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Rare breakthroughs vs. incremental development in R&D strategy for an early-stage energy technology

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ABSTRACT

Uncertainty in technological learning is a crucial factor in planning research, development, and demonstration (RD&D) strategies. Nevertheless, most previous work either models technological change as deterministic or accounts for uncertainty without fully capturing the recourse feature of the problem. This paper improves upon these approaches by developing a real options-based stochastic dynamic programming method for valuing and planning low-carbon energy RD&D investment and is the first of its kind to disaggregate the effects of R&D and learning-by-doing. This simplified model captures the relevant features of the problem and provides general insights on RD&D strategy under technological uncertainty. Results indicate that imminent deployment, high cost, lower exogenous cost reductions, and lower program funds all promote R&D spending over learning-by-doing, since under these circumstances a breakthrough, rather than slow and consistent cost reductions, will render the program successful.

1. Introduction

Accounting for uncertainty in technological learning is crucial to technology development strategies. Nevertheless, most research treats technological change as deterministic, either exogenously or with cost decreasing as an endogenous function of installed capacity. Uncertainty is an especially important attribute for technology strategies in the clean energy sector, given the increased prominence of climate mitigation on policy agendas and the prevalence of early-stage energy technologies, which with further development could reduce the cost of complying with such policies. Historically, the outcome of research, development, and deployment (RD&D) of energy technologies has been highly uncertain: some developmental technologies achieve large cost reductions and are commercialized successfully, while others never reach commercialization despite extensive investment. Accurate models of decision making under uncertainty in technology development incorporate the ability to accelerate or abandon the technology based on the performance of the RD&D program and the ability to invest in a technology with low expected value but a small probability of a high-value breakthrough.

This paper presents a novel method for valuing RD&D investments under uncertainty with specific application to low-carbon energy technologies. A climate policy is assumed to take effect at a known date in the future, motivating RD&D investment to prepare a single technology for deployment once the policy is enforced. If the technology is cost-effective by this time, it is deployed; otherwise, it is abandoned. In absence of an RD&D program, valuing this investment opportunity is similar to valuing a European put option, and it therefore fits a real options framework.[2] Real options is frequently used in the energy sector to value capital investment decisions under uncertainty in factors such as fuel costs and electricity prices (see Dixit and Pindyck (1994) for a thorough, general treatment of real options theory and applications). Real options has been applied to valuing RD&D investments, though never before in a model where RD&D spending directly influences the cost of the developmental technology. The put-option framework is appropriate for the case in which the investor anticipates a fixed amount of time in which to develop a technology to prepare for a disruptive event such as a policy shift. In this paper, the framework is augmented by the assumption that the investor can invest in a combination of R&D, which encompasses riskier and more fundamental innovation projects, and learning-by-doing (LBD), which is achieved through demonstration projects and operational experience, in order to drive down the cost of the technology. This paper is the first to separate the effects of R&D and LBD in an analytical model to yield insight into optimal investment in the two modes of development. The framing as a European put option avoids a typical result of real options analyses

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[2] A European put option represents the right, but not the obligation, to sell an asset for a given price at a given time in the future. While options theory originally arose in the context of the stock market, the field of real options adapts this theory to value capital investment decisions under uncertainty.

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involving options with infinite time horizons, which is to postpone investment beyond what may be realistic in order to resolve uncertainty.

When change in energy technologies has been included endogenously in previous decision support models, it is most often represented as deterministic learning curves that express cost as a log-linear function of installed capacity. Learning curves are characterized extensively for the energy sector (e.g. Neij, 2008 and Junginger et al., 2008). Studies that endogenize them with cumulative installed capacity as a decision variable include Riahi et al. (2004) and McFarland and Herzog (2006) for carbon capture and sequestration (CCS), Rao et al. (2006) and Barreto and Kypreos (2004) for a portfolio of conventional and renewable energy technologies, Bosetti et al. (2009) for an abstracted "breakthrough" technology, and Miketa and Schrattenholzer (2004) for two-factor learning curves for wind and solar power. Two-factor learning curves treat cost as a function of both R&D and LBD, and form the basis for the cost model used in this work.

These prior studies contain sophisticated models of uncertainty in other aspects of the climate and economy and often neglect uncertainty in technological change due to computational limitations. However, they fail to capture important aspects of the RD&D investment problem such as the value of exploratory investment in technologies with low expected value but a small probability of a breakthrough, the possibility that cost estimates could rise over time, and the ability to update the investment strategy frequently as new information is revealed. Methods incorporating risk factors (e.g. Grübler and Gritsevskyi, 2002) or risk constraints (e.g. Ma, 2010) model risk aversion by adding a penalty cost for greater variability in learning rates, but do not capture the recursive aspect of the investment problem or the value of making early-stage decisions that perform well over a broad range of future outcomes.

Since RD&D strategies operate over long periods of time, can be revised repeatedly, and are subject to significant uncertainty, stochastic dynamic programming (SDP) provides an appropriate framework for analyzing such strategies. Most previous applications of SDP to RD&D investment have used numerical optimization methods, for which computational intensity substantially limits the number of time steps and technology development outcomes (e.g. Bosetti and Tavoni, 2009). Webster et al. (2012) and Santen (2012) circumvent these limitations by developing an approximate dynamic programming method to analyze decision making under technological uncertainty, and their results demonstrate that a two-stage decision model may not be sufficient to capture the value of RD&D since it is path-dependent and operates over an extended period of time.

While models that apply numerical optimization methods to problems with few discrete outcomes and time steps can offer insight into specific cases, they may not produce generalizable results. This paper, in contrast, uses a stylized model to examine RD&D investment under uncertainty, in which the optimization step is performed analytically and the resulting partial differential equation solved numerically. This model allows for arbitrarily many time steps and a continuous representation of uncertainty and generates results that are applicable across a range of similar problems. Previous SDP-based approaches to valuing RD&D that make use of analytical techniques have been framed as real options analyses. Pindyck (1993) proposes an SDP-based method for project valuation and illustrates it with an example from the nuclear power industry in the early 1980s, accounting for both technical and market uncertainty. Huchzermeier and Loch (2001) develop an SDP-based real options model for investment decisions in a single technology under multiple uncertainties and show that the value of flexibility is reduced if uncertainty is resolved only after decisions are made. Siddiqui and Fleten (2010) model investment in an unconventional energy technology (UET) and a more established renewable energy technology, in which the investor has the opportunity to pay a lump sum to start the UET down a learning curve that follows geometric Brownian motion with negative drift. Davis and Owens (2003) use a closely related method to value investment in a renewable energy technology with uncertainty in the cost of non-renewable energy, the remaining cost of developing and switching to the renewable energy technology, and the cost of the developed renewable energy technology.

Results of real options analyses typically encourage postponing technology deployment to wait for more information. In the case of future climate policy, deployment of the technology may be largely driven by the disruptive arrival of a climate policy, a phenomenon captured more realistically in this paper than in previous work.

This paper, unlike previous studies, models the explicit effect of continued RD&D investment on cost with the constant ability to update the investment decision, in anticipation of future climate policy enactment and simultaneous deployment of the technology. The continuous cost distribution captures a realistic range of possible technology development outcomes. Unlike previous analytical SDP approaches to RD&D investment, this paper disaggregates the effect of the RD&D program into R&D and LBD. R&D assumed to be less effective on average than LBD but more likely to generate a high-value breakthrough. The simplified model–while necessarily stylized–captures key features of the problem, allows for broad exploration of the parameter space, is generalizable across similar cases, and is much less computationally intensive than strictly numerical approaches.

2. The model

The RD&D investment problem is framed as a maximization of the value of the technology less cumulative spending at time T, accounting for uncertainty as well as changes in cost exogenous to the RD&D program. The value maximization problem is expressed as

$$\max_{I_R, I_L}\left\{\mathrm{E}\left[\int_0^T -\left(I_R(t) + I_L(t)\right)e^{-rt}dt + e^{-rT}\psi(C_T)\right]\right\} \tag{1}$$

in which I_R and I_L are the rates of spending on R&D and LBD (with a budget constraint $I_R + I_L \leq q$), r is the discount rate, T is the end of the RD&D investment period and the potential deployment time of the technology, and t is a time variable that takes values between 0 and T. The function $\psi(C_T)$ is the net present value (NPV) of deploying the technology at time T, or 0 if the NPV is negative.

I consider a single technology with an associated cost, $\$C/\mathrm{tCO_2}$, of using the technology for carbon mitigation. C is assumed to follow an Itô process with a drift and volatility that are functions of the rate of spending on R&D and learning-by-doing (LBD):

$$\frac{dC}{C} = -\left(\lambda_R I_R + \lambda_L I_L + \alpha\right)dt + \gamma_R (I_R)^{\frac{1}{2}}dz_R + \gamma_L (I_L)^{\frac{1}{2}}dz_L + \sigma dw \tag{2}$$

in which λ_R and λ_L represent the expected effectiveness of R&D and LBD spending in reducing cost, such that greater effectiveness tends to result in lower carbon-mitigation cost C. These parameters are scaled in the model by the rate of investment, and the products $\lambda_R I_R$ and $\lambda_L I_L$ determine the rate of change in C in a way that is quantitatively similar to an interest rate. The parameter α is the exogenous drift rate of cost due to factors such as spillovers and changes in input costs, and γ_R and γ_L represent the standard deviation of the effectiveness of R&D and LBD spending (for brevity, henceforth termed uncertainty in R&D/LBD effectiveness). It is assumed that $\lambda_L > \lambda_R$; a basis for this assumption is Lohwasser and Madlener (2010), who estimated a two-factor learning curve for CCS by developing an analogy with flue-gas desulfurization. Lohwasser and Madlener (2010) found an LBD rate of 7.1% and a learning-by-researching (here referred to as R&D) rate of 6.6%, using the number of patents as the independent variable for learning-by-researching. It is further assumed that $\gamma_R > \gamma_L$, indicating greater uncertainty in the outcome of R&D investment versus LBD investment. The parameter σ represents exogenous uncertainty, and dz_R, dz_L, and dw are increments of standard Brownian motions.

Eq. (2) implies that C can never drop below 0, as fits a cost function,