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373
2022

July 2022

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ifo INSTITUTE
Leibniz Institute for Economic Research
at the University of Munich

Imprint:

ifo Working Papers
Publisher and distributor: ifo Institute – Leibniz Institute for Economic Research at the University of Munich
Poschingerstr. 5, 81679 Munich, Germany
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ifo Working Paper No. 373

Endogenous Technological Change in Power Markets

Abstract

Decarbonization requires the transformation of power markets towards renewable energies and investment costs are decisive for the deployed technologies. Exogenous cost assumptions cannot fully reflect the underlying dynamics of technological change. We implement divergent learning-by-doing specifications in a multi-region power market model by means of mixed-integer programming to approximate non-linear investment costs. We consider European learning, regional learning, and three different ways to depreciate experience stocks within the European learning metric: perfect recall, continuous forgetting, and lifetime forgetting. Learning generally yields earlier investments. European learning fosters the deployment of solar PV and wind onshore, whereas regional learning leads to more wind offshore deployment in regions with high wind offshore quality. Perfect recall fosters solar PV and wind onshore expansion, whereas lifetime forgetting fosters wind offshore usage. Results for continuous forgetting are in between those of perfect recall and lifetime forgetting. Generally, learning leads to the earlier deployment of learning technologies but regional patterns are different across learning specifications and also deviate significantly from this general pattern of preponing investments.

JEL Code: C61, H21, H23, H43, L94
Keywords: Endogenous technological change, learning-by-doing, forgetting, renewable energies, power market model, decarbonization

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Declaration of interests. The authors declare that they have no known competing conflict of interest or financial interests that could have appeared to influence the work reported in this paper.
Acknowledgments. We gratefully acknowledge the financial support by the German Federal Ministry for Economic Affairs and Energy (grant number 020E100374092).
CRediT author statement. **Mathias Mier:** Conceptualization; Data curation; Formal analysis; Funding acquisition; Investigation; Methodology; Visualization; Roles/Writing - Original Draft; **Jacqueline Adelowo:** Conceptualization; Formal analysis; Investigation; Methodology; Visualization; Roles/Writing - Original Draft; **Valeriya Azarova:** Conceptualization; Investigation; Methodology; Roles/Writing - Original Draft.

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1. Introduction

Recent geopolitical events expose an urgent need for European energy markets to accelerate the transition from using fossil fuels to renewable energies. The intention to do so has already been announced in the European Green Deal (2019) and confirmed by European Climate Law (2021), but the path for a cost-efficient transition to a carbon-neutral European energy system still needs to be paved. Energy system and power market models can help to coordinate and evaluate the long-term policy support needed to achieve this path.

Such models rely on numerous long-run fixed assumptions due to the long horizon considered for climate and environmental policies. One of these assumptions is about the future investment cost of technologies following from the pace and scope of technological development—usually labeled as *technological change*. Often technological change is represented exogenously as an autonomous function of time. Such an approach keeps computational complexity of models manageable but relies on modeler's subjective assumptions about cost reductions in the future. Moreover, exogenously decreasing investment costs neglect that technological developments can be an endogenous result of feedback processes occurring through market and policy channels such as accumulated experience from applying a technology—called *learning-by-doing* (LBD).[1]

Possible technological learning (e.g, lower investment cost) and related uncertainties are rather small for mature technologies such as conventional power plants burning fossil fuels. However, less mature technologies are still experiencing significant learning and thus can be expected to undergo substantial technological change (Arrow, 1962). Renewable technologies such as solar PV, wind onshore, and wind offshore belong to this group of less mature technologies and are at the same time expected to be the cornerstone of decarbonization (Creutzig et al., 2017, Luderer et al., 2022). A lack of representation of endogenous dynamics for these technologies in the long-term modeling horizon can thus bias resulting decarbonization pathways in both timing and abatement cost. Hence, realistic assumptions about the cost development of generation technologies triggered by ETC are essential to providing sound policy recommendations towards climate-neutrality goals (Berglund and Söderholm, 2006). We thus focus on solar PV, wind onshore, and wind offshore as endogenously learning technologies and use exogenous investment cost formulations for all the other technologies.

We implement LBD in the EUREGEN model—a multi-region partial equilibrium model of the European power market that dynamically optimizes (i.e., assuming perfect foresight) investments, decommissioning, and dispatch of multiple generation, storage, and transmission technologies until 2050.[2] We build on existing approaches to linearize the non-linear learning dynamics by means

[1]LBD is usually represented by learning curves that describe how much investment costs drop when the underlying experience stock of past capacity investments grows. This approach is pre-dominant in disaggregated energy system and power market models. Alternative strategies focus on accumulated knowledge through R&D activities, which is more common for dynamic computable general equilibrium (CGE) and some integrated assessment models (Gillingham et al., 2008, Barreto and Kypreos, 2004).

[2]See Weissbart and Blanford (2019) for the basics of the model, Mier et al. (2020, 2022), Siala et al. (2022) for the underlying calibration, and Weissbart (2020), Mier and Weissbart (2020), Azarova and Mier (2021), Mier et al.

of mixed-integer programming (MIP) and develop a novel way to account for *spatial learning* (on European and regional levels). We also introduce different ways to account for *experience depreciation* - perfect recall, continuous forgetting, and lifetime forgetting. We further develop a *reverse-calibration* routine that uses exogenous investment cost assumptions and the resulting model outcomes as a benchmark to calibrate the learning parameters of the endogenous technological change (ETC) formulation. This reverse-calibration enables high comparability, allowing to analyze the direct effects of endogenized technology costs.

Our findings show that European learning fosters the deployment of wind onshore and also solar PV. Regional learning relies more on wind offshore in regions with high quality wind offshore potential. Both learning metrics reduce abatement cost—measured by a carbon price following from a quantity target—and electricity prices but the regional metric does more so than the European one. Differences resulting from depreciation assumptions are smaller and often region-specific. In general, perfect recall and continuous forgetting foster solar PV and wind onshore, whereas lifetime forgetting deploys considerably more wind offshore. Moreover, a sensitivity analysis shows that lower solar PV cost lead to more solar PV but no substitution of wind onshore as well as offshore, whereas lower wind onshore cost yield a substitution of wind offshore by wind onshore, and vice versa. European learning is considerably more sensitive to changes in investment cost of solar PV and wind offshore compared to regional learning. European and regional learning are equally sensitive to changing wind onshore cost.

Implementing ETC is more complicated for more disaggregated power market models with reasonable temporal and spatial resolution compared to rather aggregated ones such as CGE or integrated assessment models—which have seen various implementations of ETC already. Power market models are often formulated as a linear program (LP) due to their granularity with respect to hourly, spatial, and technological resolution. The straightforward implementation of learning curves, however, introduces non-linear dynamics which can take already medium complex models to the limits of stable computational solutions. As a consequence, a string of literature emerged to linearize learning curves in energy system models by means of MIP (e.g., Messner, 1997, Mattsson, 1997, Kypreos et al., 2000). This approach has been applied to a large number of models including GENIE (Mattsson, 1997), MARKAL (Seebregts et al., 1998), MESSAGE (Messner, 1997, Grübler and Messner, 1998, Seebregts et al., 1998), POLES (Kouvaritakis et al., 2000), WITCH (Bosetti et al., 2006), NEMS (Ouassou et al., 2021), and REMIND (Luderer et al., 2022). The paper most closely related to ours is Heuberger et al. (2017). They apply the MIP approach to the ESO-XEL model of the UK power market and find that the implementation of learning-by-doing has a forward-shifting impact on the optimal timing of capacity investments. We confirm findings of Heuberger et al. (2017) to a certain degree but also find different patterns. In particular, we apply the MIP approach to the entire European power market (28 countries merged to 14 regions) and thus can identify regions that shift investments forward but mainly find that specific regions with high resource qualities and potentials of the respective renewable learning technology invest

(2021), Mier and Azarova (2021a,b) for applications.

considerably more in later periods. We also analyze two spatially different metrics—European and regional learning—which are not applicable to a single country power market model. Moreover, the numerical literature about ETC neglects to identify and quantify the origin of differences from exogenous investment cost with ETC formulations because exogenous model calibrations do not match endogenous learning calibrations. We close that gap by presenting a reverse-calibration routine to perfectly compare the outcomes of exogenous investment cost specifications with ETC formulations. In addition to that, Miketa and Schrattenholzer (2004) and Barreto and Kypreos (2004) point out that an empirically well-known characteristic of LBD dynamics—namely experience depreciation from organizational forgetting (Argote et al., 1990, Argote and Epple, 1990, Benkard, 2000, Thompson, 2007)—has not been taken into account in the numerical implementations of LBD in power market models yet. We explore different ways to accumulate and depreciate experience stocks and fill in this gap in the literature.

The remainder of this paper is organized as follows. Section 2 introduces our exogenous as well as endogenous formulation of technological change, including European and regional learning and different ways of depreciating experience. Section 3 guides through our reverse-calibration strategy. Section 4 presents results. Section 5 concludes.

2. Model

2.1. Notation and objective

IQ are investments into capacity (in GW) at *unit investment cost* c^{IQ} (in €/kW), Q is the capacity stock (in GW) that costs c^{Q} to operate and maintain (in €/kW), and Y is generation (in GWh) at cost c^{Y} (in €/kWh). Consider different technologies j and regions r. h is the hourly time index and $t = 2015, 2020..., 2050$ a quinquennial index that indicates *periods*. $t^0 = 2015$ is the base period of the planning horizon that does not allow for investments and $t_{step} = 5$ is the length of a period. $v = 1960, 1965, ..., 2050$ is the period of installation, which we call *vintage* in the following. We use subscripts for j, r and parentheses for h, v, t to denote variables (capital letters) and parameters (small letters), i.e., $Y_{j,r}(h, v, t)$ is generation of technology j in region r in hour h and period t that is installed in vintage v.

Power market models minimize the stream of cost $C(t)$ from investments $IC(t)$, operation and maintenance $FC(t)$ (fixed cost), and dispatch $DC(t)$ (all in million €) by choosing to install capacities $\mathbf{IQ}$, operate and maintain capacities $\mathbf{Q}$, and generate $\mathbf{Y}$. Intertemporal (dynamically optimizing) models additionally discount such cost streams by using the discount factor $\delta(t)$. The minimization problem is

$$\min_{\mathbf{IQ},\mathbf{Q},\mathbf{Y}} \sum_t \delta(t)\, C(t) \;=\; \sum_t \delta(t)\left[IC(t) + FC(t) + DC(t)\right], \tag{1}$$

subject to multiple constraints. The most important one is the *demand-equals-supply constraint*, which requires that generation, dispatch, and imports meet a certain electricity demand (so that

$IQ, Q, Y = 0$ is not the solution of the optimization problem). For parsimony, we refrain from showing them here.

2.2. Exogenous unit investment cost

Unit investment cost $c^{IQ}(t)$ vary over time, so that *investment cost* follow from

$$IC(t) = \sum_{j,r} IQ_{jr}(t) \cdot c^{IQ}_{jr}(t). \tag{2}$$

Such an investment cost specification allows to keep the model linear. Endogenous technological change turns the model into a non-linear program, which cannot be solved at a comparable (or even reasonable) temporal, spatial, and technological resolution. However, the non-linearity can be overcome by approximating investment cost by means of mixed-integer programming (MIP). Hence, all further derivations serve to changing investment cost (2) in accordance with endogenous technological change.

2.3. European learning

Perfect recall. Suppose that unit investment cost vary depending on the European *experience stock* QS that includes all past investments into capacity as well as the initial capacity stocks q^0 at the beginning of the first period t^0, i.e.,

$$\begin{aligned} QS_j(t) &= QS_j(t-1) + \sum_r \sum_{v=t} IQ_{jr}(v) \\ &= \sum_r \left(\sum_{v \leq t^0} q^0_{jr}(v) + \sum_{t^0 < v \leq t} IQ_{jr}(v) \right). \end{aligned} \tag{3}$$

The second line displays the experience stock as the sum of all initial capacity stocks installed until t^0 and all the past investments from $t^0 + 1$ onward until the respective period. Observe that such a formulation prevents forgetting of experience over time, hence, we denote it as *perfect recall*. The unit investment cost are now a function of the experience stock:

$$c^{IQ}_j(QS_j(t)) = c^{FIRST}_j \cdot QS_j(t)^{-b_j}, \tag{4}$$

where c^{FIRST}_j is the cost of the first capacity unit installed (*initial unit investment cost*) and $b \geq 0$ is the learning elasticity. Current unit costs are decreasing with the experience stock and higher learning elasticities, and increasing with the level of initial unit investment cost. Such a non-linear form is computationally challenging. We follow the piece-wise linear approximation described by Kypreos et al. (2000) to transform it into a mixed-integer linear programming problem. We first calculate the aggregate investment cost $AIC(t)$ by taking the integral of unit investment cost (4) over the experience stock, i.e.,

$$AIC_j(t) = \int_0^{QS_j(t)} c_j^{IQ}(x)\, dx \quad = \quad \frac{c_j^{FIRST}}{1-b_j} QS_j(t)^{1-b_j}\,. \tag{5}$$

The perfect recall nature of this formulation allows to start the approximation at the initial experience stock. In particular, aic^0 follows from the initial experience stock $qs^0 = \sum_r \sum_{v \le t^0} q_{jr}^0(v)$. aic^{MAX} follows from the maximum experience stock qs^{MAX}, which should be chosen slightly above the potentially realized experience stock to improve validity of the approximation. The curve between these two points is approximated by multiple linear line segments $ls = ls1, ls2, ..., LS$. We opt for an increasing length of line segments to allow for a more precise representation of the steeper curve segments at early learning phases. Each line segment covers an increasingly longer portion of the difference between aic^{MAX} and aic^0, where the portion is defined by a weighting factor[3]:

$$\zeta_{ls} \quad = \quad \begin{cases} \frac{1}{2^{LS-ls}} / \sum_{ls} \frac{1}{2^{LS-ls}} & \forall ls < LS, \\ 1 & \forall ls = LS. \end{cases} \tag{6}$$

The breakpoints of the line segments are marked by the segments' upper bounds:

$$aic_{j,ls}^{UP} \quad = \quad aic_j^0 + \zeta_{ls}\left(aic_j^{MAX} - aic_j^0\right), \tag{7}$$

where the respective lower bounds follow from $aic^{LO}_{\text{"}ls1\text{"}} = aic^0$ and $aic^{LO}_{ls+1} = aic^{UP}_{ls}$. The associated experience stocks at the (upper and lower) breakpoints are qs^{UP} and qs^{LO}. Exchanging $AIC_j(t)$ and $QS_j(t)$ in (5) by $aic^{UP}_{j,ls}$ or $aic^{LO}_{j,ls}$ and $qs^{UP}_{j,ls}$ or $qs^{LO}_{j,ls}$, respectively, and rearranging yields:

$$qs_{j,ls}^{UP} \quad = \quad \left(\frac{1-b_j}{c_j^{FIRST}} aic_{j,ls}^{UP}\right)^{\frac{1}{1-b_j}}, \tag{8}$$

$$qs_{j,ls}^{LO} \quad = \quad \left(\frac{1-b_j}{c_j^{FIRST}} aic_{j,ls}^{LO}\right)^{\frac{1}{1-b_j}}. \tag{9}$$

We can now determine the line segment slopes $\sigma_{j,ls}$ that reflect the linear approximations of unit investment cost (in €/kW) per line segment. They follow from the fraction of the difference of aggregated investment cost and experience stocks of the respective upper and lower bounds of

[3]Assuming five line segments, we obtain weighting factors $\zeta = (0.0667, 0.1333, 0.2667, 0.5333, 1)$.

each line segment, i.e.,

$$\sigma_{j,ls} = \frac{aic_{j,ls}^{UP} - aic_{j,ls}^{LO}}{qs_{j,ls}^{UP} - qs_{j,ls}^{LO}}. \tag{10}$$

So far, all necessary calculations are calibration necessities. To implement the MIP approximation in the model, we need four additional constraints that describe the evolution of the line segment-specific experience stock $QS_{j,ls}(t)$ and a binary variable $\rho_{j,ls}(t) \in \{0,1\}$ that indicates which line segment is currently active. The four constraints are:

$$QS_{j,ls}(t) \geq qs_{j,ls}^{LO} \cdot \rho_{j,ls}(t), \tag{11}$$

$$QS_{j,ls}(t) \leq qs_{j,ls}^{UP} \cdot \rho_{j,ls}(t), \tag{12}$$

$$\sum_{ls} \rho_{j,ls}(t) = 1, \tag{13}$$

$$\sum_{ls} QS_{j,ls}(t) = QS_j(t). \tag{14}$$

Constraints (11) and (12) ensure that the line segment-specific experience stock is above the lower and below the upper boundary of the specific line segment. Constraint (13) ensures that only one line segment is active per time period. Finally, constraint (14) ensures that the line segment-specific experience stock equals indeed the experience stock as defined by (3).

Using the slopes and the binary variable, we can now approximate investment cost $\overline{AIC}_j(t)$ by linearly extrapolating from the lower bound of the active line segment, i.e.,

$$\overline{AIC}_j(t) = \sum_{ls} \left[\left(\rho_{j,ls}(t)\, aic_{j,ls}^{LO} \right) + \sigma_{j,ls} \left(QS_{j,ls}(t) - \rho_{j,ls}(t)\, qs_{j,ls}^{LO} \right) \right]. \tag{15}$$

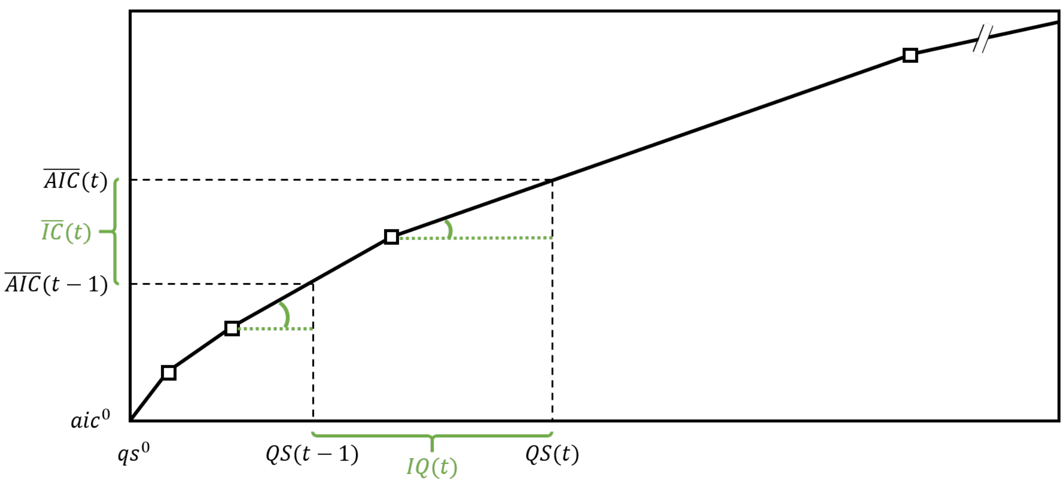
Note that the lower segment bound always reflects *exact* cost, as all segment bounds lie on the accumulated investment cost curve.[4] Only the last interpolation step is an approximation. Finally, we obtain approximated periodical cost $\overline{IC}(t)$ from the difference between current period's and prior period's accumulated investment cost, i.e.,

$$\overline{IC}(t) = \sum_{j} \left[\overline{AIC}_j(t) - \overline{AIC}_j(t-1) \right]. \tag{16}$$

[4]Equation (15) is a corrected version of Equation (43) in Heuberger et al. (2017), where we found a multiplication with the binary variable ρ to be missing in the first term.

Figure 1 provides a graphical representation of the segmentation and interpolation procedure. The x-axis shows the experience stock. The y-axis shows accumulated investment cost. The black line presents the interpolated curve of accumulated investment cost with squares representing line segments bounds. The curve starts at the initial experience stock qs^0 with initial experience stocks' accumulated investment cost aic^0. The difference between the experience stock of the current period t to the prior period $t-1$ is the investment into capacity IQ. The difference between accumulated investment cost are the investment cost of the respective period (16). Observe that such an approximation works well when climbing and skipping line segments or also staying within one line segment.

Figure 1: Illustration of the segmented accumulated investment cost curve under perfect recall



Note that it is important to distinguish the experience stock and actual installed capacity. While each of them is associated with a quantity and expenditure dimension, they can be at different levels and move in different directions in each of the dimensions. For instance, this LBD specification assumes perfect recall and therefore the experience stock is monotonically increasing in quantity, while actually installed capacity is also subject to (even endogenous) decommissioning. However, both experience stock and installed capacity are simultaneously increasing in quantity and expenditure from one period to the next by IQ. This variable therefore serves as a direct link between magnitudes of the abstract experience stock and the actually installed capacity.

We use the above specification for all the learning technologies and the default exogenous formulation from (2) for all other technologies.

Continuous forgetting. Not only capacity depreciates over time but also experience. We thus introduce continuous forgetting, that is, each year $\Delta \in (0,1)$ of the experience is lost.[5] The experience stock changes to

[5]We apply 3% per year in the remainder.

$$QS_j(t) = \begin{cases} (1-\Delta)^{t_{step}} QS_j(t-1) + \sum_r \sum_{v=t} IQ_{jr}(v) & \forall t > t^0, \\ \sum_r \left(\sum_{v \le t^0} (1-\Delta)^{t-v} q^0_{jr}(v) \right) & \forall t = t^0. \end{cases} \tag{17}$$

The second line describes the initial experience stock $qs^0_j = QS_j(t^0)$. It consists of all vintage-specific initial capacity stocks. Each of those initial capacity stocks is subject to depreciation, where $t-v$ is the distance of installation period v to the current period t. Thus, qs^0_j is already subject to depreciation. After initializing the experience stock within the second line of (17), we can always use the depreciated prior period experience stock and current investments (that are not yet subject to depreciation) to describe the evolution of the experience stock. The first part of the term in the first line of (17) represents the *depreciated* experience stock inherited from the previous period. We denote this term the *legacy experience stock* (denoted by superscript LEG), defined as:

$$QS^{LEG}_j(t) = \begin{cases} (1-\Delta)^{t_{step}} QS_j(t-1) & \forall t > t^0, \\ QS_j(t) & \forall t = t^0. \end{cases} \tag{18}$$

Note that $QS^{LEG}_j(t) < QS(t-1)$ so that the associated $\overline{AIC}^{LEG}_j(t) < \overline{AIC}_j(t-1)$. By introducing depreciation we thus allow for backward movement on the segmented aic curve. This also means that the experience stock can potentially depreciate below its initial level. Thus we do not calculate aic^0 from qs^0_j anymore but set $aic^0 = aic^{LO}_{\text{"}ls1\text{"}} = 0$.[6] Equations (7) to (15) still hold.

Finally, as $\overline{AIC}^{LEG}_j(t) < \overline{AIC}_j(t-1)$, total investment cost can no longer be calculated from (16), but instead $\overline{AIC}^{LEG}_j(t)$ needs to be identified first. This requires the duplication procedure of constraints (11) to (14) for the legacy variables, i.e.,

$$QS^{LEG}_{j,ls}(t) \geq qs^{LO}_{j,ls} \cdot \rho^{LEG}_{j,ls}(t), \tag{19}$$

$$QS^{LEG}_{j,ls}(t) \leq qs^{UP}_{j,ls} \cdot \rho^{LEG}_{j,ls}(t), \tag{20}$$

$$\sum_{ls} \rho^{LEG}_{j,ls}(t) = 1, \tag{21}$$

$$\sum_{ls} QS^{LEG}_{j,ls}(t) = QS^{LEG}_j(t). \tag{22}$$

[6]Note that setting $aic^0 = aic^{LO}_{\text{"}ls1\text{"}}$ to zero increases the space to be approximated, hence generally produces slightly poorer approximations. However, qs^{MAX}_j might differ in this depreciation specification because experience stocks that are subject to continuous forgetting are generally lower than those under perfect recall due to $\Delta > 0$. Thus, choosing a lower qs^{MAX}_j re-improves the approximation.

Note that this doubles the number of binary variables in the continuous forgetting specifications due to the mirrored legacy variables. Finally, we can define the *legacy accumulated investment cost* as

$$\overline{AIC}_{j}^{LEG}(t) \;=\; \sum_{ls} \left[\left(\rho_{j,ls}^{LEG}(t)\, aic_{j,ls}^{LO} \right) + \sigma_{j,ls} \left(QS_{j,ls}^{LEG}(t) - \rho_{j,ls}^{LEG}(t)\, qs_{j,ls}^{LO} \right) \right]. \tag{23}$$

We can now calculate the periodical investment cost as the difference between aggregated investment cost and legacy aggregated investment cost:

$$\overline{IC}(t) \;=\; \sum_{j} \left[\overline{AIC}_{j}(t) - \overline{AIC}_{j}^{LEG}(t) \right]. \tag{24}$$

The application of legacy experience stocks is crucial here to avoid distortions. Using (16) from the perfect recall specification would lead to a downward distortion of both capacity expansion and associated investment cost, because $\overline{AIC}_{j}^{LEG}(t) < \overline{AIC}_{j}(t-1)$.

Figure 2: Illustration of the segmented accumulated investment cost curve under forgetting

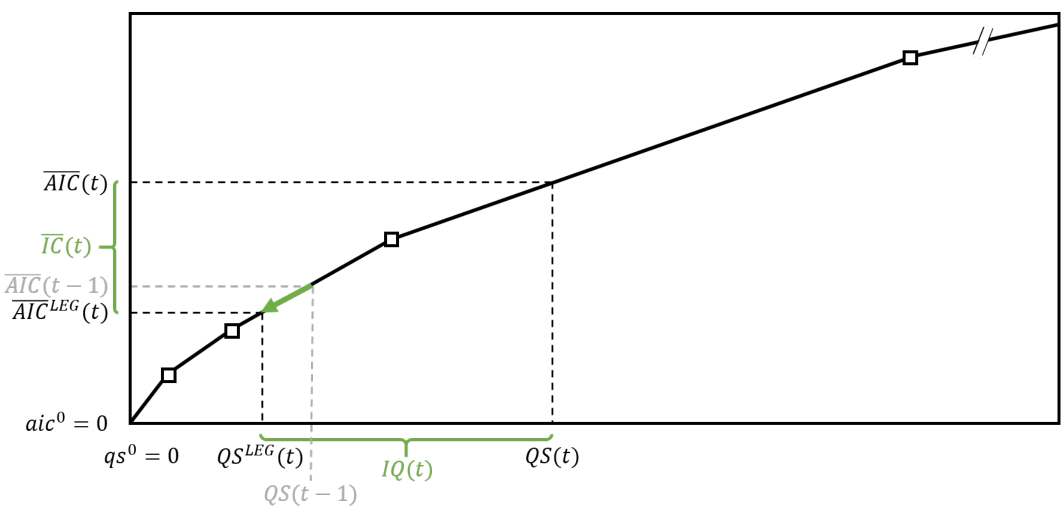


Figure 2 displays again the piece-wise linear approximation of the accumulated investment cost curve over the experience stock, here additionally accounting for forgetting (represented by the green arrow). Moreover, the approximation starts at accumulated investment cost and experience stocks of zero. Investment cost IC now becomes the difference between accumulated investment cost of the current period and the legacy accumulated investment cost associated with experience inherited from the previous period (24). The same holds true for the respective current period investments.

Lifetime forgetting. With continuous forgetting, we cannot reflect the timing of past investments. That is, there is much experience depreciation when experience is high and little when experience is low. However, it is plausible to assume that earlier investments undergo higher depreciation, for example, due to retirement-induced turnovers—where older employees with ample experience from earlier installations leave the electricity sector more frequently than younger workers (Ashworth, 2006). We thus introduce a novel way of interpreting forgetting that reflects this hypothesis through the actual lifetime of capacity. Denote by $\mathit{\Gamma}(v,t) \in \{0,1\}$ the binary parameter indicating whether initial capacities or past investments from vintage v are still active (at least potentially, that is, endogenous decommissioning is ignored here) in period t. We then need to change the experience stock to

$$QS_j(t) = \begin{cases} \sum_r \left(\sum_{v \le t^0} \mathit{\Gamma}_{jr}(v,t)\, qs^0_{jr}(v) + \sum_{t^0 < v \le t} \mathit{\Gamma}_{jr}(v,t)\, IQ_{jr}(v) \right) & \forall t > t^0, \\ \sum_r \left(\sum_{v \le t^0} \mathit{\Gamma}_{jr}(v,t)\, qs^0_{jr}(v) \right) & \forall t = t^0. \end{cases} \tag{25}$$

The experience stock now perfectly mirrors past investments but might differ from the available capacity due to endogenous decommissioning. Legacy capacity follows from

$$QS^{LEG}_j(t) = \begin{cases} \sum_r \left(\sum_{v \le t^0} \mathit{\Gamma}_{jr}(v,t)\, q^0_{jr}(v) \right) & \forall t > t^0, \\ QS_j(t) & \forall t = t^0. \end{cases}$$

All further calculations are identical to those of continuous forgetting.

2.4. Regional learning

In addition to our base model, which assumes a European-wide experience stock for LBD, we also implement regional learning. In this extreme case each region maintains its own experience stock and learns completely in isolation from other regions. We therefore need to define region-specific unit investment cost c^{IQ}_{jr}, experience stocks QS^{IQ}_{jr}, learning elasticities b_{jr}, and initial unit investment cost c^0_{jr}. *Perfect recall* regional experience stocks are given by

$$\begin{aligned} QS_{jr}(t) &= QS_{jr}(t-1) + \sum_{v=t} IQ_{jr}(v) \\ &= \sum_{v \le t^0} q^0_{jr}(v) + \sum_{t^0 < v \le t} IQ_{jr}(v). \end{aligned} \tag{26}$$

All further calculations only require adding a subscript r, except when calculating the investment cost. Equation (16) needs to be adjusted by taking the sum over all regions to enter the minimization problem.[7]

Note that the number of (binary) variables and necessary parameters as well as MIP equations is now multiplied by the number of regions, which could make the entire problem computationally more challenging. However, as opposed to European learning, in the regional specification investment decisions in one region do not impact costs in all other regions anymore. Hence, the interdependence of investment cost and intertemporal decisions is reduced in the regional model.[8]

3. Calibration

3.1. Learning-by-doing

One of the main contributions of our paper is a detailed analysis of the structural model behavior under endogenous technological change formulations. This includes insights into the structural biases (e.g., in the timing and extent of investment decisions) of intertemporal power market models that use exogenous unit investment cost specifications. In particular, we do not aim to provide the best possible (most realistic) calibration of LBD via empirical estimates, but rather aim to achieve quantifiable comparability between exogenous and endogenous cost formulations. We therefore introduce a novel approach to *reverse-calibrate* our ETC formulation to best match the assumptions of a model using exogenous unit investment cost, which we call *benchmark* in the remainder.

Simplification. We simplify the spatial resolution of the EUREGEN model from 28 countries to 14 regions (with each region being a spatial grouping of countries with similar solar PV, wind onshore, and wind offshore qualities), the temporal resolution to 89 hours, and the technological resolution to keep the MIP formulation numerically tractable and solvable within a reasonable time frame.[9] In particular, solar PV, wind onshore, and wind offshore are learning technologies. For all other technologies (bioenergy, bio-CCS, gas-CCGT and gas-ST, gas-CCS, gas-OCGT, nuclear, lignite, geothermal, hydro, transmission technologies, storage technologies), we apply the exogenous investment cost formulation. Appendix A contains details of this simplification process.

European learning. The benchmark takes unit investment cost from Table 1 as given. From the capacity investments undertaken by the benchmark, we calculate the underlying synthetic experience stocks that would occur under the different depreciation assumptions. Table 1 shows that the 2015 solar PV initial experience stock assuming perfect recall is 98 GW and increases to 525 GW in 2050. When applying continuous forgetting, optimization starts at a lower initial synthetic experience stock of 83 GW, which increases to 340 GW in 2050. For lifetime forgetting, the 2015 values are the same as under perfect recall because none of the respective technology vintages have

[7] Adjustments for continuous and lifetime forgetting are the same as for the European metric. We, however, refrain from showing results for these specifications in the remainder of the paper for parsimony.

[8] All investment decisions remain interconnected via allowed transmission between regions and a joint carbon emission target.

[9] Around one week using 10 threads with the solver GUROBI in GAMS.

reached their decommissioning age yet. However, 2050 values are fundamentally lower than for perfect recall, as they reflect maximum lifetime of currently installed capacities, while perfect recall refers to the total amount of capacity ever installed.[10] Patterns across the different depreciation assumptions are similar for the two wind technologies.[11]

Table 1: Exogenous unit investment cost for the benchmark and synthetic experience stocks that follow from the benchmark for different depreciation assumptions

	Technology	2015	**2020**	2030	2040	**2050**
Unit investment cost (€/kW)	Solar PV	1,100	**900**	810	760	**720**
	Wind onshore	1,400	**1,350**	1,250	1,150	**1,100**
	Wind offshore	3,470	**2,448**	2,193	2,023	**1,938**
Perfect recall experience stock (GW)	Solar PV	98	**125**	222	330	**525**
	Wind onshore	131	**184**	745	1,284	**1,617**
	Wind offshore	11	**19**	19	44	**262**
Continuous forgetting experience stock (GW)	Solar PV	84	**98**	161	217	**340**
	Wind onshore	113	**150**	629	967	**1,007**
	Wind offshore	10	**17**	13	31	**234**
Lifetime forgetting experience stock (GW)	Solar PV	98	**125**	205	232	**340**
	Wind onshore	131	**184**	705	1,153	**1,128**
	Wind offshore	11	**19**	19	34	**243**

There are no investments possible in 2015 but cost are depicted here for the sake of comparability with other tables. 2025, 2035, and 2045 values are not shown for the sake of parsimony.

We now take 2020 and 2050 synthetic experience stocks from the benchmark as well as the associated exogenous 2020 and 2050 unit investment cost to obtain two investment cost-experience pairs for our calibration. The two pairs have to lie on the reverse-calibrated learning curve, i.e., the calibrated ETC formulation should endogenously achieve the same unit investment cost for the same experience stock levels. We assume learning elasticities per technology to be stable over time and thus reverse-calibrate the learning elasticity b_j and initial unit investment cost c_j^{FIRST}. In particular, we solve the learning curve shown in Equation (4) for c_j^{FIRST} and create two learning curves by using the two cost-experience pairs consisting of 2020 and 2050 experience stocks, $QS_j("2020")$ and $QS_j("2050")$, with respective exogenous unit investment costs, $c_j^{IQ}("2020")$ and $c_j^{IQ}("2050")$ (see values in Table 1), solve each of the two curves for c_j^{FIRST}, set them equal, and finally solve for b_j. The learning elasticity can then be substituted in one of the learning curves to obtain initial unit investment cost. We obtain

[10] Endogenous decommissioning allows "active" capacities to fall behind lifetime forgetting experience stocks.

[11] The 340 GW for solar PV, 1,128 GW for wind onshore, and 243 GW for wind offshore assuming lifetime forgetting coincide with the potential that is intuitively competitive (see Table A.1 in Appendix A). Only the realized wind offshore potential stays behind as, economically, it is not reasonable to install 400 GW wind offshore in Ireland and United Kingdom.

$$b_j = -\frac{\ln c_j^{IQ}(\text{"2050"}) - \ln c_j^{IQ}(\text{"2020"})}{\ln QS_j(\text{"2050"}) \cdot 10^6 - \ln QS_j(\text{"2020"}) \cdot 10^6}, \tag{27}$$

$$c_j^{FIRST} = \frac{c_j^{IQ}(\text{"2050"})}{\exp \frac{\ln QS_j(\text{"2050"}) \cdot 10^6 \left(\ln c_j^{IQ}(\text{"2050"}) - \ln c_j^{IQ}(\text{"2020"})\right)}{\ln QS_j(\text{"2050"}) \cdot 10^6 - \ln QS_j(\text{"2020"}) \cdot 10^6}}. \tag{28}$$

Observe that experience stocks are transformed from GW into kW (via 10^6) because costs are measured in €/kW. This transformation ensures comparability of learning elasticities and initial unit investment cost with literature values. Applying those formulas leads to the values in Table 2. Note that the 2020 and 2050 fix-points from the benchmark do not differ in exogenous unit investment cost but in the synthetic experience stock. Hence, learning elasticities and initial unit investment cost should be lowest for perfect recall after the reverse-calibration because there is no experience loss. Observe that the resulting learning elasticities from the reverse-calibration are around 16 to 24 % (for solar PV), 9 to 11% (for wind onshore), and 11 to 12% (for wind offshore). Those rates tend to be in the lower range of literature estimates (Rubin et al., 2015).[12] Our calibration results also reflect patterns of substantial learning happening in the past. The initial unit investment cost estimates are slightly higher than in the literature. However, note that we do not seek to replicate real world values here but rather to make models with exogenous assumptions and endogenous technological change comparable.

Table 2: Learning elasticity and initial unit investment cost by technology and depreciation assumptions

	Learning elasticity (Learning rate)			Initial unit inv. cost (€/kW)		
	Solar	Onshore	Offshore	Solar	Onshore	Offshore
Perfect recall	-16.30% (10.68%)	-9.42% (6.32%)	-8.86% (5.96%)	19,001	8,099	10,806
Continuous forgetting	-19.43% (12.60%)	-10.75% (7.18%)	-8.86% (5.96%)	32,654	10,217	10,700
Lifetime forgetting	-23.82% (15.22%)	-11.28% (7.52%)	-9.12% (6.13%)	77,507	11,552	11,281

Learning elasticities and initial unit investment cost are calculated according to Equations (27) and (28). Corresponding transformation into learning rates in parentheses.

Regional learning. We largely follow the same reverse-calibration logic as before. Now, we apply regional synthetic experience stocks. Those are calculated on the basis of demand shares of the respective region, i.e., when a region builds capacities according to its demand share (from total

[12] Most empirical studies transform learning elasticities into learning rates LR (see values in parentheses in Table 2) or progress ratios PR by using $LR = 1 - PR = 1 - 2^{-b}$.

capacities build in the benchmark), then this region observes 2020 and 2050 unit investment cost as shown in Table 1. Unit investment costs are higher (lower) in case a region invests less (more) than its demand share. Details and results of those adjustments are given in Appendix B.

Calibration routine. We use the benchmark outcome to write reverse-calibration routines for each of the MIP specifications. In particular, we calculate warm-start values from the benchmark to give starting values for each model variable. We therefore use the MIPSTART option of the GUROBI solver. This enables us to start the branch-and-cut routine at MIPGAPS of 1% to 5% after processing the MIPSTART routine instead of spending multiple days of running time at MIPGAPS of 100%.[13] Additionally, we use a specification with 20 line segments for European and regional learning to produce an updated warm-start for each of the following MIP formulations of the respective metric. We finally aim for MIPGAPS below 0.1%. Higher MIPGAPS sometimes choose other local optima, producing significantly different technology mixes, e.g., one that relies heavily on nuclear power in combination with gas-CCS instead of a wind power-dominated system. This fact underlines that different technology mixes are similarly competitive when applying endogenous technological change. This issue is not relevant for linear instead of MIP formulations, as linearity of a model always ensures reaching the global optimum, whose outcome is always a wind power-dominated system. It is thus crucial to carefully re-calibrate the MIP model (number of line segments, approximation with maximum experience stock) and to review each of the outcomes in detail. Occasionally, we re-use the outcome of a particular specification, run the calibration routine on this outcome, and opt for even lower MIPGAPS to be sure about the global optimality of the calculated technology mix.

Number of line segments. We test specifications with 3, 5, 7, 10, 15, and 20 line segments to approximate investment cost (see Appendix C). 5, 7, 10, and 15 line segments produce good approximations, given that 20 is the one to match (see Appendix D for details). However, 15 line segments perform similarly in terms of solving time as 20 segments do. Likewise, 10 line segments converge slowly to reasonable MIPGAPS that ensure optimality of the resulting technology mix. The approximation quality of 7 line segments is slightly better than with 5 line segments, while there is no significant difference in solving time. We thus decide to perform all further calculations with 7 line segments.

Perfect recall vs. forgetting. We need to allow for backward movements of the experience stocks along the line segments when assuming forgetting. In particular, we need to start the approximation with zero experience stocks to allow for complete depreciation.[14] Moreover, perfect recall

[13]The relative MIPGAPS describe the difference in the objective of the MIP problem to the outcome of a linear programming relaxation where the binary variables are assumed to be free between 0 and 1. The log-files are available upon request from the corresponding author.

[14]One might also decide to calibrate for minimum values higher than zero but this does not ensure that the metric can freely move. In particular, not setting the first lower breakpoint to zero usually makes the forgetting formulations infeasible.

exhibits largest experience stocks because experience does not depreciate over time. Experience under lifetime forgetting, in turn, generally cannot be above the respective potential.[15] Continuous forgetting tends to deliver experience stocks below lifetime forgetting but the timing of decisions allows for higher values as well. Moreover, the last line segment covers around 50% of accumulated investment cost (and even more than 50% of the resource potential) and thus come with the worst approximation quality. We thus multiply the respective resource potentials by 1.5 (perfect recall), 1.25 (continuous forgetting), and 1 (lifetime forgetting) to obtain the maximum experience stocks used to approximate line segment-specific unit investment cost. Appendix E shows results of this approximation process for European learning formulations with 7 line segments. Continuous forgetting tends to have the lowest respective unit investment cost per line segment. This, however, does not per se mean that continuous forgetting exhibits lowest cost at any given time because the experience stock depreciates over time. Also, the maximum experience stocks (for perfect recall, continuous, and lifetime forgetting) are set rather arbitrarily and hamper perfect direct comparability of the calibrations. However, the general idea is to calibrate each MIP specification to the best possible extent while maintaining comparability with the benchmark and between specifications.

3.2. General calibration

We now provide some general calibration unrelated to any learning dynamics, which is thus applicable likewise to the benchmark and the MIP formulations. We apply a CO_2 emissions quantity target to reflect ambitions from European Green Deal (2019) and European Climate Law (2021). The 2020 emission cap is at 844 Mt. We assume that there are on average no CO_2 emissions from electricity generation in the period 2045 (from 2041 to 2045) anymore. For 2050, we force electricity generation to deliver negative emissions of –98 Mt. The first line of Table 3 summarizes the CO_2 emission target. Rising electricity demand (second line) reflects dense electrification of sectors and drives investment dynamics as does the emission target. The next three blocks show unit investment cost, cost for operating and maintaining capacity (fixed cost), and dispatch cost for a pre-selection of non-learning technologies. Observe that bio-CCS and nuclear have highest investment cost. Further, nuclear has highest fixed cost and lowest dispatch cost, whereas bio-CCS has highest dispatch cost. Note that dispatch does not include the implicit carbon price following from the emission target. In fact, the 2050 emission target can only be achieved by using bio-CCS, leading to 2050 carbon prices of around 220 €/ton in the benchmark as well as in all our MIP formulations.

4. Results

We begin by comparing European and regional learning-by-doing (LBD) outcomes with the benchmark (Subsection 4.1). Further on, we analyze the outcomes of different depreciation as-

[15]Endogenous decommissioning would, in principle, allow for experience stocks above the potential but we never encountered such an outcome in the optimization game. Moreover, the respective potentials used are subject to a simplification procedure and thus do not correlate with true resource potentials (see Appendix A).

Table 3: CO_2 emissions quantity target and demand as well as unit investment cost, fixed cost, and dispatch cost for selected technologies

		2020	2030	2040	2050
CO_2 emissions (Mt)		844	639	246	-98
Demand (TWh)		3,088	4,501	5,479	6,203
Investment cost (€/kW)	Bio-CCS	4,361	4,272	4,183	4,139
	Coal	1,500	1,410	1,380	1,365
	Gas-CCGT, gas-ST	850	850	850	850
	Gas-CCS	1,495	1,495	1,495	1,495
	Gas-OCGT	437	437	437	437
	Nuclear	6,006	5,082	4,488	4,356
Fixed cost (€/kW*a)	Bio-CCS	127	125	122	121
	Coal	60	56	55	55
	Gas-CCGT, gas-ST	34	34	34	34
	Gas-CCS	32	32	32	32
	Gas-OCGT	17	17	17	17
	Nuclear	264	264	264	264
Dispatch cost (€/MWh)	Bio-CCS	96	96	93	90
	Coal	18	17	17	17
	Gas-CCGT, gas-ST	33	33	33	33
	Gas-CCS	56	56	56	56
	Gas-OCGT	45	43	42	42
	Nuclear	8	7	7	7

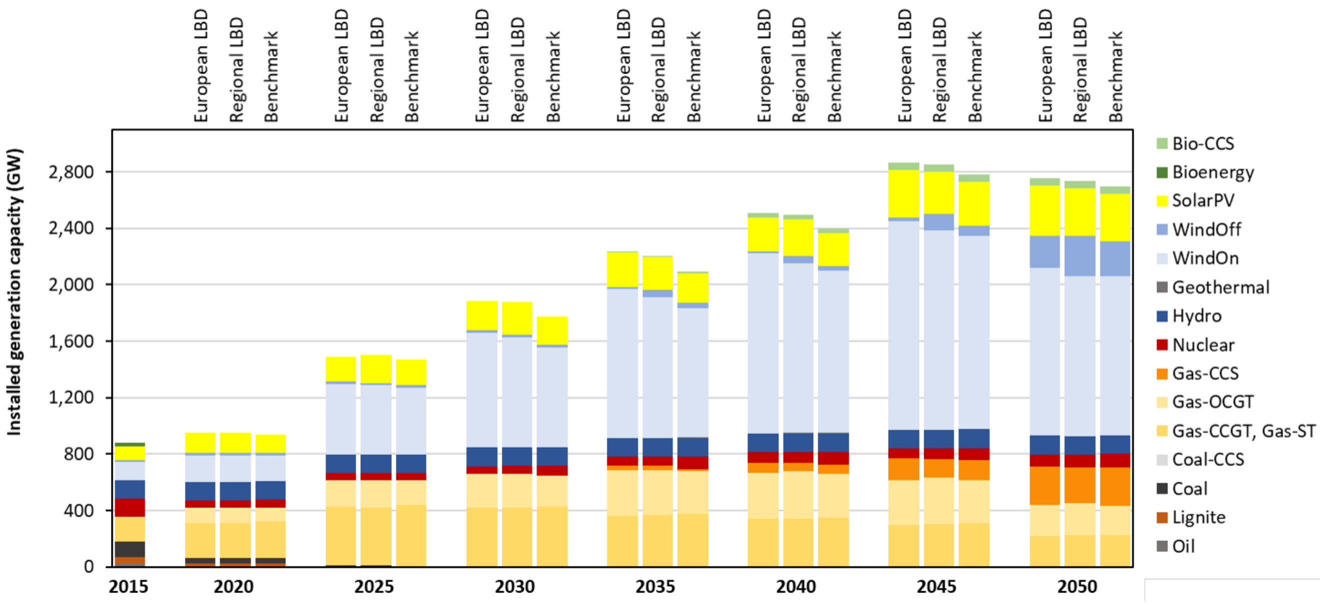
Cost are depicted for current vintages, so that dispatch cost are subject to fuel price changes and efficiency improvements over time.

sumptions (Subsection 4.2). Finally, we test sensitivity of results by changing unit investment cost and underlying learning elasticities as well as initial unit investment cost following from the reverse-calibration (Subsection 4.3).

4.1. European vs. regional learning

Figure 3 shows installed capacities (in GW) for the whole set of technologies. Outcomes are clustered in periods for European LBD, regional LBD, and the benchmark. Differences in the non-learning technology mix are mostly negligible and, thus, not discussed in the remainder. Moreover, 2015 as the calibration year has the same outcome for each specification. 2020 outcomes contain only negligible differences between specifications. European and regional LBD do not exhibit any differences in 2025 but the benchmark has slightly lower wind onshore and solar PV capacity. This trend persists for wind onshore until 2050. Observe that differences between the two LBD specifications start in 2030, where regional LBD has considerably lower wind onshore but, indeed, higher solar PV capacity. Relative differences are even higher from 2035 to 2045 because wind offshore capacity is systematically higher for regional LBD (compared to European LBD). European LBD offshore capacity is even lower than in the benchmark.

Figure 3: Installed capacities (in GW) for European LBD, regional LBD, and the benchmark



Relative differences are lower in 2050, but overall European LBD leads to the highest solar PV (354 GW) and wind onshore (1,188 GW) capacities, whereas offshore capacity is the lowest in this specification (229 GW, see also Table 4). In turn, the regional LBD ends up with the lowest solar PV capacity (331 GW) but the highest offshore capacity (291 GW). The benchmark has the lowest onshore capacity (1,128 GW). From our reverse-calibration we know that higher capacities of a respective technology under European LBD compared to the benchmark translate into lower investment costs. Thus, 2050 solar PV and wind onshore costs are lower under European LBD than assuming exogenous unit investment cost. Similarly, capacity stocks for regional learning hint that investing regions face even lower costs since those regions learn more than their respective demand shares suggest. This leads to the lowest CO_2 and electricity prices under regional LBD, whereas the benchmark delivers highest prices. It is fair to say that on the aggregate level, endogenous learning dynamics provide an incentive to invest earlier (Heuberger et al., 2017).

We can trace back differences in the capacities of learning technologies by looking at regional differences of 2050 installed capacities.[16] For example, solar PV differences can be mainly related to Britain (Ireland plus UK), France, and Iberia (Spain plus Portugal). Britain invests into solar PV under European LBD (15 GW) but not under regional LBD and only a little in the benchmark (2 GW). In particular, Britain does not exhibit investments until 2040 but afterwards abruptly invests under European learning (and the benchmark). France invests moderately under regional LBD (2 GW) but considerable amounts under European LBD (19 GW) and the benchmark (18 GW). The only investment period here is 2030. Iberia, in turn, invests considerably more under

[16] Appendix F presents 2050 installed capacities for each region.

Table 4: 2050 installed capacities (in GW) of learning technologies, 2050 CO_2 price (in €/ton), and 2050 European weighted-average electricity price (in €/MWh) for European LBD, regional LBD, and the benchmark

	European LBD	Regional LBD	Benchmark
Solar PV	354	331	339
Wind onshore	1,188	1,133	1,128
Wind offshore	229	291	245
CO_2 price	222.9	218.3	224.6
Electricity price	73.3	72.9	74.6

We calculate CO_2 prices from the marginals of the carbon constraint (see Table 3 for the assumed quantity target) and electricity prices from the marginals of the demand-equals-supply constraint (see Table 3 for the assumed demand).

regional LBD (141 GW) compared to European LBD (116 GW) and the benchmark (117 GW). Those differences mainly stem from the last investment period (2050), where Iberia adds 63 GW assuming regional LBD but only 39 GW (46 GW) for European LBD (the benchmark).

Now turning to wind onshore, we see that Denmark drives major differences in the outcomes, since generally cheaper wind onshore capacity assuming European learning leads to 24 GW, whereas regional LBD (1 GW) and the benchmark (4 GW) deliver considerably less. Such capacity differences can be mainly traced back to the investment decisions in 2035 and 2040. Benelux has a completely different pattern. Onshore capacity is the highest in the benchmark (29 GW), whereas European LBD (17 GW) and regional LBD (13 GW) fall behind. The differences here emerge in the very last investment period 2050. The opposite to the Benelux-pattern is observed in France, where our LBD specifications (224 or 226 GW, respectively) have considerably higher capacities than the benchmark (205 GW). These differences cannot be traced back to investment but rather the decommissioning decisions. In fact, accumulated investments are 20 GW higher assuming LBD.

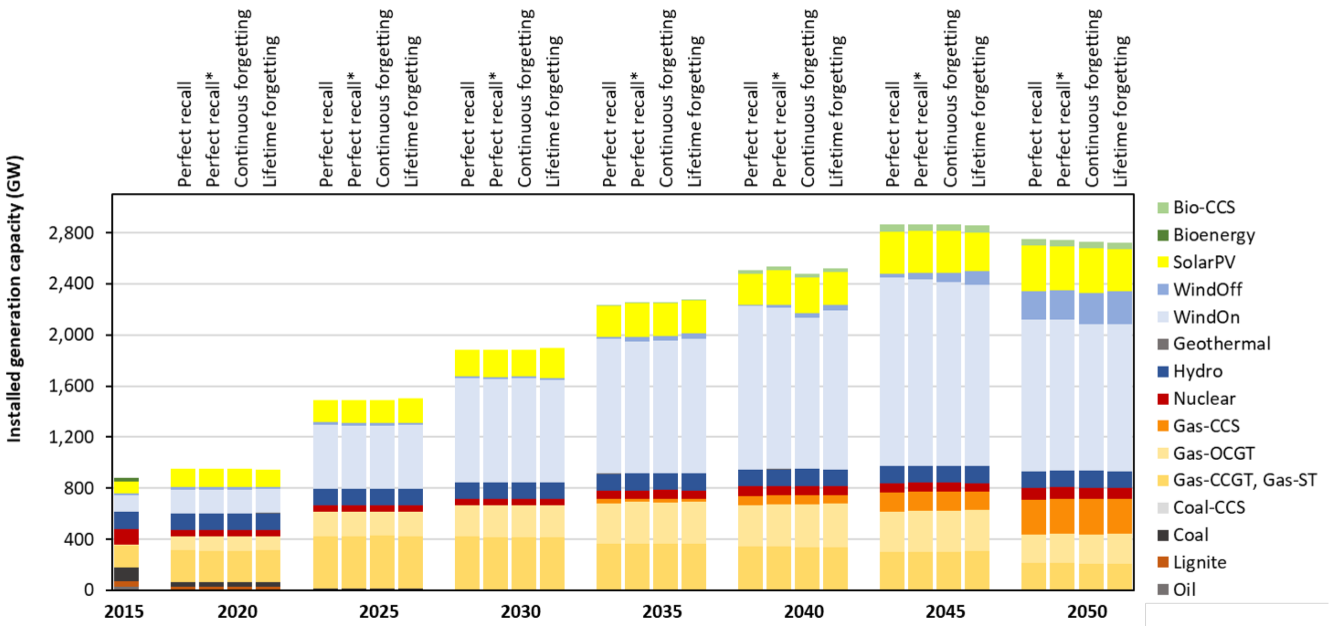
Finally, the fundamental differences in wind offshore are observed in Britain, where regional LBD delivers 2050 capacities of 203 GW and the other two specifications fall structurally behind (151 GW or 153 GW, respectively). Offshore costs in Britain drop considerably with LBD. In particular, this can be driven by the fact that this region has the best offshore quality spots across Europe. Denmark faces a similar pattern in magnitude when comparing European (22 GW) and regional LBD (36 GW). However, the benchmark is close to the regional LBD outcome (33 GW), hinting that Denmark has quite similar endogenous and exogenous offshore cost in 2050. EE-NE, also possessing high quality offshore potential, shows a different pattern. Here, offshore capacity is the lowest under regional LBD (1 GW). Such an outcome can be explained by the fact that this region's own ability to learn might not suffice to introduce larger amounts of offshore capacity (European LBD has 5 GW, the benchmark 6 GW).

Overall, the introduction of regional learning puts more emphasis on local comparative advantages among the different technologies, leading to diverse technology specializations of the different regions. Under the European metric, learning efforts are systematically coordinated based on the resource quality in intra-European comparison. At the same time, we observe that firms use positive learning externalities from other regions to build capacity in regions with inferior resource potentials.

4.2. Perfect recall vs. forgetting

Figure 4 shows installed capacities (in GW) for perfect recall, continuous forgetting, and lifetime forgetting assuming European LBD.[17] We also analyze perfect recall specifications, where the approximation starts at zero accumulated investment cost (indicated by *)—as it is the case for the two forgetting specifications. Looking at the outcomes of the different specifications over time, 2015 is again the same for each specification and also 2020 differences are negligible.

Figure 4: Installed capacities (in GW) for different depreciation assumptions under European LBD



First differences are observed in 2025 with slightly lower wind onshore capacities for lifetime forgetting, which are compensated by higher solar PV capacity. In 2035, the specifications starting the approximation at zero accumulated investment cost (perfect recall*, continuous forgetting, and lifetime forgetting) start increasing offshore capacity, whereas perfect recall falls behind. Interestingly, lifetime forgetting now has an even higher onshore capacity than the other three specifications. In 2040 the differences are even more pronounced. The offshore lag of perfect recall is still valid (as it is also in 2045). The outlier is now continuous forgetting with considerably lower wind offshore capacities. This is compensated, generation-wise, by a more intense usage of (almost carbon-neutral) gas-CCS. 2045, in turn, shows very similar capacity levels again. The higher

[17]For parsimony, we refrain from showing and analyzing these specifications for regional LBD.

offshore capacities for lifetime forgetting (103 GW), continuous forgetting (69 GW), and perfect recall* (54 GW) compared to perfect recall (29 GW) are substituted by higher wind onshore capacities (perfect recall with 1,476 GW, perfect recall* with 1,460 GW, continuous forgetting with 1,442 GW, and lifetime forgetting with 1,423 GW). Observe that onshore capacity drops in 2050 since a major share of the onshore generation is substituted by offshore that now overtakes higher market shares.

Table 5 shows 2050 capacities of the four depreciation specifications. Observe that lifetime forgetting has the lowest solar PV and wind onshore capacities but the highest wind offshore. The differences of lifetime forgetting to the other three specifications seem to occur when the approximation space in comparison to realized investments is large (solar PV and wind offshore). When the approximation space is smaller (wind onshore), the lifetime forgetting results are close to those of the other ones. Continuous forgetting results are comparable to perfect recall and, in particular, the two perfect recall specifications are quite close. Resulting CO_2 and electricity prices are also similar across specifications.

Table 5: 2050 installed capacities (in GW) of learning technologies, 2050 CO_2 price (in €/ton), and 2050 European weighted-average electricity price (in €/MWh) for different depreciation assumptions under European LBD

	Perfect recall	Perfect recall*	Continuous forgetting	Lifetime forgetting
Solar PV	354	345	352	327
Wind onshore	1,188	1,180	1,149	1,148
Wind offshore	229	230	240	264
CO_2 price	222.9	223.4	223.7	223.1
Electricity price	73.3	73.5	73.8	73.5

We calculate CO_2 prices from the marginals of the carbon constraint (see Table 3 for the assumed quantity target) and electricity prices from the marginals of the demand-equals-supply constraint (see Table 3 for the assumed demand).

A regional decomposition of differences is only sensible for lifetime forgetting.[18] Here, Britain's outcomes are decisive for solar PV (0 GW compared to 10–15 GW in the other specifications). Onshore differences are driven by France (267 GW compared to 219–224 GW), Benelux (28 GW compared to 13–21 GW), Germany (58 GW compared to 69–74 GW), and Denmark (11 GW compared to 12–24 GW). Offshore differences, in turn, occur in Britain (163 GW vs. 151–152 GW) and Denmark (31 GW vs. 22–29 GW).

4.3. Sensitivity analysis

We now test our results with respect to different 2050 unit investment cost assumptions for solar PV, wind onshore, and wind offshore. In particular, we use perfect recall as *default* specification to analyze five additional specifications for each technology that experiences a 50% lower (*–50%*), 25% lower (*–25%*), 25% higher (*+25%*), 50% higher (*+50%*), and 100% higher (*+100%*) cost

[18] Appendix F presents 2050 installed capacities for each region.

reduction from 2020 to 2050. For example, the default reduction for solar PV is from 900 €/kW in 2020 to 720 €/kW in 2050. *+100%* experiences the doubled decrease from 900 to 540 €/kW. *–50%*, in turn, sees only half of the reduction from 900 to 810 €/kW. Learning elasticities and initial unit investment cost as well as all necessary further calibration are adjusted in accordance to those changes in cost reductions. Table 6 presents the outcome of this sensitivity analysis.

We start with the sensitivity to solar PV cost. Under European learning solar PV capacity now varies tremendously from 301 (–50%) to 446 (+100%) GW. Assuming regional LBD, in turn, solar PV capacity only varies between 303 (–50%) and 355 (+100%) GW. Regional learning is thus considerably less sensitive towards solar PV unit investment cost because arbitrage opportunities from learning externalities are constrained, i.e., regions with less high quality solar PV potential do not benefit from regions with high quality (or higher quality) potential. Interestingly, onshore and offshore capacities remain almost unaffected across diverging cost specifications for both European and regional LBD.

Table 6: Installed capacities in GW for sensitivity analyses on solar PV, wind onshore, and wind offshore cost

	Solar PV cost			Wind onshore cost			Wind offshore cost		
	Solar	Onshore	Offshore	Solar	Onshore	Offshore	Solar	Onshore	Offshore
European LBD									
-50%	301	1,187	224	354	1,089	248	361	1,217	174
-25%	331	1,184	224	352	1,137	236	361	1,220	170
default	354	1,188	229	354	1,188	229	354	1,188	229
+25%	376	1,183	222	348	1,257	199	348	1,163	258
+50%	412	1,182	218	346	1,334	175	345	1,120	350
+100%	446	1,176	226	342	1,478	151	353	1,165	500
Regional LBD									
-50%	303	1,119	304	327	966	363	325	1,175	216
-25%	315	1,117	303	326	1,018	333	326	1,165	250
default	331	1,133	291	331	1,133	291	331	1,133	291
+25%	341	1,109	304	321	1,216	277	326	1,075	335
+50%	346	1,115	301	328	1,246	274	327	1,064	344.8*
+100%	355	1,115	303	326	1,317	264	326	1,071	345.2*

*We add digits here to show that there is at least a small difference in offshore capacity.

Next, we turn to the wind onshore cost sensitivity. The cost sensitivity changes wind onshore capacity in the European metric from 1,089 to 1,478 GW. A similar magnitude is now observed for regional LBD (966 to 1,317 GW). In fact, every region explores wind onshore so that lower or higher cost, respectively, impact each region similarly irrespective whether the European or the regional metric is applied. Interestingly, solar PV capacities remain almost unchanged again. However, onshore capacity substitutes for offshore capacity for both European and regional LBD.

Finally, we consider the wind offshore cost sensitivity. Offshore capacities differ from 170 to 500 GW (for European LBD) and 216 to 345 GW (for regional LBD). The impact of the sensitivity is again higher for European LBD due to positive learning externalities. Now, wind offshore substitutes for wind onshore capacity and solar PV capacities are almost unaffected. Observe that additional cost reductions from +50% to +100% in the regional metric do not yield higher offshore capacities because the cost drop is not sufficient to increase the economically viable offshore potential.

5. Conclusion

We implement endogenous technological change (ETC) in a power market model. In particular, we allow for *learning-by-doing* (LBD), that is, installing capacity leads to the accumulation of experience that reduces unit investment cost. We transform such a non-linear problem into a mixed-integer problem (MIP) by using an approximation of investment cost. We apply a *European LBD* (joint European experience stock drives investment cost) and a *regional LBD* (region-specific experience stocks drive regional investment cost) metric, as well as three different depreciation assumptions that explain how experience is retained over time. *Perfect recall* assumes no loss of experience over time. *Continuous forgetting* is subject to 3% annual depreciation of experience. *Lifetime forgetting* in turn mirrors the engineering nature of power market models by depreciating experience according to the lifetime of capacity addings, i.e., once a capacity investment reaches the end of its lifetime the entire experience gained from this investment is lost. We consider solar PV, wind onshore, and wind offshore as learning technologies and implement the ETC formulation for those technologies into a multi-region partial equilibrium model of the European power market, while keeping exogenous investment cost formulations for all remaining technologies. We simplify and reverse-calibrate our model by using the outcomes of a *benchmark* with exogenous cost assumptions for two reasons. First, we need to reduce numerical complexity without losing much prediction quality to improve stability and solving speed of the MIP formulations. In particular, we decide for a reasonable temporal, spatial, and technological resolutions. Second, the overall goal is to make results of exogenous technological change formulations directly comparable to endogenous ones with LBD to quantify the effects of endogenization. We thus calculate learning elasticities, initial unit investment cost, and the entire MIP approximation for each LBD specification (European LBD, regional LBD, diverging depreciation assumptions) from the benchmark. We apply the same carbon emission quantity target for each specification (carbon-neutrality in 2045, –98 Mt in 2050) to harmonize specifications by comparing resulting carbon and electricity prices as proxies for abatement and total system cost.

The benchmark (exogenous unit investment cost as autonomous function of time) delivers 2050 solar PV (wind onshore, wind offshore) capacities of 339 GW (1,128 GW, 245 GW). European LBD fosters deployment of solar PV (+16 GW) and wind onshore (+60 GW) but deploys less wind offshore (–16 GW). Regional LBD, in turn, fosters the deployment of wind offshore (+46 GW) but similar wind onshore (+5 GW) and slightly less solar PV (–8 GW). The dominance of wind offshore for regional LBD leads to the lowest carbon and electricity prices, whereas neglecting LBD (in the benchmark) yields the highest prices. The differences across European LBD, regional LBD, and the benchmark are traced back to developments in specific regions. For example, Ireland and

UK are responsible for higher solar PV under European learning. France explains higher solar PV under European LBD and the benchmark, but Portugal and Spain balance parts of those effects by actually deploying more solar PV under regional LBD. France explains lower wind onshore capacity in the benchmark but the Benelux region balances almost the entire effect by having higher wind onshore capacity in the benchmark. The generally higher onshore capacity under European LBD is driven by Germany and Denmark. Wind offshore differences result mainly from Ireland and UK that deploy around 50 GW more under regional learning. Estonia, Latvia, and Lithuania compensate small parts of this effect by actually using considerably less offshore under regional LBD. The diverse patterns of differences in technology expansion between European LBD and regional LBD can be explained by two intuitions. First, regional LBD encourages regional specialization based on local comparative advantages between the technologies, whereas European LBD sees more coordination of learning efforts based on local resource qualities in intra-European comparison. Second, European LBD also allows exploitation of positive learning externalities from sublime resource regions to build capacities in regions with inferior resource qualities. Moreover, higher capacities from LBD stem mainly from preponing investments to earlier periods. For example, regional LBD starts structural deployment of wind offshore in 2035 already, whereas the benchmark does so later. A similar pattern can be observed for wind onshore, in particular, under European LBD. Consequently, 2050 differences do not explain the entire process of learning because the investment cost under LBD are grounded in the respective experience stock from past capacity addings and not based on an autonomous function of time as in the benchmark. However, the general pattern of preponing investments cannot be observed for each region. On the contrary, we indeed observe diverging timing patterns.

We also analyze the role of different depreciation assumptions that explain the evolution of the experience stock over time. Lifetime forgetting delivers considerably lower solar PV (mainly in Britain) and wind onshore capacities (France, reversed by Benelux regions, Denmark) but higher wind offshore ones (Ireland plus UK, France, and Denmark). Continuous forgetting is similar to lifetime forgetting when it comes to wind onshore but is closer to perfect recall for solar PV and wind offshore. Differences resulting from depreciation assumptions are not fully negligible but can be explained by experience stock dynamics. For example, there are considerable historical solar PV addings prior to 2020 but relatively little further addings until 2030. Lifetime forgetting loses much of the early solar PV experience in 2035 and 2040, resulting in considerably lower solar PV capacities in 2050 because overall cost are slightly higher than in the other specifications. Instead, there is little pre-existing wind offshore capacity and no endogenous addings until 2035, so that offshore experience and its impact is negligible in early periods across depreciation assumptions. Lifetime forgetting then favors the deployment of such a rather recent technology because there is no cost of experience loss of 2035 investments until the end of the model horizon. One might tackle those distortions by choosing a different reverse-calibration, e.g., calibrating learning elasticities and initial investment cost for lifetime forgetting not on the basis of 2020 and 2050 benchmark outcomes (and cost) but 2035 and 2050 instead. However, we refrain from doing so to maintain comparability of results and—as consistently as possible—show how calibration affects results.

The above mentioned regional differences show that results of power market models must be reviewed carefully for each region and, in particular, that the spatial dimension is important. For example, much of the differences between LBD formulations and the benchmark with respect to wind onshore is a spatial trade-off between France and the neighboring Benelux region with similar wind onshore quality. Those regions are connected via transmission lines and already small changes in cost assumptions deliver structural differences that cannot be observed without the review of spatial expansion patterns. Moreover, lower Danish wind onshore is complemented by higher Danish wind offshore under lifetime forgetting. Such a technology switch can be again caused by marginal changes in cost assumptions or even driven by investments in other regions that in turn foster the deployment of a certain technology in other countries. It is also not only the cost of a respective technology that plays a role but also the (correlation of) time profiles (solar and wind availability) across technologies and countries.

Our results show that aggregate differences on a European level slightly differ across different learning formulations and when assuming exogenous cost developments. However, much of the relevant regional differences are overlooked when only analyzing aggregated differences. In particular, regions face diverse, sometimes opposite, patterns of employing learning technologies, depending on the underlying learning specification. European and local policy makers need to account for those structural differences when designing policies to achieve a fast and deep decarbonization at a low cost. However, this analysis is only a first step towards informing policy makers about appropriate policy making under the consideration of endogenous technological change. For more actionable insights, it is necessary to improve the empirical foundation of the calibration, i.e., whether European or regional learning is the more appropriate metric to use (for the respective technology and region) and which of the depreciation assumptions best matche observed economic behavior.

Our analysis comes with some caveats. We focus solely on three learning technologies (solar PV, wind onshore, wind offshore) and neglect learning in other (potentially relevant) technologies such as nuclear, CCS, or batteries. However, solar PV and wind technologies are the major pillars of decarbonizing the European electricity systems and at the same time also technologies where substantial LBD has already been observed in the past. Some other critics to include LBD in power market, energy system, and climate models via leaning curves was introduced by Nordhaus (2014). According to his analysis learning parameters (elasticity, initial cost) are always upward biased and not robust to specification changes. These limitations force models to opt for learning technologies with incorrectly specified learning parameters due to lower costs, thereby biasing the outcomes of the model. However, these limitations apply to all models that include LBD based on empirical estimations of learning curves. Moreover, the main goal of our analysis is to derive general economic patterns of different LBD specifications and not to produce the most accurate and unbiased projection of the 2050 technology mix in the European power sector. We further neglect other endogenous technological change channels such as learning-by-searching. The MIP formulation of the ETC problem is already numerically challenging and we thus refrain from adding a second learning skein that additionally drives cost drops. This avenue of including learning-by-searching as single-factor learning or together with learning-by-doing as a two-factor learning model could be explored in follow-up studies. Finally, recent findings (Schauf and Schwenen, 2021) show that not only unit investment cost decrease when technologies experience learning, but rather their respective technological efficiency (or full-load hours) also increases. Hence, improving the technological resolution of learning technologies might be useful for policy makers to have better projections of the optimized system. In this regard, inclusion of several learning channels and allowing for both reductions of unit investment cost and increase in full-load hours seem prominent topics for further research.

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Appendix A. Simplification process

The EUREGEN model covers the entirety of the European power market consisting of 28 countries (EU27 less islands Cyprus and Malta, including Norway, Switzerland, and United Kingdom). We simplify the spatial resolution to 14 regions, each region being a grouping of countries similar in solar PV, wind onshore, and wind offshore qualities. We thus decide to model Denmark, France, Germany, Italy, and Norway as individual countries but group Ireland and United Kingdom (to Britain), Portugal and Spain (to Iberia), Belgium, Netherlands, and Luxembourg (to Benelux), Austria and Switzerland (to Alpine), Poland and Czech Republic (to EE-NW), Latvia, Lithuania, and Estonia (to EE-NE), Hungary, Slovenia, Slovakia, and Croatia (to EE-SW), Bulgaria, Romania, and Greece (to EE-SE), and Finland and Sweden (to Fise). We further reduce the hourly resolution of a year to 89 hours as an outcome of an hour choice algorithm that produces a selection of hours to match the extremes of solar PV, wind onshore, wind offshore, and load for each of the 14 regions. We further weight those hours to reduce the difference of the reduced timeseries to annual load and full-load hours of intermittent technologies that would occur in a full hourly resolution. Finally, we maintain the relative regional competitiveness of intermittent technologies (also hydro) by scaling the resulting reduced timeseries by a factor to re-construct annual load and full-load hours (FLH) of the respective technologies from the hourly resolution. The best outcome in terms of deviations from the hourly resolution without scaling of this choice and weighting algorithm delivers around the double amount of hours but deviations (calculated for the benchmark) in the technology mix over time are negligible to the used specification with 89 hours.

We further simplify the model with regard to conventional gas technologies by merging steam turbines burning natural gas and combined-cycle gas turbines due to similar characteristics in efficiencies and cost. We also simplify learning wind and solar technologies such that there is only one resource class (instead of high, mid, and low). Moreover, we refrain from exogenous evolution of wind turbines height, growing from 80m to 100m to 120m. Instead, we use the 100m turbine height only. Further, we only make resource potentials of intermittent sources available that exceed a specific FLH level to improve the approximation. In particular, we only use the best solar and wind potentials for each region. We repeatedly run the benchmark to ensure that each of the technologies' regional potentials leave sufficient buffer, or, in other words, that higher potentials would not lead to increased deployment, respectively. In particular, merging the high quality with lower quality potentials decreases FLH of the respective technology (for the specific region) and often decreases usage of the total potential (compared to a situation where only high quality potential is available).

Table A.1 shows the outcome of this calibration process. Some smaller regions such as Benelux have only limited high quality wind offshore potential and might often hit the upper boundary in the benchmark. Adding more (medium and low) potential does not yield more wind offshore deployment than the 22 GW specified in Table A.1. In general, the competitiveness of technologies starts around 1,200 FLH for solar PV, 3,600 FLH for wind offshore, and 2,100 FLH for wind onshore. We expect considerable exploitation of solar PV potentials in Iberia, Italy, and EE-

SE (around 327 GW in total). Offshore potentials in Britain, Benelux, and Denmark seem to be competitive (around 458 GW in total)—although the 400 GW in Britain might not be fully exploited due to physical and economic transmission constraints between Britain and neighboring regions. Wind onshore is competitive in every region (even in those with FLH below 2,100) but in particular Fise, Norway, Britain, Iberia, and EE-SW have high FLH, so that we expect considerable expansion in those regions.

Table A.1: Resource potential and full-load hours by region

	Potential (GW)			Full-load hours		
	Solar	Onshore	Offshore	Solar	Onshore	Offshore
Britain	78	201	400	1,036	2,626	4,110
France	155	357	119	1,188	2,072	3,414
Iberia	198	280	110	1,800	2,581	2,211
Italy	87	37	178	1,361	1,849	956
Benelux	7	37	22	988	2,263	3,728
Germany	82	171	19	1,055	2,180	3,267
Alpine	16	58		1,039	1,963	
EE-NW	91	198	10	1,008	2,390	3,149
EE-NE	30	45	20	992	2,424	3,420
EE-SW	14	28	19	1,199	2,530	914
EE-SE	42	104	190	1,604	1,987	2,069
Denmark	10	27	36	839	2,532	4,106
Norway	45	88	963	1,052	2,711	2,317
Fise	101	92	53	884	3,346	3,003
Europe	956	1,723	2,140	1,256	2,382	2,645
	327	1,167	458	>1,200	>2,100	>3,600

Britain covers Ireland and United Kingdom, Iberia covers Portugal and Spain, Benelux covers Belgium, Netherlands, and Luxembourg, Alpine covers Austria and Switzerland (without wind offshore potential), EE-NW covers Poland and Czech Republic, EE-NE covers Estonia, Latvia, and Lithuania, EE-SW covers Slovenia, Slovakia, Croatia, and Hungary, EE-SE covers Romania, Bulgaria, and Greece, and Fise covers Finland and Sweden.

Appendix B. Regional learning

The European learning metric's calibration is rather straightforward. However, this approach is not fully applicable to regional learning. In fact, we need to make assumptions about the initial unit investment cost and learning speeds of different regions, and how growing experience stocks translate into cost reductions for each region. The problem is twofold. First, assuming same learning elasticities and initial unit investment cost for each region leaves smaller regions worse off than bigger regions that can in general produce higher experience stocks. Second, scaling regional learning according to resource potentials leaves the regions with high wind and solar potentials worse off then regions with smaller ones. In particular, our calibration routine of calculating "competitive" potentials before running the MIP specifications would violate such an approach.

We decide for (electricity) demand shares because those best reflect the size of a respective region and already accumulated experience (from installed capacities per region) accounts for the fact that some countries are more advanced in the learning process.

Table B.2 presents respective demand shares in 2020 and 2050. Observe that those shares change over time. For further calculations, however, only the 2020 and 2050 shares are relevant. We take the European experience stocks from the benchmark, and (by multiplying the European stock with the respective demand share) calculate the regional experience stocks necessary to obtain the respective 2020 and 2050 cost; meaning that regions that install capacities respective to their demand shares end up exactly with the 2020 and 2050 unit investment cost used in the benchmark. Learning elasticities and initial unit investment cost follow in the same way as for the European metric, and are depicted in Table B.2 as well. Regional learning elasticities vary around European values for all three technologies. However, regional initial unit investment cost seem to be lower because the overall lower amount (to learn) is smaller in the regional metric, so that absolute drops are also smaller. Similar learning elasticities thus imply structurally lower initial experience stock levels. This, however, does not matter for the final learning decision of regions under the regional metric because some regions start at higher unit investment cost (when their true experience stock is below the demand share experience stock) or lower ones (when their true experience stock is indeed higher). However, regions with lower true experience stock can reduce cost fast by catching up with regions that learned already.

Table B.2: Demand shares, learning elasticities, and initial unit investment cost for perfect recall with starting change

	Demand shares		Learning elasticities			Initial unit investment cost (€/kW)		
	2020	2050	Solar	Onshore	Offshore	Solar	Onshore	Offshore
Britain	11.1%	10.4%	-17.1%	-9.7%	-9.1%	15,263	6,927	9,199
France	14.6%	15.9%	-15.3%	-9.1%	-8.6%	11,792	6,351	8,736
Iberia	9.7%	10.4%	-15.5%	-9.1%	-8.6%	11,447	6,199	8,509
Italy	10.3%	11.9%	-14.8%	-8.9%	-8.4%	10,255	5,950	8,287
Benelux	6.5%	7.1%	-15.4%	-9.1%	-8.6%	10,560	5,935	8,183
Germany	17.3%	15.3%	-17.9%	-10.0%	-9.3%	18,689	7,560	9,863
Alpine	4.1%	5.1%	-14.0%	-8.5%		7,903	5,213	
EE-NW	6.7%	7.1%	-15.5%	-9.1%	-8.2%	10,812	5,993	7,405
EE-NE	0.9%	0.7%	-18.1%	-10.0%	-8.6%	11,185	5,648	8,241
EE-SW	3.0%	3.1%	-16.0%	-9.3%	-9.3%	10,242	5,721	7,499
EE-SE	4.2%	3.1%	-20.9%	-10.9%	-8.8%	23,002	7,624	7,827
Denmark	1.0%	0.9%	-18.1%	-10.1%	-10.0%	11,682	5,775	9,518
Norway	4.0%	3.1%	-20.3%	-10.7%	-9.4%	20,914	7,388	7,648
Fise	6.7%	6.0%	-17.6%	-9.9%	-9.9%	15,109	6,774	9,318
Europe	3,088*	6,203*	-16.3%	-9.4%	-8.9%	19,001	8,099	10,806

*The demand share of Europe is 100%. The values thus refer to absolute annual demand (in TWh).

Appendix C. Line segment calibration

Tables C.3 to C.5 show line segment weights, experience stock lower breakpoints and maximum stock, and line segment-specific unit investment cost for 3, 5, 7, 10, 15, and 20 line segments for European learning with perfect recall. We refrain from describing outcomes for 5, 10, and 15 line segments in detail and, instead, focus on 3, 7, and 20 line segments in the following. Start with line segment weights. Observe that 3 line segments yield equal distribution of weights. The other two specifications always double the prior weight in the next line segment, aiming for 0.5 at the fore-last line segment (so that the highest line segment weight is 1). The specification with 7 line segments almost achieves that 0.5 at the ls7 lower breakpoint. The 20 line segments specification in turn shows almost no progress (at the three digit level) from ls1 to ls9. Later "jumps", in turn, are again comparable with the 7 line segment specification.

Table C.3: Line segment weights

Number	3	5	7	10	15	20
ls1	0.3333	0.0667	0.0159	0.0020	0.0001	0.0000
ls2	0.6667	0.1333	0.0318	0.0039	0.0001	0.0000
ls3	1	0.2667	0.0635	0.0078	0.0002	0.0000
ls4		0.5333	0.1270	0.0157	0.0005	0.0000
ls5		1	0.2540	0.0313	0.0010	0.0000
ls6			0.5079	0.0626	0.0020	0.0001
ls7			1	0.1252	0.0039	0.0001
ls8				0.2505	0.0078	0.0002
ls9				0.5010	0.0156	0.0005
ls10				1	0.0313	0.0010
ls11					0.0625	0.0020
ls12					0.125	0.0039
ls13					0.25	0.0078
ls14					0.5	0.0156
ls15					1	0.0313
ls16						0.0625
ls17						0.125
ls18						0.25
ls19						0.5
ls20						1

We calculate the line segment length according to Equation (6). Observe that the values always present the relative position on the total investment cost curve (see Equation (5)) and the length of the respective line segment follows from the differences of neighboring values.

Those weights determine experience stock lower breakpoints (via accumulated investment cost breakpoints). The weights are thus reflected in those breakpoints as well. However, the relative changes differ by two reasons. First, investments into capacity get cheaper with higher experience stocks, that is, the double weight yields doubled accumulated investment cost but more than doubled experience stocks. Second, experience stocks start (ls1 lower breakpoint is the starting experience stock) at 98, 131, or 11 GW, respectively (see also Table 1). The distribution of experience stock breakpoints is further determined by the maximum experience stock. We choose QS_j^{MAX} so that perfect recall does not hit its uppermost boundary. In particular, we take the resource potential by technology (see Table A.1) and multiply it by 1.5. The maximum stocks (indicated by MAX) are thus the same for each line segment specification.

Now turn to the line segment-specific unit investment cost in the lower part. Note that weights are again presented but identical to the upper ones. Those unit investment cost always present the average unit investment cost per line segment. Observe that there are only little changes for the 20 line segments specification until ls9 (as it is the case for experience stock lower breakpoints). Later "jumps" are again comparable to the 7 line segments specification. Furthermore, the 3 line segment specification has structurally lower unit investment cost in ls1 because the first line segment spans a considerably higher magnitude with respect to the experience stock. For example, the first line segment (ls1) spans from 11 GW to 974 GW for wind offshore. The 974 GW wind offshore realization in turn might be unrealistic given the competitive potentials (the benchmark employs 243 GW). Similar problems arise for the other two technologies. This is particular important because the line segment-specific unit investment cost underestimate cost at the beginning of each line segment, arriving at the exact value (for accumulated investment cost) when entering the next line segment. Not fully employing line segments thus underestimates cost (also in the other line segment specifications). One might solve this problem by adjusting the line segment weights (e.g., formulating them linear) but initial learning (steeper curves at the beginning) would be then badly reflected.

Table C.4: Experience stock lower breakpoints and maximum stock (in GW) for European learning with perfect recall

	Solar PV						**Wind onshore**						**Wind offshore**					
Number	3	5	7	10	15	20	3	5	7	10	15	20	3	5	7	10	15	20
ls1	98	98	98	98	98	98	131	131	131	131	131	131	11	11	11	11	11	11
ls2	486	167	114	100	98	98	883	270	163	135	131	131	974	179	47	15	11	11
ls3	940	242	130	102	98	98	1,713	417	196	139	131	131	2,064	366	87	20	11	11
ls4		401	164	106	98	98		724	264	147	132	131		766	170	28	12	11
ls5		752	234	114	99	98		1,375	403	163	132	131		1,619	348	47	12	11
ls6			386	130	99	98			694	195	133	131			727	86	13	11
ls7			718	163	100	98			1,312	262	135	131			1,536	168	15	11
ls8				232	102	98				399	139	131				343	20	11
ls9				381	106	98				686	147	132				716	28	12
ls10				708	114	99				1,294	163	132				1,513	47	12
ls11					130	99					195	133					86	13
ls12					163	100					261	135					168	15
ls13					232	102					398	139					342	19
ls14					381	106					685	147					714	28
ls15					707	114					1,292	163					1,510	47
ls16						130						195						86
ls17						163						261						168
ls18						232						398						342
ls19						381						685						714
ls20						707						1,292						1,510
max						1,434						2,584						3,210

Experience stock lower breakpoints follow from Equation (11).

Table C.5: Line segment-specific unit investment cost (in €/kW) for European learning with perfect recall

	Solar PV						Wind onshore						Wind offshore					
Number	3	5	7	10	15	20	3	5	7	10	15	20	3	5	7	10	15	20
ls1	805	902	934	944	946	946	1,241	1,342	1,379	1,391	1,393	1,393	1,883	2,160	2,372	2,530	2,567	2,568
ls2	687	840	913	941	946	946	1,125	1,274	1,353	1,388	1,393	1,393	1,663	1,936	2,191	2,467	2,564	2,568
ls3	631	781	886	937	945	946	1,072	1,215	1,322	1,382	1,393	1,393	1,581	1,815	2,069	2,398	2,560	2,568
ls4		711	844	928	945	946		1,148	1,277	1,372	1,393	1,393		1,699	1,945	2,305	2,553	2,568
ls5		640	786	913	945	946		1,081	1,219	1,353	1,392	1,393		1,595	1,823	2,193	2,538	2,567
ls6			716	886	943	946			1,152	1,323	1,391	1,393			1,707	2,071	2,512	2,566
ls7			642	845	941	946			1,083	1,278	1,388	1,393			1,598	1,947	2,467	2,564
ls8				787	937	945				1,221	1,382	1,393				1,826	2,398	2,560
ls9				717	929	945				1,154	1,372	1,393				1,709	2,305	2,553
ls10				643	913	945				1,083	1,353	1,392				1,599	2,194	2,538
ls11					886	943					1,323	1,391					2,072	2,512
ls12					845	941					1,279	1,388					1,948	2,467
ls13					787	937					1,221	1,382					1,826	2,398
ls14					718	929					1,154	1,372					1,709	2,305
ls15					643	913					1,084	1,353					1,599	2,194
ls16						887						1,323						2,072
ls17						845						1,279						1,948
ls18						787						1,221						1,826
ls19						718						1,154						1,709
ls20						643						1,084						1,599

Line segment-specific unit investment cost follow from Equation (10).

Appendix D. Line segment pre-results

Running a huge set of different MIP specifications takes a considerable time. We thus search for a line segment specification that resolves the trade-off between reasonable solving time (to reach stable global optimums) and good approximation. We thus explore the validity of our approximation with respect to different line segment numbers (3, 5, 7, 10, 15, and 20). Table D.6 shows the outcome by comparing solar PV, wind onshore, and wind offshore installed capacities (in GW) and generation (in TWh) for European and regional learning with perfect recall in 2030, 2040, and 2050. Note that the specification with 20 line segments must be seen as the best (in terms of approximation quality), whereas 3 line segments solve most stable reaching lowest MIPGAPS in shortest time. For comparison, Table D.6 also shows the respective values for the benchmark that assumes exogenous unit investment cost for the three learning technologies as depicted in Table 1.

Start with solar PV. 3 line segments produce considerably higher solar PV capacities in 2030 for European learning because the specific investment cost in the first line segment are structurally underestimating investment cost. This effect turns in the long-run because later investments become relatively more expensive. There is not much of a difference across the other line segment numbers. 5 to 15 line segments fail to exactly match the outcome of 20 line segments but the differences are only around 9 GW in 2050. However, also looking at generation leaves 7 line segments close to the 20 line segment outcome. 2050 solar PV capacities are similar for the regional metric. However, 2030 and 2040 capacities are more diverse because countries with high quality solar PV potential start learning and thus invest earlier. Observe that benchmark solar PV capacity (and generation) is comparable to the regional learning outcomes.

Now turn to wind onshore. Again, the specification with 3 line segments produces considerably different wind onshore capacities (and generation). The difference is above 70 GW or 140 TWh, respectively (more than 5%). Remaining line segment numbers are similar. Turning to regional learning, observe that 3 line segments still produce the poorest outcome but the difference is smaller than for European learning. However, overall capacities are structurally below the ones of European learning, as it is generation. Benchmark capacities (and generation) are comparable to those of regional learning.

Finally, observe that wind offshore capacities tremendously differ between European and regional learning (around 30% more for regional learning), whereas benchmark capacities are close to the European metric (at 245 GW). Moreover, 3 line segments in the European metric produce a poor outcome again, whereas the remaining line segments seem to be quite good representatives (of the 20 line segment specification). In particular, 7 line segments match capacities and generation quite well.

We can further analyze differences between European and regional learning. Figure D.1 shows installed capacities for (a) solar PV on the left, (b) wind onshore (in the middle, and (c) wind offshore on the right. Capacities are depicted for European (solid lines) and regional learning (dashed lines) for periods 2030 (blue), 2040 (red), and 2050 (green). The panels depict spider charts with spider legs each representing one of the respective line segments. Observe again that aforementioned quality of the 3 line segment specification is bad, in particular, for 2040 wind onshore and 2030 as well as 2040 wind offshore capacities.

Figure D.1 adds information to Table D.6 as it is more suitable to gain a feeling of the

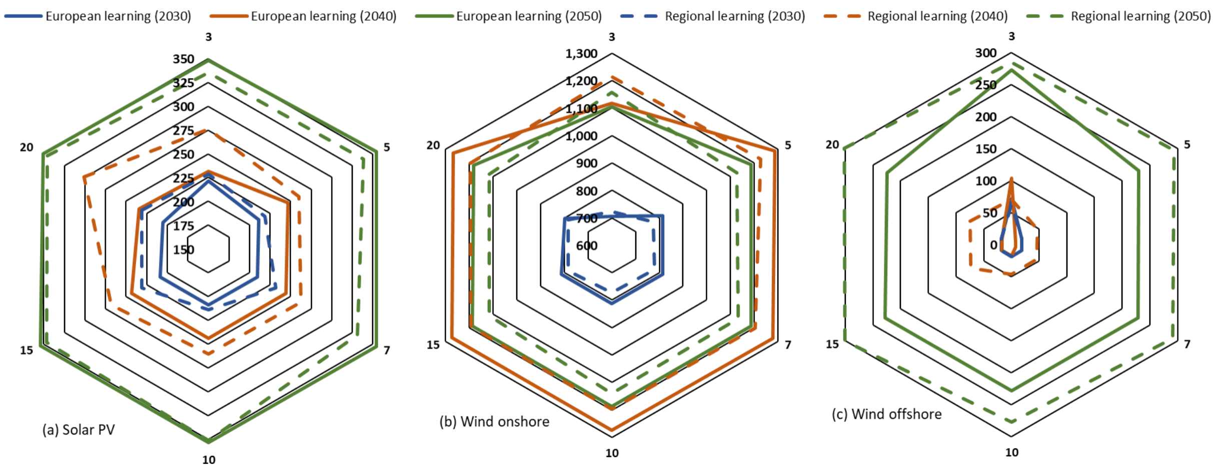
Table D.6: Installed capacities and generation from learning technologies for different line segment numbers and the benchmark

	Number	Solar PV 2030	Solar PV 2040	Solar PV 2050	Wind onshore 2030	Wind onshore 2040	Wind onshore 2050	Wind offshore 2030	Wind offshore 2040	Wind offshore 2050
European learning with perfect recall										
Installed (GW)	3	221	231	348	705	1,118	1,105	72	104	273
	5	211	247	354	815	1,287	1,188	18	8	230
	7	209	244	354	813	1,279	1,188	18	8	229
	10	209	244	354	813	1,274	1,188	18	17	228
	15	209	243	354	813	1,274	1,188	18	17	228
	20	205	234	351	798	1,270	1,182	18	17	224
Generation (TWh)	3	301	335	486	1,590	2,511	2,481	278	398	1,037
	5	286	352	491	1,832	2,859	2,629	65	28	900
	7	279	343	481	1,835	2,855	2,672	63	27	865
	10	282	349	492	1,829	2,834	2,630	65	63	894
	15	282	348	488	1,829	2,829	2,627	65	68	900
	20	278	336	482	1,796	2,830	2,628	65	64	861
Regional learning with perfect recall										
Installed (GW)	3	229	276	335	723	1,214	1,156	63	71	285
	5	218	260	339	773	1,226	1,127	18	47	294
	7	232	262	331	779	1,205	1,133	18	46	291
	10	214	260	351	774	1,196	1,140	18	46	277
	15	231	268	347	785	1,194	1,115	18	73	301
	20	231	301	346	784	1,198	1,115	18	74	302
Generation (TWh)	3	312	387	470	1,615	2,691	2,518	249	258	1,111
	5	299	371	486	1,750	2,719	2,443	65	181	1,146
	7	316	375	474	1,763	2,694	2,486	63	173	1,115
	10	293	373	496	1,752	2,669	2,491	65	182	1,082
	15	313	376	473	1,776	2,666	2,536	65	263	1,088
	20	313	403	470	1,774	2,668	2,495	66	277	1,133
Benchmark										
Installed (GW)		203	232	339	706	1,152	1,128	18	34	245
Generation (TWh)		276	337	474	1,628	2,615	2,533	65	128	938

differences between European and regional learning. The European metric produces lower solar PV capacities in 2030 and 2040 but higher ones in 2050. Wind onshore capacities are always higher for European learning (except for the bad choice of 3 line segments). Wind offshore capacities in turn are considerably higher for regional learning (again except for the bad choice of 3 line segments). Thus, European and regional differences are persistent for line segment numbers from five upwards and hint that the comparability of European and regional metric in the remainder of this section is consistent with the finally chosen line segment number.

We can already draw some conclusion from those pre-results. 3 line segments are not a reasonable choice given our assumptions about maximum potentials. One might improve

Figure D.1: Installed solar PV (a), wind onshore (b), and wind offshore (c) capacities (in GW) for European and regional learning for different line segments numbers (3, 5, 7, 10, 15, and 20) and periods (2030, 2040, 2050)



Spider arms show outcomes for the respective line segment numbers. The scales are different for technologies to improve the visibility of difference. The lowest numbers of the respective axes (150 GW for solar PV, 600 GW for wind onshore, and 0 GW for wind offshore) point to the middle of the respective chart. The second number in turn represent the first hexagon.

the approximation quality when reducing the approximation spaces in accordance to those findings. However, we opt for comparability of European and regional learning results (and with the benchmark) and thus stick with the metric of multiplying the overall resource potentials by a certain factor. In tendency, regional learning is closer to the benchmark for solar PV and wind onshore, but there is tremendously higher wind offshore deployment. Wind offshore also constitutes main differences between European and regional learning. The European metric favors expansion of the most promising technology (wind onshore) whereas regional learning concentrates on regional diverging resource potentials and qualities. Finally, 5, 7, 10, and 15 line segments produce good approximations (given that 20 is the one to match). However, 15 line segments perform similar in terms of solution speed as 20 does. Also 10 line segments converge slow to reasonable MIPGAPS. The approximation quality of 7 line segments is slightly better than those of 5 line segments, whereas there is no significant difference in solution speeds. We thus decide to perform all further calculation with 7 line segments.

Appendix E. Forgetting

Table E.7 presents the outcome for 7 line segments for all three learning technologies and deprivation assumptions. The upper part shows the experience stock upper breakpoints.[19] Perfect recall is shown with starting change (sc) and without (nosc). Continuous and lifetime forgetting always require to be applied without a starting change. Moreover, the forgetting specifications calculate the maximum experience differently because experience stocks are generally smaller. In particular, we multiply the resource potential by 1.25 to calculate

[19]It is necessary to change the metric here to upper breakpoints (compared to Table C.4 in Appendix C) because the different deprivation assumptions have diverging maximum experience stocks.

the maximum experience stocks (equal to ls7 upper breakpoint) for continuous forgetting. Lifetime forgetting in turn reflects the exact amount of capacity potentially active and we thus can set the maximum experience stock equal to the resource potential.

Table E.7: Experience stock upper breakpoints and line-segment specific unit investment cost for different deprivation and starting change specifications

Technology	Specification	Start	ls1	ls2	ls3	ls4	ls5	ls6	ls7
		Experience stock upper breakpoints (GW)							
Solar PV	Perfect recall	98	114	130	164	234	386	718	1,434
	Perfect recall*	0	10	23	53	122	279	638	1,434
	Continuous forgetting	0	7	17	39	92	218	516	1,197
	Lifetime forgetting	0	4	10	26	64	158	394	958
Wind onshore	Perfect recall	131	163	196	264	403	694	1,312	2,584
	Perfect recall*	0	27	57	123	265	569	1,223	2,584
	Continuous forgetting	0	21	45	98	213	464	1,008	2,153
	Lifetime forgetting	0	16	35	77	168	368	803	1,723
Wind offshore	Perfect recall	11	47	87	170	348	727	1,536	3,210
	Perfect recall*	0	34	73	156	334	714	1,527	3,210
	Continuous forgetting	0	28	61	130	278	595	1,272	2,675
	Lifetime forgetting	0	22	48	103	221	474	1,016	2,140
		Line segment-specific unit investment cost (€/kW)							
Solar PV	Perfect recall	934	934	913	886	844	786	716	642
	Perfect recall*	969	1,636	1,269	1,109	969	846	739	647
	Continuous forgetting	995	1,896	1,391	1,176	995	842	713	604
	Lifetime forgetting	948	2,696	1,817	1,463	1,178	948	764	617
Wind onshore	Perfect recall	1,379	1,379	1,353	1,322	1,277	1,219	1,152	1,083
	Perfect recall*	1,253	1,787	1,555	1,447	1,346	1,253	1,166	1,086
	Continuous forgetting	1,348	1,871	1,593	1,466	1,348	1,240	1,141	1,051
	Lifetime forgetting	1,417	2,002	1,690	1,548	1,417	1,298	1,188	1,089
Wind offshore	Perfect recall	2,372	2,372	2,191	2,069	1,945	1,823	1,707	1,598
	Perfect recall*	2,549	2,549	2,237	2,091	1,955	1,828	1,709	1,599
	Continuous forgetting	2,565	2,565	2,251	2,105	1,967	1,839	1,719	1,609
	Lifetime forgetting	2,652	2,652	2,318	2,162	2,017	1,881	1,755	1,639

PR* starts approximation of accumulated investment cost at zero as does forgetting specifications. Note that the ls7 upper breakpoints are the maximum experience stock of the selected specification and *Start* refers to the starting experience stock.

The lower part shows line segment-specific unit investment cost. Those cost are decisive for final investments. Observe that Perfect recall starts at fundamentally lower investment cost in ls1. Perfect recall* in turn reaches the starting capacity stock between ls3 and ls4 upper breakpoints (i.e., in the fourth line segment) for solar PV and wind onshore so that the cost approximation of ls1, ls2, and ls3 are actually obsolete. The quality of the approximation is thus worse and there is actually not much usage of perfect recall*, except for the comparison with the forgetting ones. However, the specifications cannot be directly compared with each other because accumulated investment cost drives the placement of experience stock breakpoints and line segment-specific unit investment cost. In particular, lifetime forgetting has the highest initial unit investment cost (see Table 2), so that the respective breakpoints are lowest and costs are highest. However, unit investment costs in ls6 and ls7 are comparable to perfect recall, whereas continuous forgetting tends to have the lowest respective unit investment cost per line segment.

Appendix F. Regional decomposition

Table F.8: 2050 installed solar PV, wind onshore, and wind offshore capacities (in GW) for different LBD specifications and the benchmark

	European LBD				Regional LBD	Benchmark
	PR	PR*	CF	LF	PR	
Solar PV						
Britain	15	10	11	0	0	2
France	19	19	20	17	2	18
Iberia	116	116	117	113	141	117
Italy	87	87	87	87	78	87
Germany	82	82	82	82	78	81
EE-SW	12	10	12	8	4	10
EE-SE	23	22	24	21	29	24
Europe	354	345	352	327	331	339
Wind onshore						
Britain	158	158	158	158	152	158
France	224	222	219	207	226	205
Iberia	238	238	234	237	238	229
Italy	37	37	37	37	37	37
Benelux	17	21	13	28	13	29
Germany	74	70	69	58	55	61
Alpine	58	58	58	58	58	58
EE-NW	85	84	85	84	86	82
EE-NE	21	21	18	18	22	17
EE-SW	28	28	28	28	22	28
EE-SE	44	45	43	45	44	43
Denmark	24	20	12	11	1	4
Norway	88	88	83	88	85	85
Fise	92	92	92	92	92	92
Europe	1,188	1,180	1,149	1,148	1,133	1,128
Wind offshore						
Britain	151	152	152	163	203	153
France	28	28	31	41	28	30
Benelux	22	22	22	22	22	22
EE-NE	5	5	6	6	1	6
Denmark	22	24	29	31	36	33
Europe	229	230	240	264	291	245

PR is perfect recall, PR* starts approximation of accumulated investment cost at zero as does forgetting specifications, CF is continuous forgetting, LF is lifetime forgetting. Britain covers Ireland and United Kingdom, Iberia covers Portugal and Spain, Benelux covers Belgium, Netherlands, and Luxembourg, Alpine covers Austria and Switzerland (without wind offshore potential), EE-NW covers Poland and Czech Republic, EE-NE covers Estonia, Latvia, and Lithuania, EE-SW covers Slovenia, Slovakia, Croatia, and Hungary, EE-SE covers Romania, Bulgaria, and Greece, and Fise covers Finland and Sweden. There are no solar PV capacities in Benelux, Alpine, EE-NW, EE-NE, Denmark, Norway, and Fise. There are no wind offshore capacities in Iberia, Italy, Germany, Alpine, EE-NW, EE-SW, EE-SE, Norway, and Fise.