***Endogenous Technological Change in Power Market models***

[Jacqueline Adelowo, ifo Institute for Economic Research at the University of Munich, +49 89 9224 1254, adelowo@ifo.de]

[Valeriya Azarova, ifo Institute for Economic Research at the University of Munich, +49 89 9224 1307, azarova@ifo.de]

[Mathias Mier, ifo Institute for Economic Research at the University of Munich, +49 89 9224 1365, mier@ifo.de]

## Overview

One of the most complex and pivotal questions in power market modelling is the appropriate representation of technological change (TC). TC can be understood as the “increase in outputs for a given level of inputs through the process of invention, innovation, and diffusion” [6] and has a direct impact on models’ results, for example, the level of emissions abatement for a given cost. Hence, inadequate representation of TC can lead to biased environmental/climate policy recommendations. Earlier power market models treated TC as exogenous process – an autonomous function of time, allowing sudden large capacity expansions at low cost despite lack of prior investments in the technology [10,11]. Yet the last 20 years have seen a gaining momentum in endogenizing the TC in the models, thereby allowing for a more realistic consideration of the cost reduction as functions of distinct learning factors such as experience stocks through learning-by-doing (LBD). Currently, there are several approaches to implement endogenous technological change (ETC). Among those, Mixed-Integer-Programs (MIP) of single-factor LBD curves are a popular choice of ETC representation, leading to a piece-wise constant approximation of unit cost developments [8]. In this paper, based on the example of the EUREGEN European power market model, we demonstrate how the application of various specifications of a single-factor LBD approach to ETC affects outcomes of the model in terms of installed capacity, system costs and CO2 emissions. We add to current literature in the field by developing and implementing a novel holistic metric allowing to include more sophisticated LBD features such as the integration of forgetting-by-not-doing in MIP models. Associated with employee turnover, loss of routines, and technological obsolescence of experience, past experience has long been found less valuable than recent experience in the context of organizational forgetting [1,2,4]. Its representation as forgetting-by-not-doing in bottom-up power system models has therefore been pointed out as a relevant yet blank spot by researchers [3,9]. Our framework extensions will thus contribute to closing the research gap in enhanced implementation of ETC in complex power system models.

## Methods

In order to demonstrate the impact of ETC on power market model outcomes, we apply our framework to the EUREGEN model as a case study. EUREGEN is a comprehensive partial-equilibrium model, which minimizes European power market system cost under CO2 emission reduction paths [5]. The model intertemporarily optimizes dispatch and capacity investments into transmission, storage, and generation for 16 generation technologies. In a spatial resolution of 12 European regions the model makes investment decisions in 5-year cycles. The perfect foresight planning horizon runs from 2015 to 2050. We apply piece-wise linear implementation strategies to represent single-factor LBD learning curves [8] for regional learning and learning with European spillovers. The implemented learning setting can be flexibly adjusted in three dimensions: the modeled learning regions, the number of modeled learning technologies, and the number of modeled line segments to approximate the learning curve. This enables us to analyze the energy system cost and respective price developments, the generation mix and share of specific technologies in installed capacity, and CO2 emissions in the given spatial and temporal resolution. The results under ETC are compared to exogenous TC as a function of time by choosing an initial ETC calibration that covers a similar unit cost range in cost reduction potentials as the exogenous TC assumptions. We further analyze the effects of sophisticated learning features such as forgetting-by-not-doing, as opposed to perfect recall conditions. Comparing learning implementations in non-linear and linearized settings as well as adjusting the number of line segments in the latter, allows us to assess the trade-off between accuracy and computational feasibility. The non-linear implementations are solved as a Non-Linear-Program, while piece-wise linear implementations are solved as a Mixed-Integer-Program. The learning implementations are further subjected to sensitivity checks.

## Results

We find that the relative capacity cost of renewable technologies is sensitive to the learning mechanism applied and significantly influences the timing, extent, and regional distribution of capacity expansion of renewable energy technologies. Under exogenous TC the model is incentivized, due to perfect foresight, to postpone capacity investments to later periods with lower capacity cost. Instead, under endogenized learning we observe a dissipation of this incentive, leading to earlier capacity investments for some technologies. In addition to that, regional path-dependencies become apparent and regional bang-bangs are partially reduced. Extending existing ETC implementation frameworks by depreciation of the experience stock, i.e. forgetting-by-not-doing, invokes new competitive dynamics among the learning technologies. These dynamics stem from the trade-off between cost-degressions from early LBD on the one hand and depreciation of early learning progress due to forgetting-by-not-doing on the other hand. The implementation of forgetting-by-not doing concentrates and smoothens regional investments in the time-dimension because large regional expansion time gaps become inefficient. Figure 1 underlines these dynamics for onshore wind capacity in the selected region of Britain by visualizing the dissipation of multiple expansion peaks as soon as forgetting-by-not-doing is introduced. In addition to these findings at the regional level, an off-setting effect can be observed for wind at the aggregate level. The off-setting effect, already described for LBS [3], is an optimization behavior leading to slightly increased capacity expansion to compensate and offset learning loss from forgetting. We find such an off-setting effect to be existent likewise for forgetting-by-not-doing in LBD.



Figure 1: Regionally smoothed wind expansion wave in Britain under forgetting (left panel) and aggregate off-setting effect for wind under forgetting (right panel). Both panels compare outcomes under perfect recall (left bars) vs. forgetting (right bars).

## Conclusions

This paper provides a framework extension to implement LBD in the context of ETC in power market models. We show that implementing ETC in the models is essential to represent the well-acknowledged occurrence of path-dependencies and reasonable investment behavior. New expansion strategies exhibited by the model under endogenous learning conditions provide evidence for that. We observe that regional distribution and timing of capacity expansion follow different patterns under ETC as compared to exogenous time-dependent productivity increases. Not only is the mere consideration of ETC of importance but also the specific implementation design of learning features. While earlier work has focused on implementing forgetting and time lags for LBS only, it is likewise important to consider these sophisticated learning features for LBD. We see adjusted cost-optimized expansion strategies of the model and an off-setting effect as soon as forgetting is applied. It is therefore crucial to carefully consider ETC in power system models to make efficient environmental/climate policy recommendations based on cost-optimized investment paths. As the cost-optimized energy system is highly sensitive to the magnitude of learning parameters, we suggest that a careful calibration of the model with econometric estimations of learning parameters is vital.

## References

[1] Argote, L., Beckman, S. L. & Epple, D. (1990). The Persistence and Transfer of Learning in Industrial Settings. *Management Science*, 36, 140-154

[2] Argote, L. & Epple, D. (1990). Learning Curves in Manufacturing. *Science*, 247, 920-924

[3] Barreto, L. & Kypreos, S. (2004). Endogenizing R&D and market experience in the “bottom-up” energy-systems ERIS model. *Technovation*, 24, 615-629

[4] Benkard, C. L. (2000). Learning and Forgetting: The Dynamics of Aircraft Production. *American Economic Review*, 90, 1034-1054

[5] Blanford, G. J. & Weissbart, C. (2019). A framework for modeling the dynamics of power markets - The EU-REGEN model, ifo Working Paper, No. 307, ifo Institute - Leibniz Institute for Economic Research at the University of Munich, Munich

[6] Gillingham, K., Newell, R. G., & Pizer, W. A. (2008). Modeling endogenous technological change for climate policy analysis. *Energy Economics*, 30(6), 2734-2753

[7] Heuberger, C. F.; Rubin, E. S.; Staffell, I.; Shah, N. & Dowell, N. M. (2017). Power capacity expansion planning considering endogenous technology cost learning. *Applied Energy,* 204, 831-845

[8] Kypreos, S.; Barreto, L.; Capros, P. & Messner, S. (2000). ERIS: A model prototype with endogenous technological change. *International Journal of Global Energy Issues*, 14, 347-397

[9] Miketa, A. & Schrattenholzer, L. (2004). Experiments with a methodology to model the role of R&D expenditures in energy technology learning processes; first results. *Energy Policy*, 32, 1679-1692

[10] Nordhaus, W. D. (1973). The Allocation of Energy Resources. *Brookings Papers on Economic Activity*, 4, 529-576

[11] Wing, I. S. (2006), Representing induced technological change in models for climate policy analysis. *Energy Economics*, 28, 539-562