Historical Case Studies of Energy Technology Innovation

CASE STUDY 5: KNOWLEDGE DEPRECIATION.

SOURCES AND CONSEQUENCES OF KNOWLEDGE DEPRECIATION

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AUTHORS' SUMMARY

Technological knowledge, like all knowledge, can be learned or accumulated, but it can also be lost or 'un-learned'. In other words, knowledge capital depreciates. This case study considers the different sources of knowledge depreciation including reasons why knowledge is lost (e.g., due to staff turnover) as well as why knowledge becomes obsolete (e.g., due to rapid innovation). Estimates of typical knowledge depreciation rates are reviewed, and the limited examples related to energy technologies are discussed in more detail. Knowledge depreciation rates reach 100%/year in service industries, characterized by high staff turnover. In the energy technology field, knowledge depreciation rates of between 10%/year (wind turbines) and 30%/year (solar PVs) have been identified. Illustrative calculations based on public energy R&D statistics of IEA countries show the implications of knowledge depreciation for two groups of energy technology innovations: nuclear power and energy efficiency. A conclusion is that a stable, gradually rising trajectory of policy support is as important, if not more important for mitigating knowledge depreciation than the absolute level of policy support if characterized by "boom and bust" cycles. With knowledge depreciation, continuous knowledge "recharge" becomes critical, e.g., through stable R&D efforts and sustained market formation incentives.

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1 INTRODUCTION

Not unlike physical capital, knowledge capital also depreciates. Technological knowledge, like all knowledge, can thus be accumulated (learned) but equally lost (un-learned).The underlying reasons for, as well as the rates of, knowledge depreciation hold important implications for innovation policy.

The relevance of knowledge depreciation for the knowledge basis of innovation is straightforward. And yet it is often ignored in analysis that unduly focuses on knowledge creation rather than on an integrated perspective that also includes the negative side of the knowledge equation. The topic of knowledge depreciation is thus under-researched, with no single review paper available in the literature. The explicit treatment of energy technologies within the context of knowledge depreciation is even more patchy and hence motivates this case study which reviews a (very limited) research field.

Knowledge depreciation can be conceptualized as depending on two main variables. The first is the degree of innovation-driven technological obsolescence. The second dimension is the rate by which (otherwise unchanged) technological knowledge depreciates due to turnover of the holders of that knowledge.

The rapidly changing information and communication technology or 'ICT' field provides an important example of innovation-driven technological obsolescence. ICT also illustrates the need to differentiate two types of technological obsolescence: technical and economic. Older vintages of ICTs (e.g., cell phones, computers) are discarded by consumers not because they are broken (technical obsolescence) but rather because newer, better performing models (with rapidly falling prices) are a preferred alternative (rapid innovation driven economic obsolescence). Changeover times in laptop computers are typically in the range of 3 years, and for cell phones often less than one 1 year in some markets (e.g. younger consumers in OECD countries).

The second variable influencing knowledge depreciation relates to staff turnover within organizations. Staff are the holders of the knowledge stock, and high rates of staff turnover (for whatever reason) is associated with knowledge depreciation, particularly if these staff hold key positions with respect to knowledge management.

Knowledge depreciation rates thus depend on the twin influences of the rate of innovation and the degree of policy and human capital volatility.

Knowledge depreciation is known to affect particularly settings in which knowledge remains largely tacit (i.e. uncodified, "hands-on" experience) residing in individuals (e.g., staff) or organizational entities (e.g., management) that needs to be acquired again in case of staff turnover or "stop and go" production schedules (e.g. Argote et al., 1990). A second type of depreciation occurs as old knowledge becomes obsolete. Knowledge can depreciate because of an insufficient "recharge" of knowledge (Evenson, 2002) in cases where innovation proceeds rapidly such that old technological knowledge is no longer relevant for updated processes/techniques but new learning cannot proceed quickly enough (e.g., because of financial constraints). Both dimensions of knowledge depreciation are of particular concern in energy technology innovation systems when rapid rates of innovations coincide with erratic funding and policy support (see the case studies on Solar Water Heaters, Solar Thermal Electricity, and Synfuels).

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Another (even if atheoretical and empirically largely unfounded) distinction often advanced in the energy technology innovation literature is the differentiation as sources of knowledge accumulation between "learning by searching" (e.g. R&D) and "learning by doing" (e.g., accumulated production experience or market deployment). Kouvaritakis et al. (2000) provide an example of such a model formulation). The assumed perfect substitutability of the two sources of learning, as well as formidable statistical challenges due to multi-collinearity and unknown lags, are major critiques of so-called "two factor" learning curve models (as formulated, e.g., by Miketa and Schrattenholzer, 2004).

Knowledge depreciation affects both the knowledge gained from R&D as well as the experience gained through production and market deployment. Recent work on knowledge depreciation in decisions made by US wind turbine operators shows the high rates of depreciation in a learning by doing context (Nemet, 2012). This is discussed further below, as is the case of nuclear power in the countries of the International Energy Agency ('IEA'). There is evidence of R&D knowledge depreciation of nuclear power, but also of nuclear knowledge depreciation in the ability to construct nuclear power plants as in the recent disappointing experiences at the two construction sites of the European Pressurized Water Reactor or 'EPR'. When the first EPR, the AREVA/Siemens Olkiluoto-3 project in Finland, went at least three years behind schedule and 50% over budget, AREVA could and did blame this on its foreign partners, but no such explanation was plausible for the identical Flamanville-3 EPR built by and for French institutions in France. When after a year's construction the project was a year late and 20% over budget, doubts arose about whether AREVA's last order before Olkiluoto-3, in 1992, was so long ago that critical design and construction skills may have atrophied (even in routine tasks such as quality assurance and documentation for concrete) (Grubler, 2010).

2 KNOWLEDGE DEPRECIATION THROUGH POLICY AND HUMAN CAPITAL VOLATILITY

Knowledge gained from experience may be inherently more susceptible to depreciation than other types of knowledge. Scientific knowledge goes through a process of peer review and dissemination; research and development activities are carefully monitored and often intentionally organized as experiments. In contrast, tacit knowledge may be particularly vulnerable to depreciation. This implies that learning by doing is prone to especially high rates of depreciation since that experience in production is less likely to be codified than in research and development activities.

In a study of the (temporary) wind power industry boom in California in the 1980s and 1990s, Nemet (2012) found evidence of learning by doing, both in the operation of existing wind projects and in the installation of new ones. However, this learning was subject both to knowledge depreciation and diminishing returns to experience. Knowledge gained from experience appears to have depreciated rapidly, with the half-life of new knowledge less than three months. Lessons about how to run wind farms were gained as a side effect of producing electricity. Careful codification of the outcomes of trials was unlikely to have been a priority in the context of an investment boom for an infant industry. Bankruptcies were frequent and employee attrition was high. Even if important knowledge was gained in the process of installing and operating wind turbines, it was dispersed and much of it was not available for future projects.

The rate of depreciation reported by Nemet (2012) for the Californian wind industry is very similar to that estimated by Argote, Beckman, and Epple (1990) for shipbuilding, though it is slower than the depreciation rates in other industries reported in Darr, Argote, and Epple (1995), and faster than those in Benkard (2000) and Thompson (2007). It has long been recognized in the management literature that in service industries (e.g. pizza franchises) organizational and production knowledge can be lost quickly, especially under high rates of staff turnover (that can be up to 300% per year). Argote et al. (1990), Argote (1996), and Darr et al. (1995) provide reviews and report knowledge depreciation rates from 25% to 50% *per month* in service industries. Such high rates of knowledge depreciation basically imply that after a year only 0% to 5% percent of the original knowledge of an organization remains. Kim and Seo (2009) arrive at similar high depreciation rates of some 26% per month in their analysis of Liberty ships manufacture during WWII (even if earlier studies on the same case, e.g. Thompson (2007) report much lower rates of 4% to 6% per month, highlighting the large uncertainty and challenges involved in estimating knowledge and its depreciation rates).

A classical case discussed in the literature of technological learning is the case of the Lockheed L1011 Tri-Star aircraft (Argote and Epple, 1990). Other studies in the aircraft industry suggest a significant reduction in manufacturing costs or 'learning by doing' as more production experience (output volumes) is accumulated. The Lockheed Tri-Star aircraft was an exception to that rule. When after an extended production halt, production resumed again, manufacturing costs were much higher and also did not decline subsequently, reflecting experience/knowledge lost or "un-learning" that could no longer be recovered. The reason for this knowledge depreciation was basically the same as for pizza franchises: During the production halt the entire staff of the manufacturing plant was fired (including managers that according to Mishina (1999) are the main locus of organizational learning and knowledge in aircraft manufacturing). Benkard (2000) reports corresponding knowledge depreciation rates of typically 40 percent *per year* in aircraft manufacturing. The wind industry in the study by Nemet (2012) had similar challenges due to the extreme seasonality in the California wind resources, which relied on thermal gradients between cool marine air and hot inland areas. Very little production occurred from September to March each year, although maintenance activities during the off-season helped retain a base level of knowledge generation processes.

Next to knowledge codification and preservation, human capital management is therefore key to minimize volatility-driven knowledge depreciation. Similarly, the design of policy instruments to create incentives for learning should account not only for the existence of spillovers from learning, but also for the persistence of that knowledge.

Boone at al. (2008) in their study of knowledge depreciation of professional services conclude that the extremely low rates of knowledge depreciation found in engineering design firms is explained by comprehensive knowledge documentation (earlier CAD designs are documented and kept for subsequent use), a stable business, as well as low staff turnover rates (3%/year only) particularly among senior engineers which is markedly different compared to typical service industries such as food retailing. As such, the study provides valuable lessons for improved knowledge management in energy technology and other innovation systems highlighting in particular the importance of documentation, codification, and preservation of knowledge as well as the need for a minimum degree of continuity in senior staff that are the "living memory" of organizations. Institutions practicing comprehensive reassignment (job-rotation) policies can frequently lack any institutional memory of earlier corporate strategies. At a renewable energy investment strategy workshop in an energy major attended by one of the authors (Grubler), a group of managers were entirely unaware that the company had previously invested into solar PV and biofuels but had since sold these activities.

Similarly, the case study on solar thermal electricity discusses the importance of national laboratory studies of the performance and improvements of the 350MWs of Solar Energy Generating Station (SEGS) plants in California in the 1980s. These careful studies preserved much of the knowledge about how to design, build, and operate large-scale solar power plants. The resulting reports were important in offsetting knowledge depreciation during the 15-year period in which no new commercial plants were built, the US R&D program was almost completely eliminated, and the original builder of the plants filed for bankruptcy, selling off the plants to multiple investors.

3 KNOWLEDGE DEPRECIATION THROUGH TECHNOLOGICAL OBSOLESCENCE

Estimates of innovation driven knowledge depreciation for entire industries are extremely limited. Hall (2007) provides one of the few comprehensive efforts to estimate knowledge depreciation across various industry sectors relating the market value of firms to patent data to estimate the R&D knowledge depreciation in six US industry sectors. The study found knowledge depreciation to vary significantly over time and across industries, with median R&D knowledge depreciation rates of between 15% *per year* (drugs and instruments) up to 36% per year (electrical). An alternative model formulation using a production function approach did not yield any statistical significant results of knowledge depreciation.

Watanabe et al. (2002) provides one of the few estimates of knowledge depreciation for energy technologies. By constructing a knowledge stock model for the Japanese PV industry that includes both R&D by firms and knowledge spillovers from other firms (measured via patent citations) he estimates a mean PV knowledge depreciation rate of some 30% per year. This implies that without continuous recharge (R&D) an existing technology knowledge stock is reduced to some 25% of the original value after 5 years and to less than 5% after 10 years. Nemet (2009) provides an illustration for the US wind turbine industry by analyzing citations to a set of "highly cited" (i.e. valuable) wind energy patents. He finds that 40% of all (cumulative) citations occur during the first five years, after which citations decline to basically zero after 25 years. While lags in knowledge diffusion account for the gradual increase in citations in the first 5 years, the declining trend in patent citations after year 5 reflects their decreasing significance and can be used as a proxy for knowledge depreciation, which corresponds to a rate of approximately 10% per year after the 5th year.[1] The lower number compared to the Watanabe et al. (2002) study can be explained by technology differences (PVs being on a much more dynamic technology trajectory, compared to wind turbines) but also due to the fact that the Nemet sample focuses on "highly cited" patents, i.e. only a subset of all patents which are the most successful ones whose knowledge base can be expected to depreciate at a slower rate than the industry-wide knowledge stock (i.e. by considering all patents), which was the subject of the Watanabe study.

It's important to note that the use of patent citation data helps distinguish between the effects of technological obsolescence and employee turnover. Patents require a detailed and fully public invention disclosure. This codification, including diagrams and detailed schematics, preserves knowledge that

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would otherwise be lost through employee attrition as discussed above. The depreciation rates we see in these studies essentially isolate the effect of technological obsolescence. As a result, they produce lower estimates of depreciation rates than studies that include the effects of both attrition and obsolescence.

4 SYNTHESIS OF KNOWLEDGE DEPRECIATION RATES

The available literature suggests typical knowledge depreciation rates of between 10 to 40 percent per year in industries comparable to energy, i.e., industries in which innovation and R&D play a significant role. (Human capital volatility remains an important driver independent from R&D intensiveness). Given such high rates of obsolescence of technological knowledge, continuous "knowledge recharge" and maintenance becomes extremely important. To date, no study has attempted to assess the relative contributions of human capital volatility and innovation-driven technological obsolescence to knowledge depreciation. Nonetheless, Figure 1 below provides a qualitative ranking to the rates of knowledge obsolescence reviewed above along the two dimensions of knowledge depreciation.

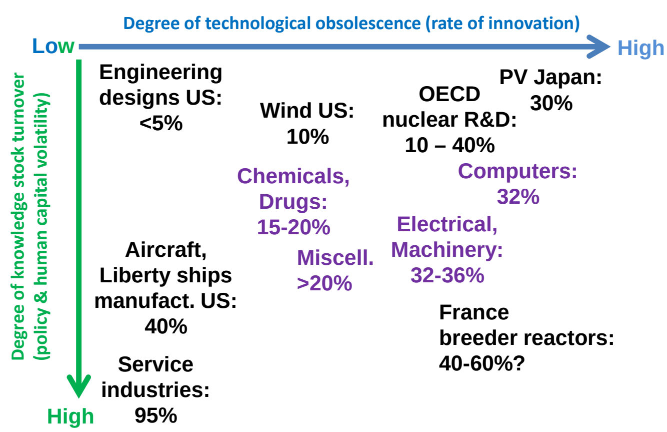

FIGURE 1. TYPICAL KNOWLEDGE DEPRECIATION RATES (% PER YEAR). NOTES: US INDUSTRIES SHOWN IN MAGENTA (HALL, 2007); SELECTED ENERGY TECHNOLOGIES AND ACTIVITIES IN MANUFACTURING AND SERVICES SHOWN IN BLACK (SEE TEXT FOR SOURCES); RATES FOR BREEDER REACTORS IN FRANCE ESTIMATED BY THE AUTHORS (SEE TEXT FOR EXPLANATION).

It is quite intuitive that knowledge depreciation rates tend to be highest in cases when rapid technological obsolescence combines with high staff turnover, and/or erratic policy support. As an illustration consider the case of an innovation failure: the French plutonium fueled fast breeder reactor program whose culmination aimed at an early up-scaling of reactor size to commercial scale in the form of the 1.2 GW Superphénix reactor in Creys-Malville, France. After completion in 1985, and a stuttering performance record until reaching full capacity in 1996, the basic design flaws of using a liquid metal (highly corrosive sodium) as coolant provided for the ultimate demise of this technological innovation. Superphénix was permanently shut down in 1998. French public sector breeder reactor R&D peaked in the years prior to Superphénix's start-up and declined precipitously along with the disappointing reactor performance and accumulating technical problems. Private sector R&D into breeder reactors was insignificant.

Breeder reactor R&D expenditures declined between 40 to 60% per year over the period 1985 to 1989/1990 (IEA, 2008). It is likely that the staff attrition in R&D engineers and in operating engineers (after the shutdown of the reactor) reached similarly high levels (explaining our speculative estimated range of knowledge depreciation rates presented in Figure 1). In such extreme cases, high-tech energy technologies and industries might not be all that different in terms of knowledge depreciation than more mundane human endeavors such as making pizzas.

5 R&D SPENDING: "HOW" IS AT LEAST AS IMPORTANT AS "HOW MUCH"

In order to illustrate the importance of R&D knowledge depreciation, we draw on the IEA public sector R&D expenditure statistics using annual R&D expenditures of all IEA countries over the period 1974 to 2007 for nuclear and energy efficiency (IEA, 2008). The two examples represent contrasting patterns of R&D expenditure: high but erratic (nuclear) versus low but stable (efficiency). We then compute the remaining knowledge stock over time using a range of knowledge depreciation rates from 0%, 10%, 20%, up to 40% percent per year. The knowledge stock estimates shown in Figure 2 describe how much of the original knowledge (cumulative R&D) remains relevant at any given year. In the case of a 0% per year depreciation rate, the knowledge stock is simply the cumulative R&D until any particular year. In the other cases of >0% depreciation rates, annual expenditures are discounted by the corresponding depreciation rate and then summed up to estimate the knowledge stock. Downward sloping curves represent a decline in technological capability (remaining knowledge stock). A simplifying assumption underlying these calculations, and which is frequently employed in the literature (e.g.,Watanabe et al., 2002), is that a linear relationship exists between R&D investment and knowledge creation. Neither increasing nor decreasing returns to R&D are assumed to exist. This restricting assumption is easier to criticize than to disprove empirically.

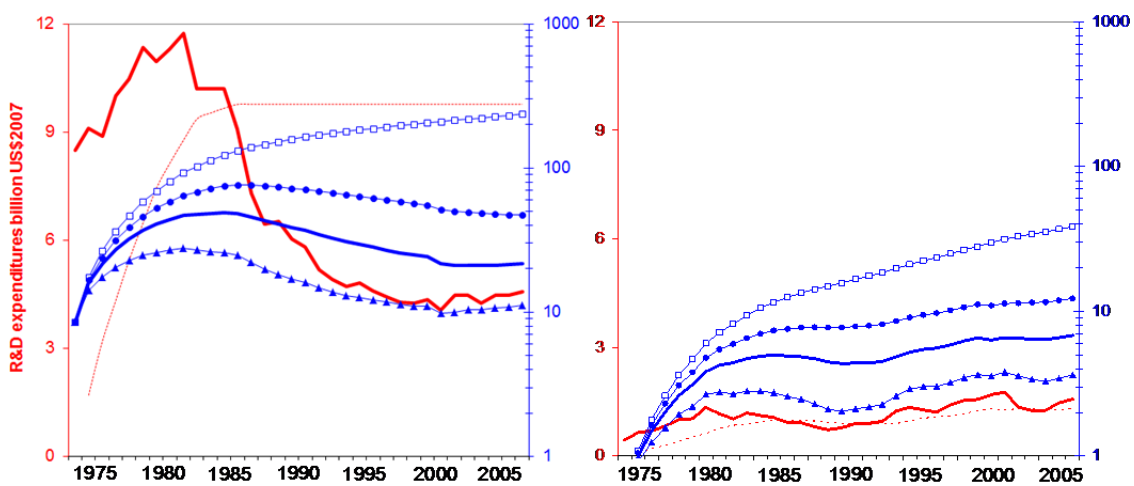

FIGURE 2. R&D EXPENDITURES IN IEA COUNTRIES & KNOWLEDGE STOCKS UNDER DIFFERENT DEPRECIATION RATES FOR NUCLEAR (LEFT-PANEL) AND ENERGY EFFICIENCY (RIGHT-PANEL). NOTES: R&D EXPENDITURES ($2007) IN IEA COUNTRIES SHOWN ON LEFT AXIS IN RED (SOLID LINES SHOW ACTUAL R&D, DASHED LINES SHOW R&D REQUIRED TO MAINTAIN KNOWLEDGE STOCK AT 20% DEPRECIATION RATE); KNOWLEDGE STOCK FROM ACTUAL R&D EXPENDITURE SHOWN IN DECREASING ORDER ON RIGHT AXIS AT 0%, 10%, 20%, AND 40% PER YEAR KNOWLEDGE DEPRECIATION RATES.

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As the distinction between the left and right-panels of Figure 2 illustrate for nuclear and energy efficiency respectively, a technology's knowledge stock is defined by two variables: the knowledge depreciation rate, and *the pattern of knowledge generation over time* (here: R&D expenditures). Erratic expenditures, as in the case of nuclear, are particularly prone to knowledge depreciation. Taking a mean knowledge depreciation rate of 20% per year, only 9% of the original knowledge remained in 2007 (22 billion US$2007 out of a total cumulative nuclear R&D of 236 billion US$2007). Conversely, in the case of energy efficiency R&D with the same assumed knowledge depreciation rate, 18% of the original knowledge remained (7 billion US$ out of cumulative R&D expenditures of some 38 billion US$). This was due to a more consistent R&D expenditure pattern allowing continuous knowledge recharge.

This finding of a much higher portion of knowledge retention in stable R&D expenditures is robust against the large variation in the rate of knowledge depreciation included in the studies discussed above. After a peak in nuclear R&D in 1982 at some 12 billion US$, R&D expenditures declined precipitously resulting in a substantial reduction of the nuclear knowledge stock. In fact, maintaining the knowledge stock would have required annual R&D expenditures to the tune of 10 billion US$ (assuming a mean knowledge depreciation rate of 20%/yr), i.e. twice above the actual R&D expenditures. This "R&D replacement" funding shortfall limited the continued knowledge recharge and consequently led to an additional knowledge depreciation beyond the "natural" rate of knowledge obsolescence. R&D into energy efficiency, while substantially below nuclear, was much less erratic and thus enabled continued knowledge recharge. Conversely, one could have achieved the same $22 billion nuclear knowledge stock in 2007 with a more stable investment pattern, similar to that of efficiency. In this illustrative calculation we assume a starting nuclear R&D budget of 1.4 billion US$ (actual: 8.5 billion US$) in 1974 growing continuously by 4%/year to 2007 (similar to the average growth in energy efficiency R&D) and a mean knowledge depreciation rate of 20%. This would have required only 100 billion US$ R&D expenditure, or 42% of the $236 billion that was actually spent over 33 years, saving $136 billion.

Table 1 provides a further illustration, again assuming a mean knowledge depreciation rate of 20%/year. Considering the entirety of energy R&D expenditures of IEA countries (IEA, 2008) suggests that only the equivalent of 53 billion US$ out of the cumulative R&D spending of 431 billion US$ over the period 1974 - 2007 may still constitute useful technology knowledge at present, i.e. some 12%, with the remainder being "lost" investments due to knowledge depreciation. Technologies such as nuclear that have suffered a particularly erratic R&D funding profile of "boom and bust" are affected much more by knowledge depreciation than technologies that have received less, but more stable funding. This is seen in Table 1 by the corresponding lower percentage for nuclear compared to efficiency in the knowledge stock variable compared to cumulative expenditures.

In other words, for knowledge management, *a continuous and regular pathway of funding is as important as the absolute level of funding* with "boom and bust" cycles being particularly detrimental in maintaining and recharging technological innovation knowledge.

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TABLE 1. CURRENT (2007) AND CUMULATIVE (1974-2007) R&D EXPENDITURES OF IEA COUNTRIES (BILLION US$2007) WITH ESTIMATE OF REMAINING KNOWLEDGE STOCK. NOTES: ASSUMES AN AVERAGE KNOWLEDGE DEPRECIATION RATE OF 20% APPLIED TO ANNUALIZED EXPENDITURE PROFILES. SOURCE: IEA, 2008.

	current R&D (2007)	(2007)	cumulative R&D (1974-2007)		remaining knowledge capital stock	
	10^9 US$2007	%	10^9 US$2007	%	US$2007	%
Energy efficiency	1.6	*13.0*	38	*8.9*	7	*12.9*
Fossil Fuels	1.4	*11.3*	55	*12.8*	6	*11.6*
Renewables	1.5	*12.3*	37	*8.7*	6	*10.6*
Nuclear-fission	3.7	*30.6*	194	*45.1*	18	*33.3*
Nuclear-fusion	0.9	*7.3*	42	*9.7*	4	*7.9*
Others	3.1	*25.4*	64	*14.8*	13	*23.7*
Total	**12.0**	*100.0*	**431**	*100.0*	**53**	*100.0*

6 DISCUSSION

This case study's survey of the literature on knowledge depreciation in the field of energy technologies identified large gaps in available knowledge. Intricate measurement issues of a complex unobservable as well as the lack of comprehensive technology-specific data on innovation inputs and outputs will be needed to overcome these research gaps. Distinctions between depreciation via obsolescence and depreciation via human capital attrition provide a promising avenue for research. Another important research area will be to examine the impacts of different technological and organizational configurations on knowledge codification, and how public disclosure can help minimize knowledge depreciation. Distributed knowledge and technology cooperation networks could hold the promise of overcoming conventional patterns of knowledge depreciation. Technology, including open source, internet-based information systems, could play an important role.

It is also important to establish empirically whether rates of knowledge depreciation are linked to the very nature of technologies themselves. In the case of knowledge accumulation this indeed seems to be the case. "Granular" small unit scale technologies appear to have twice as high rates of knowledge accumulation or learning than large scale "lumpy" technologies that by their very nature only allow experimentation at the scale of dozens to hundreds of projects compared to "granular" technologies produced and experimented with the scale of millions to billions (Wilson et al., 2012). More granular technologies, in part because they are dispersed among a large number of technological pathways with heterogeneous incentives for innovation, may also be less susceptible overall to the boom and bust cycles of prices, markets and policy associated with high rates of knowledge depreciation in the energy system.

Knowledge depreciation is an important and pervasive, yet under-recognized phenomenon of technological innovation. Knowledge depreciation rates of 10% to 40% per year seem to be common. In some situations characterized by, for example, a lack of codification, boom and bust innovation incentives, and high rates of innovation, knowledge depreciation rates are even higher. Depreciating knowledge has been observed in careful studies of a wide variety of industries, including several energy technologies. It occurs both for knowledge acquired through R&D as well as through experience.

These empirical findings and research challenges hold important implications for technology policy in terms of stability of support for knowledge accumulation as well as incentives for knowledge preservation and sharing. To mitigate knowledge depreciation, public policy support for R&D and market formation incentives should be made contingent on public disclosure of technological knowledge, from scientific papers, technical reports, patent applications, all the way to the documentation of actual market technology performance of subsidized technologies. Public disclosure of information is an essential first step for mitigating depreciation particularly associated with tacit technological knowledge by facilitating documentation, archiving and knowledge sharing.

More generally, knowledge depreciation needs to be more explicitly recognized and managed in technology policies. The life cycle of technological innovation from early experimentation to successful market deployment spans many decades (three decades being a rough rule of thumb). Recognizing this lengthy process both cautions against overambitious efforts to “scale up” innovations too quickly (e.g., the Superphénix breeder reactor) and definitively provides a cautionary tale against erratic policy signals and financial innovation support. When the pervasiveness of knowledge depreciation is taken into account, concerns about the inertia of entrenched government technology programs (Cohen and Noll, 1991) are balanced by concerns about the losses associated with volatile programming. ‘Small and stable’ as opposed to ‘big but boom and bust’ is an important policy implication which this case study on knowledge depreciation can provide to policy makers.

7 FURTHER READING

Argote and Epple (1990) is a widely cited study in the field of knowledge depreciation, particularly in manufacturing and service industries. Nemet (2012) provides a recent application of thinking on knowledge depreciation to the early Californian wind industry.

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