Time series models for forecasting technological change, particularly for energy technologies: approaches relevant to Ministries of Finance

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Overview

In the coming energy transition, the way energy is generated will change dramatically. As fossil fuels are phased out, what will they be replaced with, and how much will it cost? Several studies based on the history of many different technologies have shown that the patterns of technological change are heterogeneous and persistent. While it is not possible to predict the future innovations, it is possible to predict how the costs of technologies will likely change in the future. The costs of many technologies change slowly or not at all, while others decrease suddenly. In the first group, fossil fuels cost almost the same as they did a century ago, and nuclear power now costs roughly (if not more than) what it did in 1958. In contrast, the costs of solar photovoltaics (PV), wind power, lithium batteries, and hydrogen electrolyzers have dropped dramatically. Solar PV now costs 10,000 times less than its first commercial use in the Vanguard Satellite in 1958. The methods developed by the complexity economics group at the Institute for New Economic Thinking at the Oxford Martin School (hereafter the "Oxford group")[1] make it possible to make probabilistic predictions for both cost and deployment of specific technologies based on historical data (Way et al., 2022; Wagenwoort et al., 2024). New methods are being developed to make forecasts of costs at the national level and provide some understanding of the factors that influence costs and deployment (Baumgartner and Farmer, 2024), which can be very useful for planning and investment. Failure to anticipate the future costs of technologies has led to investments in technologies (such as nuclear power) that have not been cost-effective. This has slowed down the transition to net zero and handicapped the economies of the countries that have made bad investments.

The strengths and limitations of existing approaches to assessing technological change

The most widely used planning tools for technology forecasting are integrated assessment models (IAMs) and the energy models built by the International Energy Agency (IEA), which have been making projections about energy costs and deployment for the last 30 years. IAMs are optimization models that address the question, "What is the least expensive path to make the transition for a given warming target?," or more generally, try to find the path that maximizes economic growth taking climate change into account. The IEA's energy model makes projections of the future energy system under different scenarios, based on expert opinions. (Since their model is not public, the details of how it really works remain difficult to ascertain.) Both kinds of models have poor track records—they have consistently (and dramatically) overestimated the costs and underestimated the deployment of renewables, in particular solar and wind energy (Way et al., 2022).

There are also fundamental methodological problems with models based on optimization. Implementing the paths these models suggest would require a benevolent global decision-maker, whereas historically, individual countries have never implemented the recommended policies. This makes the models difficult to test, since when their predictions (often labeled as "projections") fail to match reality, the modelers can shrug their shoulders and say "well, my predictions weren't right because the world did not follow the policies my model recommended." Such problems have arisen in part because most IAMs make assumptions about energy technologies, such as "floor costs," which are limits on how cheap a technology can ever be. They also make assumptions about maximum rates of deployment. These assumptions have been shown to be wrong many times, as technologies have now become cheaper than the previously assumed floor costs and exhibited rates of deployment in excess of past assumed limits (Way et al., 2022). Finally, IAMs are limited to testing policies that can be implemented as taxes, or something equivalent to a tax.

The Oxford group instead asks the question of what will likely happen in the future based on past experience. The historical performance of a technology, e.g., its costs versus time, is highly informative about future performance. Technologies whose costs have been decreasing will very likely continue to come down in the future, and those whose costs have increase will continue to do so.

1 https://www.inet.ox.ac.uk/.

Based on past data on costs it is possible to build models that make probabilistic predictions about future costs (Farmer and Lafond, 2016; Lafond et al., 2018). Historical technology models of this type are limited in that their forecasts are based on typical behavior and do not address how things might change under different policies. However, they are still useful for planning, e.g., for knowing which technologies are good bets and what their costs will likely be at a given point in the future (more on this in the next section).

Similarly, it is possible to forecast future deployment based on past deployment. The diffusion of technologies follows "S-curves," which grow exponentially and then level out as the technology reaches maturity. A study of many different technologies by the Oxford group shows that the S-curves of technologies are remarkably similar, and that in the later stages of technology development, they can be used to make good probabilistic predictions of future deployment.

The Oxford group is designing agent-based models for the energy system that represent individual companies and estimate their future profits and losses under different policy scenarios. This method has the huge advantage that it makes it possible to test combinations of policies in different countries. (The policies can be of any type and are not restricted to those that are equivalent to taxes.) However, it requires many more resources to implement.

Why accurate forecasts are helpful for Ministries of Finance

Forecasts of the cost and deployment of technologies are useful as they help to determine which technologies are worth financial support, including ensuring the technologies being supported are those that will likely prevail at the global level. Support can be via tax breaks or subsidies—these models do not offer advice about the best method of support; what they do provide is advice about when technologies will likely be deployed (based on past trends) and what each technology will likely cost in the future. Of course, the policies of individual countries may affect these forecasts, but this analysis shows what will likely happen with policies such as those that have been in effect in the past. A good example is Moore's Law : the number of components on a single chip doubles every two years, leading to an exponential increase in computing power and a corresponding decrease in relative cost. However, Moore's Law has nonetheless provided chip manufacturers with a very useful way to anticipate future costs and plan accordingly, e.g., so that memory and CPU characteristics will match.[2] Good forecasts should be a key component in formulating industrial policy. It is also important to formulate policies that will provide cheap electricity for consumers. Energy planning requires coordination—for example, if solar and wind become major components of an energy system, investment in energy storage technologies becomes critical.

Key policy questions that can be addressed

When an MoF is formulating industrial policy, a natural question is "Which technologies should we support?" For example, many countries have provided substantial support for nuclear power. This has now been shown to be a bad investment, as nuclear power plants take a long time to build, and the electricity they produce is very expensive (Way et al, 2022). Historical data-based technology forecasts indicate that this is very unlikely to change in the future, particularly as solar energy and wind continue to get cheaper, making their relative costs much lower (Farmer and Lafond, 2016). These trends are pervasive. Small modular reactors, for example, have been proposed as a way to introduce mass production, and "bring nuclear reactors down a learning curve," but their starting costs are so high that implausible learning rates would be required for them to ever catch up. From an economic development perspective, forecasts for auxiliary technologies, such as batteries and hydrogen-based fuels, are also important to coordinate energy strategy.

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2 Pixar provides an excellent example. The creators of *Toy Story* had the technology ready before they had the computer power to implement it. The fact that they knew that Moore's Law would bring costs down in the future allowed them to raise money and scale their effort well in advance so that they could complete the film. (This is an anecdote shared by Alvie Ray Smith, one of the lead designers). Similarly, knowing that in the future the costs of solar and wind are very likely to be much lower than those of other technologies enables a finance ministry to invest accordingly.

Use of new approaches in practice

Use in practice requires historical data on both the cost and deployment of technologies, which must be collected and curated. It also requires computer code that implements the forecasting algorithms. Macrocosm Inc., a University of Oxford spinout, has developed Excel-based tools that make it possible to use its models with a user-friendly interface that connects to Macrocosm servers and runs the code on its historical data on the performance of many different technologies. These models can also be implemented as computer code inside of other models—the existing code is in Python but the underlying software is relatively simple and is publicly available on GitHub.

Learning and challenges

With the user interface mentioned above, these models are easy to use and can be easily linked to any other models. They produce probabilistic forecasts, meaning that they forecast the likelihood of different outcomes. Users will need to master the user interfaces, but this is relatively simple.

Conclusions and recommendations

Historical time series models for forecasting technological change can be a valuable component in planning any decisions that involve anticipating the likely future costs and deployment levels of technologies. This should of course be augmented by other factors, such as the expertise and infrastructure available in any given country.

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