ENVIRONMENTAL RESEARCH
LETTERS

Induced innovation in energy technologies and systems: a review of evidence and potential implications for CO_2 mitigation

To cite this article before publication: Michael Grubb *et al* 2021 *Environ. Res. Lett.* in press https://doi.org/10.1088/1748-9326/abde07

Induced innovation in energy technologies and systems

a review of evidence and potential implications for CO_2 mitigation

Invited submission to *Environmental Research Letters*
Special Issue: Focus on Evidence Synthesis for Climate Solutions

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Cite: Grubb M., P.Drummond, A.Poncia, W.McDowall, D. Popp, S.Samadi, C.Penasco, K.Gillingham, S.Smulders, M. Glachant, G.Pavan, G.Hassall, E.Mizuno, E.Rubin, A. Dechezlepraitre (2020). Induced innovation in energy technologies and systems a review of evidence and potential implications for CO2 mitigation, *in review with Environmental Research Letters*

Funding acknowledgement.
This work was supported by the Institute of New Economic Thinking, Washington DC (https://www.ineteconomics.org/), Grant ID #INO19-00004, *"Induced innovation in energy and industrial systems: Evidence and implications for climate change policy"*

Abstract

We conduct a systematic and interdisciplinary review of empirical literature assessing evidence on induced innovation in energy and related technologies. We explore links between demand-*drivers* (both market-wide and targeted); *indicators of innovation* (principally, patents); and *outcomes* (cost reduction, efficiency, and multi-sector/macro consequences). We build on existing reviews in different fields and assess over 200 papers containing original data analysis.

Papers linking drivers to patents, and indicators of cumulative capacity to cost reductions (experience curves), dominate the literature. The former does not directly link patents to *outcomes*; the latter does not directly test for the causal impact of on cost reductions). Diverse other literatures provide additional evidence concerning the links between deployment, innovation activities, and outcomes.

We derive three main conclusions. (1) *Demand-pull forces enhance* ***patenting***; econometric studies find positive impacts in industry, electricity and transport sectors in all but a few specific cases. This applies to all drivers - general energy prices, carbon prices, and targeted interventions that build markets. (2) ***Technology costs*** *decline with cumulative investment* for almost every technology studied across all time periods, when controlled for other factors. Numerous lines of evidence point to dominant causality from at-scale deployment (prior to self-sustaining diffusion) to cost reduction in this relationship. (3) ***Overall Innovation*** *is cumulative, multi-faceted, and self-reinforcing in its direction* (path-dependent). We conclude with brief observations on implications for modeling and policy.

In interpreting these results, we suggest distinguishing the economics of active *deployment*, from more passive *diffusion* processes, and draw the following implications. There is a role for **policy diversity and experimentation,** with evaluation of potential gains from innovation in the broadest sense. Consequently, **endogenising innovation in large-scale models** is important for deriving policy-relevant conclusions. Finally, seeking to **relate quantitative economic evaluation to the qualitative socio-technical transitions literatures** could be a fruitful area for future research.

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1. Introduction

The last few decades have seen a huge growth of literature around the economics of technological innovation from diverse perspectives. A common theme is that innovation is at least partly entwined with, not separate from, economic and policy conditions - it can be *induced* by these factors. This could have important implications for the economic effects of, and policy strategies towards, deep decarbonisation - as suggested most powerfully by the rapid development of modern renewable energy technologies.[1]

However, innovation processes are complex and hard to model. Most national energy-economy models, and large-scale global Integrated Assessment Models (IAMs) that seek to represent global energy systems and their economic and environmental interconnections, often take energy technology cost developments as *exogenous*. In this case, any projected improvements are input directly in assumptions, arriving like 'manna from heaven' in terms of modelled future cost reductions. In addition (and perhaps, partly in consequence), there is often also controversy over the use of innovation-related arguments to justify policies which promote (currently) more expensive technologies (OECD, 2013).[2]

This is partly because of complexity, in both modelling and policy appraisal, but also because the evidence base on induced innovation remains diverse and sometimes disputed, and quite poorly characterised. Gillingham, Newell, & Pizer (2008) concluded a decade ago, following an extensive review of the representation of innovation dynamics across a range of IAMs that "our ability to conceptually model technical change has outstripped our ability to validate models empirically."

It is almost a decade since Kemp & Pontoglio (2011) described studies of the innovation effects of environmental policies in terms of the "blind man and the elephant", and called for mixed-methods approaches to try get a fuller picture of innovation processes. This paper aims to answer that call, through a systematic review of the *empirical* literature on induced innovation in low-carbon and energy-efficient technologies: specifically, the evidence on the extent to which 'demand-pull' forces induce technological innovation. Such literatures tend to be quite disparate, using sometimes radically different methodologies to look at different aspects or metrics of innovation processes.

Most of the studies included in well-known reviews such as Popp, Newell, & Jaffe (2010), extended in Popp (2019) use patents as the major indicator of innovation, as does the widely-cited analysis of the automobile sector by Aghion et al (2016). These represent the tip of iceberg of hundreds of studies, which in this review we note now constitutes an emerging literature quantifying the 'elasticity' of patent generation with respect to market prices.

There is little overlap between these studies and the more engineering-based experience curve literature which maps correlation between cumulative deployment[3] and cost reduction, as reviewed for example for energy supply technologies by Rubin, Azevedo, Jaramillo, & Yeh (2015) and Samadi (2018), and for energy-demand-side technologies by Weiss et al (2010). We do not seek to duplicate

[1] By 2017 solar PV costs had fallen below what experts had earlier predicted for the year 2030 (Nemet, 2019). Auctions in many countries since then have seen prices below the cost of conventional power generation (Bloomberg/CFLI, 2019). See also Section 6.

[2] "Market-based approaches like taxes and trading systems consistently reduced CO_2 at a lower cost than other instruments. Capital subsidies and feed-in tariffs were among the most expensive ways of reducing emissions." (OECD, 2013)

[3] Cumulative deployment is generally interpreted as the total capacity manufactured or installed over time. Much literature also uses the terms deployment and diffusion almost interchangeably; this paper suggests a distinction between these (Sections 2 and 9).

these reviews, but rather, to complement them by exploring also evidence around cause-and-effect from disparate sources, including quantitative (econometric), qualitative and mixed-methods studies.

In covering these other literatures, and by setting both patent and experience curve metrics in a wider view of innovation in our discussion (section 8), we also explain the limited overlap between these two disparate quantitative literatures, arguing that to a significant degree they measure different parts of overall innovation processes.

Other reviews explore the impacts of different energy-climate policy instruments on varied outcomes including innovation, such as Peñasco, Anadon, & Verdolini (*Accepted*) and del Rio & Bleda (2012). Our topic also has some overlap with reviews of the Porter Hypothesis – the idea that environmental regulation could stimulate improved corporate performance (e.g. reviews by Cohen & Tubb, 2018; Ambec, Cohen, Elgie, & Lanoie, 2013**)– but only to the (limited) extent that those reviews cover studies that assess the 'weak' and 'strong' forms of Porter Hypothesis for *technologies* (as opposed to business practice) in *energy* (Section 8, note 32).

Our review thus aims to provide a uniquely broad coverage of findings from disparate areas that have so far mostly been studied in isolation. It offers a first attempt to systematically review the empirical evidence for energy technology innovation induced by demand-pull factors across these literatures. We also explore the major factors that give rise to demand-pull phenomena. From this, we seek to provide a much fuller picture of the nature, drivers and potential implications of induced innovation, with particular relevance to the challenges of modelling and policy for deep decarbonisation.

We start by outlining a general framework for understanding some of the different 'parts of the elephant' in Section 2. Section 3 describes our focus and methodology, and Section 4 the broad characteristics of the literature found. Section 5 presents our findings concerning the impact of market-wide drivers (focusing upon energy prices and carbon pricing). Section 6 summarises the main findings concerning the role of targeted demand-pull policy instruments, in the context also of literature on experience curves, delving into the specific conclusions concerning different component influences; Section 7 considers the cross-cutting and survey literature on policy mixes. Section 8 considers emerging literature on macro-economic dimensions. In Section 9 we draw together these findings into broader integrated conclusions about the evidence on induced innovation, and finally in Section 10, we discuss the primary conclusions and implications for energy system decarbonisation modelling and policy.

2. Context: innovation processes in energy technologies

Innovation is generally understood to be the outcome of a system of interacting actors, technologies and institutions (Freeman, 1987; Gallagher et al., 2012; Hekkert, Suurs, Negro, Kuhlmann, & Smits, 2007). Within that systemic context, new technologies typically undergo a process of maturation, from invention, through innovation and diffusion: in this broad characterisation, *we interpret innovation as the multiple processes that improve the realised characteristics of a technology (including cost) as it evolves from invention to widespread diffusion.*

The resulting concept of an 'innovation chain' is depicted in Figure 1. This emphasises the different stages, the feedbacks between them, and the way that innovation in a given technology is situated within the broader innovation system context comprising the knowledge processes, adoption stages, actors, and financial resources involved, all of which of course also interact.

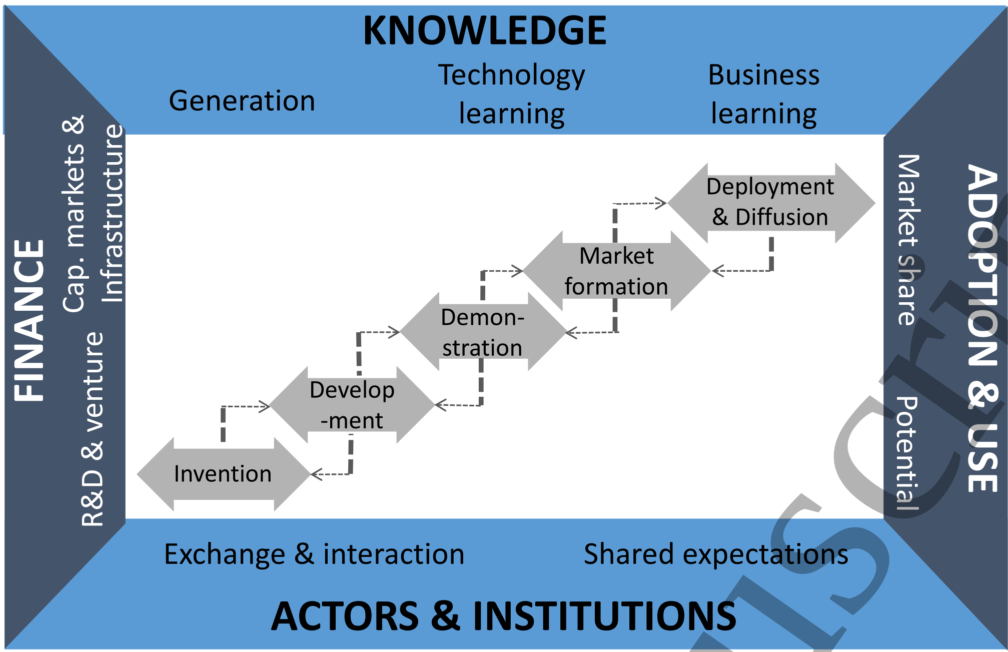

Figure 1: The innovation chain, with feedbacks and broader context

Source: Adapted from Grubler & Wilson (2013), with authors' permission

Innovation studies traditionally distinguish between 'technology-push' policies (for example, research grants that directly aim at increasing the supply of innovation) and 'demand-pull' factors that create a market for innovations. Figure 2 represents schematically the shift from technology-push to demand-pull as a technology matures, and correspondingly, often from mainly public to primarily private funding (this simplified linear form does not capture the feedbacks, but the fact remains that any technology needs to pass through all these stages to reach maturity).

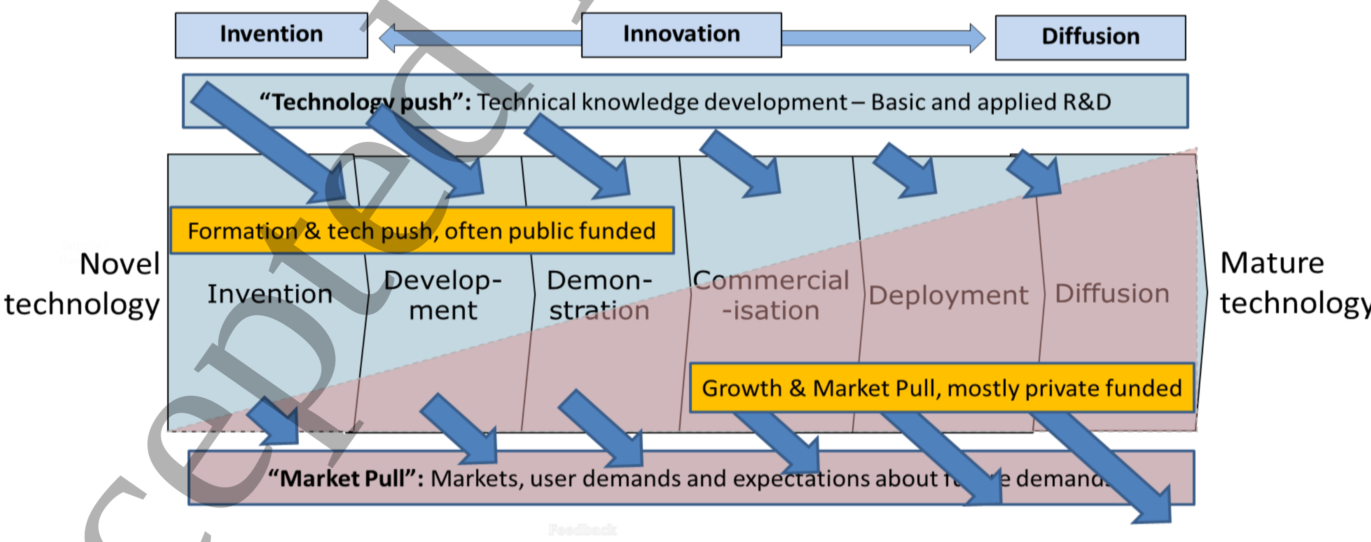

Figure 2 Innovation chain from novel to mature technology, technology push and market pull

The impact of demand-pull on innovation likely varies across sectors and will reflect, to an important degree, how well the stages – the 'push' and 'pull' - are connected in each sector depending on their characteristics. Sectors that are commonly recognized as highly innovative, like IT and pharmaceuticals, typically spend 10-15% of their turnover on R&D (though in practice they still draw heavily on underlying public R&D).[4] Grubb et al. (2014)** suggest that in these sectors, demand-pull is intrinsically a powerful force for innovation because there is high product differentiation, with huge profits for successful new products. Moreover, for IT at least, the 'technology-push' is (or at least was) relatively cheap and rapid. The profits from the Apple Mac and iPhone alone, with product innovation and expansion through rapid cycles, were enough to propel Apple to being one of the biggest companies in the world.

Energy is different. Some of the major energy-using sectors, notably industry and transport, have R&D intensities typically around 3-5% of turnover; the energy supply sector itself has traditionally spent less than 1% of its turnover on R&D, a huge discrepancy underlined by Grubb, Hourcade, & Neuhoff (2014, Chapter 9)**.[5] In these sectors, more efficient energy-using technologies generally have to compete on the basis of energy cost, rather than offering new and better functionality. Energy supply technologies tend to be big, complex, expensive and slow to develop; and new entrants must sell into established markets dominated by incumbent industries selling the same product – electrons, or hydrocarbon molecules. Neither has scope for supernormal profits. A broad literature exists on energy supply technologies and the 'technology valley of death', reflecting large risks and much reduced incentives for private innovation.

This specificity of the energy sector does not make demand-pull forces irrelevant - indeed, that same literature cautions against the state simply trying to substitute with stronger technology-push (for a recent review, of literature and case studies on both the 'valley of death and the technology pork barrel', see Nemet et al., (2018))**. It does, however, justify the need for a detailed evaluation of the evidence around how and when demand-pull forces have influenced innovation in energy specifically, and the role of varied forms of public demand-pull policy.

The classic innovation chains as presented in Figure 1 suggests a simple step from market formation to diffusion and justifies a focus on the 'RD&D' stages – addressing the classically recognized market-failure of spillover – assuming that the market can then take over. In Figure 2, however, we indicate between these, a discrete step of *deployment* (and to enhance clarity, suggest the preceding step as the *commercialization* dimension of market formation). The literature often treats deployment and diffusion as almost synonymous. In drawing conclusions from the literature (notably, sections 6 and 8), we articulate why it seems useful to distinguish a distinct step in which a technology is deployed at scale, *before* it is cost-competitive with incumbents (without targeted support) . As a technology – perhaps in combination with changes in the surrounding system – becomes more inherently competitive, it thus enters the phase of self-sustaining diffusion.

3. Focus and Methodology

Systematic reviews use a clear *a priori* strategy for obtaining literature, and standardised process of extracting and synthesising findings (Uman, 2011). The requirement for transparent research design and justification of study exclusion criteria aims to improve replicability and rigour of the review (Pullin, Frampton, Livoreli, & Petrokofsky, 2018; Tranfield, Denyer, & Smart, 2003). In this section we

[4] In *The Entrepreneurial State* (Mazzucato, 2012))** underlined that in fact government spending has had a hugely important role in contributing, for example, to the technologies underpinning the iPhone.

[5] Literature comparing innovation across sectors seems limited, but the observation goes back at least 20 years; Frank et al (1996)** observed that energy/environmental technologies received barely 2% of US Venture Capital, compared to over 15% in each of biotech, health, and telecoms – remarkably similar to the data on R&D spend reported in Grubb et al. (2014)**.

clarify the focus, and the three stages of review as guided by Pullin et al. (2018) guidelines for evidence synthesis: search strategy; screening; and data extraction.

Against the background sketched above, we made four choices regarding the scope of this review:

First, our focus is on *innovation in low-carbon and energy-efficient technologies* including both new products and new production processes, with ‘innovation’ reflected by ‘indicators’ of innovation activities and ‘technology outcomes’ mainly in terms of cost reduction and energy-efficiency improvements. Although the set of potential indicators of innovation activities in the scope of our review is wide, the available literature is heavily skewed towards a rather narrow range of indicators of innovation processes. There is a need to develop data on wider range of innovation activities, including those related to private R&D, finance, technology characteristics, firm entry and exit dynamics, and others. This is important for developing a clearer picture of the diverse processes that underpin energy innovation, as discussed in Sections 9 and 10. We do not consider other ways in which innovation may generate qualitative changes in the services provided by energy technologies (e.g. ‘smart’ energy appliances).

Second, we explore the role of *‘demand-pull’ factors* in driving innovation, including both energy prices and policy instruments, ranging from those correcting broad market failures (e.g. carbon pricing) to more targeted instruments (e.g. feed-in tariffs). We have *not* sought to include studies that focus solely on the impacts of ‘technology push’ (i.e. publicly-funded RD&D) – for which the purpose, of driving innovation, is self-evident and evaluated in other literatures - nor do we attempt to weigh the relative importance between ‘demand-pull’ and ‘technology-push’ influences.

Third, we have not directly examined the impact of demand-pull drivers on the simple diffusion of technologies, nor on changes to firm-level competitiveness (the Porter Hypothesis literature), to maintain our core focus on innovation in technologies and technological systems, and avoid conflation with issues of individual and organisational behaviour.

Finally, beyond the usual scope of energy-innovation studies, we also review the literature that examines macro-level indicators of innovation induced by demand-pull factors, to explore whether innovation in specific technologies has produced a measurable impact at sector and economy-wide levels.

Because a primary interest of this review is to explore *how*, as well as *if*, demand-pull factors induce technology innovation, we include econometric, qualitative and mixed methods empirical studies in our review. Whilst the econometric literature may demonstrate correlations or connections between factors, it is less suited to empirically exploring *why* they are connected. For the qualitative and mixed-methods literature, the opposite is generally the case.

Relational components of the innovation process

We structure our review based on the framework shown in Figure 3. We delineate Demand-pull Drivers, Innovation activities and Innovation Outcomes as numbered nodes in the innovation process. The focus of the review, and consequently on our literature search strategy, is on the nature of the links between these nodes. We term these links ‘Search-Links’, and denote them using numerals. The search links are described as follows.

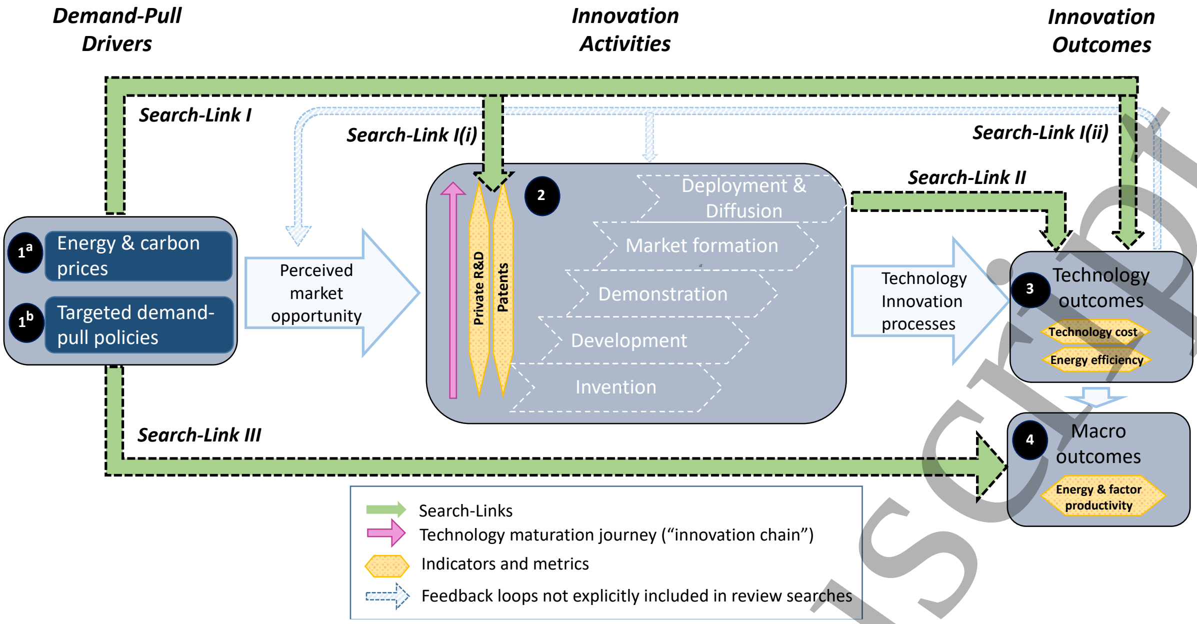

Figure 3. Innovation interactions: drivers, activities and outcomes

- ***Search-Link I (SL-I):*** the impact of demand-pull drivers (**1**) on innovation *activities* - the compressed innovation chain represented by (**2**) - and *outcomes* (**3**). The literature on the former is large and dominated by patent-based studies; fewer look at outcomes such as cost. The Drivers cover both market-wide (energy and carbon) prices (1a) and targeted policies and instruments (1b); the links covered include how these drivers impact both activities (SL-I(i)), and innovation outcomes (SL-I(ii)).
- ***Search-Link II (SL-II)***: The impact of (often cumulative) deployment, the final element of (**2**), on innovation outcomes (**3**), in particular cost reduction, drawing most directly from the 'experience curve' literature, along with other literatures which examine cost decompositions, and qualitative studies.
- ***Search-Link III (SL-III)****:* Sector- or economy-wide 'macro' outcomes (such as energy productivity) (**4**) that can be attributed to technology innovation induced by demand-pull drivers (**1a** and **1b**)

These distinctions inform the design of our literature search methodology. Our review is limited to published, English-language, peer-reviewed, academic journal articles that report empirical analysis of the relationships described above. The review did not impose any geographical or temporal constraints, nor is the review restricted to any particular form of analysis.

Search Strategy

Search terms for each of the three Search-Links described in Section 3 were developed iteratively through author suggestions, trial database searches, and consultation with external subject-matter experts (principally Lead Authors in the IPCC's 6th Assessment Report, through an information meeting in April 2019). Terms for each Search-Link were tested individually, and those which either had no impact on the number of returned articles, or resulted in a large number of irrelevant results, were substituted or excluded. Specific points about the Search strategy to note:

Search-Link I: Demand-pull drivers to innovation activities and technology outcomes. The major market-wide drivers comprise energy prices and carbon prices.[6] Targeted demand-pull policies identified through author consultation were dominated by feed-in-tariffs, renewables portfolio standards and auctions[7].

Search-Link II: Deployment to technology outcomes. Due to the high volume and low specificity of results pertaining to searches of technology deployment/diffusion and innovation outcome and indicator terms, our approach to Search-link II focused on energy and decarbonisation technologies directly, using a similar consultation and testing process, which we combined with 'learning' process terms to capture relevant experience curve literature.

Search-Link III: Demand-pull drivers to macro outcomes. This extends the Search-Link I terms to include macro-level outcomes and related terminology using the 'OR' and 'AND' Boolean functions, with results largely a sub-set of results from Search-Link I, though 'macro' studies that were retrieved by Search-Link I but were not included in this sub-set were subsequently transferred during screening (a total of 40, of which 17 were retained).

Table 1 presents *example* search terms for each link. For a full list of search terms, see Appendix I.

Table 1: Structure of literature search strategy with example terms

Search-Link	Search string structure	Example search terms[a,b]
SL-I: Demand-pull drivers (**1a** & **1b**) → innovation activities (**2**) & technology outcomes (**3**)	[*market-wide drivers* OR *demand-pull policies*] AND [*innovation activities* OR *innovation outcomes*]	• energy regulat* • carbon trad* • oil pric* • cost reduc* • increase* productivity • patent
SL-II. Deployment & diffusion (**2**) → innovation outcomes (**3**)	[*energy generation, efficiency* OR *decarbonisation technologies*] AND [*Technology innovation processes*]	• wind • carbon capture • fuel cell • batter* • learning-by-doing • experience curve
SL-III: Demand-pull drivers (**1a** & **1b**) → macro- outcomes of technology innovation (**4**)	[*market-wide drivers* OR *demand-pull policies*] AND [*innovation activities* OR *innovation outcomes* OR *macro-level innovation indicators*] AND [*macro-level terms*]	• aggregate technology stock • capital accumulation • structural change • absorption capacity • endogenous growth

[a] full search strings given in Appendix I
[b] '*' indicates truncation

Searches were conducted for each link between April and June 2019 in the Web of Science Core Collection database, selected for its comprehensive coverage of science and social science literature. Terms were formulated into Boolean search strings, using term truncation where appropriate to allow

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[6] Our original search included terms regarding market structures (particularly related to liberalisation and the degree of competition). We concluded that the literature in this area was too diverse, as were the results (showing no consistent relationships of market structure to innovation partly because of national specificities), to draw useful conclusions in the context of this review.

[7] The following energy-related demand-pull policies were explicitly searched: auctions, efficiency and technology standards, renewables certificates, renewables portfolio standards, time-of-use pricing, taxes and trading, feed-in-tariffs, network regulation, capacity mechanisms, consumer subsidies, though any returned demand-pull policy was considered in-scope during article screening.

for flexible word permutations. In total, 4,798 results were generated (dominated by **SL-I**, which returned 3,431 results).

Literature Screening

Studies were considered in-scope if they i) related to energy generation technologies, the energy use or efficiency of energy-using technologies, technologies for energy efficiency, or low carbon technologies, ii) examined the influence of demand-pull drivers on innovation, iii) were based on empirical evidence and presented original analysis, and iv) were published in an English-language peer-reviewed academic journal. For SL-II, studies on demand-side technologies were considered in scope if the deployment and diffusion of the technology may be reasonably considered an intentional result of government policy targeting decarbonisation or energy efficiency. This allows the link between demand-pull drivers of innovation, and innovation outcomes, to be maintained.

Studies were screened against these criteria (applied in parallel) first by title, then abstract, then whether or not they had been subject to peer review, and finally by full text. If at any stage at least one of the criteria was found not to be met, the study was screened out. In cases of uncertainty, a precautionary approach was taken and articles were retained to the next stage. Literature screening was carried out by two of the principal authors. These authors worked closely together and conduced double-coding of a random selection of studies to ensure consistency of approach. The final pool of studies were then distributed for data extraction and synthesis to different author sub-teams (depending on specialisation and interests), facilitated by the sub-division of demand-pull drivers into market-wide (energy and carbon) prices (1a) and targeted policies and instruments (1b). Owing to the very different nature of their research approach, qualitative and mixed method studies were separated and reviewed independently from quantitative literature. This left five categories of studies that were evaluated separately by the author sub-teams, as summarised in Table 2.[8]

Table 2: Screening statistics

		Screening Stage				
Search-Link	**Evaluation Group**	**Initial results**	**Titles**	**Abstracts**	**Peer review**[9]	**Full texts**
SL-I(i)	Energy and carbon prices → innovation indicators & outcomes (SL-I quantitative)	1181	133	85	77	30
SL-I(ii)	Targeted policies → innovation indicators & outcomes (SL-I quantitative)	2250	320	189	166	36
SL-II	Deployment → cost reduction (experience curve and related quantitative literature)	1082	205	92	92	63

[8] Studies relevant to a particular evaluation group that were picked up by an alternative Search-Link were transferred for evaluation as appropriate. In cases where a study was relevant to more than one evaluation group, it was reviewed under both groups though only the distinct relevant data was extracted by each in order to avoid duplication.

[9] This explicit step was added to remove studies that are contained within Web of Science, but were not published in a peer-reviewed academic journal (e.g. conference proceedings).

SL-I and SL-II	Qualitative and mixed-method literature	(identified from above)	129	107	107	50
SL-III	Demand-pull drivers (1a and 1b) → macro-level indicators of technological change	285	67	62	60	26
	Total	**4798**	**854**	**535**	**502**	**205**

Table 2 shows how the various screening stages reduced the initial pool of 4,798 results to 205 satisfying the inclusion criteria at the final screening stage. More than 80% of the studies initially retrieved across all searches were excluded during the title screening stage, mostly because they were not related to energy or decarbonisation technologies (especially for SL-I, where the search terms contained no specific constraint for energy generating, energy efficient or low carbon technologies). A further 7% of the initial pool were excluded following the review of abstracts, frequently due to either a lack of focus on innovation, or on the influence of demand-pull drivers. The remainder of exclusions were generally due to the lack of empirical evidence or (in a few cases) unclear methodologies, discovered when reviewing full texts of the remaining studies.[10] Accounting for studies included in more than one Search-Link, a total of 197 unique studies were included in the final review.

Studies that were bought to the attention of the authors during the course of the review, and which satisfied the inclusion criteria but did not appear in the initial search results, were subsequently added. An additional 31 studies were added this way, producing a final pool of 227 studies (with a total of 239 results across the five Search-Link categories, including overlaps).[11]

Data Extraction

Following standard practice (Cohen & Tubb, 2018; Pullin et al., 2018), publication-level information (authors, title, year of publication), scope of analysis (geographical, technological, temporal), methodological description (data source and observations, key variables, methodology, utilisation of instrumental and lagged variables, robustness) and results (description, effect sign, effect size, significance), were extracted for each study considered to be in in scope. Cross-author consistency was tested through trial data extractions for a common set of studies, and the coding strategy was clarified or modified accordingly.

4. Overall characteristics of the literature

[10] Our initial search also included studies around energy market liberalisation and competition, later excluded (see Note 6). Seven further studies were subsequently screened out on this basis (from SL-I), and are excluded from the 'Full Texts' values in Table 2.

[11] From Section 5 onwards, single asterisks (*) indicate studies added to the review in addition to those produced by our systematic search, through subsequent review and discussion with co-authors and others, and which satisfy the eligibility criteria outlined above. These studies are included in the statistics presented in Figure 4, below. Studies denoted by a double asterisk (**) are studies that fall outside the formal scope of the review, but which are cited to provide wider context to the discussion. Such studies are not included within the statistics reported in Figure 4.

Figure 4 provides a summary of the characteristics of the resulting literature included in the review.

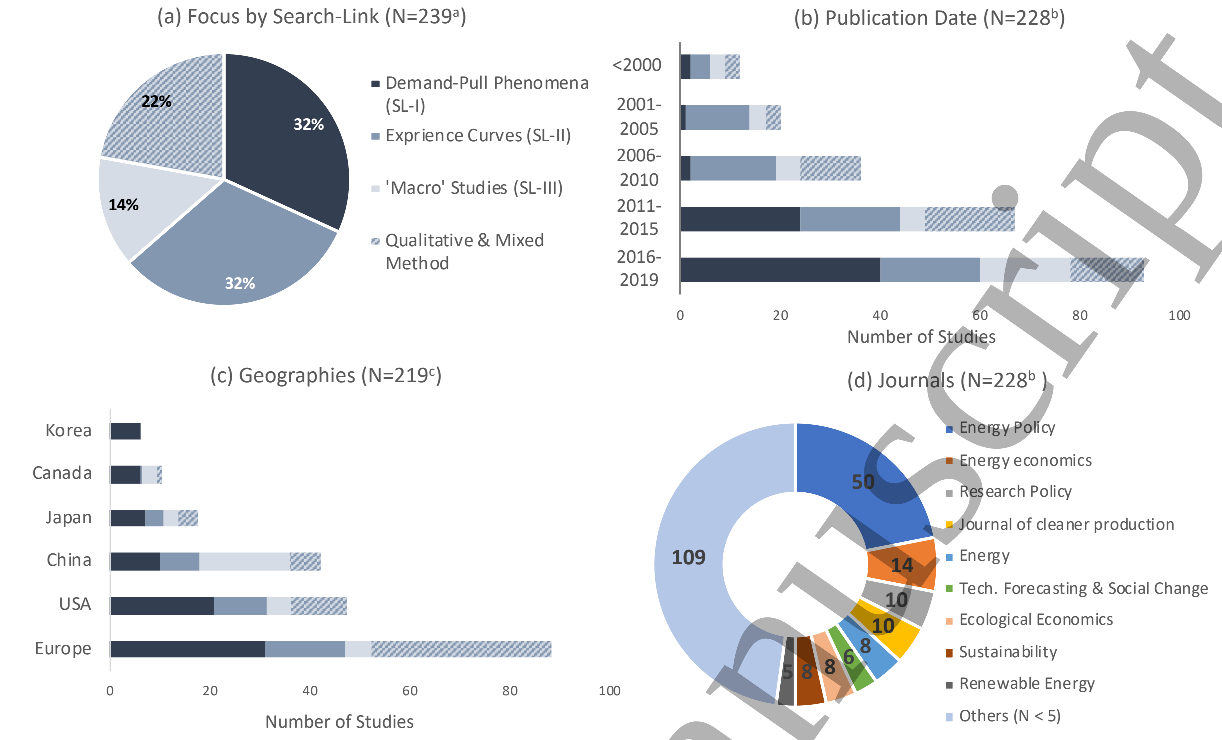

Figure 4: Characteristics of studies reviewed

Notes: [a]cumulative number of studies across Search-Links, including overlapping studies; [b]total number of unique studies, excluding overlaps; [c]value represents total number of results for geographies shown, excluding overlaps between Search-Links. Geographies with <5 results are excluded from this chart. The total number of geographies examined is higher than the number of studies, as some studies examine more than one geography. For experience curve studies that examine global-level dynamics, geography is associated with the source of the cost data used.

As illustrated by Figure 4a, studies most commonly examined SL-I (76), with a reasonably even division between drivers 1a and 1b. The vast majority of these used indicators of innovation (rather than outcomes) – and particularly patent activity – as the dependent variable. 76 studies examined SL-II, with a dominant focus on experience curves in renewable energy technologies. Just 34 studies examined SL-III. In total, around a quarter of studies (53) across all search-links employed qualitative or mixed-method approaches. Analysis of OECD countries accounted for around three-quarters of all studies, with Europe and the USA dominant, and with non-OECD country studies overwhelmingly concentrated on China (for which studies examining SL-III had a particular focus). Over 40% of all studies reviewed examined innovation surrounding renewable energy technologies, with the remainder examining innovation across a range of sectors and technologies – but with particular attention on the manufacturing, automotive and buildings and appliances sectors.

Figure 4b shows that the majority of studies were published within the last decade (with almost half published since 2016), with studies examining SL-I driving this trend (although studies examining LIII increased substantially since 2016, with little earlier literature apparent, implying a nascent yet expanding field). Studies were published in 82 different journals (73 of which published four or fewer of the studies reviewed, and 53 of which published just one). As illustrated by Figure 4d, *Energy Policy* was by far the most common, publishing over 20% all studies reviewed.

The following sections present our specific findings. From a standpoint of modeling and policy, the issues of greater interest concern which factors influence innovation. Consequently, Section 5 assesses the evidence concerning the impact of *sector/market-wide* drivers (**1a:** specifically, energy and carbon prices), whilst Section 6 explores the conjoined evidence around the impact of *targeted policies and deployed scale* **(1b and SL-II)**. Section 7 considers policy packages and Section 8 considers the *macro* impact of induced innovation in the energy sector (**SL-III**).

5. The impact of energy and carbon prices on energy-related innovation

5.1. Overview

In a relatively early study of the effects of the substantial rise in energy prices during the energy crisis of the 1970s, (Lichtenberg, 1986, p.75) found that "Energy price increases appear to have induced innovation [measured by private R&D expenditure] both directly, via their impact on the [U.S manufacturing firms'] own energy costs, and indirectly via their impact on customers' costs".

Subsequent research has tended to focus more on patent generation as an indicator of innovation induced by energy price dynamics. Relative to data on private R&D, patent data are both more widely available and provide greater detail on the types of innovative activity (Popp, 2019)**. The greater variety and granularity of such data, over a broader range of technologies and longer time periods, has buttressed and elaborated the broad conclusion that increasing energy prices induces greater levels of innovative activity surrounding demand-side technologies.

In addition to expanding patenting across fossil fuels and many energy using technologies, the past quarter century has seen an explosion of patenting across most low carbon technologies, which as indicated in Figure 5 grew almost exponentially (except for nuclear) from the late 1990s to 2010. The overall volume was dominated by PV and electric vehicles, with wind, batteries and biofuels patents also rising sharply 2005-2010 (to the range 1000-2000 patents/year). Oil and gas exploration patents followed a somewhat similar pattern. Since peaking in the early 2010s, patent counts for most energy technologies have fallen, although they remained at higher levels than in 2005.[12]

Compared to the twenty-seven studies (quantitatively) analysing the impact of energy and carbon prices on patents, we identified only three which examined explicitly their impact on innovation *outputs* (i.e. technology cost or performance), namely Taghizadeh-Hesary et al. (2019); Kim et al. (2017); and Newell et al. (1999).

[12] Patenting for oil and gas exploration & development technologies (drawn also from OECD patent stats, but a different database) was higher until the early 2000s (rising from about 400/yr to 750/yr over 2000-2005), and also then increased but not to the same extent; after a peak in 2013 they also declined sharply. While a few recent working papers consider possible explanations for the recent decline in energy patenting (e.g. Acemoglu, Aghion, Barrage, & Hemous, 2019; Ko, Simons, Adams, Popp, & Sanderson, 2020; Popp, Pless, Haščič, & Johnstone, 2020)**, the literature does not yet offer definitive conclusions.

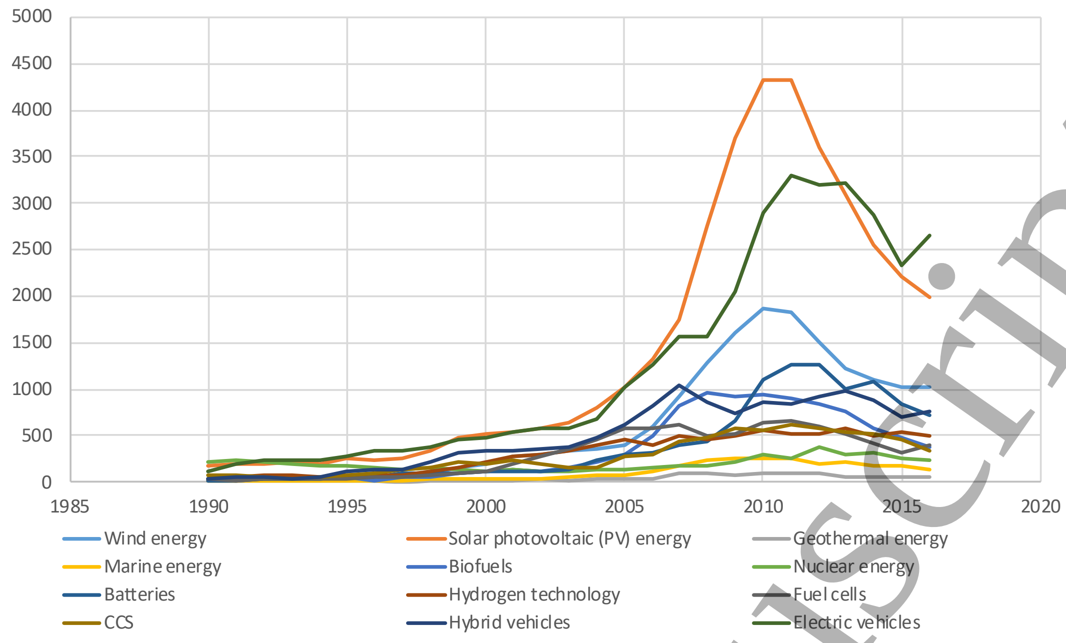

Figure 5: Low carbon patents from 1990 by technology. The figure shows patent families (family size ≥ 2) by priority date, with technologies identified using the CPC-Y02 classes. The data was taken from the OECD database of indicators of innovation in environment-related technologies.

Source: (OECD, n.d.)

Patent elasticities: an emerging metric

A common metric reported in the literature is the price elasticity of patent activity - the ratio of change in patents (either granted or applied for, depending on the study), to the change in energy price (i.e. a value of 0.5 indicates a 5% increase in patents for every 10% increase in price).[13]

Popp (2002) examined the effect of energy prices on patent applications in the US from 1970 to 1994. Across six supply- and five demand-side technologies he estimated a short-run **price-to-patents elasticity (e_{pp})** of 0.03-0.06[14] on aggregate, with a long-run price elasticity five to ten times larger (0.35) in his preferred specification. Verdolini & Galeotti (2011) extended such analysis to 17 OECD countries for 1979-1998, also adding wind energy, finding consistent positive short-run (1-year lag) effects with e_{pp} averaging 0.04-0.06.[15] The largest study, by Kruse & Wetzel (2016), covered patent applications over 1978-2009 for 11 'green' technologies in 26 OECD countries, yielding a total of over 175,000 patent counts, but found a statistically significant aggregate e_{pp} (0.53 for a 1-year lag, rising to 0.85 for a 3-year lag) only for the period since 1998.

Most studies examining the influence of energy prices on patent activity (including those deriving elasticities) find that results differ substantially between technologies, and many studies focus on the

[13] All energy prices are final (end-user) prices (i.e. including taxes and levies), unless otherwise stated. Studies vary in the type of patents (e.g. applied or granted). For studies examining 'clean' or 'green' patents various definitions are used, with one important reference point being the OECD Indicator of Environmental Technologies (see Haščič & Migotto, 2015).

[14] All values are presented to two significant figures.

[15] Note that in China, Li & Lin (2016) find a statistically insignificant relationship between energy prices and patent applications across energy supply technologies over 1999-2013, which the authors suggest is a result of energy prices being regulated to artificially low (and relatively constant) levels.

dynamics within a specific sector. We therefore organise discussion of the findings around three sectors: transport; electricity and industry; and buildings and appliances. Table 3, below, presents the key elasticities of patent activity for the first two of these three; the one study identified that attempted to generate relevant elasticities for the building and appliances sector Noailly (2012) found an insignificant connection for their primary, aggregate specification (but positive results for specific, 'portable' technologies – see Section 5.4).

Study	Geography	Years	Independent Variable	Dependent Variable	Patent Elasticity
Multi-sector					
Kruse & Wetzel (2016)	26 (OECD) Countries	1998-2009	Average Energy Price	Ratio: Green Patents (11 technologies) : All Patents (A)	0.53*
Verdolini & Galeotti (2011)	17 (OECD) Countries	1979-1998	Industrial Energy Price	Patents (12 technologies) (G)	0.4
Popp (2002)	USA	1970-1994		Patents (11 technologies) (G)	0.35
Oil & Transport					
Aghion *et al* (2016)	80 Countries	1986-2005	Fuel Price	'Clean' Patents (G)	0.97
				'Grey' (Fuel Efficiency) Patents (G)	0.28
Kruse & Wetzel (2016)	26 (OECD) Countries	1998-2009	Average Energy Price	Ratio: Energy Efficiency in Transport Patents: All Patents (A)	0.77*
		1978-2009		Ratio: Biofuel Patents : All Patents (A)	-0.64*
Guillouzouic-Le Corff (2018)	22 (OECD) Countries	1985-2009	Household Oil Price	Biofuel Patents (A)	1.5
Fredriksson & Sauquet (2017)	French Civil Law Countries**	1986-2005	Fuel Price	'Clean' Patents (G)	2.32
	Common Law Countries***				1.2
Kessler & Sperling (2016)	USA	1976-2013	Oil Price	Biofuel (2nd Generation) Patents (A)	0.25
Jang & Du (2013)		1977-2010		Ethanol Patents (A)	0.04
Crabb & Johnson (2010)		1980-1999	Gasoline Retail Price Markup	Automotive Energy Efficiency Patents (A)	0.45
			Gasoline Price		0.36
			Domestic Wellhead Oil Cost		0.24
Electricity & Industry					
Kruse & Wetzel (2016)	26 (OECD) Countries	1978-2009	Average Energy Price	Ratio: Solar Patents: All Patents (A)	1.12*
				Ratio: Energy Storage Patents : All Patents (A)	1.08*
				Ratio: Ocean Energy Patents : All Patents (A)	0.61*
				Ratio: CCS Patents : All Patents (A)	0.56*
		1998-2009		Ratio: Geothermal Patents : All Patents (A)	0.37*
Ley *et al* (2016)	18 (OECD) Countries	1980-2009	Industrial Energy Price	Ratio: 'Green' Patents : All Patents (A)	0.48
				'Green' Patent (A)	0.34
Brolund & Lundmark (2014)	14 (OECD) Countries	1978-2009	Electricity Price	Bioenergy Patents (A)	0.87
			Ratio: Biomass : Light Fuel Oil Price		-0.33
Vincenzi & Ozabaci (2017)	11 (OECD) Countries	1990-2008	Electricity Price	Solar Patents (A)	0.12
Lin *et al* (2018)	China	2000-2012	Industrial Energy Price	'Clean' (Utility) Patents (A)	0.61
				Ratio 'Clean' Patents : All (Invention) Patents (A)	0.51
				'Clean' (invention) Patents (A)	0.38
Lin & Chen (2019)		2006-2016	Electricity Price	Renewable Patents (G)	0.78
He *et al* (2018)		2006-2013		Biomass Patents (A)	-0.41
				Renewable (Wind, Solar, Geothermal, Ocean, Biomass) Patents (A)	-0.72
				Wind Patents (A)	-0.72
				Solar Patents (A)	-0.8
Ye *et al* (2018)		2008-2014	Energy Price	Energy Conservation & Emission Reduction Patents (A)	0.14

Table 3 – Energy price-to-patent elasticities (e_{pp} *)* (notes: values presented are from the primary or preferred specification of each study, as either explicitly stated or inferred, unless otherwise indicated. Only statistically significant results are presented. '(A)' denotes patent **Applications**, '(G)' denotes patents **Granted**.
* Within their study covering data across 26 countries 1978-2009, Kruse & Wetzel (2016) also tested the more recent period 1998-2009. The result for biofuels changed from a negative influence to insignificant, whilst ocean and CCS technologies changed from a positive to an insignificant influence. However, results for solar and geothermal increased in the value and significance, and energy efficiency in transport and energy storage both moved from insignificant, to positive. The result for all technologies on aggregate also changed from insignificant, to positive. **Peru, Netherlands, Turkey, Italy, Belgium, France, Indonesia, Brazil, Luxembourg, Russia, Netherlands Antilles, Greece, Venezuela, Argentina, Mauritius, Malta, Spain). ***Bermuda, Hong Kong, Belize, Dominica, Thailand, Singapore, South Africa, Israel, UK, Australia, India, USA, Ireland, Sri Lanka, Cayman Islands, New Zealand, Barbados

5.2. Transport

Using a methodology similar to Popp (2002), Crabb & Johnson (2010) found an e_{pp} elasticity for energy efficient vehicles in the USA (1980-1999) of 0.24 for the cost of domestic oil production, and 0.36 for retail gasoline price. Using a panel of 12 countries from 1990 to 2012, Kim (2014) find that higher *gasoline* prices promoted patents in automotive technologies and discouraged it on oil extraction. However, countries with larger oil endowments generated comparatively less patent activity on efficient or alternative vehicle technologies.

Alternatively-fuelled vehicles. The impact of gasoline prices on innovation in alternative fuelled vehicles appears particularly strong, and path-dependent. (Aghion et al., 2016) find almost unitary elasticity (e_{pp}=0.97) between end-user fuel prices and such patent generation; innovation in conventional technology, including fuel efficiency, was also stimulated, but to a lesser degree. They also find evidence of innovation path dependency; firms previously engaged in 'clean' innovation are much more likely to continue to do so in response to fuel price stimuli. Fredriksson & Sauquet (2017) find that this effect is strongest for firms located in countries with French civil law, rather than those (mainly Anglophone countries) with common law, suggesting that the relative 'rigidity' of civil law may provide greater certainty regarding future legislation and lessen incumbents' lobbying, increasing the incentive to innovate.

Barbieri (2015) finds a positive effect of EU transport fuel prices on global 'green' patenting by the automotive sector worldwide (1999-2010) but with the effect lower within the EU, where he argues that *vehicle taxation* in the EU (inclusive of ownership and circulation taxes, which increasingly reflected CO_2 intensity) was instead the primary driver of vehicle innovation. Barbieri (2016) builds on this to conclude, from a wider international dataset, that such 'green' patenting induces by fuel prices occurs at the expense of, rather than in addition to, patenting in 'non-green' (gasoline) vehicle technology (though the form and magnitude of the coefficients produced by these two studies are difficult to interpret from the information provided).

Biofuels. Jang & Du (2013) and Kessler & Sperling (2016) examine how oil price increases enhanced biofuel-related patenting in the USA, between the late 1970s and early 2010s, Jang & Du (2013) found e_{pp} elasticities of 0.04 (for ethanol-related technologies), while Kessler & Sperling (2016) find a value of 0.24 (for 2nd generation biofuels only, using their preferred patent classification method, but up to 0.64 using a different method, and 0.4 for 1st generation biofuels). However, both studies highlight the important role of directed policy support (see Section 6). Expanding to 22 OECD countries over 1985-2009, Guillouzouic-Le Corff (2018) finds (household) oil prices to be a huge driver for biofuel-related patenting (e_{pp} =1.5), but Kruse & Wetzel (2016) find a far more complex picture.[16]

In terms of innovation *outcomes*, studies that explore the relationship between fuel prices and vehicle efficiency (e.g. Li et al. 2009**) tend to measure improvements in the average efficiency of new sales – a function of technological improvement, but also consumer choice – which are often not disentangled. An exception is Knittel (2012)*, who finds gasoline prices to have been the principal driver behind a 60% improvement in fuel efficiency in passenger cars and trucks sold in the USA over 1990-2006, once the counteracting influence of increasing vehicle weight and engine power is controlled for (he concludes that fuel economy standards played a small or insignificant role during that period, when fuel economy standards were unchanged – see Section 6.3).

5.3. Electricity and industry

Energy prices

Electricity generation. Many electricity sector studies investigate induced innovation in renewable generation technologies. Bayer et al. (2013) find that for 1990-2009, for each $2 increase in oil price,

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[16] Kruse & Wetzel (2016) find *negative* e_{pp} = -0.64 for biofuels (across 26 OECD countries, for 1978-2009) – perhaps reflecting continued expansion of biofuel activities in some countries whilst oil prices declined from peak in 1980 to 2000 - but this turns positive (but insignificantly so) for the subsequent period of rising environmental stringency and then rising prices (1998-2009). Their results for vehicle energy efficiency patents also move from insignificant to positive (and significant), for this period.

patents filed for solar PV and wind technologies increased 13% on average over the following year (across 74 countries, with the impact greatest outside the OECD). Within the OECD, Cheon & Urpelainen (2012) demonstrate that the marginal effect of increasing oil prices on renewable patent applications increases with existing share of renewables in electricity generation, which (as with alternate vehicle technologies) suggests an important role for the existing knowledge stock and path dependency in innovative activity, found also by Kruse & Wetzel (2016), who in their primary specification (1983-2009) find highly varied energy price to patent elasticities across a range of eleven (low carbon) supply and energy efficiency technologies, including e_{pp} =1.12 (Solar PV); 0.56 (CCS); 0.37 (geothermal), and 0.61 (ocean energy). Under their alternative specification (for the period 1998-2009), energy prices also become influential for energy storage technologies, and more so for solar and geothermal, but insignificant for ocean energy and CCS.

Vincenzi & Ozabaci (2017) find an impact of *electricity* prices on patent applications for solar PV (e_{pp} = 0.11-0.12) across several EU countries, Japan and the USA, 1990- 2008. In China, Lin & Chen (2019) find for renewable energy patents over 2006-2016, e_{pp} = 0.78. However He et al. (2018) find a negative relationship for 2006-2013 (up to -0.8 for PV), , which they attribute to inframarginal effects in electricity pricing.[17] Brolund & Lundmark (2014) find that across 14 OECD countries for 1978-2009, the electricity price was a major determinant of patent applications for *biomass electricity* technologies, with e_{pp}=0.87.

Industry. Ley et al. (2016) examine energy price-induced patenting for 10 manufacturing sub-sectors (chemicals, basic metals and paper, pulp and print, to wood and wood products), across 18 OECD countries. These industries account for over 95% of all 'green' patents granted worldwide, for 1980-2009. Patent elasticities increase with the lag period: for 'green' patents granted, e_{pp} reached 0.34 at a five year lag, and 0.48 when considering green patents as a proportion of all patents granted. Adopting the same methodology, Lin et al. (2018) find 'clean' patent applications across 29 industrial sectors in China reaching e_{pp} = 0.61 (2000-2012), however Ye et al. (2018) find positive results only after an in-year negative impact, attributable to short-term budgetary constraints.[18]

Triguero et al. (2014) find that *on aggregate* for over 5,000 SMEs based across 27 EU countries in 2011, energy prices were not a significant determinant for in-house innovation. However, as might be expected, the influence was found to be much greater on firms that are energy-intensive, have strong management and technological capacities and capabilities, and engage with wider 'knowledge networks' (e.g. collaborate with research institutions). Garrone et al. (2017) come to a similar conclusion on the role of energy intensity on response to fuel price stimuli (although they do not distinguish between development and adoption of innovations).

Energy taxes and carbon prices

Several studies have explored the impacts of energy-related taxes and carbon pricing on manufacturing in different European countries. In Austria, Germany and Switzerland, Stucki et al. (2018) find that although energy-related taxes are positively associated with investments in internal process innovation in energy efficiency and renewable technologies, they are negatively associated with the propensity to create and sell new energy-efficient or renewable products or services. The

[17] Specifically, they suggest lower prices increase the *relative* profitability of low-marginal cost renewables (and thus incentive to innovate), compared to a system heavily dominated by fossil fuel incumbents, as electricity prices reduce (and vice versa).

[18] For industries across China in 2008-2014, Ye et al. (2018) find in-year negative impact on patent applications for energy conservation and emissions reduction technologies, turning to +0.14 The authors suggest that R&D budget is initially diverted to pay energy bills, but then firms begin to compensate and innovate to reduce the additional cost burden, increasing the elasticity.

authors explain this as the incentive to invest in process innovations draws resources away from investment in product and service innovations, and indeed find this effect is reduced for firms operating at the technological frontier or have larger financial resources. Costa-Campi et al. (2017) find the role of general energy taxes negligible in driving private environmentally-related R&D in the manufacturing sector in Spain (2008-2013), however they find an elasticity of 0.28 for more targeted pollution-related taxes.

Many studies examine the influence of the European Union Emissions Trading System (EU ETS), which from 2005 created an EU-wide carbon price for electricity generation and heavy industry. Calel & Dechezlepretre (2016) found that the EU ETS increased patent applications for technologies or applications for mitigation or adaptation to climate change by 9.1% (and 0.8% for other technologies, suggesting no crowding-out), by firms accounting for 80% of regulated emissions, for 2005-2009. However, Bel & Joseph (2018) find that the oversupply of emission permits in the transition from Phase 1 (2005-2007) to Phase 2 (2008-2012) of the EU ETS, reflected in repeated price collapses, dampened patent applications for mitigation-related technologies.

Six studies examine whether and how firms realigned innovation activities in response to the EU ETS using a qualitative or mixed-methods approach. Most of these studies (Borghesi et al., 2015; Hoffmann, 2007*; Rogge & Hoffmann, 2010; Rogge, Schneider, & Hoffmann, 2011*) reported that the introduction of the EU ETS did indeed accelerate R&D activities within regulated firms, particularly those reliant on coal, but a radical shift in innovation strategy did not occur. Increased R&D activity was largely focused on CCS and efficiency, rather than renewables. Schmidt et al. (2012)* found that the perceived stringency of Phase 3 (2013-2020) increased RD&D investment in low-carbon technologies by firms who perceive it as a threat to their business (no such effect was found for Phases 1 and 2). Similarly, Gulbrandsen & Stenqvist (2013) found the EU ETS to have influenced firm innovation strategies, increasing focus on energy efficiency, but it had not generated a sufficiently strong investment signal to scale up or deploy radical new technologies. Interestingly, most of these studies note that the EU ETS induced organisational changes in firms, giving CO_2 emissions greater managerial attention.

Similar results have been found by studies examining other carbon pricing instruments. Christiansen, (2001) observations of the Norwegian carbon tax suggest it contributed to incremental, rather than radical, innovation in the oil and gas sector, such as development and adoption of efficient processes and measures to reduce flaring. Scordato et al. (2018) note that the Swedish CO_2 tax had an influence on innovation leading to higher energy efficiency in the domestic pulp and paper industry, though it was perceived to have been minor relative to other drivers (such as rising power prices). Kim et al., (2017) found that carbon pricing has had an insignificant influence on patent applications for wind and solar PV across 16 OECD countries (for 1991-2006 and 1992-2007, respectively). Zhang et al. (2019) examined the role of the seven carbon pricing pilot schemes introduced in China in 2013 on 'green' patent applications by regulated firms, and found a significant positive correlation (over 2013 and 2014), however the link was less strong for sectors in which there is high levels of competition between regulated firms, which the authors suggest reflects such firms having fewer resources to invest in R&D.

One likely explanation for diverse findings concerning the impacts of general energy taxation, and particularly carbon prices, on renewables innovation is the impact of other factors, and differences in the degree to which they have been controlled for in the studies examined. For example, aside from targeted policies (considered in Section 6), Hoppmann et al. (2013) found that increasing silicon prices drove the direction of PV-related R&D towards interest in thin-film technologies.

These findings appear to be partially echoed by the few studies which attempt to explicitly examine the link between energy and carbon prices and technology cost reduction, of which only two explore renewables. Taghizadeh-Hesary et al. (2019) find that oil price rises are linked to reducing solar module prices in the USA, Japan and China (but not Germany and South Korea). However, they again found that existing knowledge stock, along with interest and currency exchange rates, to be of greater influence in all five countries (from 1992 in Germany, Japan and the USA, 1993 in South Korea, and 2007 for China, to 2015 in all cases). However Kim et al. (2017), despite finding carbon taxes to have an insignificant impact on patent applications for wind and solar PV, found they had a significant influence on reducing installed system costs for these technologies (for wind power, in particular).

Finally, we note that our review did not find a literature on the innovation effects of carbon pricing via technology standards for carbon emissions, such as a New Source Performance Standard (NSPS) for power plant emissions. Compliance with standards of this type often requires the installation of technology (e.g., a carbon capture system) whose cost imposes a carbon price indirectly. To date, however, standards of this type have not yet been imposed on carbon emissions. Nonetheless, evidence from studies of other power plant emission controls suggests that indirect pricing of this type, were it to be adopted, could have a significant impact on energy technology innovation (e.g., Rubin, Yeh, Antes, Berkenpas, & Davison (2007))**.

5.4. Buildings and appliances

Just three studies focus on the impact of energy prices or taxes on patenting in buildings-related technologies and appliances. Noailly (2012) found that end-user energy prices of across 9 European countries did not have a statistically significant impact on *aggregate* patenting across the sector; however patent applications for visible, '*portable*' technologies that may be modified with relative ease by the building's occupant (e.g. boilers, lighting and air conditioning technologies), showed statistically significant elasticities of 0.7 to over 1.15 (depending on the specification). This contrasted sharply with the less visible and 'non-portable' technologies that cannot be easily modified by the occupant such as heat distribution, ventilation and building materials. The authors suggest that principal-agent issues may give rise to this disparity, a conclusion echoed in other studies covering energy efficiency technologies (e.g. Kruse & Wetzel, 2016).

The second study, Costantini, Crespi, & Palma (2017a), found taxation on residential energy consumption to be strongly linked to patent applications for energy-efficient technologies in buildings across 23 OECD countries (1990-2010) when controlling for a range of other factors (including public R&D), which they found to be significantly less influential. By contrast, Girod et al. (2017) found taxes on residential energy consumption to be a negligible factor in the patent applications in the construction and lighting sector (1980-2009). The difference between these results may be in part explained by the design of the individual studies. Whilst Costantini et al. (2017) considered the ratio of energy tax to total price over time, Girod et al. (2017) employed a high-level proxy indicator for the presence of energy taxes (and other policy variables).

We identified only one, twenty-year-old study of the impact of energy prices on cost reductions in appliances. Newell et al. (1999) found that electricity and natural gas end-user price increases induced cost reduction in (room and central) air conditioners but not in gas water heaters., although overall energy efficiency improvements were induced in all three technology groups (5-16% between 1973 and 1993 – up to half of the efficiency gains experienced over the period). However, these conclusions are complicated by the fact that the introduction of labelling requirements appears to have increased apparent price-responsiveness.

5.5. Market-wide impacts on innovation – Qualitative insights and conclusions

From the econometric literature there is clear and unambiguous evidence that energy and carbon pricing can substantially influence innovation, primarily as measured by patents. Specifically, rising energy prices and the introduction of carbon (and other) environmental pricing has generally enhanced patenting in low carbon and energy efficient technologies, but the impacts vary substantially by technology and sector.

Other aspects of the econometric literature are also striking. The impact of prices on patents tends to be lagged, sometimes by several years, and those studies which include knowledge stock as a variable find innovation to be path dependent – the propensity to patent is greater when sectors have grown and accumulated more knowledge on which to build. The impact of energy prices and carbon pricing on innovation in industrial efficiency (particularly for more energy-intensive sectors) is clear, but incremental; influence on more radical innovation appears lacking. Studies on patenting in renewable energy usually find positive results (with higher elasticities found for studies using electricity prices as the independent variable, rather than a broader energy price definition).

Other contextual conditions influencing innovation could include the existence and/or credibility of transparent information (e.g. product labels), national targets, and the wider political environment: Kruse & Wetzel (2016) for example suggest that the higher patent elasticities they generally found after 1998 might reflect the adoption of legally-binding emission targets under the Kyoto Protocol the year before, thus sensitizing industry and enhancing the likelihood that low carbon innovation would prove strategically valuable, as well as cost-saving given higher energy prices.

In the econometric literature, the evidence linking to innovation *outcomes* is far more skeletal. The relative paucity of such literature is perhaps a surprise. Especially for energy efficiency, it relates in part to the challenge of attributing sector-wide energy intensity changes to technology innovation specifically, as discussed more broadly in Section 8. For energy supply technologies, examining innovation outcomes is complicated by the range of interconnected influences that contribute to cost reduction (in particular), as illustrated in the next two sections.

Whilst econometric studies (whether on innovation indicators or outcomes) aim to disentangle different influences, the qualitative and mixed-methods literature tends to view the forces driving innovation inherently as a mix of factors, of which energy and carbon prices are just two examples. Many qualitative and mixed-methods studies focus on the actions of actors, and the (often multiple) rationales for those actions, in which the distinction between innovation 'indicators' and 'outcomes' (see Section 3) may also be less clear-cut. A further complication is that several such studies ascribe changes in the policy environment to moves in energy prices (e.g. Bergquist & Soderholm (2016)), or policymaker expectations about future energy prices (Nemet, 2009b). Price shocks are often reported to have influenced subsequent energy and innovation policies, which then have more direct effects on innovation – particularly regarding energy efficiency (e.g. Borghesi, Crespi, D'Amato, Mazzanti, & Silvestri, 2015; Gulbrandsen & Stenqvist, 2013; Scordato et al., 2018), but also energy-environmental policy more broadly.

An important finding from such studies is that the institutional context can influence the innovation response to price changes. Institutional factors that may inhibit innovation responses include an absence of clear quality standards (e.g. M. Taylor, 2008); unclear regulatory regimes with weak compliance (Kivimaa, Kangas, & Lazarevic, 2017); and weak networks between innovators, users and finance (Skold, Fornstedt, & Lindahl, 2018). Christiansen described a case in which the presence of an intermediary organisation to facilitate innovation boosted the innovation response to a carbon tax (Christiansen, 2001). These findings about the importance of the institutional context are aligned with the large literature that describes innovation as the outcome of a socio-technical system (Gallagher et al., 2012**; Geels, Sovacool, Schwanen, & Sorrell, 2017**; Hekkert et al., 2007**)

6. The impact of targeted demand-pull policies and deployed scale on innovation

6.1 Introduction

This section probes the evidence on the interrelationships between targeted demand-pull policies (Ib), deployment (2), and the indicators and outcomes of innovation (see Figure 3). Assessment is complicated by multiple factors, including the sheer diversity of types of policy intervention, and the interrelationship of the elements, including the bi-directional nature of their relationships.

We take the approach, however, that it is precisely by considering these aspects together that important insights can be gained from the literature. The assessed literature is large and diverse. Our search (after screening) identified around 150 studies, divided approximately equally between studies assessing targeted policies, and those estimating experience curves. For the former, the large majority evaluated impacts on patents, and our analysis complements a major review of the impact of ten policy instruments (Peñasco et al., *Accepted*)**, which also included innovation. The next largest estimating the impact various measures of eco-innovation, many of which are more to do with business model rather than hard technology innovations. A small group of other studies, both econometric and mixed-method, shed light on the processes involved in other ways.

In this section, we evaluate first the quantitative literature on how targeted policy interventions, grouped between economic incentives and regulatory measures, have affected patenting. We then assess the limited literature around the impacts of these interventions on innovation *outcomes*, before turning to the experience curve literature. We seek to fill out the picture by looking at additional evidence, including feedback between deployed scale and *indicators* of innovation, cost decomposition, and other evidence gleaned from considering the feedbacks involved (as illustrated generically in Figures 1-3).

Many of these examine evidence relating to wind and solar electricity. Because these draw on by far the largest renewable energy resources globally, in recent decades these have been a major focus of targeted interventions in energy-climate policy, with impressive developments in cost and capacity as shown in
Figure 6. Over the past two decades, these technologies have emerged from relative obscurity and high costs, to being a major part of national and global strategies, based upon this rapid growth and increasing competitiveness in many markets (note that the biggest drop in PV prices corresponded to the period of fastest exponential growth, and followed the commodity boom of the 2000s which drove up material (especially silicon) prices until the 2008 financial crisis). They correspondingly dominate much of the relevant literature (most of all, for experience curves) and learning the right lessons is important.

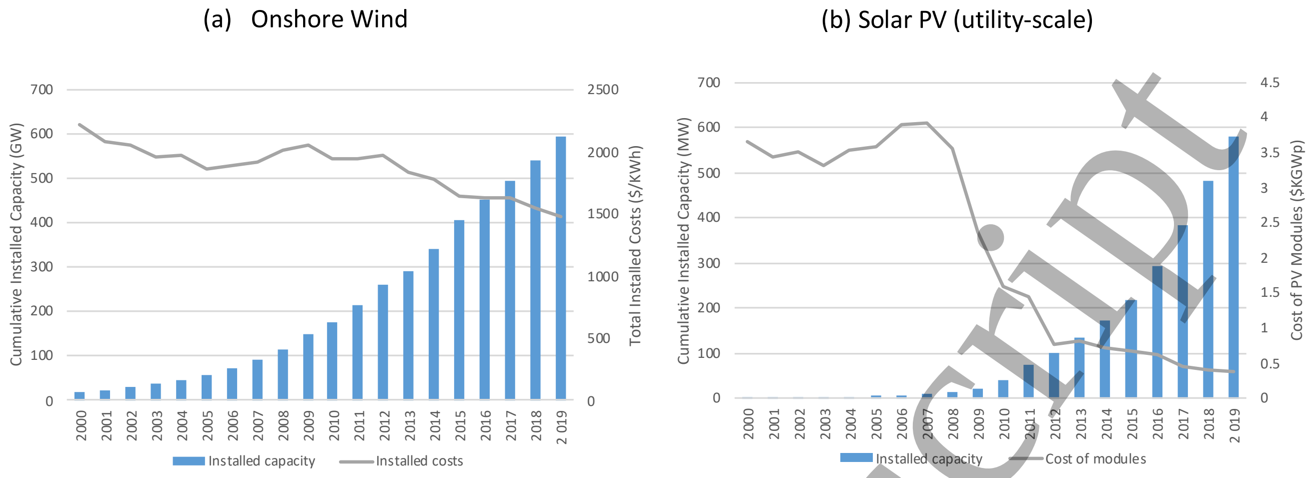

Figure 6: Evolution of global installed capacity and global weighted-average installed costs for onshore wind (panel (a)) and global installed capacity and cost of modules for utility-scale solar PV (panel (b)), 2000-2019

Source: (International Renewable Energy Agency (IRENA), 2020.; Lafond et al., 2018)**

6.2 Targeted economic incentives – impacts on patents

The dominant instruments which create a direct economic incentive to deploy clean energy sources have either fixed the price (usually for 10-20 years), or set a target quantity. In electricity, the former has comprised feed-in-tariffs (FiTs), accompanied more recently and for larger generators by auctioned contracts. The latter comprise renewable obligations, often known as renewable portfolio standards (RPS) implemented with tradeable certificates, widely used for electricity particularly in the US, and more widely, as mandates for biofuels.[19] Instruments for demand-side technologies have usually differed, with regulatory instruments as considered in section 6.3 more prevalent.

Most (though not all) of the literature finds that targeted economic incentives have increased patenting for solar PV and wind, and (echoing the literature on overall energy and price impacts) has begun to estimate elasticities of response (e.g. the percentage increase in patent applications for every percentage increase in the FiT support level). One major foundational study (Johnstone et al., 2010), using a panel of 25 countries over 1978–2003, found that many factors enhanced patenting, with some clear patterns: in general, the broader the application of a measure (including overall public energy R&D expenditure, and the adoption of the Kyoto Protocol), the more statistically significant the result on *aggregate* renewables patenting. However, more targeted instruments proved more important for particular technologies. Intriguingly, they found specifically that the (more broad-based) RPS enhanced patenting in wind but not solar, whilst FiTs had a large impact on solar but negative correlation with wind patenting (which the authors describe as an unexpected result, but don't elaborate further).

In one of the largest subsequent studies, covering 13 countries over 1978-2008, Palage et al. (2019) found that FiTs positively influenced solar PV patent applications with elasticities ranging from 0.11 to

[19] A variety of terms are used, all of which refer either to obligations to secure a certain proportion of energy from renewables, or the instrument used to implement this, variously terms tradeable green certificates (TGCs) or renewable energy certificates (RECs). We use the generic terms renewable portfolio standards (RPS) for electricity and biofuel blending mandates for biofuels.

0.20 (with the larger values found when employed in combination with public R&D support), with a lower but still statistically significant elasticity of RPS stringency to patent applications of 0.03. Nicolli & Vona (2016), based on 19 EU countries (1980-2007), and Vincenzi & Ozabaci (2017), with 9 EU countries plus Japan and US, similarly find FiTs increased patenting in solar PV, though the latter found greater impact from changes in electricity prices (Section 5). The former also found that FiTs negatively influenced patent applications for wind, whilst RPS had a positive effect (also for solar thermal). Like Johnstone et al. (2010) they suggest that an RPS may stimulate greater innovation in more mature technologies. However, also as with Johnstone et al. (2010), Nicolli & Vona (2016) used a dummy variable found that expectations on the future policy context after signing the Kyoto protocol appears to take the place of the positive effect of RPS. Horner et al. (2013) find that RPS in California, Texas and Minnesota were significant drivers of wind-related patenting, where an increase in the RPS annual obligation of 1 TWh would be associated with an increase of around 2% in wind patenting.

Schleich et al. (2017) and Grafstrom & Lindman (2017) found no impact of FiTs on patent applications for wind technologies across 12 OECD countries (1991-2011) and 8 EU countries (1991-2008), respectively). However, in contrast to these two studies, along with Johnstone et al. (2010) and Nicolli & Vona (2016), Lindman & Soderholm (2016) conclude that for Denmark, Germany, Spain and Sweden over 1977-2009, FiTs increased patent applications for wind energy, with an elasticity of 0.3-0.4. The difference to Johnstone et al. (2010) may be explained, as the authors suggest, by the extended assessment horizon; since the early 2000s, European countries have reduced their FiT levels as costs have reduce. The difference with Schleich et al. (2017) may be explained by their use of a dummy policy variable that does not adequately capture design features, such as level or duration of support. As Lindman & Soderholm (2016), Nicolli & Vona (2016) and Grafstrom & Lindman (2017) all use a more detailed policy variable representing actual levels of support provided by FiTs, the difference could be explained through the difference in geographic scope.

The results for other technologies are mixed. For bioenergy, biofuels and fuel from waste technologies, Brolund & Lundmark (2014), across 14 OECD countries (1978-2009), found that FiTs have increased patent filing, with elasticities increasing with contractual agreement length, reaching 0.10-0.24 for agreements longer than 10 years, but found RPS to be an insignificant influence. Lundmark & Backstrom (2015), across 13 OECD countries (1979-2008), conclude that each $1 (US) per MWh increase in FITs tariff increased the patenting for biotechnologies by 0.2%. Unlike Brolund & Lundmark (2014) – perhaps due to different definition of the policy variable - they also found a positive (though modest) impact of RPS, with countries with RPS having double the rate of bioenergy-related patent applications than those without. Nicolli & Vona (2016) found both instruments to have been an insignificant influence on biofuels and waste patenting.

Johnstone et al. (2010) & Nicolli & Vona (2016) found FiTs and RPS to have been insignificant in encouraging patenting for geothermal. Johnstone et al. (2010) find both measures to have been insignificant with regard to marine energy patenting, but Nicolli & Vona (2016) find them to have be negatively associated. Although Boehringer, Cuntz, Harhoff, & Asane-Otoo (2017) find FiTs to have had a positive influence on aggregate across range of technologies in Germany, they find negative or insignificant influences at the individual technology level (including for solar PV and wind) – although when they test the effect of the interaction between the average and technology-specific coefficients of FIT support, the effect becomes positive (and significant) for all technologies examined, except biomass.

For liquid biofuels, Guillouzouic-Le Corff (2018) found biofuel blending mandates (equivalent to RPS, requiring a certain percentage of biofuels in fuel sold) in 22 OECD countries over (1985-2009) to have increased production of the dominant *first generation* biofuels (ethanol), rather than stimulating new innovation. Costantini, Crespi, Martini, & Pennacchio (2015) find blending mandates in (mostly) OECD countries (1990-2010) to have had an impact on patenting for first generation technologies, but not on the overall rate of biofuel patenting. For the USA (1997-2011), Jang & Du (2013) found biofuel mandates to be an insignificant influence on patent activity. However, following this, Kessler & Sperling (2016) found that fuel mandates in the USA (1995-2010) enhanced patenting in both first and second generation biofuels, but with lesser effect on the latter.[20] Together, these studies suggest that blending mandates have potentially rewarded incremental (but not radical) innovation, akin to some of the findings for RPS.

Qualitative and mixed-methods studies on FiTs have frequently observed that they induced firms to increase innovation efforts (e.g. Borghesi, Crespi, et al., 2015; Reichardt & Rogge, 2016). They highlight that the simplicity of FiTs enables entry of new and diverse of market players. This serves to (a) help foster the social legitimacy of the technology (e.g. Chowdhury et al., 2014; McDowall et al., 2013), facilitating future policy support; and (b) support the development of a nascent industry and related advocacy coalition (Hendry & Harborne, 2011). Another key attribute of FiTs, highlighted by Reichardt & Rogge (2016), is that they reduce uncertainty faced by investors.

The qualitative and mixed-method studies focussing on RPS find mixed results. Breetz et al (2018) describe how they enabled the development of firms that wielded political influence, thus developing the advocacy coalition required to sustain policy and thus reward innovation. However, Fevolden & Klitkou (2017) and McDowall et al. (2013) provide examples of RPS policies that failed to generate durable innovation, for reasons of both policy design and policy framework instability, respectively in Norwegian biofuels, and the UK non-fossil fuel obligation.[21]

The econometric evidence in the literature on the effect of other specific types of economic instruments, such as grants, excise duties and tax credits – again, largely confined to OECD experience - is small and tentative. *Investment incentive schemes* are found by Johnstone et al. (2010) to have increased renewable energy patent applications overall, however, within the sample, results are only statistically significant for geothermal, and biomass and waste. Brolund & Lundmark (2014) similarly find an insignificant effect on wind and solar PV patents, but conclude that targeted investment policies increase patent applications for biofuel and waste. Costantini et al. (2015) find that exempting biofuels from fuel excise duties was the main factor inducing biofuel-related patenting in OECD countries. Horner et al. (2013) find tax credits, either production or investment, not to have induced patent grants for wind technology.

Beyond supply technologies, for the household sector Girod et al. (2017) find that investment support schemes in the form of grants for efficient appliances and fiscal subsidies in the form of tax reductions,

[20] Driven by the introduction of the 2005 Renewable Fuel Standard, and the subsequent requirements of the 2007 Energy Independence Security Act – RFS2.

[21] In the case of Norwegian biofuels, the market support mechanism (a biofuel mandate) was lower than the industry had expected, and contained no sustainability criteria that would have supported advanced biofuels. It was also introduced alongside a phasing-out of the prior tax break for biodiesel. This shift led to a market preference for imported corn- or sugar-derived ethanol, which, coupled with the uncertainty induced by the conflicting policy signals, prevented companies developing advanced biofuels from raising capital. McDowall et al. (2013) report the failure of the UK's Non-Fossil Fuel Obligation (NFFO) to drive significant innovation activity in wind power. This introduced unfettered auctions, leading to 'winner's curse' – almost half the winning bids never proceeded to construction - with high investor risks and high barriers to entry, undermining the establishment of a viable innovation system for wind power technologies. Having invested in wind R&D during the 1980s, the UK effectively lost its stake in onshore wind manufacturing as Denmark and Germany established more stable support systems. These examples illustrate the importance of policy design, and its suitability to technologies at particular stages of maturity.

together with labelling instruments, have been the most important driver for energy efficiency patenting. However, in general, economic instruments have been rarely applied on the demand-side, with direct regulation much more prevalent.

Qualitative and mixed-method studies describe a wide range of other instruments that were reported to have positively influenced innovation activities by firms, or outcomes of such activities. These include tax incentives for production or investment (Fevolden & Klitkou, 2017; Kamp, Smits, & Andriesse, 2004; Nemet, 2009b); eco-labelling (Borghesi, Crespi, et al., 2015; Ruby, 2015); public procurement (Fevolden & Klitkou, 2017) and programmes providing tax exemptions in exchange for engagement in a set of eco-innovation related activities (e.g. Scordato et al. 2018).

Conclusions regarding impact of targeted incentives on patents

A decade on from the seminal study of Johnstone et al. (2010), the literature appears to have reinforced their broad conclusion[22], and added a significant dynamic element to their insights. The security and specificity provided by feed-in tariffs – particularly for solar PV - created a strong incentive for innovation and patenting particularly when combined with wider trends in electricity and environmental policy, including (energy and carbon) pricing and emission targets as discussed in Section 5. Other incentives like RPS or investment supports play a more modest, or relatively negligible role for those technologies 'new to market'. However, these broader instruments like RPS tend to encourage innovation - usually more incremental - in the more mature technologies best placed to capture the biggest share of this support at least cost. Without an equivalent for FiTs for some other technologies, including most obviously biofuels, other instruments tended to play a stronger role.

Less clear in this account is the role of *sector*-wide measures, notably renewable energy targets. Whilst Johnstone et al. (2010) and Nicolli & Vona (2016)'s inclusion of a dummy variable for signing of the Kyoto Protocol suggested it had a clear impact on overall clean energy patenting, Nesta, Vona, & Nicolli (2014) concluded that it had no impact on renewable energy patenting in the OECD. Vincenzi & Ozabaci, (2017) conclude that neither renewable energy targets nor emission targets for Europe, Japan and the US had impact on *PV* patenting.

6.3 Regulatory instruments – impact on patents

Efficiency and CO_2 emissions standards establish limits for energy and CO_2 intensity for a given technology or technology group, and have been largely applied in the building and transport sectors. For the building sector, Kim and Brown (2019) conclude that minimum energy performance standards (MEPS) for lighting across 18 OECD countries consistently induced an increase in both domestic and foreign patent activity (1992-2007). For MEPS contained in building codes, Noailly (2012) concludes that across 7 EU countries, a 10% increase in the stringency of insulation induced an increase in energy efficiency-related patenting by 3% (1981-2004). However, Girod et al. (2017) found MEPS for appliances and buildings across 21 EU countries to be statistically insignificant in inducing patent applications in energy efficiency-related technologies (with other instruments found to be more important, as discussed below). The authors state the reason for the difference with the finding form Noailly (2012) requires further research, but suggest the reason may be the difference in policy variable definition.

[22] Johnstone et al. (2010), as also quoted in Brolund & Lundmark (2014) – 'Targeted subsidies such as feed-in tariffs are more efficient in stimulating innovations in newly-emerged and less developed technologies with high operating costs, while more general policies such as quota obligations with tradable green certificates stimulate innovations in mature technologies that have already been subject to innovation and learning-by-doing cost improvements'.

Results for vehicles appear to differ in particular between US and European studies, reflecting very different policy regimes. Barbieri (2015) concludes that announcements introducing planned increases in the stringency of CO_2 standards for vehicles in the EU intensified the generation of green patents in the transport sector, by firms based both within and outside the EU (1999-2010). On average, each 1% reduction in maximum CO_2 intensity permitted generated an increase in patent applications by 0.56% (increasing to 1.39% for firms based in the EU). However, for the US (1980-1999), Crabb & Johnson (2010) found fuel prices to be substantially more influential than Corporate Average Fuel Efficiency (CAFE) in stimulating patents, echoing the findings of (Knittel, 2012)* on efficiency improvements; however both of these reflect a period in which regulatory standards were largely static and the conclusions are challenged by other evidence.[23] Sierzchula and Nemet (2015) highlight that firms are heterogeneous in their innovation response to technology-forcing regulations. They found that the stringency of the California Zero Emission Vehicle mandate was a significant factor in driving both patenting and prototypes, but the picture is complicated by the diversity of commercialisation strategies of the global automotive companies subject to the regulation.

Literature on other environmental standards, noted in our concluding discussion (Section 9), sheds additional light on regulatory impacts.

Qualitative and mixed-method studies have explored several cases in which technology standards have driven innovation responses in various sectors, including buildings (Gann, Wang, & Hawkins, 1998), vehicles (Calef & Goble, 2007; Wesseling, Farla, & Hekkert, 2015), and in energy efficiency (Ruby, 2015). All those examined observe innovation responses to regulation—though the risk of publication bias should be noted (studies are more likely to be conducted on regulations perceived to have had an innovation outcome).

Conclusions regarding impact of regulations on patents

The econometric literature linking patents to regulations is more limited than for prices, presumably because regulation is more specific and harder to quantify in general for econometric purposes. This more limited evidence base suggests regulations to a major driver for buildings-related innovation, and generally (though not universally) significant in vehicles.

In general, the regulatory studies place greater emphasis on case studies. Aside from reinforcing the econometric findings, these illustrate some of the mechanisms – and diversity – of responses. They also shed light on the co-evolutionary dynamics, with innovation driving regulation as much as the other way around. Ruby (2015) observed that firms that had developed high-efficiency circulator pumps sought to establish a market by establishing a (government-supported but voluntary) labelling scheme. This was sufficiently successful to induce competitors to invest in R&D to develop similarly highly-efficient pumps. All these firms anticipated future regulation, and this anticipation drove innovation efforts. Policy makers became interested in the opportunity to drive increased efficiency, and regulation—when it eventually came—drove both diffusion of the higher-efficiency products and further innovation in higher-performing pumps. Similarly, Wesseling et al. (2015) observed how the lobbying activities of specific automotive firms were influenced by their innovation capabilities with

[23] Between 1984 and 2010, US CAFE standards remained essentially static. A broader study of the impact of vehicle emissions regulation (Lee et al, 2010)**, covering the impact of US legislation adopted from 1970 to 1998, finds that standards did have a substantial impact on both vehicle patenting and performance in the US. The fact that the EU maintained high gasoline prices through taxation for most of the period, whilst US gasoline prices reflected much more strongly the fluctuations in international oil prices, could also explain some differences between US and EU findings concerning the relative importance of price compared to regulatory changes.

regard to cleaner vehicles. Firms worked to shape the regulatory environment to suit their technology strengths, and as a result firms with good low-emission vehicle technology became more supportive of the policy.

6.4 The policy-deployment nexus: innovation indicators and cost reductions

Compared to the extensive literature on how policies have influenced patents – and equally extensive literature on experience curves summarised in the next section - a much smaller literature tries to trace the explicit impact of policies on innovation outcomes (particularly cost reduction), and the feedback from deployment itself to patenting.

Kim et al., (2017) also examined the specific impacts of RPS, FiTs and the combined effect of the public procurement of renewable electricity and public investment in facilities, infrastructure and systems, on the installed cost of solar PV (1992-2007) and wind (1991-2006), for up to 16 OECD countries. They find that public procurement and investment reduced the installed cost of both technologies; RPS reduced PV costs; and FiTs did not have significant influence on costs of either.[24] They also found that *cumulative capacity* had a positive impact on patent applications across the range of OECD countries (particularly for wind); and also influenced (but to a lesser degree) *installed costs* (particularly for solar PV). The results imply an increase in patent applications for solar PV and wind of 15.7% and 43.5% for each doubling of installed capacity (as a proportion of all patent applications), in turn implying "that the more the renewable energy technologies diffuse, the more learning and knowledge from customers or stakeholders are undertaken, which broadens the scope of new ideas and facilitates inventions faster and easier" (ibid, p.221). The results also imply learning rates of 12.9% and 6.1%, respectively, which the authors attribute to 'learning-by-doing' effects.

Tang (2018) found that both RPS and generation-based tax credits had a positive influence on the average capacity factor of wind farms in the USA (2001-2012), whilst capital investment incentives were insignificant. Note also a close relationship of experience curve studies, reviewed in the next section, with the implied impact of quantity-based policies (RPS and biofuel blending) on cost reductions (clearest where national targets dominated an industries' development, as with Brazilian bioethanol).

For demand-side technologies, as noted in Section 5, (Knittel, 2012)* found gasoline prices rather than CAFE standards to be a substantial driver of increasing fuel economy for passenger cars and trucks in the USA over 1980-2006. Newell et al. (1999) found energy efficiency regulations in the USA to have had an insignificant influence on the *cost* of air conditioners and gas water heaters, but as with energy prices (discussed in Section 5), they induced energy *efficiency* improvements of 7.1% and 7.6%, respectively, for room air conditioners and water heaters between 1973 and 1993 (24% and 68% of the total increase in efficiency over this period). By contrast, Van Buskirk, Kantner, Gerke, & Chu (2014), Wei, Smith, & Sohn (2017b) and Smith, Wei, & Sohn (2016) discussed in the next section, all find increases in learning rates for lighting and various appliances (largely in the USA) to be strongly correlated to the introduction of energy efficiency standards (see note 23 concerning US auto standards).

Some studies use technology deployment as a proxy for policy presence or stringency on innovation indicators or outcomes. For example, Dechezleprêtre & Glachant (2014)* find annual additional wind power production, as a proxy for deployment support, clearly enhanced wind patent filing across OECD countries (1991-2008), with the time lags in realized innovation making the causal direction

[24] The authors suggest this is result of market competition induced by RPS, stimulating cost reduction in technologies with the greatest potential for it, such as solar PV.

unequivocal. Both domestic and foreign deployment positively affect innovation, but the marginal effect of domestic policies is 12 times higher than that of foreign policies. However, since for most countries the total market is dominated by foreign deployment, each 100 MW of wind energy capacity deployed, on average, induced the development of one domestic patent and two patents abroad.

Similarly, Peters et al. (2012)** used annual deployment of new PV capacity as a measure of the level of PV deployment support policies, and found that both domestic and foreign demand-pull policies were important for the patenting in solar PV across 15 OECD countries (1978-2005). Nemet (2009b) documents an interesting absence of correlation between investment in new wind capacity (a proxy for demand-pull policies) and the number of high-quality patent filings over the period 1975-2005. In other words, deployment policies might induce more incremental innovation, but not more radical innovation.

Relatively few studies explicitly attempt to examine the link between deployment and patent activity in its own right. Boehringer et al. (2017) finds increasing installed capacity of a range of renewable electricity technologies to have a substantial influence on patent applications, both in Germany and the wider OECD. De Freitas & Kaneko (2012)* finds a causal relationship between ethanol diffusion in Brazil (measured by Brazilian consumption) and the number of ethanol-related patents filed at Brazil's National Institute for Industrial Property.

Conclusions from econometric analysis of policy-deployment with patent-cost reduction feedbacks

A major challenge to interpreting innovation-related data is the bidirectional nature of interactions, which is a fundamental insight of the systems innovation literature as discussed in Section 2. This poses some particular challenges for interpreting the impact of demand-pull policies which, in one way or another, drive deployment, but may also have wider influences on innovation processes. Nevertheless, the predominant findings of literature in this section clearly support positive bi-directional interactions, with demand-pull policies associated with cost reductions, and consequent deployment clearly associated with enhanced patents – all of which contributes to interpreting the more extensive, but simpler, literature on correlations explored in next section.

6.5 Experience curves and beyond

While a substantial literature demonstrates the links between demand-pull policies and patents, these studies provide less evidence on the effects of greater patenting on innovation outcomes, such as cost reductions. This section summarises the main findings from literature on 'experience curves' which chart the relationship between cumulative deployment and cost reductions. We then consider the various types of evidence around causality in this relationship.

Context

Stemming from techniques originally used by Wright (1936)**, who observed that every time aircraft production volumes doubled, the time required to produce new aircraft reduced by 20%, 'experience curves' (and their implied 'learning rates', defined as the percentage reduction in costs for every doubling of cumulative installed capacity)[25] have been used to examine the relationship between production volumes and costs for numerous technologies (e.g. Boston Consulting Group, 1972) and further extended to map costs as a function of *cumulative deployment*, usually at a global level. The

[25] We apply the term 'experience curve' rather than the often-used 'learning curve', to avoid the inference that all cost reductions observed may be attributed to 'learning'. However, we continue to apply the term 'learning rate' as defined above, but with the caveats discussed below.

studies reviewed in this paper derive experience curves and subsequent learning rates for different combinations of technologies, and use a range of deployment measures, cost measures, and methodologies.

Although Wright (1936)** concluded from his observations that we 'learn by doing', the causal (inverse) relationship between cumulative deployment and technology cost remains somewhat contested in economics, and is not often applied within energy-economy system modelling, for at least three reasons. Firstly, in contrast to the grounding of patent elasticities in the theoretical basis of directed technical change by Hicks (1932)** there is less obvious, well established theoretical underpinning for this relationship in mainstream economics. Secondly, it introduces increasing returns to scale, which can create path dependence and challenge the uniqueness of economic equilibria, thus for example vastly complicating the operation of optimising models. Thirdly, the causality is unarguably *bidirectional* – deployment may drive cost reductions, but the reverse may also be expected. We take the view that these factors only increase the value in probing the evidence carefully.

Studies examining 'single-factor' experience curves and learning rates derived from them are common (e.g. Garzon Sampedro & Sanchez Gonzalez, 2016; Junginger et al., 2005), however they do not attempt to disentangle the threads of the relationship between deployment/diffusion and cost reduction, which as illustrated by Figure 3, is not simple or closed (or unidirectional, as noted). Simple interpretations of the results of such studies therefore run the risk of attributing all cost reductions in a given technology to 'learning-by-doing' induced by cumulative deployment. Two- or multi-factor experience curves (Miketa & Schrattenholzer, 2004; Soderholm & Klaassen, 2007; Y. Yu, Li, Che, & Zheng, 2017; Zhou & Gu, 2019) – although less prevalent – attempt to separate one or more of these threads, which may include economies of scale, changes in key resource costs, 'learning-by-searching' (the fruits of continued public or private R&D) and spillovers from other technologies or sectors, to measure their relative influence. The major factors that contribute to uncertainty and variability in learning curve formulations are elaborated in Yeh & Rubin (2012)**.

Overview of experience curve literature characteristics

We limited our search for experience curves (Search-Link II) to conventional electricity generation technologies, and other technologies for which deployment may reasonably be considered to be the result of (or substantially encouraged by) targeted-demand pull policy interventions (see Appendix II). Of the initial pool of 1,082 results, we retained 63 for review. The majority of the studies excluded were so because they either reported previous results produced by other authors (as part of a literature review or as input to further work), or projected experience curves into the future, rather than empirically deriving results from historic data (and in many cases, both). A further 12 studies were added to these results as they came to light through reviewing the initial results, for this and other Search-Links. Figure 7 presents the technology coverage of the 75 studies that presented original empirical results.

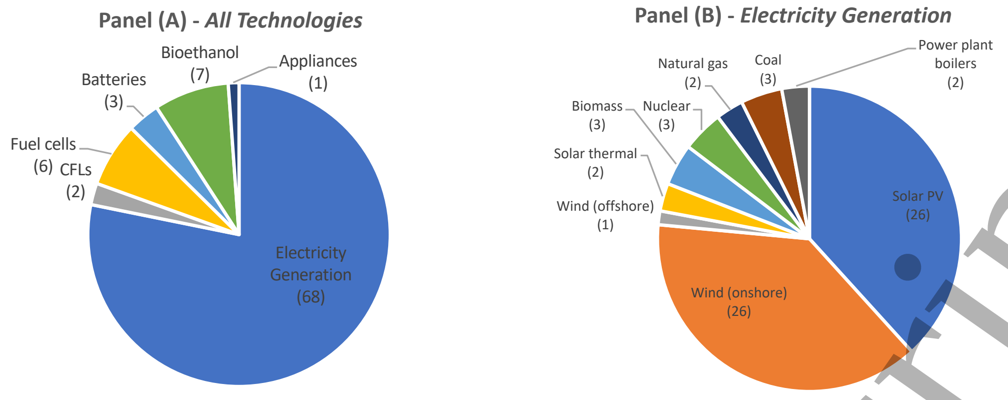

Figure 7: Technology coverage of experience curve studies, for all technologies (Panel A) and the electricity generation technology subset (Panel B).
Note: The total count of coverage for all technologies (87) exceeds the number of studies, as some studies examine more than one technology

Of these 75 studies, 58 examine *electricity generation* technologies. Of these, 23 were also included within a review by Rubin et al. (2015)**, and 45 were reviewed by Samadi (2018)**. The remainder were not covered in these reviews largely due to their more recent publication. We also draw on the review of experience curves of several demand-side technologies by Weiss et al (2010)**, and review (the few) relevant studies published since, for selected technologies.

This section summarises and builds upon the lessons learned in these previous reviews. The vast majority of studies for electricity generation technologies derive learning rates based on cumulative production of capital stock (e.g. MW of installed capacity),[26] whilst technology cost is represented most commonly by the production cost or purchase price per unit of installed capacity (52), followed by the cost of per unit of electricity generated (usually a derived Levelised Cost of Electricity - LCOE) (16)[27]. Most of these studies derive one-factor learning rates, with the limitations noted. Of these 58 studies, 26 studies each derive experience curves for solar PV and onshore wind, respectively (with some overlap).

Solar photovoltaic and wind energy

The modern wind power industry began in the 1970s and commercialised significantly for power generation from the 1980s onward. As a technology for grid-connected electricity production, solar PV is a more recent entrant to the market, and has expanded from a much smaller base, but more rapidly, since about 2000.

Figure 6). The studies calculating learning rates for onshore wind and solar PV (26 each) all find clear and unambiguously positive learning rates, but with substantial variation reflecting differences in temporal and geographical coverage, and specific metrics used, as summarised in Figure 8 and Figure 9.

[26] The exceptions being 7 studies that derive learning rates based on cumulative energy generation (e.g. MWh), and 6 based on technology 'units' installed, sold or produced.
[27] For cost metrics, a few studies used other cost measures, including engineering, procurement and construction (EPC) costs, or cost components (e.g. balance-of-system (BOS) costs and non-fuel operations and maintenance (O&M) costs).

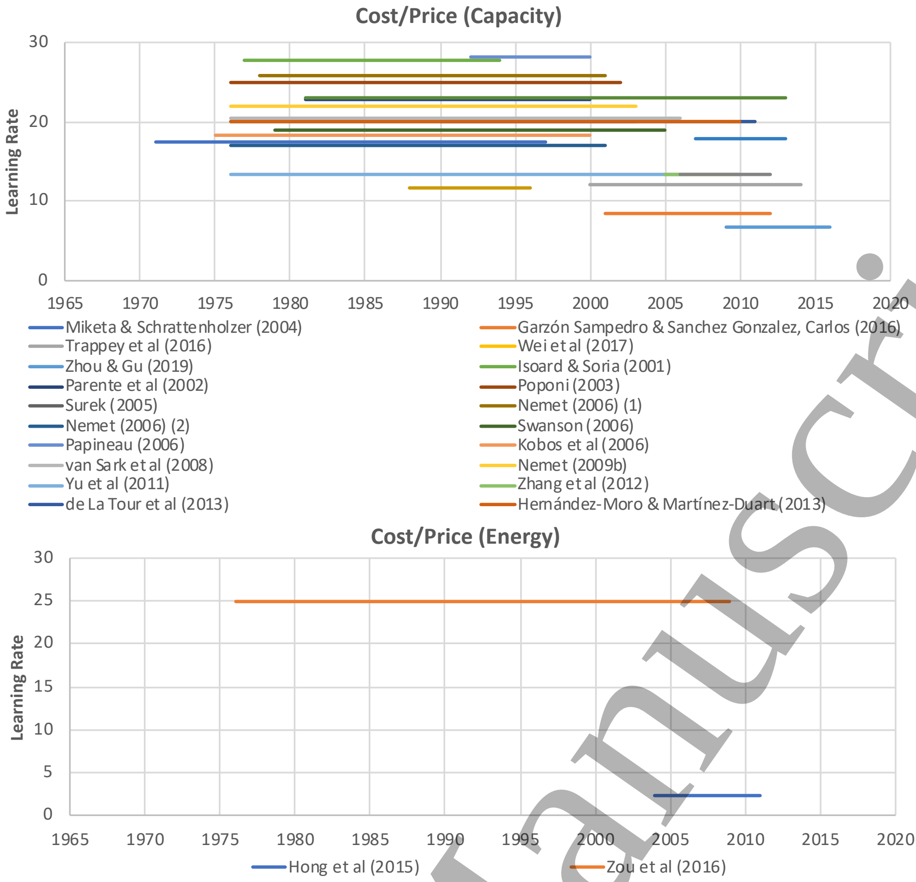

Figure 8: Learning rates for solar photovoltaic (PV), for cost/price of capacity and energy generated. Note: The primary result for each technology and dependent variable from each study has been selected. In studies with more than one learning rate per technology per dependent variable, the learning rate with the highest R2 value was selected for figures, or if not specified then the longest data analysis period. If neither of these are specified, the highest rate was selected.

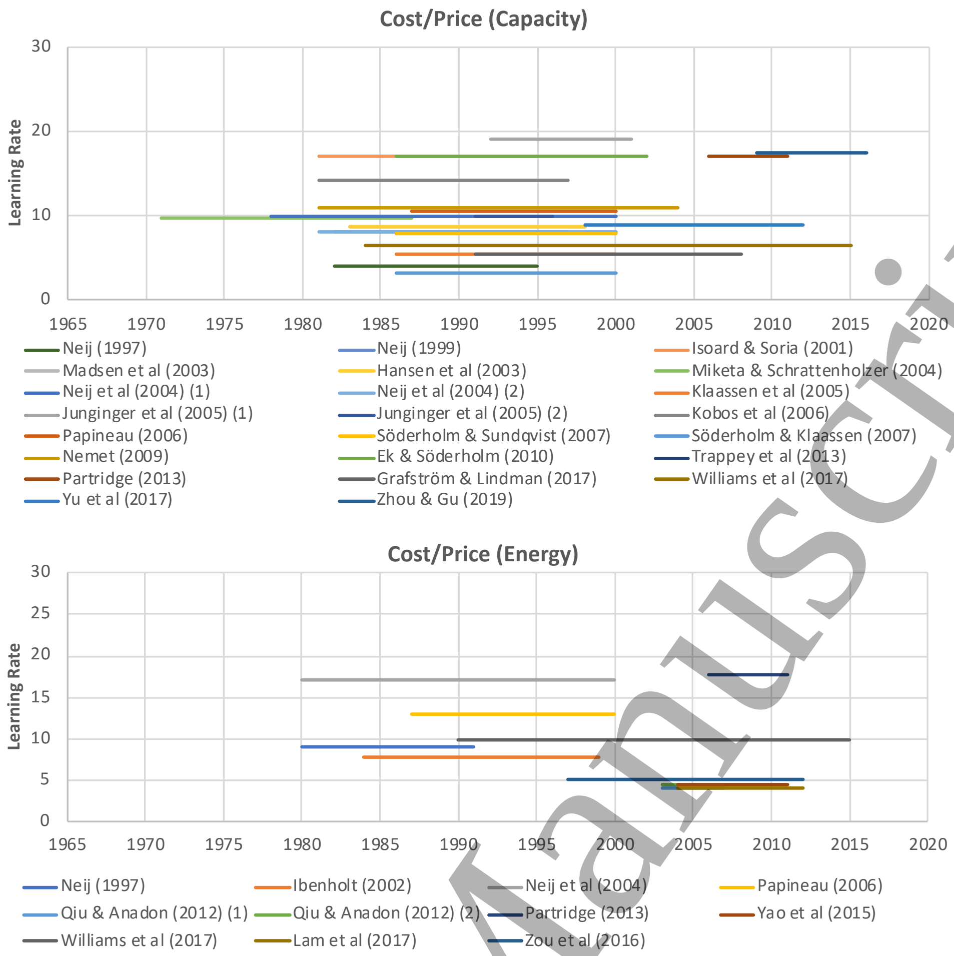

Figure 9: Learning rates for onshore wind, for cost/price of capacity and energy generated. Note: The primary result for each technology and dependent variable from each study has been selected. In studies with more than one learning rate per technology per dependent variable, the learning rate with the highest R2 value was selected for figures, or if not specified then the longest data analysis period. If neither of these are specified

Photovoltaics. The global learning rate as measured by cost (or price) per unit capacity has sustained at around 20±6% for most of the past four decades, although with two- or multi-factor studies producing values at the lower end of this range, and some outliers particularly during a period (c.2003-2010) of supply-side bottlenecks with high silicon prices. Variations between geographies and over time were identified, there is little evidence to suggest that learning rates have declined over time – particularly when controlling for input prices (notably silicon costs - see Section 6.6). Learning rates may differ somewhat between residential and utility-scale systems, partly reflecting lower learning rates (around 10%) observed in the non-hardware 'balance of system' costs (Elshurafa, Albardi, Bigerna, & Bollino, 2018).[28,29]

Onshore wind. Studies focus on Europe (and particularly Denmark), given the historic concentration of installed capacity (with many including data from the 1980s, although relatively few extend their

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[28] This study is excluded from Figure 8, as it it's focus on BOS costs means it is not directly comparable with learning rates for the technology more broadly.

[29] Although not within he technical scope of this review, another study examining BOS costs is Bollinger & Gillingham (2019)**, who find a learning-by-doing contribution of 15% to the one-third reduction in BOS costs in PV installations in California (2002-2012).

analysis significantly beyond 2000). Observed rates for the price or cost of installed capacity tend to cluster at 5-15%, again with two- and multi-factor studies producing results at the lower end. As innovation over time (e.g. increasing turbine height, rotor blade diameter) has led to increasing capacity factors, learning rates for LCOE has tended to be slightly higher (8-13%), particularly as derived by studies using longer time series data. We identified a single study in the peer-reviewed literature attempting to derive an experience curve for offshore wind. van der Zwaan et al. (2012) find an installed cost learning rate of 5% for offshore wind in Europe (1991-2008), once the influence of key commodity prices and supply chain constraints are accounted for. However, the authors acknowledge that this is based on limited data with a poor statistical fit.

Other electricity generating technologies

The limited literature relating to conventional thermal power stations points to early learning but subsequent literature is thin and experience varied. Colpier & Cornland (2002) and Ostwald & Reisdorf (1979) found significant deployment-related learning for natural gas power plants in the past; we did not find subsequent literature. For coal power plants, deployment-induced learning appears to have taken place throughout much of the last century, although since the late 1960s, construction costs appear to have largely plateaued (McNerney, Farmer, & Trancik, 2011; Ostwald & Reisdorf, 1979; Yeh & Rubin, 2007).

More clearly, in many countries that have built nuclear power plants, initial cost decreases have been observed, followed by pronounced cost increases since the late 1960, leading to negative learning rates (Lang, 2017; Ostwald & Reisdorf, 1979; Rangel & Leveque, 2015). However, these and various other studies that examine trends and drivers in the cost of nuclear (e.g. Berthélemy & Escobar Rangel, 2015**; Grubler, 2010**; Kahouli, 2011**) typically focus on a relatively limited time period (1970s-1990s), and on installations in the USA and France - countries which represent just a quarter of all nuclear installations constructed. More recent evidence from other countries (such as Japan and South Korea) suggests that costs elsewhere have remained stable or even declined since this period (Lovering, Yip, & Nordhaus, 2016**; Matsuo & Nei, 2019**).

Nuclear has relatively unique characteristics among electricity generating technologies in use to date, which may make attempting to discern drivers of cost development particularly difficult, and highly context-specific. Lovering et al., (2016)** suggest that even aside from changes in specific reactor technology and design, cost drivers such as utility structure, reactor size, regulatory regime, and international collaboration have played a greater role in determining trends in nuclear costs than any learning effects to date; to which Eash-Gates et al. (2020)** add labour productivity trends.

Studies of bioenergy-based power generation, which also generally uses conventional thermal power generation, have found positive learning for both investment and LCOE-based costs. However, the three studies reviewed are narrow in geography and timeframe (Junginger et al., 2006; Lin & He, 2016; Wang et al., 2018).

Other technologies

Biofuels. Seven studies charting experience curves in biofuels produced exceptionally divergent results (see Appendix II), with learning rates varying from slightly negative to almost 40% between different studies and periods. One major reason for this appears to be the dominant role of the Brazilian biofuels industry, with the derived data being strongly influenced both by exchange rate fluctuations and the vagaries of the sugar market. The studies taking the longest view – from the mid 1970s – have gravitated towards a long-term average of 16-20% for Brazilian ethanol, though one of these suggests much of this may have been due to exogenous technology spillovers. Two studies of US ethanol find comparable but slightly lower learning rates.

Demand-side technologies: household and consumer goods. The seminal study of experience curves in demand-side technologies (Weiss et al, 2010)** found an average, cross-technology learning rate of 18% (±7%) across fifteen technologies (mostly building and appliance-related). However, rates of

20-30% were found for consumer electronics and components, heat pumps, and compact fluorescent light (CFL) technologies, with high learning in CFLs in particular reinforced by several subsequent studies.

Demand-side technologies: low-emission vehicles. Early studies found relatively low rates of learning for hybrid vehicles (well below 10%), probably in part because initial deployment represented a very small, loss-leading fraction of sales by major global car companies (notably, Toyota), but potentially also because relatively small difference to full-internal combustion engine vehicles hybrid vehicles represent. Studies of both full battery-electric vehicles (BEVs), and their components – particularly lithium-ion batteries - find consistently higher learning rates, mostly in the range 9-16%.

Demand-side technologies: energy storage. Learning rates for stationary battery technologies (including lead-acid) have tended to find similar, though perhaps slightly lower learning rates than their mobile counterparts. Despite a huge variety of competing technological options, learning rates for stationary fuel cells seem to find consistently higher learning rates, in the range 15-25%, with a few notable, localised exceptions. For many of the designs, the technologies remain in relatively early stages, and the deployed base, modest.

Statistical conclusions on experience curves

In short, the general findings from experience curve studies are unambiguous: excepting extremely large and complex industrial facilities characterised by nuclear and large coal power stations, expanding deployment and cost reductions have been clearly and positively correlated across a huge range of technologies. The literature is strongly suggestive of higher learning rates in smaller, more modular and relatively less complex technologies (as also concluded by e.g. Malhotra & Schmidt, 2020), with indications also of higher learning rates in earlier stages of deployment, implying declining learning rates as technologies become more established and mature - though this remains to be seen in some technologies, including solar PV. The question is, what does this actually imply about induced innovation?

6.6 Interpreting experience curves

As noted, experience curves measure a correlation, not causation. The cost and diffusion of a technology are influenced by a multitude of factors. The relationship between them is complex, including (as emphasised by Nordhaus, 2014)**, the feedback loop illustrated in Figure 3, as technology improvements (in cost or efficiency) should enhance diffusion. Only a few of the experience curve studies analysed explicitly state this (e.g. Junginger et al., 2005; Strupeit & Neij, 2017). Only one of the studies examined (Isoard & Soria, 2001) performs a statistical test for causality (a Granger test), and find that for solar PV and onshore wind, cumulative installed capacity causes capital cost changes for both technologies, without feedback.

Some insights come from the relatively few studies producing two- and multi-factor learning rates, the majority (Klaassen, Miketa, Larsen, & Sundqvist, 2005; Y. Yu et al., 2017; Zhou & Gu, 2019) of which suggest that R&D expenditures are an important contribution to cost decreases – although specific values differ considerably, and are associated with high uncertainties. There are several reasons for this, including difficulties with accurately accounting for private R&D expenses due to a lack of available data, and establishing an appropriate time lag between R&D expenditure and its effect on technology costs. Moreover of course deployment increases revenues which enhance not only the incentive, but the financial capacity, for private R&D, as noted below. Finally, R&D expenses tend to increase over time, as do many other potential independent variables (e.g. size of wind turbines), making it difficult to separate the impacts made by each variable. (Söderholm & Sundqvist, 2007 p.2575) find that adding a time trend in their regression analysis leads to negative learning-by-searching (i.e. R&D-related) rates that are no longer statistically significant, as the time trend tends "to pick up most of the variation previously ascribed to the R&D-based knowledge stock."

In addition, the studies of how targeted demand-pull policies influence innovation already covered in this section also clearly inform our understanding of causality in experience curves. To the extent that technologies are deployed when they are much higher cost than incumbents, it is reasonable to assume that the direct feedback from cost reduction to deployment is weak. Private investors are unlikely to deploy much more of a technology which is still 50% more expensive than incumbents, just because they were previously twice as expensive. There could of course be some feedback to policies which support deployment, which become less expensive as the cost difference declines, as discussed in the qualitative and mixed methods literature.

An important additional line of evidence for causality in learning curves comes from cost decomposition studies. Several studies demonstrate that key input prices, as well as various forms of economies of scale (upsizing of technologies, more individual plants per project, larger manufacturing plants for key components) influence derived experience curves. Input price changes have been shown to explain part of the observed deviations from a constant learning rate for solar PV (de la Tour, Glachant, & Meniere, 2013; Gan & Li, 2015; Mauleon, 2016; Trappey et al., 2016), onshore wind (Grafstrom & Lindman, 2017; Partridge, 2013; Qiu & Anadon, 2012; Y. Yu et al., 2017) and offshore wind (van der Zwaan et al., 2012). The upsizing of technologies has been shown to have a considerable effect on early wind turbine cost developments (Madsen, Jensen, & Hansen, 2003; Söderholm & Sundqvist, 2007; Y. Yu et al., 2017), while it has been suggested that the continuous increase in the size of PV manufacturing plants may explain a considerable share of historic cost decreases of PV modules (Isoard & Soria, 2001; Kavlak, McNerney, & Trancik, 2018; C. F. Yu, van Sark, & Alsema, 2011).

Nemet (2006) and Kavlak et al. (2018) apply bottom-up cost models to identify the contribution of different technical factors to overall cost changes in solar PV. Their approach provides a rich description of the proximate factors resulting in declining costs (such as module efficiency, or silicon usage), which both studies then relate to the driving forces of learning-by-doing, R&D, and economies of scale in manufacturing processes. Both studies highlight the major role played by both public and private R&D in enabling the cost reductions observed, and a strong role for economies of scale; Kavlak et al. (2018) find a smaller role for pure learning-by-doing, though obviously there are linkages which are hard to disentangle.

Kavlak et al. (2018) also find an important shift over time. Echoing the finding by Kruse & Wetzel (2016) on patents noted earlier[30] they estimate that over 1980-2000, public R&D and spillovers accounted for almost 50% of cost reductions, double that attributable to economies of scale and learning-by-doing combined. From 2001-2012, however, these forces reversed: public R&D and spillovers accounted for maybe one quarter of the observed cost reduction, whilst scale economies and learning-by-doing accounted for half. Moreover, Kavlak et al. (2018) suggest that the balance, attributed to private R&D, was largely catalysed by policies to support deployment (such as feed-in tariffs). This effect—of deployment support resulting in increased private R&D expenditure—was observed by Hoppmann et al. (2013) with regard to the solar PV industry. Taken together, these studies suggest that the cost reductions observed in solar PV, commonly seen as an example of learning-by-doing, are better understood as a process of increasing returns associated with a combination of mechanisms, including scale economies and induced private R&D expenditure alongside learning-by-doing, as well as (for cost of energy), declining cost of finance associated with maturation of the industry. Finally, we note that the balance between global and local experience and cost trends, seems so far to be little studied.

[30] Section 5; Kruse & Wetzel (2016) also note major changes in patenting between technologies: "For biofuels and fuel cells, we see a significant increase during the 1990s, after which patent activities began to decrease. A completely different picture emerges for wind and solar energy. Here, we observe an above-average growth starting from the mid-1990s, with exceptionally high growth from the mid-2000s."

Conclusions on interpreting experience curves

The experience curve data charted in Section 6.5 combines the impact of many factors, some easier to disentangle and measure than others, but cannot be neglected simply on grounds that 'correlation does not prove causation'. The causal-test, multi-factor, and cost-decomposition studies reviewed in this section complement the evidence surveyed in Sections 6.2-6.4, to fill out a broader picture of the innovation dynamics at play, to which we return in our discussion in Section 9.

7. Policy mixes and survey evidence

As is evident from the previous sections, a relatively large literature examines the impact on innovation of energy prices, taxes, and a variety of more targeted individual instruments, whilst the experience curve literature tracks the simple correlation of deployment and cost reduction, as 'learning rates'. In reality, instruments are usually introduced as part of a policy 'mix', often to address deficiencies that an existing instrument does not or cannot tackle, and learning rates leave causality to be inferred. Moreover as noted, the wider environment (including price shocks) often stimulates more targeted policies. Relatively few studies explicitly examine the influence of instrument *mixes* on either indicators (e.g. patents) or outcomes (e.g. cost or energy efficiency) of innovation.

Patents

Palage et al. (2019) found patent applications following public R&D support for solar PV increased when combined with FiTs, across 13 countries (1978-2008), although RPS schemes produced little marginal effect (possibly due to the stronger technology selection pressures, discussed in Section 6). Girod et al. (2017) found the number of 'demand-pull' instruments for the residential and industry sectors to enhance the generation of energy efficiency patents in each sector, across 21 European countries (1980-2009). Costantini et al., (2017) reach a similar, but more nuanced conclusion for the residential sector for 23 OECD countries (1990-2010). They find that a balance between technology-push and demand-pull policy instruments in a policy mix, and comprehensive mix of demand-pull instruments, both induce greater patenting than an imbalanced and less comprehensive mix. However, they note that demand-pull comprehensiveness does not necessarily equate to instrument count, and simply adding instruments without sufficient consideration for instrument interaction, may reduce the overall impact on innovation.

In contrast, Nesta, Vona, & Nicolli (2014) finds a policy instrument mix to have had no significant effect on renewable energy patenting in the OECD (1976-2007), when accounting for the endogeneity of policy (i.e. when the increased likelihood of policies to encourage renewable energy deployment being introduced in countries that are already active in their development) is controlled for. However, when removing this control, the impact is positive, providing further evidence for the interrelated path dependency in both technology and policy making.

Other innovation indicators

From their analysis of the Spanish manufacturing sector (2008-2013), Costa-Campi et al. (2017) conclude that a policy mix would encourage *private R&D* to a greater degree than instruments applied individually. For the Chinese manufacturing sector, Guo & Wang (2018) find the combination of public R&D support with environmental regulation to have enhanced product innovation as measured by energy efficiency, whereas environmental regulation alone appeared insufficient.

Survey literature

A much wider literature derives evidence from surveys, either self-constructed, or using well-known international surveys as the European Community Innovation Survey (CIS), or national equivalents. These surveys tend to focus on the manufacturing and service sectors, and include questions on the role of public policy in inducing 'eco-innovations'; a term that may be broadly defined, and which may include both product and process innovation (including adoption of existing techniques, but which are new to the firm), and span beyond energy and CO_2 to all environmentally-related actions. Disentangling the effects relevant to our scope of interest in this review in many cases therefore proves challenging, but is helped in some studies by a narrow definition of the policy variable. However, in many cases policy variables are usually broadly defined (often simply as a single policy or regulation 'dummy'), with specific instruments or instrument types often not discernable.

However, a contribution of this survey literature is its ability to consider factors that econometric studies often do not (or cannot) consider, including innovation that is hard to patent or otherwise difficult to quantify. Surveys may therefore highlight factors relevant to a broad set of theoretical approaches and explanatory variables concerning innovation, including the 'systems of innovation' perspective, evolutionary economics and the resource-based view (RBV) of the firm (del Rio, Penasco, & Romero-Jordan, 2016). As they stated, green innovation is not a systematic response only to environmental policy instruments, but the result of a mosaic of interactions with other factors. Consequently, where identified in our search, we consider these to be in scope.

Much of this survey literature focuses on Western European countries, particularly Germany and Mediterranean countries (Borghesi, Cainelli, et al., 2015; Cainelli & Mazzanti, 2013; Crespi, Ghisetti, & Quatraro, 2015; Horbach, Rammer, & Rennings, 2012; Jove-Llopis & Segarra-Blasco, 2018; Penasco, del Rio, & Romero-Jordan, 2017; Veugelers, 2012; J. Weiss, Stephan, & Anisimova, 2019). Only two studies were found on other countries - China (Liu & Wang, 2017) and Korea (Joo, Seo, & Min, 2018). Despite the caveats regarding definitional granularity discussed above, a common conclusion is that environmental regulation (Borghesi, Crespi, et al., 2015; Horbach et al., 2012; Joo et al., 2018; Penasco et al., 2017; Veugelers, 2012; J. Weiss et al., 2019) and future or expected regulation (Crespi et al., 2015; Joo et al., 2018) plays a key role in promoting eco-innovation. Stucki et al. (2018) find energy-related taxes and regulations can *reduce* product innovation if they do not create demand for the product, although this effect is removed for firms at the technological frontier. In China, (Liu & Wang, 2017) found that regulation does not stimulate corporate technological upgrading in China's energy intensive industry, but market-based policies (i.e. economic incentives) do. Taken together – between traditionally more and less market-based economies respectively - this could be considered to also point to the value of diverse incentives to stimulate innovation.

Grants, subsidies and other provision of public financial support generates more mixed evidence. Positive impacts are found mostly for technologies and innovation associated to CO_2 abatement technologies (Cainelli & Mazzanti, 2013; Jove-Llopis & Segarra-Blasco, 2018; Veugelers, 2012) and for national public aid (Penasco et al., 2017). However some authors find little impact on innovation (Borghesi, Crespi, et al., 2015; Horbach et al., 2012).

Qualitative and mixed-method literature

This literature also provides a rich insight into the dynamic, complex interaction between policy mixes and innovation. Such studies typically do not attempt to disaggregate the impact of individual instruments (and it is not always straightforward to identify the distinction between 'demand pull' and 'technology push', as noted by Taylor (2008)), but rather seek to observe the mechanisms through which a policy mix interacts and generates innovation. This literature suggests that interaction effects can be important (McDowall et al., 2013; Nemet, 2009a; Reichardt & Rogge, 2016; Ruby, 2015) – and both positive and negative (Borghesi, Crespi, et al., 2015). Whilst policy instruments themselves and their design are influential, such studies often report that it is their interaction and characteristics of the policy mix as a whole that are decisive in terms of their impact on innovation – for example by influencing the expectations of innovators about the future market and policy conditions. This literature highlights the importance of consistency between instruments, and between instruments and policy strategy (Reichardt & Rogge, 2016). Unsurprisingly, policy processes and implementation issues (such as lack of coherence, poor or inadequately skilled enforcement) have also been observed to determine the efficacy of instruments, quite apart from the design of the instruments themselves (Kivimaa et al., 2017).

As with surveys, this qualitative and mixed methods literature reveals some limitations of an 'instrument-by-instrument' view of policy. The wider enabling policy environment – e.g. as reflected in the borders of Figure 1 – cannot be fully separated from the introduction of targeted instruments. These factors include e.g. brokering, enabling, providing information and building capacity (e.g. (Hasanbeigi, Menke, & du Pont, 2010), issuing and enforcing property rights, developing and institutionalising safety and other codes and standards, and adapting regulatory structures and permitting processes.

The impact of demand-pull instruments and policy mixes also depends on industry structure. A striking example of the complexities concerns power networks, which as natural monopolies are typically highly regulated. The difficulty of drawing generalised insights is then further compounded by policy interactions, as clearly illustrated by the case of UK electricity privatization, with initial collapse of R&D (Dooley, 1998);* Jamasb & Pollitt (2008))* and the subsequent regulation of its networks, which involved increasingly overt additional incentives for innovation, and recovery of R&D spend (Jamasb & Pollitt, 2015).[31] Studies have noted several other ways in which public authorities have used their influence on network regulation to facilitate market formation for emerging technologies. For example, in Denmark's early phase of developing offshore wind power, utilities were encouraged to experiment with offshore wind, and were allowed to pass on costs to consumers (Smit et al. 2007), and several countries require grid companies to cover the costs of connecting renewables (Reichardt & Rogge, 2016; M. Taylor, 2008).

All these interactions constrain the conclusions that can be drawn about the impact of any single instrument, but is perhaps most limiting concerning broad-based measures. For example, the EU ETS has an impact on patenting which can be directly measured, and compared against a 'control' of non ETS firms below the threshold. But what about the impact higher-up the supply chain (on technology providers)? The impact downstream through cost pass-through? The further effects through knowledge spillovers (positive) and product market rivalry (negative), including across borders? The potential crowding-out effects on other types of innovation of all these impacts? Further general equilibrium effects? Credibly assessing the full effect of broad-based instruments like carbon pricing on innovation is, in totality, infeasible.

Governments also influence expectations which help shape private sector activity (Nemet, 2009a; Reichardt & Rogge, 2016). Expectations of the future policy landscape can affect innovation (Ruby, 2015), which complicates analysis of the time-lags associated with innovation responses to policy.

[31] After privatisation, the UK introduced a simple price regulation for networks, based on retail price index minus an annual improvement factor ('RPI-X'). Network companies, not known for their innovation, further reduced R&D spend to maximise short term gains. To try and compensate for this, the regulator then introduced a series of innovation funds and competitions, requiring participation and co-financing of network companies and some pass-through of R&D expenditures (Jamasb & Pollitt, 2011, 2015), and then moved to a new form of price regulation based on 'Revenue = Investment, Innovation and Outputs" (RIIO). Disentangling the impact of liberalisation, funds, and new forms of network governance to find general rules would thus be almost impossible.

Uncertainty about future demand-pull policy appears to weaken the *amount* of innovation, but it apparently can also influence the *direction*, notably by changing the extent to which policy induces radical innovation, or incremental steps that mostly exploit existing technology designs (Hoppmann et al., 2013; Nemet, 2009a).

Finally, these wider activities can be strongly influenced by the nature of the state (Calef & Goble, 2007; Hadjilambrinos, 2000; Mikler & Harrison, 2012), such that the way in which technology support programmes are selected, designed and implemented can have significant national characteristics. Such studies highlight that policy instruments that 'work' in one context might be less (or more) effective elsewhere. Thus, conclusions may be robust, but still not necessarily universally applicable.

8. Multi-Sector and Macro-level technological change

The highest-level approach to assessing induced innovation examines the effect of regulation and policy-induced price changes not on specific technology outcomes, but on broad sets of sectors or at the aggregate macroeconomic level (Table 1, Search-Link III). Induced-technology effects at this level tend to be observed and deduced from changes in multi-sectoral and aggregate energy use, and in aggregate productivity measures.[32]

The initial search for literature on broad multi-sector and macro-level technological change identified 285 studies, of which only 26 peer-reviewed publications were deemed in-scope. These predominantly use econometric techniques to study the impact of energy prices (10), or of energy or environmental policy or regulation (9). Other independent variables included foreign direct investment (3) and knowledge stock measures (3). Studies measured aggregate energy intensity and total-factor energy efficiency (5 for each), whilst others estimated changes in total factor productivity due to environmental regulations or oriented towards green technologies (8). These studies varied greatly in the rigor, clarity, reproducibility or representative data sampling of their empirical approaches: based on the quality of the journals and our own assessments of these factors, we focus our review on the highest-quality work, whilst acknowledging the potential relevance of the broader literature in this inherently complex field.

Aggregate technical change is traditionally measured in terms of changes in "total factor productivity" (TFP), which is typically calculated by dividing GDP by the weighted average of labour and capital inputs in an economy. Section 5 noted clear evidence that energy price rises have induced more private R&D and patenting in energy, particularly energy-intensive industries, but not necessarily overall. In terms of the *direction* of innovation (e.g. towards low carbon technologies), a natural aggregate indicator could be the carbon intensity of energy supply, or ratios of CO_2 to sectoral (value-add) or economy (GDP) outputs. However, none of the relevant sector- and macro-level econometric analyses identified in our search tests for such *decarbonisation*, and there are plausible reasons for this.[33]

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[32] This has some relationship to the literature on the 'Porter Hypothesis' that environmental regulation can enhance firm competitiveness across sectors for which (positive) evidence is summarised in two major reviews (Ambec et al., 2013)** and Cohen & Tubb, (2018)**. However, that literature is mainly at the micro/firm-level and is not mainly about induced technological innovation, but more often about innovation in firm practices and adoption of better technologies – the impact of regulation/prices on profits through 'X-efficiency'. We however look for effects on technology *per se*. Also, the Porter literature rarely focuses on energy or separates energy from other factors.

[33] The biggest large-scale, cross-country drivers of change were the oil shocks of the 1970s, and then early 2000s, without any overt carbon-related signal. Initial responses did indeed include nuclear, and where feasible, expansion of hydro, but these tended to be quite overt, publicly driven rather than market-led induced

Correspondingly, the relevant macro-literature concentrates on how energy efficiency or energy intensity is impacted by energy prices, rather than any specific low carbon policies. Even so, assessment is intrinsically fraught with difficulties. At the aggregate level, it is difficult to disentangle the drivers of technology innovation from structural changes (i.e. shifts between sub-sectors) and the multiple effects of simple factor substitution (e.g. using more labour instead of energy), capital substitution (using more efficient equipment), import substitution (e.g. outsourcing energy-intensive activities), and behavioural innovations by firms (adopting more efficient working practices or new-to-the-firm technologies). Equally importantly, TFP is affected by numerous forces outside the energy sector, so it can be challenging to pick up the (small) signal from any energy-related results at all.

A huge literature documents the response of energy demand to prices (usually by calculating price elasticities of energy demand) and investigates how the response changes under the influence of technical change. The studies differ greatly in whether, and if so how, they seek to disentangle this role of technical change, which means also that our review covers only a very small subset of the elasticities literature.

A small niche within the energy-elasticities literature considers whether elasticities are asymmetric – that changes induced by large price rises do not reverse when prices fall. This can be taken to indicate induced innovation (which would not be expected to reverse), but similar data also could reflect incorporation of some exogenous efficiency improvements into capital stock. This small literature – not captured in our search terms – was stimulated by studies pointing to such apparent asymmetry in gasoline demand, which declined with the 1970s oil price shocks but did not rebound to nearly the same extent after prices fell (Dargay, 1992*; Gately, 1993**; Walker & Wirl, 1993*). Griffin & Schulman, (2005)* challenged these studies' interpretation, finding that the effects could also be explained by stochastically varying exogenous trends, similarly with the subsequent Agnolucci (2010) *study of UK demand.* This in turn was disputed by (Hunt & Ninomiya, 2005*) for Japan, and (Huntington, 2010)* for US petroleum, and by Adeyemi & Hunt (2007*, 2014*) in cross country studies. The conclusion of their 2007 study that "OECD industrial energy demand incorporates asymmetric price responses but not exogenous energy-saving technical change" was tempered by a warning that this finding was not robust for all countries and studies; their follow-up seven years later, analysing 15 OECD countries over 49 years, concludes that: "almost all of the preferred models for OECD industrial energy demand incorporate both a stochastic underlying energy demand trend and asymmetric price responses" and they present elasticity estimates for each of the four dimensions implied.[34] In other words, the evidence is that energy-saving innovation is a combination of both exogenous and price-induced effects.

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innovation. Significant demand-pull policies for renewable energy technologies only emerged from the early 2000s. Given the time lags in compiling data, its acquisition, and publication in journals, not many studies secured in our review go beyond about 2012, and none have data beyond 2016. Innovation in new low carbon technologies such as modern renewables, in volume terms has only become significant in a few countries in the last few years. As illustrated in Figure 6 (Section 6), the growth of renewables has been very rapid but even by 2016, at a global level, only accounted for a small fraction of overall energy supply in most countries. Hence, presumably, the exclusive focus of sector- and macro-level econometric studies on energy intensity.

[34] "Estimated *long-run income* elasticities (0.34 to 0.96); estimated *long-run price-maximum elasticities* (−0.06 to−1.22); estimated *long-run price-recovery elasticities* (0.00 to −0.27); and estimated *long-run price-cut elasticities (0.00 to−0.18)".* Hence they conclude, "when modelling industrial energy demand there is a place for 'endogenous' technical progress and an 'exogenous' underlying energy demand trend … any modelling strategy should start by including both and only impose restrictions if accepted by the data" (Adeyemi and Hunt, 2014)*. The niche nature of this literature to date is reflected in the fact that their reference list, covering a forty-year span, finds only about 30 studies, within which only about half a dozen names feature prominently.

Multi-Sectoral decomposition studies

A sizeable literature singles out the role of induced technical change by decomposing observed changes in energy use into components of structural change and real efficiency improvements. Micro-level decisions by firms and consumers to reduce energy and develop energy-saving technologies translate into aggregate energy reductions. Decomposition methods have been used to separate spending shifts within firms/sectors and spending shifts between firms/sectors. However this still says little specifically about induced innovation unless separate components of the decomposition can then also be related to determinants like R&D, prices, regulations to test for an induced technology channel.

Steinbuks & Neuhoff (2014) focus on the role of technology embodied in the capital stock using a panel model across five OECD manufacturing sectors. They distinguish short-run price responses (given vintage structure of the capital stock) from long-run price responses (changes in the vintage structure towards energy-efficient capital goods), thus separating short-run substitution from long-run investment response. Based on energy price series together with other input prices and cost shares, they find that technical change is responsible for at least three quarters of the total efficiency improvement across US manufacturing sectors. However, this still does not separate the impact of regulatory policies or directly relate to innovation - the model takes energy efficiency improvements in capital as exogenous and focuses on how prices lead this to be embodied in capital stock.

Moshiri & Duah (2016) decompose aggregate energy demand in Canada into a scale, composition, and technique (intra-sectoral energy intensity changes) effect. In regression analysis the composition effect is driven by price changes, as expected, but the technique effect is significantly driven by price changes in only a subset of specifications, which implies some evidence of price-induced innovation.

Sue Wing (2008) assessed data for 35 industries in the US, 1958-2000, in a model which also included changes in quasi-fixed (capital) inputs and allowed for exogenous (time-trend) energy saving/using technical change, whilst price-induced technical change is measured by the effect of cumulative energy price changes. They found that up until the 1970s energy price shocks, innovation was energy-using and almost exclusively exogenous. In contrast, over the period 1980-2000 technical change became energy saving and by 2000, 40% the reduction in aggregate energy intensity coming from technical change was attributed to induced technical change (Figure 7 in Sue Wing (2008): 3.5/9=.39).

Determinants of economy-wide energy demand

As an alternative to the decomposition method, a number of studies estimate an aggregate production function or frontier (which leaves intersectoral substitution implicit) and identify how price changes and regulation have affected macro-economic measures of energy efficiency, energy productivity, and energy-biased technical change. Three different methods allow varied measures of innovation: aggregate energy demand studies; estimates of the determinants of economy-wide factor-biased technical change; and stochastic-frontier-analysis based on aggregate energy-efficiency studies.

Aggregate energy demand studies aim to explain economy-wide energy demand or intensity as a function of production inputs and other determinants, such as R&D, regulation, and energy price changes. If regulation decreases energy demand *ceteris paribus*, this is viewed as implicit evidence for induced technical change. The role of technical change can only be separated from the role of substitution if the estimations control for the energy price, as measured by the full user price and capturing the cost effects of regulation. Including controls for aggregate (private and public) R&D expenditure disentangles drivers as well as effectiveness and direction of innovation.[35]

It turns out that very few studies that study economy-wide energy demand control for all three factors - R&D, price, and regulation. As a result, the impact of specific regulatory policies on induced innovation remains largely untested. Dong et al. (2018) control for R&D and price, and find a positive correlation between energy intensity and total inhouse R&D at the provincial level in China; we learn from this study that R&D has contributed to energy saving in general, but cannot comment on induced technical change. Fei et al. (2014) use a similar method for Canada, Ecuador, Norway, and South Africa (1974-2011), but find no significant effect of R&D on energy use. Taking a different approach, Murad et al. (2019) explain per capita energy consumption from energy-efficiency patent applications and a proxy for the energy price, using a time series approach, finding that specific innovation (patents) towards energy saving is effective.

Aggregate production function studies aim to explain energy-specific aggregate productivity levels with policy and price shocks. Many economy-wide studies estimate a production function that allows for energy-specific technological change, but few then measure if energy saving is related to price and policy shocks. In one of the earliest studies, Watanabe (1992) clearly identifies that innovation in Japan was driven by response to the oil shocks – including government R&D – substituting for oil.

Carraro & De Cian (2012) estimate an aggregate production function for 12 countries (Western Europe and US, 1989-2001) on the basis of national income, capital, labour and energy inputs;[36] they find that the stock of (general) R&D has a strongly significant positive partial-equilibrium impact on energy-saving technological change, but also increases energy-using capital investment; the net effect is that more R&D increases energy demand. The study finds clear evidence for *endogenous* factor-specific technical change, but the study does not have a measure of regulation so cannot separate explicitly *policy-induced* innovation.

Using a similar approach, Fisher-Vanden et al. (2006) estimate aggregate production possibilities in China, with similar results, but also control for ownership structure and trade exposure to capture major transformations in the Chinese economy. Using firm-level data they find that technology development is energy-saving, and capital-, labour-, and materials-using. General R&D investment reduces economy-wide energy intensity and the size of this effect is similar to the effect of sectoral shifts (page 695), but this study does not test separately for policy/regulation effects.

Based on CES production function, Hassler et al. (2012)** also examined US energy and oil price data, finding that the implied measure of energy-saving technical change appears to respond strongly to the oil-price shocks in the 1970s. In the short run, they find low substitutability between energy and capital/labor but much greater substitutability over longer periods due to technical change.

Stochastic-frontier analysis aims to estimate the technical frontier and explore what shifts this frontier. Using this to quantify aggregate energy-efficiency and its correlation with various influences,

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[35] On the one hand, if the regression controls for *total* R&D and energy price, the coefficient on energy regulation measures the *direction of innovation* (and its strength) towards energy-saving innovation (holding fixed total R&D). On the other hand, if the regression includes energy-specific R&D and controls for the full user price of energy, the coefficient on energy-specific R&D measures the *effectiveness* of R&D spending (holding fixed the direction of R&D). The latter is not evidence of a policy-induced or price-induced effect, unless the interaction of energy-specific R&D with regulation and/or price is included.

[36] They use CES (constant elasticity-of-substitution) specification for the production function, which requires that factor prices and time x factor input interactions are included.

Yang, Shao, Yang, & Miao (2018) find that capital deepening and FDI improve technical efficiency, whilst increased fossil energy use and R&D intensity in general reduce technical efficiency.

Zhang & Fan (2018) estimate an energy efficiency frontier across Chinese provinces and then test for the impact of the Chinese provincial pilot CO_2 emission trading systems launched from 2011. Based on data to 2015, they do not find a statistically significant trend break as evidence for policy-induced innovation from these pilot systems. Zhu & Ye (2018) find that environmental (SO_2) regulation in China is correlated with improved green technology, and also find that spillovers from Overseas Foreign Direct Investment in developed countries increases green technological progress, in developing/transition economies reduces it.

Managi, Opaluch, Jin, & Grigalunas (2005) find that environmental regulation of oil and gas industries in the Gulf of Mexico improved overall TFP, including both marketable and environmental outputs, but not marketable output alone. Several other studies also explore how environmental regulation can influence TFP when polluting inputs and pollution reduction are explicitly accounted for (sometimes called “green TFP”). These include Shen et al. (2019a), Song & Wang (2018), Tao & Li, (2018), Wang et al. (2018), Zhang et al. (2018). Such studies use various frontier analysis methodologies and sometimes quite limited datasets, although collectively they tend to at least suggest that there are some gains from innovation induced by environmental regulation.

Conclusions on multi-sector and macro-level technological change

Overall, our review reveals that the aggregate sectoral or macro level literature is surprisingly limited, which is likely a testament to the difficulty in extracting robust findings. We do note that the findings tend to complement the findings from Section 5, that energy price increases raised patenting levels, and innovation has been embodied in the subsequent capital stock. But few studies precisely pin down the contribution of induced technology innovation at the aggregate level. We see this as a nacsent area that so far has broadly (but not universally) been pointing to an effect of environmental regulation on innovation at the aggregate level. Overall though, there is plenty of scope for more research to pinpoint the contribution of induced technology innovation to resolve tensions of economy and environment at macro levels.

9. Interpretation: the processes of induced innovation

If the study of innovation is, as Kemp & Pontoglio (2011) suggested, like the proverb of the blind man and the elephant, what light has our review shed on its overall shape? First, we stress our conscious choice to focus on the role of demand-pull factors. Public investment, from universities to public R&D labs and demonstration plants, is clearly important, but so is innovation induced by demand-pull in many forms. To pursue the analogy, if technology push represents the back of the elephant, our study explored the front, recognizing that neither is much use without the other. The results of this review must therefore be paired with reviews of studies examining the role of technology push dynamics, to allow a more full (but not necessarily complete) understanding of the elephant.

We stress that our review has focused on energy, and that sectors are different, as emphasized by the data cited in Section 2. For energy however, we conclude that the evidence, following the structure of our review, is as follows.

Market-wide / energy & carbon pricing -> patents. Changes in energy prices and carbon pricing creates incentives first and foremost for incumbent industries to improve performance of their existing technologies, and to generate options to maintain their comparative advantage in a higher fossil fuel or carbon price world. The literature identifies both lags between market impacts and patenting, and that patents tend to be path dependent, building on earlier ideas and progress.

Industrial energy users and vehicle manufacturers clearly responded to the incentive of major energy price rises, with corresponding (if less extensive) evidence of impacts also from energy taxation and carbon pricing. On the supply side, the oil price shocks in particular also hugely enriched the oil companies, enabling greater investment in R&D across the board, particularly in oil exploration and development, and biofuels which could also utilize much of their existing expertise and assets. Hence, the strong and unambiguous impact of market-wide changes on patent filings in these areas.

Patents for renewable electricity sources were also stimulated by the energy prices. They had less to build on particularly after the first (1970s) oil shocks, when the rise in government R&D probably played a major role, and were less aligned to the core interests of incumbent energy producers. Clean energy patents for wind and solar especially expanded far more after about 2000 (see Figure 5). As reviewed across Sections 5 and 6, the literature suggests that many factors contributed to this, including strategic signaling (the adoption of the Kyoto Protocol in 1998, with entry-into-force in 2005), renewed energy price rises from early 2000s, and the more targeted incentives discussed below.

The most notable *lacunae* observed are in buildings, where evidence of energy price rises stimulating innovation (including in appliances, with some exceptions – e.g. Newell et al., 1999) is both limited and mostly inconclusive This, presumably, reflects the large literature arguing that most building-related decisions face multiple problems of split incentives, low materiality, and various behavioural biases that weaken any responses to price signals.

Market-wide / energy & carbon pricing -> outcomes. The major energy price rises correspondingly yielded clear improvements in established areas, such as oil extraction, industrial energy efficiency, and the efficiency of vehicles. The outcome measures pick up the value of additional elements of innovation which yield cost reductions (such as deployment-induced learning-by-doing, customer and market development), but which may not be so readily patentable. The limited numbers of studies exploring this link do suggest a strong role for market-wide incentives. In addition to the shale revolution, this is most clearly in vehicle efficiency where a large, established and innovation-intensive industry – in many jurisdictions, prompted by regulatory sticks as well as market carrots - clearly regarded improving vehicle efficiency as an important selling point (and regulatory hedge).

Targeted interventions -> patents. More specific demand-pull policies which target emerging clean technologies provide relatively more (and more direct) incentive for their deployment, and hence for their commercialization and learning including by new entrants. For the earlier stages of development, much of the relevant knowledge may be codifiable, though propensity (or capacity) to patent may be varied; incentives extend to more radical innovations particularly where funding is relatively generous and guaranteed, to cover the higher risks. Hence the patterns found in PV and biofuels (Section 6), where more competitive instruments (e.g. ROCs and portfolio standards) yield patenting on more established technologies (e.g. PV silicon wafers, first generation biofuels), whilst feed-in-tariffs may incentivize more R&D in advanced and risky technology (e.g. PV thin-film, second generation biofuels). However, the impact of different instruments on patenting also varies with the stage of technological maturity – the broader the instrument, the more likely are efforts to focus on incremental improvements of technologies already in the market.

Targeted interventions -> outcomes. The most obvious impact of demand-pull instruments, particularly those targeted upon emerging technologies, is to increase the scale (and overall value) of the associated industries. This has multiple channels of impact on innovation and cost reduction.

First, it creates both incentives and resources for potentially patentable innovations, though this draws upon both technology-push and demand-pull; the 'multi-factor' experience curve literature helps to identify the contribution of other factors (like public R&D) but still finds a large component of deployment-related cost reduction.

Just a few studies trace causality *directly*, but many others shed light upon it. The cost decomposition studies indicate that as well as private R&D, the impacts of enhanced deployment includes economies of scale (at all levels of units, factories, and industry), as well as learning-by-doing. Moreover, policy support for new industries also implies political support for overcoming regulatory barriers (which otherwise tend to favour incumbents), and to support institutions and infrastructure which further reduce risks. All this reduces financing costs, increases revenues, and aids the growth of these technology-industries with all the attendant tacit learning and multiple scale economies. These further reduce costs to the market. The findings from the qualitative, mixed-methods and survey literatures, underline further the way in which increasingly competitive costs also enhance confidence and market stability, feeding wider market diffusion, and potentially creating a virtuous circle (and hence, path-dependence) of establishing a new technology-industry at scale (as now achieved for wind and solar).

Most of the carbon-energy-policy related instruments have created financial incentives in one form or another, particularly for supply technologies. Regulatory policies have also been important, either in complementary support roles (e.g. industry codes and standards), or as driving forces where price-based incentives had obvious limitations (most notably, the limited literature on energy-related innovation in buildings). Wider literatures from SO_2 control (e.g. (Taylor et al. 2003, 2005)** and automobile regulation (Lee, Veloso, Hounshell, & Rubin, 2010)** underline the contribution of regulatory measures in driving innovations and cost reductions from other environment-related regulatory controls.

Broadening frameworks for understanding induced innovation

Before completing with the evidence around policy mixes and the multi-sector/macro literature, we seek to locate the above findings in a broader framework in the search for a more coherent picture of 'the elephant'. Specifically, in attempting to draw from this a richer understanding of induced innovation, we suggest two elements which can help to broaden traditional conceptions of innovation processes.

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The first element is clarifying a distinct role for *deployment,* as flagged in Section 2, which notes that the literature often considers this as synonymous with diffusion. However, we have collected evidence around the patent generation associated with the early growth of renewables (and demand-pull in energy efficient technologies), including the critical role of associated demand-pull policies, and discussed how studies of cost components help identify mechanisms through which deployed scale leads to cost reductions. Thus deployment can have a crucial bridging role between initial commercialization, and self-sustaining diffusion. We therefore suggest that mechanisms of induced innovation can be distinguished more clearly by considering a distinct step in which a technology is deployed at scale, *before* it is inherently cost-competitive with incumbents.

Crudely, we suggest *deployment* be particularly associated with stages of market development driven by actions taken with expectation of future benefits, associated with scale or experience; whilst *diffusion* is a more autonomous, self-sustaining process. The motivation for such deployment is then expectation of some benefits beyond the immediate revenues. In the absence of policy, this may be loss-leaders by industry (e.g. the Toyota Prius), commercialization being entwined with deployment to establish market presence and delivery capability, brand, and customer base. Conversely, public policies to drive deployment might be (at least in part) motivated by expected innovation benefits, thereby helping to build new industries. More formally, in the context of the debate about causality in experience curves, we might tentatively suggest a delineation of *deployment* as a stage of market development in which the dominant causality is from scale to technological advance, whereas *diffusion* is the succeeding stage, where established technology performance becomes the dominant driver of market share, and any learning becomes a secondary by-product.

This helps to frame an important question, namely when and where the pull of established markets, supported by public R&D, is sufficient to form a vibrant innovation system. In the absence of policy, commercialization may be entwined with deployment if there are either high revenues, or commercially motivated loss-leaders. However, this is far less evident for energy, for the reasons already indicated in section 2 (e.g. lack of product differentiation). With public policy, aside from possible short-term justifications, deployment may be a strategic driven at scale by government incentives (Grubb et al. 2014 use the term 'strategic deployment'), like feed-in tariffs, to build up new clean technology-industries which may ultimately become competitive with incumbents (particularly if policy also evolves to factor in other externalities over time, as with carbon pricing).

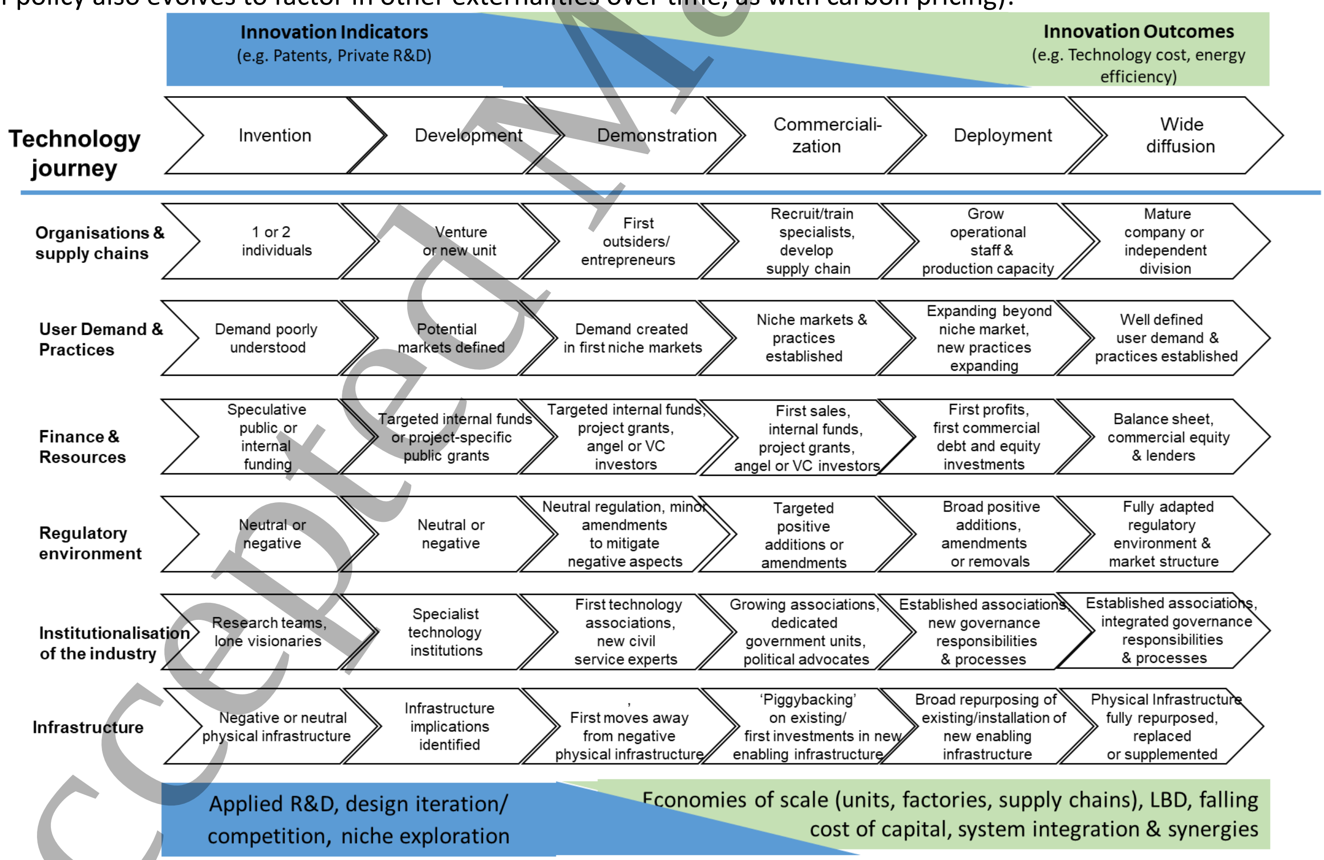

Figure 10 Expanded innovation chain – the multiple journeys

*Source: Developed and adapted from Grubb, McDowall and Drummond (2017**).*

The second element in gaining a fuller picture is to recognize that the terrain of innovation is not just wide – a long journey from invention to mature technology widely diffused - but deep. The core interests in considering the economics of decarbonization are to do with outcomes – more efficient energy production and consumption, and cheaper clean energy technologies. Technology cost and performance is ultimately influenced by many factors beyond 'hardware' alone. Figure 10 illustrates multiple factors which need to develop on the journey from a new invention to its widespread diffusion. In parallel to the technology journey itself, this may require evolution of business structures and supply chains, the customer base, financing routes, regulatory environments, and potentially institutions and infrastructure. Above and below this we suggest how the evidence presented in this Systematic Review can be related to these processes.

Clearly, the relative importance of these other dimensions may depends on the technology in question, context, and indeed, the organizations involved. A technology which is developed by large incumbent industries, and which fits well with their comparative advantage and existing market structures, will already have its financing structures and routes to markets established, and may benefit little from regulatory, institutional or infrastructure changes. The competitiveness of radically new and disruptive technologies however may hinge crucially upon these factors, as underlined also by developments particularly in multi-level transition theories (e.g. Geels, 2014)**.

In general, all indicators are potentially relevant, because though they overlap, they also point to different dimensions of overall innovation. Moreover, in this wider context, it seems that literature reviewed here is skewed towards a rather narrow range of indicators of innovation processes. There is a need to develop robust data on wider range of innovation activities, including those related to private R&D, finance, technology characteristics, firm entry/exit dynamics, and others. This seems important for developing a clearer picture of the diverse processes that underpin energy innovation.

Correspondingly, policy-induced innovation, particularly if seeking more radical transformation of polluting sectors, cannot realistically resort to one or two individual instruments (like R&D plus carbon pricing). Nor indeed, is the choice of environmental policy instruments a simple debate between market-based and regulatory approaches. As suggested over a decade ago in a review essay by Rosenbaum (2007)** if the goal is transformative, policy can hardly avoid elements which do not fall easily into either category, being more targeted at industrial strategy. In that context, some demand-pull policy is necessary to induce successful innovation, and the challenge is not whether to do it, but how to do it well, as underlined by Nemet et al. (2018)**.

The limited econometric literature on policy mixes (Section 7) seems to underline the relevance of well-crafted 'packages' of complementary instruments to encourage innovation (expressed through, *inter alia*, patenting and cost reduction), whilst qualitative, survey and mixed methods literatures – including most case studies - underline the multi-faceted complexity of real-world decisions on innovation, influenced by a host of direct and indirect considerations. Those literatures, complementing both the 'standing on the shoulders' findings of patent literatures, and experience curve data defined in terms of cumulative deployment, also underline the path-dependent and self-reinforcing nature of some of these processes.

Sector-wide and macroeconomic impacts (Section 8) necessarily involve all the above, but crucially, also pick up the 'crowding out' impact of switching innovation efforts from fossil fuel technologies – and maybe from other sectors - to low carbon and energy efficient technologies.

10. Conclusions and research gaps

Hicks (1932)** was right. The direction as well as pace of innovation is influenced by economic conditions, expectations, and experience. The evidence drawn from almost half a century of dramatic changes in energy markets, and growing energy-environmental policy, yields at least three broad headline findings.

1) *Demand-pull forces enhance* ***patenting***. Table 3 (Section 5) summarizes how patents across numerous energy technologies and sectors have responded to energy prices over the decades, finding positive impacts in industry, electricity and transport sectors in all but a few specific cases. Studies of carbon pricing, and most (though not all) more targeted interventions (Section 6) similarly show patents responding to demand-pull incentives.
2) ***Technology costs*** *decline with cumulative deployment*. Figures 7 and 8 (Section 6) shows unambiguously positive correlations, as measured by 'learning rates', for all studies of wind and solar energy across all time periods. The same holds true for almost all the technologies studied, for both production and use of energy. Numerous factors (including correlation of targeted market subsidies and deployment with patents but also many other lines of evidence), point to dominant causality from deployment (as we have defined it) to cost reduction in this relationship.
3) ***Overall Innovation*** *is cumulative, multi-faceted, and self-reinforcing*. Patent evidence points to strong path dependence, with patents 'building on the shoulders' of earlier developments. Aside from the experience curve data, the qualitative and policy mix literatures also point to the importance of combined spillovers, technology-push, and cumulative learning; the influence of multiple policy incentives that enhance confidence and shape expectations; and the reinforcing tendency of successful, expanding technology-industries to foster institutions and coalitions that sustain progress.

The bulk of the evidence comes from micro-economic analysis of patents, technology costs, and processes, on which we have organized our search, review and analysis through the four specific relationships as set out in Table 1, with results as summarized in the previous section.

Implications for modeling

These findings have at least two broad implications for modeling. First, results from models which assume technology costs to be either fixed, or to change exogenously, need to be scrutinized to consider whether endogenizing innovation would change their findings. In many applications, of modest changes to national energy markets and systems, this may be a reasonable assumption, but it should not be just an unchallenged 'default'. For models looking at larger scale changes, in terms of global reach, depth and/or timescale of transitions, assuming technology costs to be exogenous needs to be recognized as an explicit assumption that is not supported by the evidence.

We cannot draw meaningful conclusions about the cost of deep decarbonization using models which assume the cost of future low carbon technologies to be unaffected by how strong are the incentives, or much those technologies are actually deployed. Nor of course would the standard exogenous assumptions make much sense for modeling the economics of policy directed at deploying new and expensive technologies that have clear potential for economies of scale and learning.

A recent review of evidence on wider dynamics in relation to 'Integrated Assessment Models' (Grubb, Wieners, & Yang, 2020) notes that, fortunately, many of the more sophisticated IAMs now do include elements of induced innovation, as do some recent stylized models. Some also include the cumulative, path-dependent nature of innovation. The review notes the extent to which these factors may affect results, particularly concerning optimal investment in a cost-benefit setting.

Second, for this increasingly rich variety of energy-economy models which do seek to endogenize innovation, our results may help to inform the characterization and parametrization of such models. Responding to the conclusion of Gillingham, Newell, & Pizer (2008) cited in our introduction, our findings might indeed help to inform choices between, and validate the parameters for, a potentially bewildering variety of such models which have lacked firm empirical foundations.

Implications for policy

Our findings also have implications for policy. This has not been our main focus, but some seem inescapable – a study almost two decades ago (M. Grubb, Köhler, & Anderson, 2002) identified five types of potential policy implications of induced innovation – concerning long run costs; timing; policy instruments & cost distribution; first-mover economics; and spillover and leakage concerns.

Given the unambiguous finding that market-wide prices do generally influence patents, the case for carbon pricing is enhanced further, in light of the push it may give to low carbon innovation, amplified with path dependency (as found in the modeling review cited above). However, carbon pricing alone may be a very blunt way of stimulating innovation, particularly for sectors like energy which have very low natural levels of innovation as measured by private R&D (and potentially, innovation biased towards incumbent interests). As Grubb et al (2014) later observed, "if the innovation chain is broken, carbon pricing alone won't fix it." The clear impact of targeted demand-pull policies on innovation – outcomes as well as patents – underlines that successful innovation needs pull as well as push and that well-designed, targeted policies may provide a far stronger and more focused pull than any plausible level of general carbon or other externality pricing. Such targeting may also mean they have far less widespread impacts on the economy and face far lower political obstacles.

Essentially, as emphasized by Gillingham & Stock (2018)**, policy evaluation must consider dynamic as well as static efficiency, and this may change both the costs and optimal instruments associated with decarbonisation policy.

Moreover, the qualitative, mixed methods, survey and case study literatures all yield basically the same message – that innovation is a complex and mutli-faceted process, with numerous interdependencies, as well as uncertainties. Consequently, for a company, innovation is a gamble, the case for which is influenced by a wide variety of policy instruments, incentives, and strategic signals about the extent to which a government is really committed to a certain course, e.g. in terms of decarbonization or other sectoral change. And for a government, policy likewise carries uncertainty, enhancing the case for policy diversity, experimentation, evaluation, and learning.

Without digging deeper into systems innovation theories, the evidence does indicate that the simple framing of 'two market failures' – technology spillovers plus externalities - is inadequate to the real complexity of the challenge, and the various policy implications noted flow from this.

Research gaps

Innovation is complex and limitations in knowledge remain striking. The literature linking energy prices to patents may be robust enough to generate elasticity estimates, but only a minority of these studies consider equally important questions: to what extent do energy-related patent trends reflect substantial technical change away from fossil fuels? Or, is patenting more about incremental innovations to help maintain the position of incumbent industries? This may be crucial to judging the balance between broad and targeted measures, if the latter are more likely to bring forth radical and disruptive technologies.

The gap in the literature on experience curves is even more striking. Amongst almost a hundred studies, few have any test for causality, taking it as assumed that cost reductions are driven by deployment rather than the other way round. The idea that deployed scale has predominantly driven cost reduction has occasionally been formally demonstrated, but mostly it rests on inference and assumption. Our conclusions on causality are predominantly inferred, most notably from cost decompositions and a wide body of case studies. It seems likely that as technologies mature from initial deployment to more self-sustained diffusion, the feedback from cost reduction to diffusion grows, with 'learning rate' correlations increasingly reflecting this two-way relationship.

Beyond these two main areas of statistical studies are other outstanding questions. We did not find studies tracing the impact of technology patents (at scale) through to innovation outcomes (beyond potentially, some case studies). Also as noted, the complexities of disentangling specific innovation from numerous other factors at the macro level has limited the robust literature. Finally, a full welfare assessment should seek to include environmental costs and benefits as part of the overall macro metrics ("Green GDP"), adding more complexity; overall, this remains an area for further research.

More obvious research gaps, lacking at least in terms of formal tests, could be inferred from the matrix of Figure 10. The econometric literature has focused heavily on patents, as patents are the most readily-available data, but these only reflect codifiable (and codified) knowledge. The tacit knowledge and capabilities associated with deployment contribute to the other main observable metric – final costs or prices, but these aspects are little charted. Studies of the contribution from the declining cost of finance as a technology-industry matures has only just begun to receive appropriate academic attention (e.g. Egli, Steffen, & Schmidt, 2018)**. It remains unclear how one might test in any quantified way the impact of the lower rows on final costs. The contribution from appropriate regulatory structures, supportive institutions, and infrastructure is, in terms of quantified economic metrics, almost uncharted territory at least as applied to the low carbon transition.

One can of course debate the semantics as to whether this should be included as part of innovation, but it certainly contributes to cost reduction. Arrow (1971, p. 224)** noted that "Truly among man's innovations, the use of organisation to accomplish his ends is among both his greatest and his earliest"; to which Williamson's (2000)** review of institutional economics adds, "inasmuch as these two work in tandem, we need to find ways to treat technical and organisational innovation in a combined manner."

Particularly given the scale of changes implied by deep decarbonization, it may thus be fruitful to explore whether and how the quantitative techniques developed in economics can be related to the qualitative socio-technical literature on the wider dynamic of – and obstacles to – transformation. The future frontiers of research may be less about the drivers of technology and patents *per se*, but – as the qualitative literature covered in this review suggests - more about their co-evolution with the way society organizes its economic systems to support low carbon innovation, in its many dimensions.

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Appendix I – Systematic search terms

Search-Link I(i) terms:

(((electricity OR energy OR fuel OR oil OR gas OR coal) NEAR/0 pric*) OR ((“energy supply” OR energy) NEAR/0 shock*) OR ((energy OR oil OR fuel) NEAR/0 embargo*) OR ((energy OR electricity) AND “market competit*”) OR ((energy OR electricity) AND libera*))

AND

(((cost OR price) NEAR/0 (reduc* OR saving*)) OR ((increas* OR improve*) NEAR/0 (productivity* OR yield* OR output* OR “energy efficiency”)) OR “increasing returns to adoption” OR ((induced OR eco OR environment* OR “low carbon” OR techn* OR clean OR corporate) NEAR/0 innovat*) OR "learning-by-doing" OR "learning-by-searching" OR ((learning OR experience) NEAR/0 rate*) OR ((experience OR learning) NEAR/0 curve) OR ((directed OR endogenous) NEAR/0 “techn* change") OR "private R&D" OR patent*)

Search-Link I(ii) terms:

(((environment* OR energy OR climate OR eco) NEAR/0 (polic* OR regulat*)) OR ((demand OR market) NEAR/0 pull) OR ((supply OR technology) NEAR/0 push) OR ((energy OR electricity OR heat OR fuel OR oil OR gas) NEAR/0 (auction OR tender OR “efficiency standard*” OR “technology standard*” OR label*)) OR ((green OR “renewable* obligation”) NEAR/0 certificat*) OR “renewable* portfolio standard*” OR “time of use pric*” OR ((carbon OR emission* OR CO2) NEAR/0 (pric* OR tax* OR trad*)) OR “feed in tariff*” OR “feed in premium*” OR (energy AND “network regulation*”) OR (capacity NEAR/0 (market OR mechanism*)) OR “consumer subsid*” OR “public procurement”)

AND

(((cost OR price) NEAR/0 (reduc* OR saving*)) OR ((increas* OR improve*) NEAR/0 (productivity* OR yield* OR output* OR “energy efficiency”)) OR “increasing returns to adoption” OR ((induced OR eco OR environment* OR “low carbon” OR techn* OR clean OR corporate) NEAR/0 innovat*) OR "learning-by-doing" OR "learning-by-searching" OR ((learning OR experience) NEAR/0 rate*) OR ((experience OR learning) NEAR/0 curve) OR ((directed OR endogenous) NEAR/0 “techn* change") OR "private R&D" OR patent*)

Search-Link II terms:

(“wind” OR “solar” OR “photovoltaic” OR "renewable*" OR “hydrogen energy” OR "electric vehicle*" OR “electric car*” OR “hybrid vehicle*” OR “hybrid car*” OR “fuel cell” OR “biofuel*” OR “biodiesel” OR “biogas” OR “biomass” OR “bioenergy” OR "Marine energy" OR CCGT OR “natural gas” OR “fossil fuel” OR “carbon capture” OR “co2 capture” OR “hydro” OR “coal” OR “CCS” OR “nuclear” OR (“power” AND technolog*) OR “power generation” OR “geothermal” OR “batter*” OR “CFL” OR “compact fluorescent” OR “heat pump*” OR “hydrogen” OR “wave energy” OR “tidal energy” OR ((energy OR electricity OR power) NEAR/0 sector))

AND

("learning-by-doing" OR ((learning OR experience) NEAR/0 rate*) OR ((experience OR learning) NEAR/0 curve))

Search-Link III terms:

(((environment* OR energy OR climate OR eco) NEAR/0 (polic* OR regulat*)) OR ((demand OR market) NEAR/0 pull) OR ((supply OR technology) NEAR/0 push) OR ((energy OR electricity OR heat OR fuel OR oil OR gas) NEAR/0 (auction OR tender OR "efficiency standard*" OR "technology standard*" OR label*)) OR ((green OR "renewable* obligation") NEAR/0 certificat*) OR "renewable* portfolio standard*" OR "time of use pric*" OR ((carbon OR emission* OR CO2) NEAR/0 (pric* OR tax* OR trad*)) OR "feed in tariff*" OR "feed in premium*" OR (energy AND "network regulation*") OR (capacity NEAR/0 (market OR mechanism*)) OR "consumer subsid*" OR "public procurement" OR "Tax reform"OR ((electricity OR energy OR fuel OR oil) NEAR/0 pric*) OR (("energy supply" OR energy) NEAR/0 shock*) OR ((energy OR oil OR fuel) NEAR/0 embargo*) OR ((energy OR electricity) AND "market competit*") OR ((energy OR electricity) AND libera*))

AND

(((cost OR price) NEAR/0 (reduc* OR saving*)) OR ((increas* OR improve*) NEAR/0 (productivity* OR yield* OR output* OR "energy efficiency")) OR "increasing returns to adoption" OR ((induced OR eco OR environment* OR "low carbon" OR techn* OR clean OR corporate) NEAR/0 innovat*) OR "learning-by-doing" OR "learning-by-searching" OR ((learning OR experience) NEAR/0 rate*) OR ((experience OR learning) NEAR/0 curve) OR ((directed OR endogenous OR induced OR biased OR "energy using" OR "energy saving") NEAR/0 "techn* change") OR "private R&D" OR patent* OR "total factor productivity" OR "aggregate technology stock" OR "capital accumulation")

AND

((("general equilibrium" OR macroeconomic) NEAR/0 effects) OR spillover* OR rebound OR "structural change" OR "absorption capacity" OR "crowd* out" OR "crowd* in" OR "market structures" OR Schumpeter* OR "endogenous growth" OR "structural decomposition")

Appendix II - Experience curves in renewable energy sources and selected demand-side technologies

Solar PV

For solar PV, most studies produce learning rates for unit prices or costs based on *global* cumulative deployment. Of the rates presented in Figure 8, 18 represent global learning rates for PV modules or PV systems that cover a time period of 10 years or more[37]. 15 of these rates were between 14% and 28%. Studies deriving two- or multi-factor experience curves, where factors such as R&D (Kobos, Erickson, & Drennen, 2006; Miketa & Schrattenholzer, 2004), and economies of manufacturing scale (C. F. Yu et al., 2011) are controlled for, tended to be at the lower end of this range. Some two- or multi-factor experience curve studies (de la Tour et al., 2013; Gan & Li, 2015; Mauleon, 2016; Trappey et al., 2016; C. F. Yu et al., 2011) show that for PV the effect on the learning rate of controlling for input prices (especially the price of silicon) has a varied impact on the learning rate depending on the analysis period (as they themselves have shown variation over time).

The studies examined indicate there has been little to no reduction in the learning rate over time. While Nemet, (2009b) found global learning rates for PV modules appearing to decrease over sequential 10-year periods between 1976 to 2006, this finding is strongly influenced by the temporary PV module cost increases caused by supply constraints in the mid- to late-2000s. When the subsequent easing of these constraints are taken into account, however, Mauleon (2016) found that such a long-term trend has not been evident.

[37] Following Nemet (2009b) a minimum period of 10 years is chosen here as for learning rates based on a shorter period of time there is a higher risk of them being strongly affected by short-term influences not correlated to deployment (for example by fluctuations in input prices or by market imbalances leading to temporary deviations in the cost vs. price developments).

Only two studies calculated learning rates using the (real or estimated) cost or price of electricity generated. Zou et al. (2016) calculate a rate of 25% using a derived LCOE in China (1976-2009), whilst Hong et al. (2015)estimate a rate of 2.3% for the average traded power price for solar PV and total power traded in South Korea (using a two-factor approach, controlling for knowledge stock). They suggest this may indicate a large technology gap with other high-income countries – however as they use quarterly data over a short period (2004-2011), they caution against overinterpretation.

Studies published since the review by Samadi (2018) have focused on learning rates in individual countries and/or balance-of-system (BOS) costs[38].

For residential PV systems, Wei et al., (2017b) found a rate of 33% from 2006 to 2011 for Germany and a rate of 20% from 2009 to 2011 for the USA. These rates are higher than those evident in previous years, and the authors speculate this may be in part be due to changes in deployment programs in both countries[39]. Zhou & Gu (2019) construct two-factor experience curves for both utility-scale (> 1.000 kW, for 2009 to 2016) and residential PV plants (< 10 kW, for 2007 to 2016) in the USA, finding learning-by-doing-related learning rates of 7% and 11 %, respectively (however they also find that public R&D led to additional, and greater, cost reductions over the observed period).

For non-hardware (e.g. planning and installation) costs of small-scale PV systems in Germany for 1991-2012, Strupeit & Neij (2017) find a learning rate of 10%. The authors note that this rate is lower than those typically found for hardware components (e.g. modules and inverters), explaining the growing share of non-hardware costs in PV systems over the past few decades. They also identify a need for further research to better understand the drivers of non-hardware cost reductions. Elshurafa et al. (2018) find an average learning rate of 9% for BOS costs for residential installations, but with considerable variation between countries.

Concentrating Solar Power (CSP)

Only two studies examined experience curves for CSP. Hernandez-Moro & Martinez-Duart (2013) derive a global learning rate of 11% for installed costs for 1984-2010, with data dominated by parabolic trough (PT) systems, which by 2010 accounted for over 90% of installations..Lilliestam, Labordena, Patt, & Pfenninger (2017) examined separate learning rates for PT and solar tower (ST) installations, with results later corrected by Lilliestam, Labordena, Patt, & Pfenninger (2019). For PT installations with little or no storage capacity, they find rates of 21% or 30% for investment costs depending on the data source used, for the period 2011-2014 (R^2=0.97), with a sixth of the improvement due to improved solar resource for new projects (this rate remains unaffected in their correction). The authors also examine data from 1984 and find a value of 2.7%, but due to cost increases over 2008-2011, an experience curve fit over the full period is extremely poor. No R^2 value is provided for the learning rate to 2010 reported by Hernandez-Moro & Martinez-Duart (2013). For PT installations with 6-8 hours storage, Lilliestam et al., (2019) finds a (corrected) learning rate of 6.8% (R^2=0.513) for 2008-2017), or 7.2% (R2=0.149) when focused on 2011-2017. For PT installations with greater storage capacity and ST installations no experience curves were discernible, largely due to the very small number of installations.

Onshore wind

Studies examining experience curves for onshore wind focus on Europe - and particularly Denmark - due to the historic concentration of installed capacity. The majority of these studies derive learning

[38] Balance-of-system costs refer to all non-module costs of an installed PV system, such as the costs of converters, cables, mounts and labour.

[39] Wei et al., (2017b) stress that they do not have any hard evidence for a causal relationship between learning rates and deployment programs, but they speculate that deployment programs may stimulate new thinking among manufacturers and/or may incentivise new product designs.

rates using turbine prices or investment costs[40], with many using data extending back to the 1980s. Of the 18 learning rates for unit price or cost in Figure 9 covering a period of 10 years or more, 15 cluster between 5-15%, with rates derived from multi-factor studies again tending towards the lower end of this range (e.g. Grafstrom & Lindman, 2017; Hansen et al., 2003; Soderholm & Klaassen, 2007).

For wind power, the relationship between rated capacity and electricity generation is relatively complex. Over time, changes in turbine design (such as higher towers, longer rotor blades and improved control electronics) increase efficiency and produce higher capacity factors. As a consequence, in the 10 studies (and 11 learning rates) that employ LCOE as a cost metric, learning rates are typically slightly higher (at around 8% to 13%, for studies covering 10 years or more). A sub-set of studies derive rates using both unit prices (or costs) and LCOE and installed capacity; Neij et al. (2004) for Denmark (1981-2000), Papineau (2006) for Denmark and Germany (1987-2000) and Williams et al. (2017) for the world (1984/1990-2015) all find higher learning rates using LCOE (with Partridge (2013) deriving similar values for both metrics for India, 2006-2011). However, Lam et al. (2017) find slightly lower learning rates using LCOE than for capacity for China (2004-2012). The authors suggest this may be due to a decrease in average estimated capacity factors in China over the observed period, as the industry's swift expansion has run into location and infrastructural constraints.

Three studies found were not examined by Samadi (2018), due to their more recent publication. The first is Lam et al. (2017), discussed above. Williams et al. (2017) derive a global learning rate of 7% for project investment costs for 1984-2015, and a rate of 9% for LCOE for 1990-2015, both based on one-factor experience curves. The LCOE rate increases to 10% and the curve's goodness of fit (R^2 value) improves when site quality, material costs and USD exchange rates are considered. Finally, Zhou & Gu (2019) derive two-factor experience curves for the USA for 2009-2016, finding a relatively high learning rate of 18%, despite attributing 42% of the observed cost reductions to public R&D. The authors suggest this result reflects an increase in the rate of learning, however this may be a faction of the time period examined, which immediately followed a period of high commodity prices, a high and value of the US dollar, and supply constraints, all of which subsequently reduced, along with wind power costs (Wiser et al., 2018)**.

We identified a single study in the peer-reviewed academic literature that attempted to derive an experience curve for offshore wind. van der Zwaan et al. (2012) find an installed cost learning rate of 5% for offshore wind in Europe (1991-2008), once the influence of key commodity prices and supply chain constraints are accounted for. However, the authors acknowledge that this is based on limited data with a poor statistical fit.

Bioenergy

Three studies derive learning rates for electricity generated from biomass. Junginger et al. (2006) find a rate of 23% for investment costs, and 9% for average electricity production costs (8% for marginal production costs) for biomass CHP plants in Sweden (1983-2002). For biomass power in China, Lin & He (2016) find rates of 5.6-7.8% for investment costs, and 2.2-6% on an LCOE basis (2005-2012), which the authors attribute to a combination of LBD and LBS. Wang et al. (2018) find a similar value of 4.5% (2006-2014) on a calculated LCOE basis, with a variable representing a combined LBS and LBD influence statistically significant, but a reasonably minor factor in declining costs (compared to, for example, changes in O&M costs). Junginger et al. (2006) was also the only study identified that derived learning rates for average biogas production costs, finding rates of 15% and 24% (1984-1991) in Denmark, depending on the data sources used (with both exhibiting high R^2 values), but with no cost reductions found for 1991-2001).

[40] Investment costs are the full costs of installing a wind turbine. The cost of the turbine itself constitutes about 70 to 80 % of the total investment costs (Grafstrom & Lindman, 2017).

Four studies examine the learning rates for bioethanol in Brazil. In 1975, Brazil launched a National Alcohol Program (Pró-Álcool), which set (generally) increasingly stringent mandates for a percentage of bioethanol from sugarcane blended with gasoline, with an objective to decrease oil dependency, largely in response to the oil crisis of the early 1970s (Moreira & Goldemberg, 1999)**. The first study was Goldemberg (1996)*, which found a learning rate of 30% for 1982-90, reducing to 10% over 1990-95, with the authors ascribing this shift as moving from a period of rapid expansion of production and associated technological progress, followed by stagnating production levels (as sugar was instead exported rather than converted to ethanol, as world sugar market prices in 1989/90), and a reduction in the rate of technological progress and cost reduction (Moreira & Goldemberg, 1999)**. The second study, Goldemberg et al. (2004), found rates of 7% for 1980-85 and 29% for 1985-2002 - seemingly a reversal of those found in the previous study. However, the time periods examined enhance or dilute the expression of different short-term phenomena. Over 1975-1985, bioethanol prices in Brazil were regulated at the cost of production, after which they were set at prices below production costs in an attempt to curb inflation, artificially reducing costs. From 1997 prices were liberalised, and in 1999 prices reduced substantially due to overestimated demand and excessive harvest (before recovering the following year) (Bake, Junginger, Faaij, Poot, & Walter, 2009)*, skewing the (short-term) learning rate derived.

However, Bake et al., (2009) find a long-term learning rate of 20% for 1975-2004, and goes further to construct learning rates for feedstock (sugarcane) production costs and processing costs excluding feedstock costs, deriving rates of 32% and 19%, respectively. However, they note that the rates derived by this and the studies described above are heavily influenced by both a fluctuating currency exchange rate (with analysis in all studies conducted in USD), and calculations of pre-1975 cumulative production (with bioethanol production in Brazil beginning in 1931). Subsequently, Chen et al. (2015) found an overall learning rate of 16%, over a slightly extended timeframe (1975-2010) and using different data sources. They also find that the only statistically significant driver of the cost reduction experienced to be exogenous spillovers rather than endogenous learning or other phenomena, however the authors recommend caution with this result, citing a limitation in the use of aggregate industry-level data.

In 2005 Brazil launched a National Biodiesel Production and Use Program (PNPB), also expressed primarily as a blending mandate with diesel of increasing stringency. Nogueira et al. (2016) find a learning rate of biodiesel production costs in Brazil over 2006-2014 (during which the blending mandate increased from 2% to 7%) to be negative, at -1.7% (with -4.6% for 2006-2010, but positive at 40.7% for 2011-2015). The authors suggest the trend in prices was driven largely by feedstock costs, with little technological progress achieved, although they attribute the (substantially) positive learning rate in later years also to economies of scale, as production shifted from small to larger plants.

Two studies derive experience curves for (mainly corn-based) bioethanol production in the USA. The first is Hettinga et al. (2009), which find a learning rate of 18% for total production costs (1980-2005 - with a rate of 45% for corn production costs, and 13% for ethanol processing costs). They estimate that 84% of the cost reductions achieved are due to technological learning. Chen & Khanna (2012) employ the same data as Hettinga et al. (2009), and find a similar learning rate of 12% for 1983-2005. In addition, they find changes in annual corn prices and LBD to account for 95% of the cost reductions experienced in ethanol processing. However, both studies raise issues with data, both in estimating cumulative production before the time period examined, and on consistent and reliable data on production costs.

Demand-side and other technologies

Weiss et al., (2010, p.411)** provided the first "comprehensive review of experience curve analyses for energy demand technologies", synthesising studies of fifteen technologies (largely building heating, lighting and appliances), and found an average, cross-technology rate of 18% (±7). The learning rates for domestic appliance technologies vary substantially (across both unit price and cost, depending on the technology), from 9% (refrigerators) to 23% (washing machines - with laundry driers, dishwashers, freezers and television sets at 11-16% - and residential heating, excluding heat pumps, at 10%), and with substantial variation within technologies. The authors explain differences between technologies as result of changes in product design and services over the time periods analysed (and which are not considered in the rates derives), and possible data issues in calculating cumulative production for products that have been produced commercially for around half a century. By contrast, other consumer electronics, electronic components and heat pumps exhibit high rates of 26%, 22% and 32% respectively, which the authors posit is due to the use of reasonably novel materials and components, for which a large potential for manufacturing (including scale) efficiencies were possible. The authors suggest that such efficiencies are less available in products such as building insulation and glazing (with a rate of 18%). Finally, they find average learning rates of 21% for compact fluorescent bulbs (CFLs), and 16% for (electronic and magnetic) ballasts thereof. However, for all rates presented, the authors highlight that as study sample sizes are small, and with each employing different performance measures, geographical boundaries, and timeframes, definite conclusions are difficult to draw.

Few studies since have sought to build upon the rates synthesised by Weiss et al., (2010)**. Two notable exceptions are Smith et al. (2016) and Wei et al., (2017b), both of which derive experience curves and assess correlations with technology deployment programmes. (Smith et al., 2016) derived experience curves for CFLs for 1990-97, and for 1998-2007. For the first period, they find a global rate of 21%, and a rate of 22% for North America (consistent with the average rate derived by Weiss et al., (2010)**, but for the second period, they find rates of 51% and 79%, respectively. The authors suggest this increase is due to technology standards and public deployment programmes, coupled with technology improvements, increased competition and a changing trade environment. Using the same data, Wei et al., (2017b) produce the same results (and explanations) for the USA. For electronic CFL ballasts, they find rates of 8% (1986-92) and 24% (1993-2005), and 16% (1981-89) and 39% (1990-93) for magnetic ballasts. These rates largely concur with those reviewed by Weiss *et al* (2017), and in some cases draw on the same data, with the authors also attributing the higher rates in later years, for electronic ballasts in particular, to technology standards and CFL deployment programmes. Wei et al., (2017b) also find time-varied rates for General Service Fluorescent Lighting (GSFL) in the USA, of 21% (1960-68, due to intense market competition), 0% (1969-85, due to market consolidation and technological quiescence) and 42% (1986-94, due to state and federal standards).

A third study, Van Buskirk et al., (2014), finds that learning rates for refrigerators, washing machines and air conditioning units in the USA, and refrigerators in the Netherlands, all increased with the introduction (or increasing stringency of) energy efficiency regulations (in terms of both unit price, and lifecycle cost).

In the face of growing deployment, some recent literature has begun to turn its attention to experience curves for hybrid-electric (HEVs) and battery-electric vehicles (BEVs), and their key components (particularly lithium-ion batteries). For the Toyota Prius, the first mass-produced HEV, Weiss et al (2012) find a learning rate (using retail prices as a proxy for production costs) of 6% in the USA and Germany (2000/2001-10), but just 1% in its first market of Japan, for 1997-2010 (the authors suggest this lower rate may be due to Toyota internally subsidising the Prius during the first years of its availability). Aggregated for all available HEV models, the study finds learning rates of 8-10% in the USA (1999-2010) and 5% in Germany (2001-10), with Weiss et al. (2019) finding the rate for Germany remains stable (6%) for 2010-16.

For BEVs, however, Weiss et al. (2019) find a much higher rate of 23% (also in Germany, for 2010-16), although Safari (2018) found a rate of just 9% for the same years at the global level. Aside from the different geographical scope, this difference may be explained at least in part by issues of direct comparability of the product (BEVs and HEVs are not homogenous, either between models or over time), and the use of market prices rather than cost (and thus (non-)consideration of geographically and time-varied factors, such as sales taxes and profit margins). However, both rates are generally higher than those found for HEVs, which Weiss et al. (2019, p.1484), citing (Safari, 2018), suggest is due to "rapid technological learning in the manufacturing of traction batteries, which constitute the largest individual cost component of an electric powertrain…[which in turn] constitutes a higher share in the overall production costs of electric cars than it does in the production costs of plug-in hybrids". Matteson & Williams (2015) find a learning rate of 22% for lithium-ion batteries for 1993-2005, although the authors highlight that such batteries were primarily used in small portable electronics during this time. Nykvist & Nilsson (2015) conduced a systematic review of 85 cost estimates (reported 2007-14) for lithium-ion batteries for use in BEVs specifically, and derived an average global learning rate of 9%, with Schmidt et al. (2017), deriving a global rate of 16% for 2010-16.

Schmidt et al. (2017) also derive learning rates for a range of battery and other technologies employed for energy storage. They find similar rates for a range of different systems and scales; 12% for both residential and utility-scale lithium-ion systems (based on German market data for 2013-16, and US data for 2010-15, respectively), 13% for residential lead-acid systems (for Germany, 2013-16), and 11% for utility-scale vanadium redox-flow systems (for the USA, 2008-2015). Kittner, Lill, & Kammen (2017) find a global learning rate of a 15.5% for lithium-ion cells over 1991-2015. Matteson & Williams (2015) find learning rates of 10% and 4% for small (up to automotive size) and large (including utility-scale) lead-acid batteries (in the USA, 1989-2012), but with a poor statistical fit. However, when the authors control for material price volatility, the rates increase to 24% and 19% respectively (with R^2 values improving considerably).

Various studies derive experience curves for fuel cells, largely for stationary applications. The first was (I Staffell & Green, 2009) who derive a rate of 19.1-21.4% for residential proton exchange membrane fuel cell (PEMFC) CHP systems in Japan (2004-08), revised to 15% with data extended to 2012 by the same authors (Staffell & Green, 2013), and to 18% for with data extended to 2015 by Schmidt *et al* (2017). Including derived rates in Korea (18%, 2006-10) and an anonymous manufacturer (15%, 2007-11, (Iain Staffell & Green, 2013) derive an average rate of 16% for PEMFC systems. Schoots et al. (2010) calculate learning rates for manufacturers of three types of fuel cells used in transportation; alkaline (AFC), phosphoric acid (PAFC) and PEMFC, and find rates of 18% (1964-70), 25% (1993-2000) and 30% (2002-2005), respectively. For PEMFCs, the authors also derive a global rate (across manufacturers) of 21%.

Rivera-Tinoco et al. (2012) were the first to derive experience curves for solid oxide fuel cells (SOFCs), principally used for stationary purposes. They derive an overall (global) learning rate of 35% for 1996-2008, but when excluding economies of scale and automation effects, the rate reduces for 20% for 'pure learning' phenomena (including learning-by-searching). They also find varied rates of 16%, 44% and 12% for the 'R&D stage', 'pilot stage' and 'early commercial stage' respectively, with 'pure learning' rates of 16% (attributed to pure learning-by-searching), 27% (with economies-of-scale for component materials being dominant), and 1% (with economies-of-sale for manufacturing technologies dominant). Complementing the studies described above, (Wei, Smith, & Sohn, 2017a) derive an experience curve for SOFC residential CHP systems in Japan (which have deployed in parallel, but to a far lesser degree, to PEMFC systems), and find a rate of 18% for 2005-15. The further indicate that "the observed cost reduction can be explained by three components [of] roughly comparable magnitude: economies of scale, product design improvements, potential cost reductions in installation cost and other soft costs, and other factors" (*ibid*, p.353). The authors also find that for

SOFC, molten carbonate (MCFC) and PAFC systems in California, cost reductions (and thus learning rate) have been negligible (2007-15, 2003-14 and 2001-13, respectively). Various possible explanations for this are provided, including the use of (variable) system rather than fuel cell stack costs, a lack of market competition, and manufacturers recouping their investment costs through increasing margins.