of the simulation are compared with a baseline set of predicted values (without expenditure shock). The results are presented in Figure 10 below. As hypothesised, the risk minimisation strategy is consistently the intermediate result, performing better than augmented business-as-usual, but worse than perfect information. Governments would generate more innovation capacity in intermittent renewable energy generation technologies if they targeted storage technologies rather than by targeting the generating technologies directly.

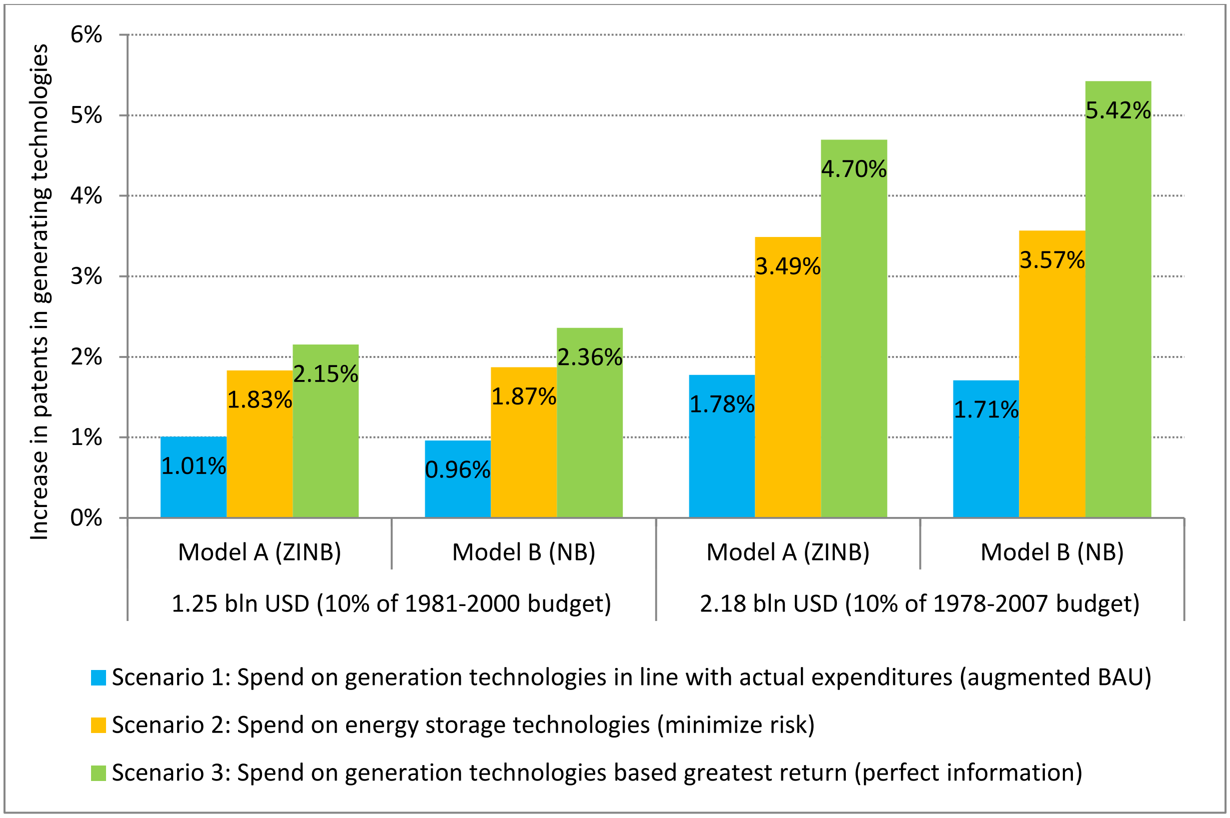
Moreover, it is important to bear in mind that storage is a GPT whose benefits extend beyond their use as complements to intermittent renewable generating technologies. Innovation in this area is also complementary to the development of technologies for electric vehicles and for off-grid applications.[20]

---

[19] In all three cases, the spending shock is allocated over time uniformly every year during the time period concerned, allocated across countries proportionately to countries' effort (budgets) in a given year.

[20] As a robustness check, we also conducted the same simulation exercise using models estimated on a sub-sample with the US excluded (the US is responsible for both a significant share of R&D expenditures and patenting activity). The major difference is a somewhat higher simulated yield overall, for all scenarios, but particularly under scenario 2 (approx. double).

Figure 10. Simulated change in patenting from an increase in targeted R&D
(Effect of a 10-percent R&D expenditure shock spent during a 20-year period 1981-2000)



7. Conclusions and Further Research

In this paper the benefits of targeting R&D expenditures at storage technologies rather than generating technologies have been assessed. It has been hypothesised that such a strategy is preferable for since it is more parsimonious with respect to information requirements for the government. Since innovation in storage technologies is an important complement to innovation in all intermittent renewable generating technologies such a strategy reduces the risks of (not) picking winners. Moreover, the technologies are at a relatively early stage of development, with greater need for public support.

The hypothesis has been tested through the use of patent data, comparing the patent 'yields' when public support is targeted at storage on the one hand and generating technologies on the other hand. In both cases, the yield was measured in terms patents in the generating technologies (and not storage technologies). A two-stage model has been estimated, with innovation in storage technologies estimated in the first stage. The predicted values are used to generate a measure of knowledge stocks in storage technologies, which is then included in the estimation of generating technologies. Simulations are then performed to compare different allocations of a 10% increase in R&D expenditures.

Our hypothesis is borne out by the results. Targeting R&D at storage results in a patent yield in generating technologies which is almost twice the size that would be the case if the additional R&D effort was targeted at the generating technologies themselves in line with past expenditure patterns. Moreover, targeting storage generates yields which are not far from those obtained in a scenario in which the government had benefited from perfect foresight (in terms of maximising patent yields) in the choice of generating technology to support.

However, it must be emphasised that the work is preliminary, and a number of improvements and extensions are envisioned. For instance, further refinement of the search strategy is likely to be possible based upon an improved tagging system developed by the EPO. In addition, it is clear that other efforts which increase grid flexibility such as grid management innovations should be assessed. Similarly, it is likely that different strategies to include power system flexibility (grid extensions and management, storage, trade) are likely to be determined simultaneously, and thus questions of endogeneity should be assessed. And finally, further avenues for research include an assessment of the impacts on generating capacity (and ultimately CO_2 emissions), rather than innovation outputs.

References

Acemoglu, D., Aghion, P., Bursztyn, L. and Hemous, D. (2009). "The Environment and Directed Technical Change", NBER Working Paper 15451.

APS (2010). "Integrating Renewable Electricity on the Grid: A Report by the APS Panel on Public Affairs", American Physical Society, Washington D.C. http://www.aps.org/policy/reports/popa-reports/upload/integratingelec.pdf

Arthur, B. (1994). *Increasing Returns and Path Dependence in the Economy* (University of Michigan Press).

Bosetti, V., Carraro, C., Duval, R. and M. Tavoni (2010). "What Should we Expect from Innovation? A Model-Based Assessment of the Environmental and Mitigation Cost Implications of Climate-Related R&D," CESifo Working Paper No. 2998.

Cameron, A.C. and Trivedi, P.K. (1998). *Regression Analysis of Count Data*. Cambridge: Cambridge University Press.

David, P. and P. Aghion (2008). "Science, Technology and Innovation for Economic Growth: Linking Policy Research and Practice in 'STIG Systems' ", MPRA Paper no. 12096.

Duff, D. and Green, A. (2008). "A Comparative Evaluation of Different Policies to Promote the Generation of Electricity from Renewable Sources", In: S. Bernstein et al. (editors) *A Globally Integrated Climate Policy for Canada* (Toronto, University of Toronto Press).

EPO (2010), Worldwide Patent Statistical Database (PATSTAT), April 2010 edition, European Patent Office.

EurActiv (2010). "EU renewable energy policy", EurActiv.com (Last accessed on 9 November 2010 at http://www.euractiv.com/en/energy/eu-renewable-energy-policy-linksdossier-188269).

Fischer, C., Parry, I.W.H. and W.A. Pizer (2003). "Instrument choice for environmental protection when technological innovation is endogenous", *Journal of Environmental Economics and Management* 45: 523–545.

Griliches, Z. (1990). "Patent Statistics as Economic Indicators: A Survey", *Journal of Economic Literature* 28: 1661-1707.

Griliches, Z, (1995). "R&D and productivity: econometric results and measurement issues", In: Paul L. Stoneman (ed.), *Handbook of the economics of innovation and technological change*, Cambridge, MA: Blackwell Publishers, 52–89.

Gross, R., Heptonstall, P., Leach, M., Skea, J., Anderson, D. and T. Green (2007). "The UK Energy Research Centre Review of the Costs and Impacts of Intermittency", In: Boyle, D. (ed.) *Renewable Electricity in the Grid*, Chapter 4, London: Earthscan.

Hall, P.J. and E.J. Bain (2008). “Energy Storage Technologies and Electricity Generation”, *Energy Policy* 36: 4352-4355.

Haščič, I., Johnstone, N., Watson, F. and Kaminker, C. (2010) Climate policy and technological innovation and transfer: an overview of trends and recent empirical results. OECD Environment Working Paper ENV/WKP(2010)16 (www.oecd.org/env/workingpapers).

Haščič, I., Johnstone, N. and Kalamova, M. (2009). “Environmental Policy Flexibility, Search and Innovation”, *Czech Journal of Economics and Finance* 59(5): 426-441.

Hausman, J., Hall, B.H., and Z. Griliches (1984). Econometric models for count data with an application to the patents-R&D relationship. *Econometrica* 52: 909-938.

Heal, G. (2009). “The Economics of Renewable Energy”, NBER Working Paper No. 15081.

IEA (2010). Energy Technology Research and Development Budgets. OECD/IEA, Paris.

IEA (2009a). Global Renewable Energy Policies and Measures Database. OECD/IEA Paris. (Last accessed on 4 March 2010 at http://www.iea.org/textbase/pm/index_effi.asp).

IEA (2009b). *Electricity Information*. OECD/IEA, Paris.

IEA (2009c). *Renewables Information*. OECD/IEA, Paris.

IEA (2009d). *Energy Prices and Taxes Database*. OECD/IEA, Paris.

IEA (2008). *Empowering Variable Renewables: Options for Flexible Electricity Systems*. OECD/IEA, Paris.

IEA (2005). “Variability of Wind Power and Other Renewables: Management Options and Strategies”, International Energy Agency, OECD/IEA, Paris.

IEA (2004). “Renewable Energy - Market and Policy Trends in IEA Countries”, International Energy Agency, OECD/IEA, Paris.

Inage, S.I. (2009). “Prospects for Large-Scale Energy Storage in Decarbonised Power Grids”, International Energy Agency, OECD/IEA, Paris.

Infield, D. and S. Watson (2007). “Planning for Variability in the Longer Term: The Challenge of a Truly Sustainable Energy System”, In: Boyle, D. (ed.) *Renewable Electricity in the Grid*, Chapter 11, London: Earthscan.

Johnstone, N. and Haščič, I. (2011). “Environmental Policy Design and the Fragmentation of International Markets for Innovation”. In Ghosal, V. (ed.) *Reforming Rules and Regulations: Laws, Institutions, and Implementation*, Chapter 4, pages 79-103, Cambridge, Mass: MIT Press.

Johnstone, N., Haščič, I. and Popp, D. (2010). “Renewable Energy Policies and Technological Innovation: Evidence Based on Patent Counts”, *Environmental and Resource Economics* 45 (1): 133-155.

Lambert, D. (1992). “Zero-inflated Poisson regression with an application to defects in manufacturing,” *Technometrics* 34: 1-14.

Maddala, G.S. (1983). *Limited-Dependent and Qualitative Variables in Econometrics*. Cambridge: Cambridge University Press.

Milborrow, D. (2007). “Wind Power on the Grid”, In: Boyle, D. (ed.) *Renewable Electricity in the Grid*, Chapter 2, London: Earthscan.

Neuhoff, K. (2005). “Large-Scale Deployment of Renewables for Electricity Generation”, *Oxford Review of Economic Policy*, Vol. 21, No. 1.

OECD (2009). “Indicators of Innovation and Transfer in Environmentally Sound Technologies: Methodological Issues”, OECD Environment Directorate, General Distribution Document ENV/EPOC/WPNEP(2009)1/FINAL (www.oecd.org/environment/innovation).

Popp, D., Haščič I. and N. Medhi (2010). “Technology and the diffusion of renewable energy”, *Energy Economics* (forthcoming).

Popp, D. (2003). “Pollution Control Innovations and the Clean Air Act of 1990”, *Journal of Policy Analysis and Management* 22(4): 641-660.

Prado, M. and M. Trebilcock (2009). “Path Dependence, Development and the Dynamics of Institutional Reform”, *University of Toronto Law Journal* 59: 341-379.

REN21 (2008). “Renewables 2007: Global Status Report”, Renewable Energy Policy Network for the 21st century (REN21), Paris: REN21 Secretariat and Washington, DC: Worldwatch Institute.

Sinden (2007) “Renewable Resource Characteristics and Network Integration” In: Boyle, D. (ed.) *Renewable Electricity in the Grid*, London: Earthscan.

Vuong, Q.H. (1989). “Likelihood ratio tests for model selection and non-nested hypotheses”, *Econometrica* 57: 307–333.

Wooldridge, J.M. (2002), Econometric Analysis of Cross Section and Panel Data”, MIT Press, Cambridge, Mass.; London, England.