Capital Adjustment Costs and Nationally Determined Contributions - How to Avoid Double Transitions of Energy Capital?

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Abstract

The energy transition is fundamentally a capital and technological transition. Countries face the joint challenge of expanding clean energy capacity while phasing down dirty assets in an orderly way to sustain growth, meet climate goals, and limit adjustment costs and stranded assets. While emission-intensive energy technologies still hold a productivity advantage, this gap is rapidly closing. Using a state-of-the-art growth model with sector- and technology-specific capital stocks, we compare optimal transition paths of an advanced industrialized economy to that of an emerging economy, using detailed calibrations stylized on the EU and India. In India's context, rising demand and clean-technology catch-up drive immediate clean investment, with modest carbon pricing preventing a double transition of its energy capital stock. In the EU context, with limited remaining carbon budget, decommissioning high-emission legacy capital stock must begin immediately, and a higher carbon price is needed to drive the transition. For both jurisdictions, more ambitious climate policy entails modest economic losses, and carbon pricing outperforms net-zero mandates by reducing stranded assets and adjustment costs.

JEL Codes: E22, H23, O41, Q43
Keywords: Low carbon transition, optimal investment, capital adjustment costs, carbon pricing, net zero commitment.

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1 Introduction

The energy transition is fundamentally a capital transition: emission-intensive assets must be phased out in favor of clean energy sources (like renewables) and durable equipment adapted to their use (like electrification). The question for societies is how much and how fast to transform these capital stocks. Clean technologies are rapidly catching up in competitiveness, but emission-intensive energy technologies still retain a productivity advantage. Investment in emission-intensive capital persists although it may need to become obsolete in its lifetime. The Paris Agreement, to which nearly all countries in the world are party, creates a framework for meeting the collective goals of limiting global climate change through the provision, updating, and financing of Nationally Determined Contributions (NDCs). In addition to communicating greenhouse gas (GHG) emissions goals, over 100 countries—accounting for more than 80 percent of global emissions—have adopted net-zero pledges alongside their NDCs. Individual countries thus face delicate intertemporal trade-offs between exploiting the remaining productivity advantage of emission-intensive technologies and phasing down dirty assets in an orderly way to sustain growth, meet climate goals, and limit stranded assets.

The central challenge of the clean energy transition crucially depends on country-specific conditions, including existing energy capital stocks, the pace of clean-technology catch-up, the ambition of climate targets, and the magnitude of adjustment costs. Therefore, the optimal timing, scale and policy mix to achieve the transition, as well as its economic costs, will differ between advanced and emerging economies. In advanced economies such as the EU, overall energy production capacity is well established, so the transition primarily entails rapidly transforming an existing capital stock under very limited remaining carbon budgets. By contrast, emerging economies like India face rising energy demand and limited legacy capacity, while the principle of common but differentiated responsibilities affords them more time to transition to clean energy. Their key challenge lies in building a capital stock that supports growth while avoiding counterproductive lock-in to carbon-intensive infrastructure. While the principle of common but differentiated responsibilities affords emerging economies more time to transition, it is not clear if following the historical path of industrialized economies is in their interest, given the dwindling productivity advantage of fossil-reliant technologies, the long-lived nature of energy infrastructure, and the costs of jeopardizing 1.5°C targets.

This paper analyzes optimal investment paths for the clean energy transition under different NDC policy regimes, accounting for differing initial conditions in advanced and emerging economies. Using a three-sector growth model with unbalanced growth, we characterize optimal capital adjustment for the EU and India and examine the implications of

alternative emission reduction targets.

One central contribution of this paper is to quantify two factors which critically shape the transition and its costs for our two representative regions: existing energy-related capital stocks and the size and future path of the productivity gap. Initial clean and dirty capital stocks are estimated using the perpetual inventory method, drawing on energy-related investment data constructed from production and trade flows. Clean capital includes assets running on electricity or renewable energy (e.g., electric vehicles, electric boilers, and renewable generation), while dirty capital uses fossil fuels (e.g., combustion vehicles, gas boilers, and fossil power plants). Around 2020, clean capital accounted for 10 percent of total capital in India and 19 percent in the EU, while dirty capital accounted for 5 percent and 12 percent, respectively. To capture clean-technology catch-up, we construct a dirty productivity advantage index based on levelized costs of representative clean and dirty technologies across five sectors: buildings, electricity and heat, manufacturing and construction, and transport. Dirty technologies currently hold an approximate 25 percent cost advantage, projected to disappear by 2030 in India as well as the EU.

The existing climate commitments of the two regions are another important factor shaping transition paths. NDCs typically combine two types of targets: emissions trajectories or cumulative emission budgets, often modeled through carbon pricing, and net-zero targets mandating a full shift to carbon-free energy by a specified date. The former provides price incentives to limit emissions within a carbon budget, while the latter acts as a technology mandate requiring anticipatory investment. We calculate energy-related carbon budgets for each of our regions based on third-party assessments of NDCs and 1.5°C-consistent mitigation shares.

We use these capital, productivity, and policy target estimates to extend and calibrate the three-sector carbon-constrained growth model of Burda et al. (2025). In the model, final output is produced using capital, labor, and an energy input that can be generated from clean or emission-intensive sources, both requiring capital and labor. An important feature of the model is the representation of clean and dirty sources as perfect substitutes in the provision of energy, relying on sector-specific capital, the evolution of productivity gaps, and convex capital adjustment costs to limit and endogenize substitutability over different timeframes. We extend the model by incorporating policy regimes: a cumulative carbon budget implemented via carbon pricing, a stylized net-zero emissions (NZE) mandate requiring full reliance on clean energy by a target date, and a combination of both. The model is calibrated to the contexts of the EU and India in 2020, targeting dirty energy's GDP share, the capital-output ratio, and emissions as a share of the remaining carbon budget, with climate targets based on NDCs and energy-related CO_2e. Economic welfare is measured in terms of consumption equivalents, excluding any valuation of utility losses

arising from climate damages.

For the advanced economy context of the EU, we find that the energy carbon budget from the current NDC—or stated policy scenario (STEPS)—could be met with a 28 EUR/tCO_2e carbon price (above policies implicit in the 2020 calibration) for all energy related emissions by 2030, leading to a gradual decline in dirty energy capital and a full phaseout by 2073.[1] All carbon prices would need to be on top of existing carbon prices. A higher price of 67 EUR/tCO_2e accelerates the phaseout to 2055, reducing the carbon budget by 41 percent at an economic welfare cost of less than 0.3 percent. Combining this budget with a 2040 net-zero target lowers the required carbon price to 38 EUR/tCO_2e. The additional net zero constraint at 2040 would slightly increase economic losses and adjustment costs overall, but it would substantially increase stranded assets from 1.5 percent to 9.4 percent of GDP. A stand-alone 2050 net-zero mandate—without any carbon budget—would lead to emissions 23 percent higher than the STEPS scenario and leave stranded assets at 14.4 percent of GDP. Across different sensitivity scenarios, average annual energy-related adjustment costs range between 0.18 and 0.5 percent of GDP—nearly twice as high relative to our developing country example of India—highlighting that in economies with large legacy stocks of dirty capital and lower growth rates, adjustment costs play a particularly significant role.

For an emerging economy, the alignment of the expected clean-technology catch-up with rising energy demand drives an immediate expansion of clean investment; in India's case, optimal clean investment in early years is double that of its still more productive dirty counterpart. Under the reference calibration, India's NDC budget for energy related emissions could be met with an additional carbon price of 0.8 USD/tCO_2e in 2030, allowing a dirty capital buildup before phaseout in 2063. A modestly higher carbon price of 2.3 USD/tCO_2e largely prevents this buildup and brings forward the phaseout to 2055, with only a 0.07 percent economic welfare cost. It yields an even lower but comparable level of stranded assets ($\approx$ 2 percent of GDP) and energy-related adjustment costs ($\approx$ 0.2 percent of GDP) to the reference NDC scenario, while achieving 36 percent greater emission reductions than the NDC pathway. In India's case, the 2050 net-zero mandate without carbon pricing would lower emissions by 1 percent relative to STEPS but increase stranded assets by 9 percentage points.

For both regions, under the central calibrations of the model, policies consistent with limiting warming to 1.5°C entail economic welfare costs that are quite modest, particularly in comparison to published estimates of climate damages, which are excluded from our

[1]Because our carbon price reflects an average across all energy-related emissions, it is not directly comparable to the price in the European Union Emissions Trading System (EU ETS). The EU ETS—although much higher in recent years at around 70–90 EUR/tCO_2e—covers only about 40% of total EU GHG emissions (European Commission, 2025).

model.[2] Overall, carbon pricing tied to stringent budgets achieves a smoother transition, with lower emissions, fewer stranded assets, and slightly reduced adjustment costs compared to simple net-zero mandates.

The contribution of this paper is threefold. First, we add to the emerging literature analyzing the optimal transition of an economy with clean and dirty capital with costly adjustments. For example, Campiglio et al. (2022) develop a dynamic stochastic general equilibrium model, calibrated to global data, taking into account the effects of capital inertia, technological change and uncertainty. Consistent with our findings, they show that actively disinvesting from dirty capital can be optimal. Likewise, using a model with long-lived abatement capital and convex investment costs, Vogt-Schilb et al. (2018) find that it is optimal to launch a long-term emission-reduction strategy with significant early abatement investment, even if the optimal carbon price initially remains low and rises gradually over time. Our study highlights the importance of anticipatory investments for the transition and the capital stock and cost parameters driving those strategies. van der Ploeg and Rezai (2020) outline the different types of stranded assets during the transition and different drivers leading to stranded assets. Our paper offers a quantification of stranded assets in the form of fossil capital infrastructure becoming useless once the economy switches to renewable energy sources in the context of different jurisdictions.

Our approach to the role of clean and dirty inputs in the transition has other distinctions from these examples and from many conventional macro-climate models like Golosov et al. (2014), Hassler et al. (2021), and Barrage (2020). The common approach is to assume a constant elasticity of substitution specification between clean and dirty energy, which limits long-run substitutability. We instead follow Burda et al. (2025) in assuming perfect substitution between clean and dirty energy, where short-run limitations stem solely from adjustment costs and the sector-specific nature of capital. Assuming a constant elasticity of substitution implies that the cost of substituting clean energy with dirty energy increase substantially the more energy has already been replaced. In contrast, our definition makes costs depend on the amounts of investment necessary and the possibilities to smooth investment over time. Our modeling choice aligns with our definition of the energy good as the *function* performed by energy in the production process (i.e. heat, motion, etc.).[3] Both our measure of energy capital stocks and productivity differences are designed around this definition. If providing specific functions is fundamentally more costly using clean technolo-

[2]For instance, Bilal and Känzig (2024) estimate that a 1°C increase in global temperature reduces world GDP by 12 percent.

[3]This differs from the interpretation as units of energy which may indeed be imperfectly substitutable depending on the context. For example, energy is stored in a battery may be better suited for some applications compared to a given quantity of gasoline and vice versa. However, once the energy has been converted to heat or motion the source no longer matters.

gies, this enters the model through the productivity difference. In contrast, if a function is currently performed by fossil energy-fueled technology because of existing infrastructure and capital while a competitive clean technology exists, transition costs only arise from the the endogenous limit on short-term substitutability induced by adjustment costs. We further extend this literature by highlighting systematic differences between advanced and emerging economies in terms of near-term dirty energy investment, cumulative adjustment costs, and stranded assets. Our transition cost estimates are solely based on reaching a certain carbon budget without taking into consideration climate damages. Bilal and Känzig (2024) show that 1°C of global warming reduces world GDP by 12%. Similarly, Barrage (2020) finds large welfare gains from carbon taxes ranging between $10-46 trillion ($2005 lump-sum consumption equivalent). Hence, the inclusion of climate damages is would increase the benefits of the transition and at the same time accounting for climate damages would increase the carbon tax Traeger (2023). Accounting for climate damages is necessary to estimate the social cost of carbon. Excluding climate damages hence implies that our estimates offer an upper bound for cost estimates for the clean energy transition but likely a lower bound for carbon taxes. Only accounting for the necessary incentive to change the energy system allows to separate the policy goal of energy taxation. Carbon taxes serve as price incentive for the energy system shift, while leaving out the internalization of climate damages.

Second, we extend the literature analyzing the impacts of different climate policy instruments on dynamic transition paths, looking beyond carbon pricing. Rozenberg et al. (2020) show that feebates, mandates, and performance standards can have markedly different implications for stranded assets compared to first-best carbon pricing. Our results show that a net-zero target—a pure technology mandate by a certain deadline—may generate significantly larger economic disruptions than consistent carbon pricing, highlighting the importance of formulating NDC contributions based on keeping an overall emission budget.

Third, we develop an approach to calculating country- and sector-specific capital stocks and provide new datasets on the evolution of energy capital in the EU and India. Our estimates are broadly consistent with the global estimates of Campiglio et al. (2022) and US-specific estimates of Fried et al. (2022), who report dirty energy capital shares of 8 and 10 percent of total capital, respectively. Since Golosov et al. (2014) highlight the sensitivity of transition costs to technological progress, we construct a new index that tracks productivity differentials between clean and dirty technologies over time. While recognizing the importance of endogenous growth effects such as learning by doing — empirically shown by e.g. Way et al. (2022)) and implemented in a model context by Hambel et al. (2020) — we use an exogenous technology process but assume that clean energy productivity is catching up in line with our productivity index. We find that clean energy shares in India

and the EU can be expected to be large by 2040, even without ambitious policies. The results concur with those of Arkolakis and Walsh (2023), who study a narrower context of electricity supplies and find that the world's power system is likely to be dominated by renewables by 2040 across a wide range of scenarios, with substantial welfare gains even in the absence of policy.

The remainder of the paper proceeds as follows. Section 2 estimates the size of the clean and dirty energy capital stocks, distinguishing among the investment into power, transport, industry, and residential sectors, and quantifies the clean-dirty energy productivity gap. Section 3 provides an overview of the three-sector unbalanced growth model of Burda et al. (2025) and the additional climate policy scenarios analyzed. Section 4 describes the overall calibration strategy. Section 5 provides an analysis of the net-zero transition paths in an advanced versus an emerging market economy and compares the impact of different NDC policies. Section 5.4 provides a sensitivity analysis on the role of adjustment costs. Section 6 concludes.

2 Quantifying energy capital stock differences

To model the energy transition, we must distinguish between the initial quantity and productivity of clean and dirty energy capital stocks across economies. The aggregated data to parameterize our model is built on a foundation of sector-specific information that defines and quantifies different kinds of energy capital and their costs, as well as the rate of productivity convergence.

2.1 Estimating stocks of clean and dirty energy capital

The initial composition of clean and dirty energy capital stocks plays a pivotal role in shaping the optimal transition path for both advanced and emerging economies. Differences in the structure of energy capital between these economies are a key determinant of the variation in their respective transition dynamics. Direct data sources for capital stock and investment by technology are not readily available. To this end, we construct estimates of the evolution of clean and dirty energy capital stocks based on available data for the EU and India. In prior work, Campiglio et al. (2022)[4] calculate a global dirty capital stock

[4]Campiglio et al. (2022) identify the clean and dirty capital based on the World-Input-Output database containing sectoral capital stock data for 43 countries at NACE level 2 disaggregation. Where possible they employ data from the Exiobase multi-regional input-output database to further disaggregate capital stocks and filter out those capital stocks directly related to the use of fossil fuels like extraction and exploration of oil, coal, and gas. For their disaggregation they assume that the share of fossil-related capital stock of a particular sector is equal to the share of fossil-related output in total sectoral output. They do not identify clean capital separately since they assume all capital not being dirty to be clean.

using mainly the World-Input-Output Database. Fried et al. (2022)[5] use data on private fixed assets and consumer durables in the US. In contrast, we build the capital stock series using the perpetual inventory method, based on economy-specific estimates of investments in clean and dirty energy technologies. The approach results in similar estimates for the dirty capital stock of around 10 percent of the overall capital stock, although our estimation differs with respect to geographic focus as well as underlying data sources.

First, we approximate energy-related investments using annual industrial production data in combination with export and import data on energy-related capital goods as a proxy. We begin by identifying all goods from the industrial production, export and import data that need energy to function. Next, we classify the different energy-using products as clean or dirty according to the energy source. We use the AI tools MAi and ChatGPT to provide descriptions of each good's typical use and the type of energy it utilizes. To ensure a robust categorization into clean and dirty, we combine automated insights with human reasoning.

Items that directly rely on fossil fuels—such as diesel, gasoline, natural gas, fuel oil, or LPG—are classified as dirty. Goods classified as dirty (such as combustion-based vehicles, kerosene heaters or diesel generators for backup power generation) would need to be replaced or phased out completely in a transition towards 100 percent clean energy capital. In contrast, products powered by electricity or direct renewable energy sources (e.g., solar, wind, nuclear) are considered clean. Goods considered clean include items like rail-based infrastructure, electric heat pumps, electricity based household appliances, renewable and nuclear power generation or electricity based machinery in the industrial sector. We assume that electricity-based capital goods do not require to be replaced for the transition. To accomplish an entirely clean energy capital stock it would be enough to change the electricity production to fossil-free electricity production.

Domestic investment for each product j in year t is calculated as:

$$Investment_{jt} = \text{Sold production value}_{jt} - \text{Exports value}_{jt} + \text{Imports value}_{jt} \qquad (1)$$

The approximation for clean and dirty energy investment is created via summing up

[5]Fried et al. (2022) use detailed data from the BEA on private fixed assets and consumer durables to construct the ratio of fossil to total capital in the U.S. economy. The classification largely follows the 3-digit NAICS codes. They categorize capital into three groups: (1) capital that is fossil or partly fossil across all sectors; (2) capital that is fossil or partly fossil only within sectors specialized in fossil energy use; and (3) all other types of capital. However, Fried et al. (2022) do not distinguish between clean and non-energy capital in the data analysis. Instead, their analysis focuses solely on the share of fossil capital relative to total capital. Their data includes capital stock information disaggregated by asset type (e.g., mainframes) and sector (e.g., farms). They define fossil capital as assets specifically designed to use fossil fuels—for instance, internal combustion engines in any sector are classified as fossil capital, as is "special industrial machinery" in sectors directly linked to fossil energy, such as oil and gas extraction.

these three variables for all products classified as clean and dirty at each point in time. For the EU we use annual statistics on the production, exports and imports of manufactured goods (PRODCOM) in EU27 countries. For India's domestic production data we use the Annual Survey of Industries (ASI). To account for trade flows contributing to the energy related capital stocks in India we use Comtrade data, which provides data on bilateral trade flows. We further cluster all clean and dirty energy-related products into different sectors mirroring the categories of our productivity index (see section 2.2) including power generation, heating, transport and industry. We further split industry into residential energy related goods mostly composed of electricity based appliances.

Second, we construct a time series for energy-related capital stocks using the perpetual inventory method, in which the capital stock in a given period reflects the depreciated sum of the history of previous investments.[6]

$$K_{it} = \sum_{t=2000}^{2020} (1 - \delta_i)^{(2020-t)} \times I_{it} \tag{2}$$

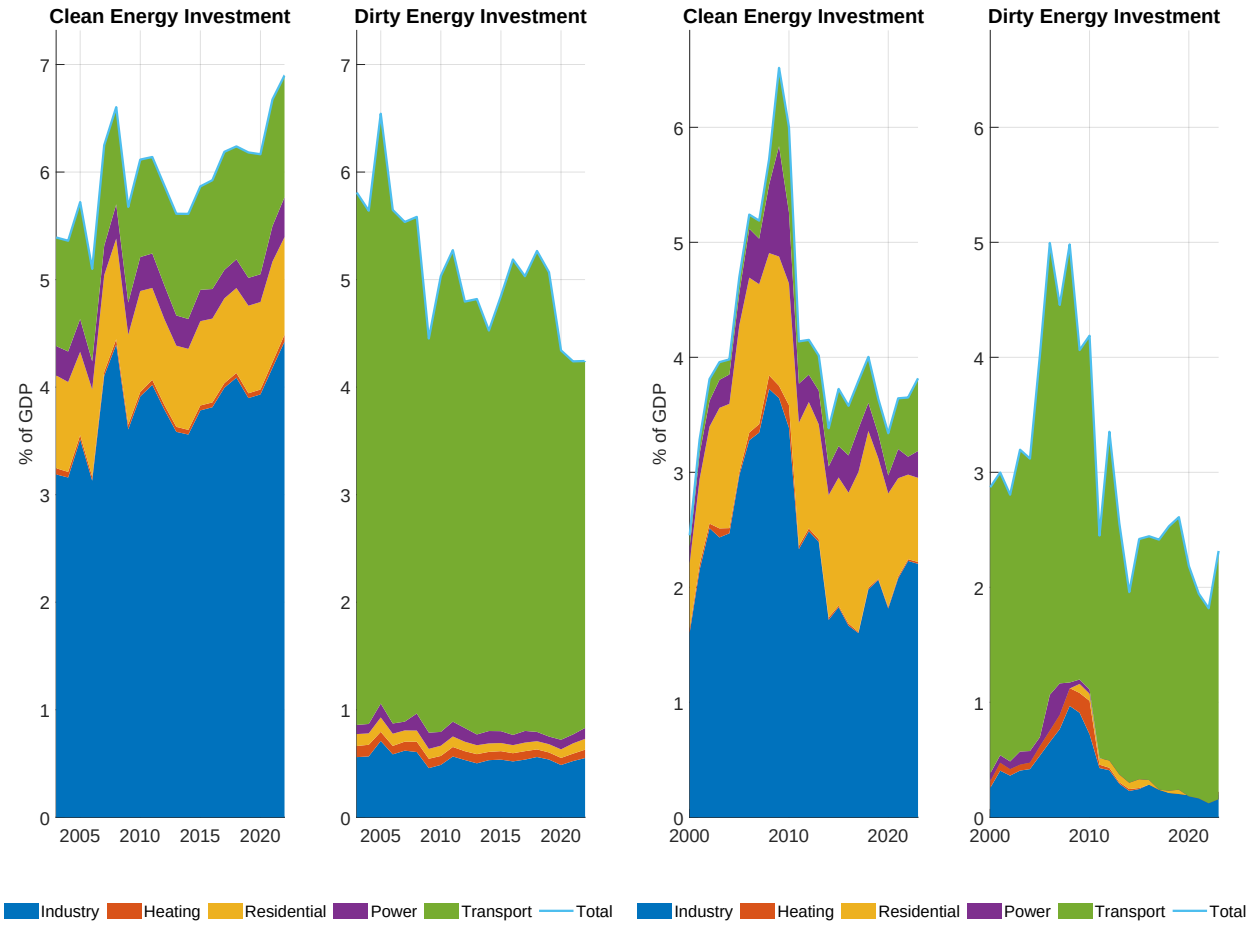
This method is applied to sector-specific investment series, accounting for sectoral differences in depreciation rates across power, transport, and combining industry heating and residential. Further details on the use of the perpetual inventory method are documented in the Appendix B.2. To calculate the share of clean and dirty energy capital in total capital, we use the IMF Investment and Capital Stock Dataset as a benchmark for the aggregate capital stock in India and the EU-27.

This approach faces several challenges, particularly regarding the treatment of spare parts and intermediate goods, as well as the difficulty of accurately valuing certain existing capital assets or physical structures. Moreover, short investment series constructed from product-level production values, exports, and imports are known to introduce additional uncertainty into the Perpetual Inventory Method. Nevertheless, in the absence of more comprehensive and precise data, this procedure offers a systematic way to approximate the distribution of investment across energy technologies.

Figure 1 presents the aggregated investment estimates over time, by category, sector grouping, and country. In the EU, within the clean category, electricity-related industrial investment constitutes the largest component, whereas fossil-fuel-based transportation dominates the dirty category. In India the largest clean energy related investment took place in the electricity based industrial sector and second in the residential sector hence electricity based appliances. As in the EU, dirty energy capital additions in India are mainly driven by transport investments, which peaked around 2009 and have declined ever since as a share of GDP. In recent years, clean power and clean transport have begun to accelerate as well.

[6]For the EU data is only available from 2003 onwards.

Figure 1: Energy-related investment by sector

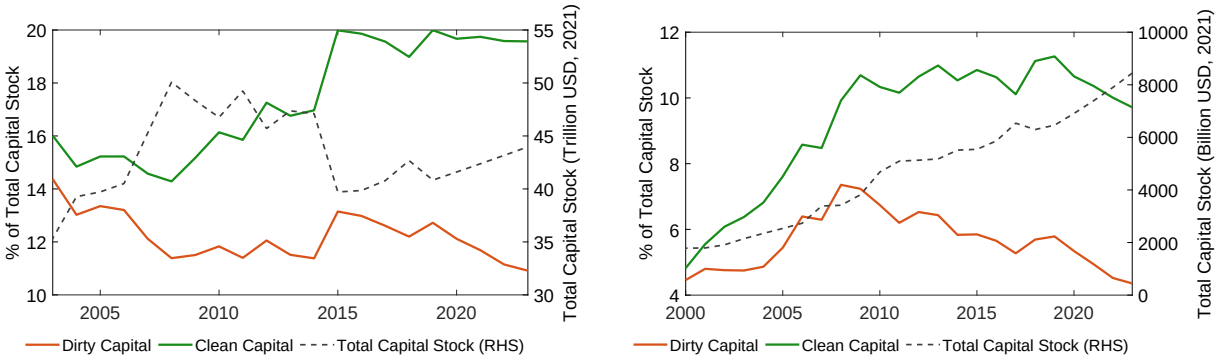


(a) EU **(b)** India

Sources: own calculation based on EU PRODCOM, ASI (India), Ember, Enerdata, IEA.

Figure 2 shows the corresponding perpetual inventory estimates for the development of the clean (green line) and dirty (red line) energy capital stocks in the EU and in India, respectively. The dotted lines depict the evolution of the total capital stocks (mapped to the right axis).

Figure 2: Development of the energy capital stocks in the EU and India



(a) EU **(b)** India

Sources: Own calculation based on EU PRODCOM data, and ASI, Comtrade data for India and the IMF Investment and Capital Stock Dataset International Monetary Fund (2021). The figure displays the shares of clean and dirty capital over the total capital stock (left axis) as well the development of the overall capital stock in billions of 2021 USD (right axis).

In the EU, dirty energy–related capital has accounted for roughly 11–14 percent of the total capital stock over the sample period, while clean energy–related capital has accounted for about 16–19.5 percent. Clean energy capital has been larger from the outset, and the gap between the two has widened, particularly since 2020. The pronounced decline in dirty energy capital and the corresponding rise in clean energy capital are driven primarily by falling investment in fossil-fuel transport and increasing investment in electricity-based capital goods in the industrial sector.

In India the share of dirty energy related capital has ranged between 4.5 and 7.5 percent of the total capital stock since 2000, whereas clean energy capital has doubled from 5 to 10 percent, peaking at 11 percent in 2018. While the overall share of the energy-related capital stock in India is lower than in the EU, in both regions, clean energy capital has always been larger and increased at faster rates than dirty energy.

Overall, the evolution of energy-related capital stocks reveals two key patterns. First, electricity-based capital has consistently exceeded fossil-fuel-based capital since the turn of the century. Second, the declining shares of dirty energy related capital observed in both the EU and India indicate that the energy transition is underway, with industrial electrification emerging as the main driver. As a result, decarbonizing power-generation infrastructure becomes the pivotal challenge. At the same time, transitioning transport-related capital remains an equally substantial task for advanced and developing economies alike.

2.2 Indexing the clean-dirty productivity gap

Modeling energy capital productivity over time requires capturing both the initial cost advantage of dirty energy and the convergence dynamics of clean technologies. Assuming otherwise identical production functions, these depend only on the evolution of the ratio of total factor productivity of the dirty versus clean technologies (represented by M_D/M_C in the following). To measure the differences between clean and dirty energy related technology in the EU and India, we create a new index comparing levelized costs of energy (LCOE) for clean and dirty technology in the primary sectors for energy-related consumption and hence emissions. The LCOE estimates provide an indication of relative costs, as well as of the share of those costs attributed to capital as opposed to operation.

Energy-related emissions arise from energy-intensive activities across several sectors, including buildings, electricity and heat, manufacturing and construction, and transportation. For each sector, drawing primarily on data from International Energy Agency (2023b), we approximate the productivity advantage of dirty technologies by comparing the levelized cost of electricity (LCOE) of one dominantly used clean technology with that of one dirty counterpart. Where possible, we adopt conservative 2030 cost estimates, better aligned with current or stated policy scenarios, which we take as our reference case. Table 1 reports two sets of productivity differences: an unweighted ratio and a weighted ratio, where the latter is adjusted by each sector's 2020 emission share. Further details on the construction of these measures are provided in Appendix B.1.

Table 1 shows that large differences exist between sectors. Based on value-adjusted LCOE in electricity generation, renewable based electricity generation is already more productive than fossil based electricity generation in the EU as well as in India. However, given that for India, the IEA projects a relatively higher decline in costs of combined cycle gas turbines (CCGT) compared to clean electricity comprised of wind, solar and nuclear the competitiveness of renewables is declining compared to 2022. In contrast, in the industry sector dirty steel is still more than two times as productive in the EU and 50 percent more productive in India.[7] According to this productivity index, the dirty technology advantage in 2021/2022 amounts to about 48% in the EU and 26% in India. In both cases, this advantage disappears by 2030. In our model, we capture this dynamic through the clean exogenous catch-up factor (see Section 3.1).

Our estimates of the productivity index should be interpreted with important caveats and are best viewed as conservative benchmarks. First, our projections for the electricity sector rely on the IEA's Stated Policies Scenario, which assumes no additional policy

[7] A note of caution here is that steel is still one of the sectors the most difficult to decarbonize due to the intense heat required during its production.

Table 1: Productivity advantage of dirty energy technology (M_D) over clean energy technology (M_C) in the EU and India.

EU

	2021/22		**2030**		
Sector	$\frac{M_D}{M_C}$	**Share**$\times \frac{M_D}{M_C}$ †	$\frac{M_D}{M_C}$	**Share**$\times \frac{M_D}{M_C}$ †	**Measurement Unit**
Electricity generation	0.57	0.48	0.52	0.36	VALCOE*
Heating	1.19		0.78		LCOH**
Transport	1.46	0.44	1.18	0.36	LCOD***
Industry	2.27	0.34	1.50	0.22	Indicative prod. costs****
Average [weighted]	1.37	[1.26]	1.00	[0.94]	

India

	2021/22		**2030**		
Sector	$\frac{M_D}{M_C}$	**Share**$\times \frac{M_D}{M_C}$ †	$\frac{M_D}{M_C}$	**Share**$\times \frac{M_D}{M_C}$ †	**Measurement Unit**
Electricity generation	0.89	0.65	0.98	0.55	VALCOE*
Heating	1.19		0.78		LCOH**
Transport	1.46	0.19	1.18	0.16	LCOD***
Industry	1.39	0.34	1.10	0.27	Indicative prod. costs****
Average [weighted]	1.23	[1.18]	1.01	[0.98]	

† Weighted by sectoral emission shares from Climate Watch (see Appendix B.1).
* VALCOE = Value-adjusted cost of electricity (International Energy Agency, 2023b).
** LCOH = Levelized cost of heating.
*** LCOD = Levelized cost of driving.
**** Indicative production costs for crude steel via electrolytic hydrogen-based DRI.

interventions beyond those already enacted. With policy-driven learning effects, the productivity advantage of dirty technologies could diminish even more rapidly (International Energy Agency, 2023b). Second, while some clean technologies exhibit higher capital intensities—and therefore a larger share of CAPEX in total costs—there is no clear evidence that, at an aggregate level, clean and dirty energy technologies differ substantially in their overall capital intensity. Third, we do not account for changes in the composition of capital stocks over time. To the extent that this assumption underweights electricity capital, it likely overstates the productivity gap and, consequently, the costs of the clean energy transition.

3 Model

The framework applied for studying the green transition uses the model developed in Burda et al. (2025), who extend the deterministic model of unbalanced growth of Acemoglu and Guerrieri (2008) by introducing capital adjustment costs, specific energy capital stocks, and a cumulative emissions budget.[8] Our focus is on exploring the implications of alternative policy scenarios for reaching dirty energy phaseout for advanced economies (EU) as compared to emerging ones (India).

3.1 Macroeconomic features

This section briefly explains the central features of the baseline model. For more details see Appendix A.

Preferences. Households have standard preferences over consumption C_t of a homogeneous final output good. They discount the future at rate $1/\beta - 1$ and their elasticity of intertemporal substitution is $1/\theta$.

Production. On the production side, there is an energy sector Y_e and a non-energy sector Y_n, which subsumes all other sectors. A final-good-producing sector combines non energy and energy intermediate inputs with respective weights γ and $1-\gamma$ in a production technology with constant substitution elasticity ϵ. Energy and non-energy goods are both produced using Cobb-Douglas technologies with constant returns to scale in capital and labor. Labor is in fixed supply.

[8]For a detailed description of the model and its solution see Burda et al. (2025). Their results are based on the calibaration developed in this paper. For reference, we also present some model equations in Appendix A.

For energy, two production technologies are available: Y_d for dirty, which causes GHG emissions, and Y_c for clean, which does not. Clean and dirty energy are perfectly substitutable as inputs for final good production. However, their short run substitutability is limited by the availability of clean and dirty energy capital stocks and capital adjustment costs. The three technologies differ in their capital intensity $(1 - \alpha_i)$ and total factor productivity (M_{it}) for $i \in \{n, d, c\}$.

Environment. The dirty technology use causes greenhouse gas emissions, which accumulate in the atmosphere according to:

$$G_t = G_{t-1} + \mu Y_{dt},$$

where μY_{dt} is the flow of emissions at time t, and G_t is the stock of accumulated emissions. With μ measuring the "CO_2 efficiency" of dirty energy production.

Adjustment costs. The central feature of the Burda et al. (2025) model is having convex capital adjustment costs $\Omega^i(K_{it}, K_{it-1})$ in each technology, which restrict the short-term substitution possibilities between energy sources, despite the perfect long-run substitutability:

$$\Omega^i(K_{it}, K_{it-1}) = \frac{c_i}{2}\left(\frac{I_{it}}{K_{it-1}} - \delta_i - z_i\right)^2 K_{it-1} \quad \forall\, i = c, d, n$$

Here c_i is the adjustment cost parameter, δ_i is the capital depreciation rate, and z_i is the growth rate of the respective capital stock on the model's unbalanced growth path.[9] Adjustment costs are thus a convex function of deviations from the investment rate that keeps up with standard growth in the steady state. The presence of δ_i reflects the assumption that adjustment costs are only incurred on net investment, while replacement investment is free. The motivation is that maintaining the current capital stock is done routinely, which makes it less costly than expanding production capacity by installing new machines or reducing it by selling and re-purposing old ones. Overall, excess investment below and beyond depreciation and growth incurs adjustment costs. This particular form ensures that adjustment costs do not affect long-run outcomes and follows Aguiar and Gopinath (2007). This property grants us that our model converges to the unbalanced growth path described in (Acemoglu and Guerrieri, 2008).[10]

[9]The steady state growth rate of each technology z_i differs between technologies $i = c, d, n$ and is an endogenous model outcome. The steady state state of our model resembles the long run growth properties of the unbalanced two sector growth model of Acemoglu and Guerrieri (2008). Our model converges to their two sector growth model in the long run since in the long run the dirty energy sector Y_d ceases to exists and implies that z_d is zero. However, numerically, our results do not depend on the inclusion of z_i in the adjustment costs function.

[10]Goeth (2025) shows the implications of choosing adjustment costs on net or gross investment.

Technology and clean catch-up. Total factor productivity of dirty energy and non-energy technology grows at constant and exogenous rates m_d and m_n respectively. To capture the fact that many clean energy technologies are not yet mature, but improving at a rapid pace, we introduce exogenous catch-up growth. We model catch-up growth in a simple manner, by assuming that TFP in the clean technology approaches that of the dirty technology in the long run. During the transition the distance between the productivities shrinks at a constant rate. Specifically, we define a catch-up factor

$$a_{ct} = 1 - \frac{b_M}{(1+\kappa_M)^t}$$

where $\lim_{t\to\infty} a_{ct} \to 1$, κ_M is the catch-up rate and b_M determines the initial distance to the long-run constant-rate growth path. The level of TFP in clean energy production then follows

$$M_{ct} = a_{ct} M_{dt}.$$

The catch-up factor a_{ct} captures our finding that for both countries the dirty productivity advantage disappears in 2030. We calibrate κ_M and b_M such that they capture the different path of clean technological catch up we find in the data for the EU and India (see Table 1).

Treating technological progress as exogenous is a strong simplification, given that clean energy technologies have experienced substantial cost declines as cumulative capacity expanded through learning-by-doing (Way et al., 2022). Nevertheless, we adopt this assumption because our productivity estimates do not account for the additional learning effects that could arise under more ambitious climate policies. Moreover, technological learning is only partly local and is strongly influenced by global spillovers, particularly from large markets such as the United States and China, which drive much of the progress in low-carbon technologies. The omission of learning-by-doing is particularly important when interpreting our results on simple net-zero targets, since such technology improvements would materialize only if clean investment were accelerated early on.

3.2 Policy scenarios

We consider several different policy scenarios, each corresponding to a social planner problem with a different objective regarding the path of emissions. These social planner solutions meeting a carbon budget constraint can also be implemented as an equilibrium in a decentralized economy by setting the optimal excise tax on dirty energy, τ_{dt}.[11]

[11]The fact that one instrument is sufficient to achieve one target is in line with the Tinbergen rule.

3.2.1 Carbon budget constraint

As a baseline, we consider a carbon budget (cost-effectiveness approach), as in Burda et al. (2025). That is, the social planner chooses a feasible path of consumption to maximize welfare of the representative agent subject to the constraint:

$$\frac{G_T}{\bar{G}} \leq 1. \tag{3}$$

where $\bar{G}$ is the target carbon budget. Constraint (3) will bind at some finite time $\bar{T}$ on the optimal growth path, which implies, $L_{dt} = 0$ for all $t \geq \bar{T}$. Because of adjustment costs, however, K_{dt} might remain positive after time $\bar{T}$. All K_d left in the economy after the carbon budget binds is considered stranded assets, since it is not used for any production. In this approach the social planner can also choose the time $\bar{T}$ when the pre-determined carbon budget is optimally depleted. For the carbon budget scenario to reveal a carbon price, we consider a decentralized economy with a Ramsey planner who maximizes social welfare by choosing an excise tax τ_{dt} on firms operating the dirty energy technology.

3.2.2 Net-zero target

The second policy case we consider is a social planner who maximizes welfare of the representative agent subject to the constraint that dirty energy is phased out by time $\hat{T}$—the net-zero target.

$$Y_{dt} = 0 \quad \forall\, t \geq \hat{T}. \tag{4}$$

This constraint also implies that $L_{dt} = 0$ for all $t \geq \hat{T}$. Comparing this to the Carbon Budget approach, however, the social planner has no direct incentive to reduce emissions during the transition phase, leading to a much more abrupt transition to net zero at time $\hat{T}$, moderated primarily by capital adjustment cost planning. This scenario is a strong stylized version of the net-zero targets adopted by many countries, since intermediate targets are not considered.

The implementation of such a target presupposes that the social planner can credibly commit to net zero, even in the face of potentially disruptive transition costs during execution. It also rests heavily on the assumption of exogenous technological progress. Under this assumption, clean technologies improve over time without requiring early investment in clean capital—an investment that would be necessary if the model accounted for learning effects in clean technology.

3.2.3 Net-zero target overlapping a carbon budget

The third case combines the first two. Here the social planner has to respect a cumulative emissions budget as in constraint (3) subject to the the additional restriction that emissions have to reach zero by a certain year $\hat{T}$ e.g. 2050 as in constraint (4). Notice that the solution to this problem will coincide with the pure carbon budget if $\bar{T} \leq \hat{T}$. That is, the second constraint is not binding, if it is optimal to reduce emissions to zero before $\bar{T}$ anyway.

4 Calibration strategy

We calibrate the model parameters to match four empirical targets found in the data for India and the EU: (1) the initial dirty energy share in GDP, (2) the initial capital output ratio, (3) the initial emissions as a share of the remaining carbon budget, as well as (4) the initial labor share. We use an annual frequency, starting our simulations in 2020.

4.1 Externally and internally calibrated parameters

Nine parameters which are equal across India and the EU are drawn directly from data and the existing literature. They include the input substitution elasticity ϵ, intertemporal substitution elasticity θ, discount factor β, labor intensity in the clean α_c and dirty α_d energy sector and depreciation rate δ_i of all three sectors $i \in \{n, d, c\}$. For an overview see the upper panel of Table 11 in Appendix.

Eight parameters are calibrated externally and differ across the jurisdictions of India and the EU. These parameters include emission intensity μ determined by each jurisdiction's current emission and their respective share of energy in GDP. In addition, four parameters—the initial energy capital shares $(\frac{K_{c0}}{K_0}, \frac{K_{d0}}{K_0})$ and technology catch-up parameters (b_M, κ_M)—are determined from our own estimates. Additionally, we set a common trend growth rate $m = m_c = m_d = m_n$ to match the 10-year average growth rates for the EU and India. Adjustment cost parameters c are set according to estimates in the literature and subject to sensitivity analysis. For an overview see the lower panel of Table 11 in Appendix.

Given these externally calibrated parameters, we jointly calibrate the remaining four parameters —the non-energy input weight in production γ, starting level of the capital stock K_0, emission intensity of dirty energy production μ, and non-energy labor intensity α_n— internally, so that four outcomes in the model baseline CBSTEPS scenario (see Section 5) match the four empirical targets mentioned above. Table 13 in the Appendix report the parameter values that we calibrate internally for both jurisdictions.

4.2 Calibration results

The two main differences in the general economic context between the two economies we account for regard the labor income shares and the average GDP growth rates. The labor share in India is about 6 percentage points lower than in the EU, due to an abundant but low-paid labor force. Since India is still accumulating its capital stock and catching up with its overall development the average growth rate for the last 13 years was about 4 percentage points higher than in the EU. Related to the net zero transition the main difference between the EU and India is that India has a much larger remaining carbon budget (63 $GtCO_2$ vs EU 30 $GtCO_2$) in the 1.5°C scenario. However, India is facing an increasing energy demand requiring it to extend the energy capital stock to meet this growing demand with or without the transition to a net zero economy.

Table 2 shows the fit of the model moments with the empirical targets of the EU and India. Importantly, for the transition paths below, our best estimate of the output elasticity with respect to labor is 0.63 in the non-energy sector in the EU and 0.57 in India. In both cases, we assume that the output elasticity with respect to labor in the clean and dirty energy sector is 0.3. The energy energy sector is thus much more capital-intensive than the rest of the economy. The best estimate of the initial share of dirty energy in total output 6% and 7% for the EU and India, respectively.

Table 2: Moments Matched

		EU		**India**
Empirical Targets	**Model**	**Data**	**Model**	**Data**
all in %				
Initial dirty energy share in GDP $\frac{p_{e0}Y_{d0}}{Y_0}$	6	6	7	7
Initial capital output ratio $\frac{K_0}{Y_0}$	2.55	2.55	2.1	2.1
Initial emissions as share of remaining carbon budget $\frac{\mu Y_{d0}}{G}$	4.8	4.8	2.3	2.3
Initial labor share $\frac{w_0 L}{Y_0}$	58.2	58.2	52.2	52.2
Average output growth rate betweem 2015-2023	2.24	1.7	5.22	5.8

Notes: The empirical target of the average growth rate was set externally outside our the optimal solving procedure we used to find the optimal parameter such that the model moments equal the data moments.

4.3 Calibration of carbon budgets for CBSTEPS and CB+1.5°C

Since by 2020 (our starting date), some climate policies had already been in place and were expected to continue going forward, the calibration must be consistent with policy expectations at the time. We thus use a Stated Policies Scenario (CBSTEPS) or current NDC scenario as our baseline, from which to analyze other, more ambitious policies. Similarly, technologies are expected to evolve over time. Here we describe in more detail our efforts to carefully calibrate the dirty productivity advantage and the starting variables consistent with CBSTEPS. For more details on the calibration strategy see Appendix C.

First, to calibrate our baseline scenario (CBSTEPS) for the EU and India we use emissions projections from Climate Action Tracker, reflecting the stated NDCs as of 2022. This scenario serves as a basis for comparison to more ambitious climate policy secenario (CB+1.5°C).[12] These estimates include all GHGs, converted to CO_2e. We calculate cumulative emissions using Climate Action Tracker annual emission projections until 2030 in the "Policies and Actions" scenario and add a linear extrapolation of annual emissions from 2030 until 2050. We use the same procedure for India and the EU. This scenario estimates the expected level of emissions if all current policies are fully implemented. Second, since our model only represents energy-related emissions, we need to exclude other emissions, such as those from land-use change.

For the carbon budget aligned with the 1.5°C goal globally, we use an average estimate of the carbon budget for the EU and India found in the literature. In India and the EU we assume a carbon budget left of 63 and 30 $GtCO_2$e respectively. The sizes of the carbon budgets used for 1.5°C are within a range of estimates found in the literature for our representative regions (see Appendix C.1, Figure 9). Nevertheless, there is always some arbitrariness of carbon budgets assigned to national jurisdictions.

4.4 Calibration caveats and interpreting carbon prices

The lack of a clean "No Policy"scenario raises some questions for how best to interpret the value of the initial (present value) carbon tax we find.[13] Is it the sufficient tax to meet the NDCs, or is it the tax that is needed in addition to unmodeled pre-existing policies? Our calibration must explain initially observed levels of variables, like clean energy shares and emissions, which are a product both of historical policy interventions and policy expectations. Pre-existing policies are not explicitly captured by the carbon budget, but the preexisting subsidies and taxes were most likely substantial to the build up of the energy

[12]Our calibration starts in 2020 due to data limitations, however, the climate action tracker takes into account policies implemented in 2021 and 2022 as well. This may also lead to some inconsistencies.

[13]Optimal price paths subsequently grow exponentially at the rate of interest.

capital stocks found in 2020. Furthermore, many unrepresented policies do not take the form of carbon pricing, as exemplified by the EU Green Deal and a host of member state policies and programs. To the extent these policies have contributed to making the NDCs easier to achieve, the absolute carbon price coming out of the model will be biased downward.

Another caveat regards the technology and emissions assumptions. First, we do not capture hard-to-abate sectors specifically. Although we do include their higher abatement costs in the cost advantage index of dirty energy, our energy composite does not capture compositional changes over time that would imply increasing marginal abatement costs and changes in the emission intensity of dirty energy. Second, clean and dirty energy are modeled as perfect substitutes, which may be appropriate for a large share of energy services, but ignores the final fraction of uses that are truly hard to avoid.[14] These simplifications of the abatement process may make getting to net zero appear easier than it is in reality.

Given these shortcomings, as always with numerical modeling, the specific results should be taken with a grain of salt. Nevertheless, the model produces a number of useful insights into the role of capital adjustment costs and policies for the low-carbon transition. One outcome is consistent throughout all scenarios considered for the EU and India: underestimating adjustment costs has larger implications for transitional welfare costs than the incremental costs of greater ambition.

5 Results

In this section, we compare the structural transformation of the economy as it optimally reaches zero GHG emissions in the EU and India calibrations. In both scenarios, the social planner chooses the optimal path of emissions and the optimal time at which the carbon budget is depleted ($\bar{T}$). Implicitly, these choices define an optimal carbon price path (see Section 3.2.1).

1. **CBSTEPS**: This scenario represents the transition path that is optimal for a carbon budget consistent with the current or stated policies scenario amounting to 51 and 98 $GtCO_2$ for the EU and India respectively. It serves as the baseline, reflecting already implemented climate policies. The CBSTEPS scenario is operationalized through an optimal carbon price.

2. **CB+1.5°C**: This scenario reflects a more ambitious carbon budget under which it is optimal to phase out dirty energy around 2050. Drawing on the literature, we calibrate the carbon budget for the EU and India to align with their indicative shares

[14] Models assuming constant elasticity of substitution have their own shortcomings, of course, compared to the reality of abatement options.

of the global budget consistent with meeting the 1.5°C goal, decreasing the available cumulative budget to 30 and 63 $GtCO_2$ for the EU and India respectively. The implementation again occurs via optimal carbon pricing, which is higher than in the CBSTEPS scenario, due to the more stringent carbon budget.

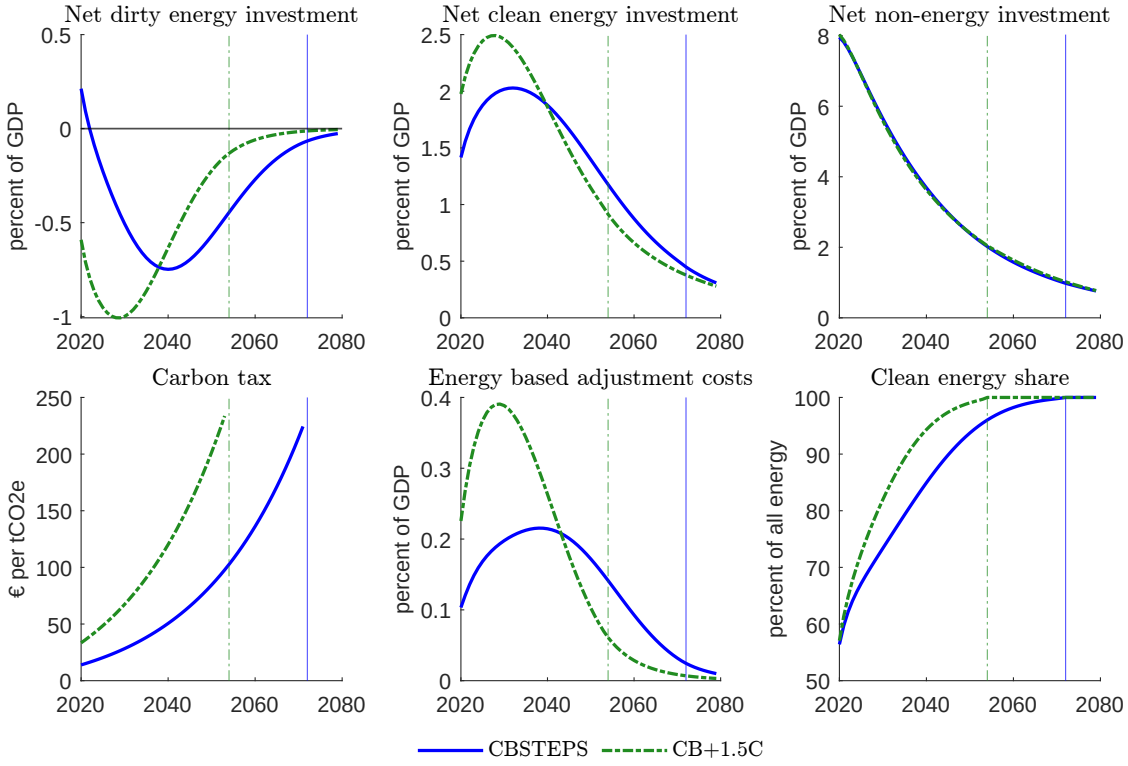
In Figure 3 the blue solid line shows our baseline scenario CBSTEPS and the green, dot-dashed line shows the CB+1.5°C scenario for our advanced economy, the EU, and our emerging economy, India. The vertical lines indicate the year when the carbon budget becomes binding optimally, and hence dirty energy production has ceased.

The energy investment paths reveal important similarities and differences. The EU's optimal investment path requires an almost immediate and increasing disinvestment in dirty energy assets while rapidly building up clean energy to replace them. India's optimal investment path initially continues significant additions to dirty energy capital but quickly decreases them; meanwhile, the scale of investment into clean energy technologies is from the outset larger and more enduring—even without further climate policy—due to anticipation of the productivity convergence. It would be too costly to set up the energy capital stock entirely based on fossil fuels, decommission and then rebuild clean again. Overall, India has higher energy-based adjustment costs as a share of GDP in the first decade, due to this need for rapid capital growth.

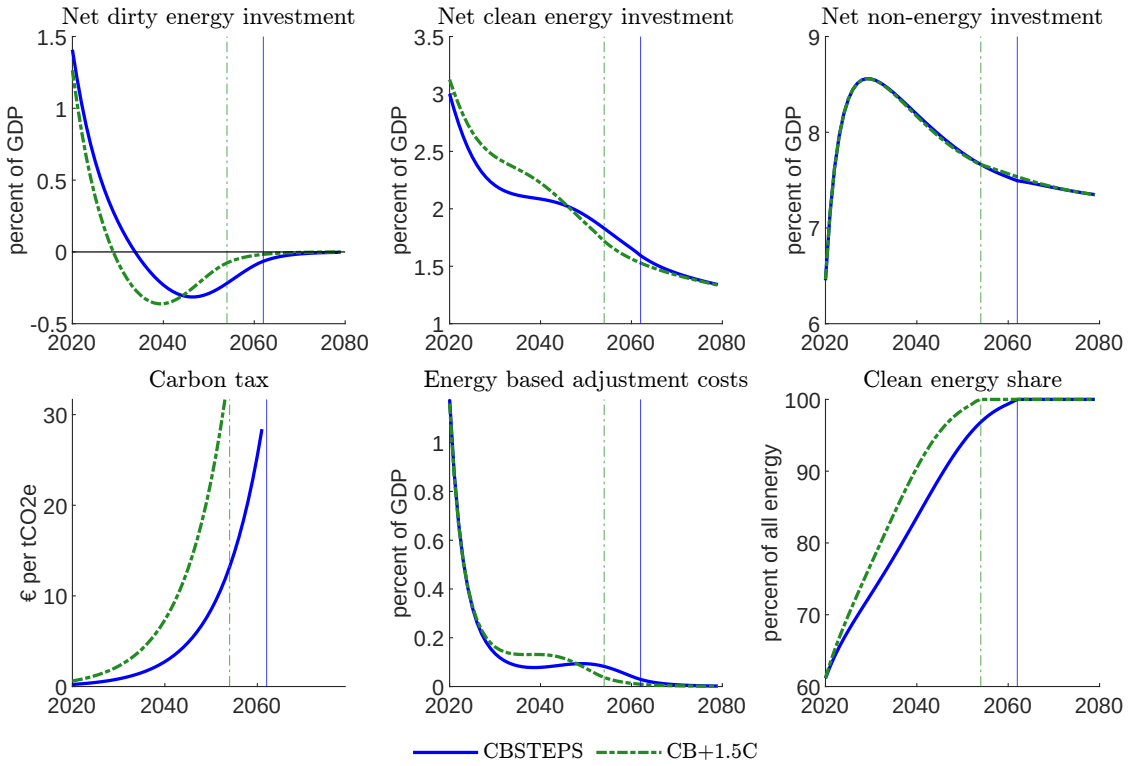
Meeting the CB+1.5°C targets require both economies to accelerate clean energy investment and dirty energy disinvestment, which appears more challenging in some ways for the EU than for India. For the EU, the additional net clean energy investment amounts to 0.5 percent of GDP annually from 2020-2030, and the increase in dirty disinvestment is even larger. As a result, the EU's energy-based adjustment costs more than double in the first decade, although after 2040 they are lower than in the CBSTEPS scenario. In India, the additional net clean energy investment compared to CBSTEPS amounts to only 0.25 percent of GDP in the 2030s. These additional costs are largely offset by avoided dirty net investments in the first decade, and the additional energy-based adjustment costs are not significant until the second decade. This result reflects that India has the time to plan for meeting growing energy needs.

Important differences in scenario outcomes across these economies arise from a combination of factors: different capital compositions, different stages of development, and different stringencies in the carbon budgets. As a result, the starting (real) carbon price necessary for CB+1.5°C is much higher for the EU (67 USD/tCO_2) than for India (2.2 USD/tCO_2). In India, even a low carbon tax—on top of any existing measures—slows an initial buildup in dirty capital. With CBSTEPS, the model indicates the EU would take more time than India to complete its transition, to spread out its dirty capital disinvestment costs. The pursuit

Figure 3: Transition paths under CBSTEPS vs. CB+1.5°C for the EU and India



(a) Transition paths EU



(b) Transition paths India

Source: Own estimation. By net investment we refer to the change in the respective capital stock $(K_t - K_{it-1})/Y_t$ for i $\in [c, d, n]$. Energy based adjustment costs refer to the share in overall adjustment costs contributed to changes in the clean and dirty energy capital stock $(\Omega_c + \Omega_d)/Y_t$.

of the 1.5°C climate target significantly accelerates the transition in both regions and aligns their dirty energy phaseouts to 2055. The more stringent budgets curtail emissions by more then 41 percent in the EU and 35 percent in India relative to CBSTEPS (see carbon budgets in Appendix B and Table 3 and Table 4 respectively).

5.1 Net-zero target versus carbon pricing

This section compares the trajectories of the **CBSTEPS** and the **CB+1.5°C** of Section (5) with two additional scenarios.

1. **NZ2050** reflects a scenario of meeting the net-zero technology constraint at 2050 without a corresponding cumulative carbon budget constraint. Hence, it requires all energy demands to be met with carbon-free sources by 2050, after which CO_2 intensive technologies can no longer be used. The NZ2050 scenario does not require any carbon pricing policy (see Section 3.2.2). The possibility to implement a net-zero target relies on the credibility of the social planner to commit to the future implementation. Additionally, the optimal path of this standalone net zero 2050 mandate heavily relies on the assumption of exogenous cost improvements.

2. **CB+1.5°C +NZ2040** models the path that meets the same carbon budget necessary to meet CB+1.5°C (or the share of the 1.5°C global budget) while also meeting a more ambitious net-zero target of 2040 (see Section 3.2.3). Adding the net-zero target by 2040 forces the social planner to use only renewable energy technology already by 2040 instead of 2050 as in the previous scenario (CB+1.5°C); a lower carbon price is thus required to meet the same carbon budget as CB+1.5°C.

Scenarios CBSTEPS, NZ2050 and CB+1.5°C are thus associated with different levels of total emissions as well as costs and prices. Scenarios NZ2050 and CB+1.5°C compare those results for a similar timing of the phaseout of dirty energy. Currently, no country has a pure net-zero technology mandate, since most countries have some interim objectives (e.g., reaching 25 percent of renewable electricity by 2030). Hence, in practice, most NDC formulations recognize the importance of interim targets (Climate Watch, 2024). Another caveat of the NZ2050 scenario is that, due to the delay in investment it causes, the technological progress is likely to occur more slowly in a context where technological progress exhibits learning-by-doing effects (which we currently ignore due to our assumption of exogenous clean catch-up growth).

Overall, the NZ2050 scenario serves as an illustrative example of a forward-looking technology-focused mandate without additional direct incentives for reducing emissions

along the way. [15] Scenarios CB+1.5°C and CB+1.5°C +NZ2040 then allow for a comparison of the cost-effectiveness of the overlapping net-zero target, while maintaining the same carbon budget. The latter scenario is essentially the combination of the cumulative energy emissions targets and net zero pledges.

5.2 NDCs and transition paths

Figure 5 illustrates the transition paths under the different scenarios for the EU and India calibrations. The blue solid line shows our baseline scenario CBSTEPS; the orange dotted line plots NZ2050; the green, dot-dashed line shows the CB+1.5°C scenario; and the red long dashed line shows CB+1.5°C +NZ2040. The vertical lines show the dates when the carbon budget becomes binding (and dirty energy is phased out) in each scenario.

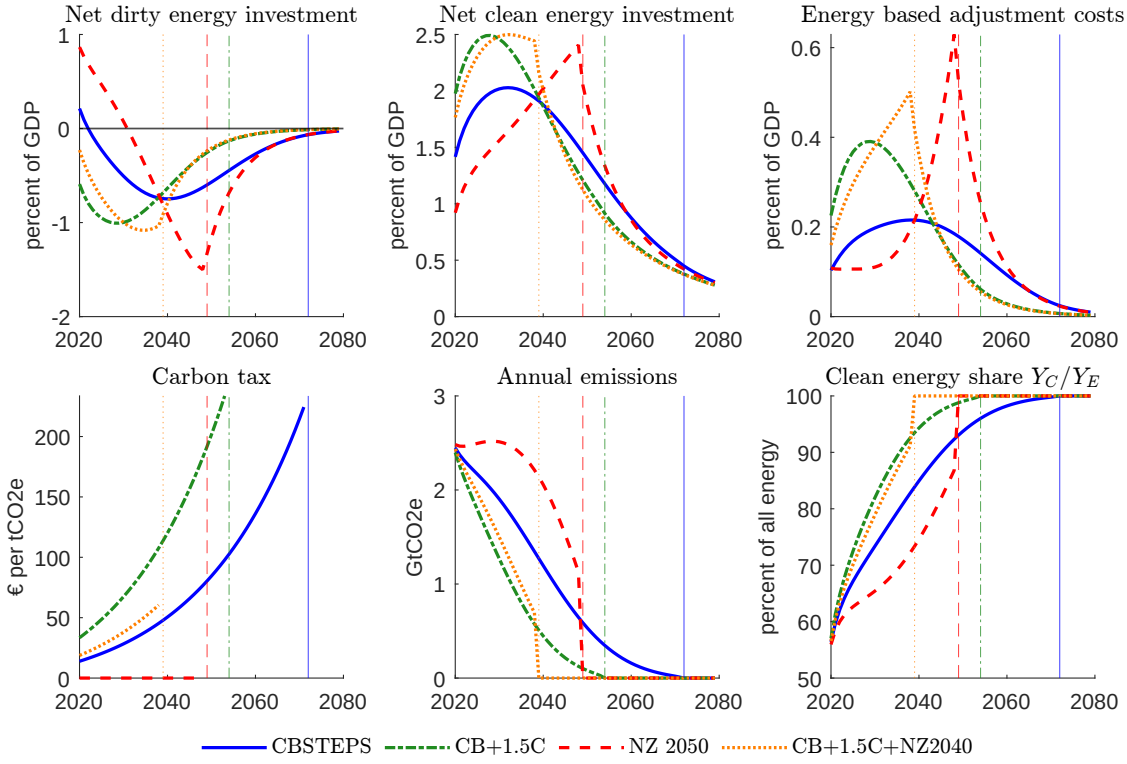
For the EU in particular, the simple net-zero (NZ) 2050 scenario allows for higher initial dirty energy investments compared to the cumulative carbon budget (CB) + 1.5°C scenario. In the NZ2050 scenario, the EU postpones its disinvestment activities and maintains its dirty capital; net dirty energy investment remains almost 0.75 percentage points of GDP above CBSTEPS until 2040. From 2040, it therefore needs to fall much more sharply to reach net zero by 2050. By contrast, the EU's clean energy investments ramp up quickly in all scenarios, but the cumulative carbon budget scenario (CB+1.5°C) sees a faster and more substantial acceleration compared to the NZ2050 pathway. If no carbon pricing is applied, as is the case in NZ2050, net clean energy investment even remains about 0.5 percent of GDP below the CBSTEPS scenario in the early years.

Energy-based adjustment costs for the EU increase gradually for CB+1.5°C and CB+1.5°C +NZ2040, peaking around mid-century when the energy transition is most intense. The CB+1.5°C +NZ2040 scenario exhibits higher adjustment costs during that period, reflecting the rapid phase-out of fossil fuels. Unlike more aggressive decarbonization pathways, NZ2050 allows for a slower transition in the beginning, meaning that adjustment costs even decrease until 2030. However, starting in 2040, adjustment costs surge and peak around 2050, aligning with the deadline for full decarbonization. At their peak adjustment costs are even 20 percent higher than in the CB+1.5°C +NZ2040. Because the NZ2050 scenario does not impose strong early constraints on emissions, businesses and industries face less economic pressure in the short term. However, this also means that the transition occurs later, leading to higher stranded assets in the long run and to much larger use of emissions.

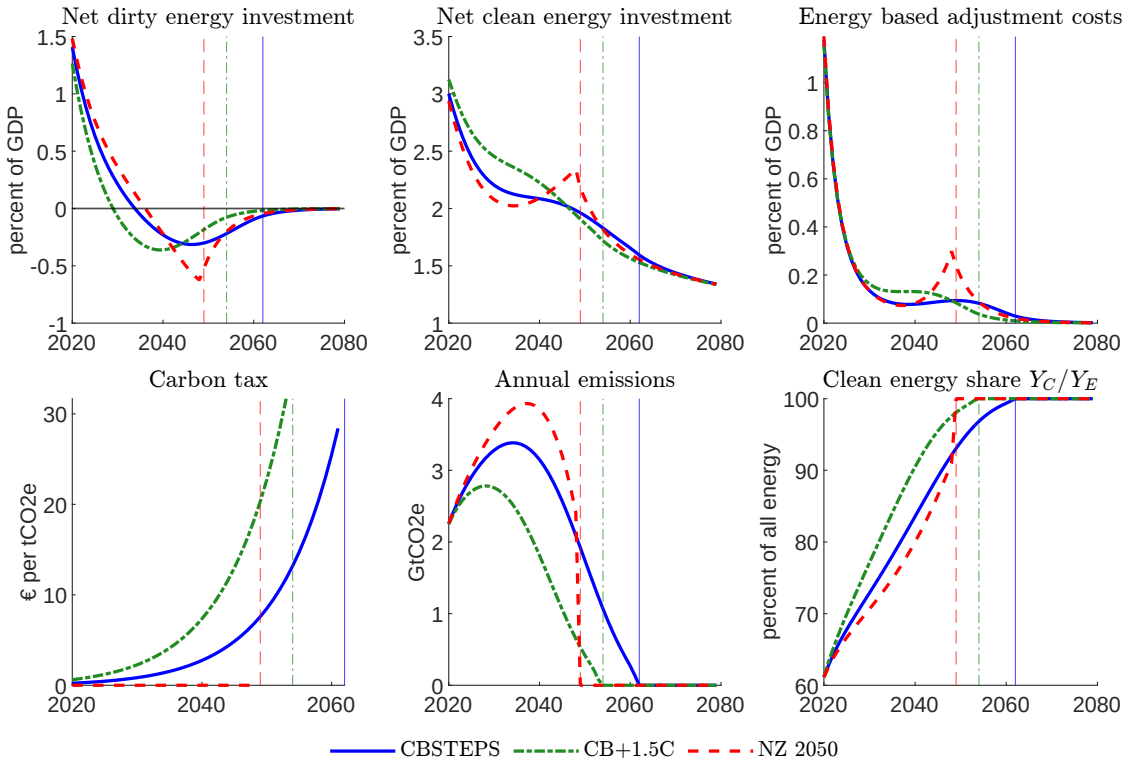
While the NZ2050 pathway allows for less costly adjustment in the short-term, it leads

[15] Broadly it resembles policies such as Ethiopia's ban on gas-powered private vehicles or the EU's planned 2035 phaseout of combustion-engine cars.

Figure 4: Transition paths under different NDC policies for the EU and India



(a) EU



(b) India

Source: Own estimation. By net investment we refer to the change in the respective capital stock $(K_t - K_{it-1})/Y_t$ for i $\in [c, d, n]$. Energy based adjustment costs refer to the share in overall adjustment costs contributed to changes in the clean and dirty energy capital stock $(\Omega_c + \Omega_d)/Y_t$.

to higher economic disruptions later on due to the delayed nature of clean energy investments. In contrast, more aggressive policies (such as CB+1.5°C) front-load costs but provide a smoother and more predictable transition to a low-carbon economy. Topping up the CB+1.5°C scenario with a net zero by 2040 constraint increases the level of economic disruption slightly right before the carbon budget becomes binding.

For India the more ambitious policy scenarios represent less of an acceleration of its transition, as compared to the EU, so the changes to its pathways are less pronounced. These differences can in part be observed by the distances between the vertical lines, representing the phase-out years The STEPS carbon budget of 98 $GtCO_2e$ for energy-related use (blue line) is almost identical to the 97 $GtCO_2e$ associated with the NZ2050 target (dashed red line), but the time paths of emissions are quite different.

Overall, investment dynamics in India broadly mirror those of the EU, but differ in both magnitude of clean energy investment and in the trajectory of dirty energy investment. In all policy scenarios, net dirty energy investment in India begins at a slightly higher level of roughly 1.3 percent of GDP. Furthermore, it remains positive until at least 2030, and subsequent disinvestment needs of between 0.5 and 1 percentage points of GDP are consistently lower than in the EU. By contrast, clean energy investment is consistently higher in India, averaging 1–1.5 percentage points more than in the EU, and exceeding dirty energy investment throughout the entire transition. Owing to India's higher growth rate, a sustained build-up of energy capacity is required during the transition to maintain aggregate production.

5.3 NDCs and economic welfare along the transition

Tables 3 and 4 compare important summary outcomes across all scenarios considered for the EU and India, respectively. The outcomes include the fossil phase-out year, cumulative emissions, present-value carbon price required, stranded assets, cumulative adjustment costs, and economic welfare changes. Also included are scenarios based on high adjustment costs (Ω^{high}), which are discussed in more detail in Section 5.4.

Three dimensions of transition costs are presented. Stranded assets are the value of dirty capital remaining in the economy in the year when fossil energy is phased out. Average adjustment costs are measured as the annual energy-related adjustment costs as a share of GDP incurred through 2060. Our measure of welfare is the percentage variation in consumption between 2020 and 2060 that would compensate the agent in any other scenario to achieve the same utility as in the CBSTEPS scenario.[16] It can thus be considered economic welfare, since the values of emissions changes are excluded. Welfare changes under

[16]For details of the calculation of transitional welfare see Appendix B.

alternative policy scenarios are reported in percentage terms relative to the corresponding reference scenario, CBSTEPS or CBSTEPS Ω^{high}, in the case of the sensitivity analysis.

For the CB scenarios, cumulative emissions are the carbon budgets the social planner tries to implement. The carbon budget for the CBSTEPS scenario is backed out by the emission projections of the climate action tracker (for details of the construction see below Appendix B). For the NZ2050 scenarios the emission reductions are a model outcome.

Table 3: Economic welfare comparison between transition scenarios in the EU

EU Scenario	**Phase -out year**	**Cumulative emissions ($GtCO_2e$)**	**CO_2 Price (EUR/ton)**	**Stranded assets $\frac{K_D(\bar{T})}{Y(\bar{T})}$**	**Avg. adj. costs $\frac{\Omega_E}{Y}$ to 2060 (%)**	**Δ Economic welfare through 2060 (% change from CBSTEPS scenario)**	
						Ω^{base}	Ω^{high}
CBSTEPS	2073	51	28.30	0.76	0.18		
CBSTEPS Ω^{high}	2062	51	57.33	8.10	0.39	-2.11	
NZ2050	2050	63.3	0	14.40	0.23	-0.02	
NZ2050 Ω^{high}	2050	61.4	0	20.14	0.39		-0.01
CB+1.5°C	2055	30	67.37	1.46	0.23	-0.27	
CB+1.5°C Ω^{high}	2047	30	129.70	10.36	0.50		-0.54
CB+1.5°C +NZ2040	2040	30	37.93	9.37	0.24	-0.33	
CB+1.5°C +NZ2040 Ω^{high}	2040	30	93.76	15.38	0.49		-0.58

Table 4: Economic welfare comparison between transition scenarios in India

India Scenario	**Phase -out year**	**Cumulative emissions ($GtCO_2e$)**	**CO_2 Price (USD/ton)**	**Stranded assets $\frac{K_D(\bar{T})}{Y(\bar{T})}$**	**Avg. adj. costs $\frac{\Omega_E}{Y}$ to 2060 (%)**	**Δ Economic welfare through 2060 (% change from CBSTEPS scenario)**	
						Ω^{base}	Ω^{high}
CBSTEPS	2063	98	0.84	2.26	0.18		
CBSTEPS Ω^{high}	2062	98	1.16	8.42	0.34	-3.63	
NZ2050	2050	96.9	0	11.46	0.21	-0.06	
NZ2050 Ω^{high}	2050	84.2	0	13.89	0.36		-0.11
CB+1.5°C	2055	63	2.26	2.02	0.19	-0.07	
CB+1.5°C Ω^{high}	2052	63	3.66	7.73	0.36		-0.12

Note: Scenarios containing Ω^{high} correspond to the high adjustment cost case ($c_i = 20$). All other scenarios use $c_i = 5$ for $i \in [c, d, n]$.

For the EU calibration, the CBSTEPS carbon budget for energy emissions equals 51 $GtCO_2e$, and optimally allocated over time, it would require a 28 euro/ton CO_2 price in 2030, causing dirty energy to phase out in 2073. Requiring that phase out to occur by 2050 (NZ2050)—a 23-year acceleration of the transition—with only a net-zero technology

constraint (and zero carbon price) would allow emissions to accumulate to 23% above CBSTEPS, with minimal change to welfare. Stranded assets, on the other hand, would increase significantly.

The 1.5°C-aligned target for the EU would be associated with a carbon budget of 30 $GtCO_2e$, or a 41% reduction below CBSTEPS, achieved with a 67 EUR/tCO_2 price in 2030. The associated economic welfare costs of this additional ambition are 0.27% of the present value of consumption. Stranded assets double relative to CBSTEPS but remain modest, and average adjustment costs are 28% higher, a similar amount to those with NZ2050. The final policy combining the 30 $GtCO_2e$ carbon budget with a more ambitious 2040 net-zero target lowers the carbon price by 44% but significantly increases stranded assets compared to a phaseout date in 2055.

In the India calibration, some notable differences emerge. Mandating net zero by 2050—a 13-year acceleration of the transition—without explicit carbon pricing (NZ2050) entails a slight (1%) reduction in emissions from CBSTEPS, rather than an increase as occurs in the EU calibration. At the same time, the small associated decrease in economic welfare and larger increases in stranded assets and adjustment costs remain similar to those for the EU, due to the postponement of disinvestment in dirty assets.

A comparison of the 1.5°C scenarios reveals both similarities and differences across regions. In both cases, the optimal phase-out date is 2055, but India can achieve this with a present-value carbon price of $2. The economic welfare cost of additional ambition is less than 0.1%, and stranded assets actually fall slightly relative to CBSTEPS. This outcome reflects both lower initial accumulation of dirty capital and earlier investment in clean energy capacity. The modest economic costs should also be weighed against the value of the additional emission reductions, which can have greater co-benefits in the context of an emerging economy like India that bears a heavy burden from air pollution.[17]

Taken together, the comparisons underscore that even moderate carbon pricing can smooth investment dynamics, reduce stranded assets, and prevent a "double transition" of the energy capital stock. In contrast, a simple net-zero target without emission pricing tends to result in a front-loading of emissions: the absence of carbon pricing allows industries to exploit the short-term economic advantage of dirty energy technologies, delaying clean energy investments and necessitating a rapid catch-up phase later. Such a pathway risks inefficient capital allocation and a more abrupt transition, which may heighten economic and social disruptions.

[17]In India, health costs associated with local air pollution ($PM_{2.5}$) are severe, reducing average life expectancy by 5.3 years nationally and by almost 12 years in Delhi (Air Quality Life Index, 2023).

5.4 Sensitivity to adjustment costs

Tables 3 and 4 also compare summary outcomes from the policy scenarios for high ($c_i = 20$) adjustment costs (Ω^{high}) as well to those from the baseline calibration ($c_i = 5$) (Ω^{base}).Adjustment costs still accrue to net investment; higher marginal adjustment costs imply more convex costs to deviating from the growth and maintenance trend, hence replacement investment is still free but depreciation is more costly.[18]

We observe that, for equivalent policy targets, higher adjustment costs raise the required carbon prices, stranded assets, average adjustment costs, and economic welfare costs. For example, in the EU calibration, when comparing the optimal path under the same carbon budget as in CBSTEPS but with higher adjustment costs (CBSTEPS Ω^{high}), dirty energy is optimally phased out even earlier—by 2062 instead of 2073—and the additional carbon price required to implement the carbon budget doubles, reaching 57 EUR/tCO_2e. This acceleration of the transition under higher adjustment costs suggests some interesting dynamics: at the same time that ramping up clean energy is more costly, it is also more costly to decrease fossil-reliant capital stocks, meaning the carbon budget is depleted more rapidly. Unsurprisingly, average annual energy-related adjustment costs more than double to 0.39 percent of GDP, and stranded assets increase more than ten fold, as higher costs lead the planner to spread out the depreciation of dirty capital over a longer period. From an economic welfare perspective, the costs of achieving CBSTEPS is more than 2 percentage points larger in consumption values with the high adjustment cost parameterization.

In the India calibration, the effects of higher adjustment costs on the CBSTEPS scenario are similarly to increase stranded assets, average adjustment costs, and particularly economic welfare costs. As a faster-growing economy, the additional costs to building both clean energy and non-energy stocks are more pronounced. However, higher adjustment costs have only small effects on the optimal phase-out year and the carbon price required.

Higher adjustment costs seem to have different impacts on the incremental effects of NZ2050 relative to CBSTEPS. For the EU calibration, the increase in cumulative emissions is a bit smaller, as is the increase in stranded assets. With the India calibration, net-zero by 2050 now leads to significant (15%) reduction in cumulative emissions relative to CBSTEPS, and a smaller increase in stranded assets (6 percentage points of GDP, as opposed to 9 with baseline adjustment costs).

When comparing the scenarios with higher climate ambitions (CB+1.5°C) without and with higher adjustment cost parameters, the effects appear similar to those with the CBSTEPS scenarios. The dirty phaseout date is accelerated, carbon prices are driven upwards,

[18]The only change in the model that we do is to change the adjustment cost parameter from c=5 to c=20, all other parameters stay the same as in our baseline calibration for both jurisdictions.

and stranded assets increase, but not as strongly. The incremental losses in economic welfare from greater ambition are modestly higher with higher adjustment costs: 0.25 percentage points for the EU and 0.05 percentage points for the India calibration.

Figures 5a and 5b illustrate some of the underlying processes for these summary changes by showing key transition paths for the CB+1.5°C scenarios. In both economies, higher adjustment costs temper large changes in investments; for the EU, this means less pronounced dirty disinvestment and clean investment early on, requiring more to be continued later. For India, higher adjustment costs mean less build-up of dirty assets early on, but also less investment more generally, resulting in lower emissions in the first two decades.

Overall, both parameterizations show that stronger climate ambitions cause modest welfare losses, more stranded assets, and higher adjustment costs. Higher adjustment costs amplify economic burdens of any transition path, also because non-energy investment costs increase, which helps explain why the increases in the incremental costs of additional ambition remain modest. Qualitatively, the adjustment cost parameter does not alter the shape of the transition, but higher costs make any rapid changes in economies more difficult.

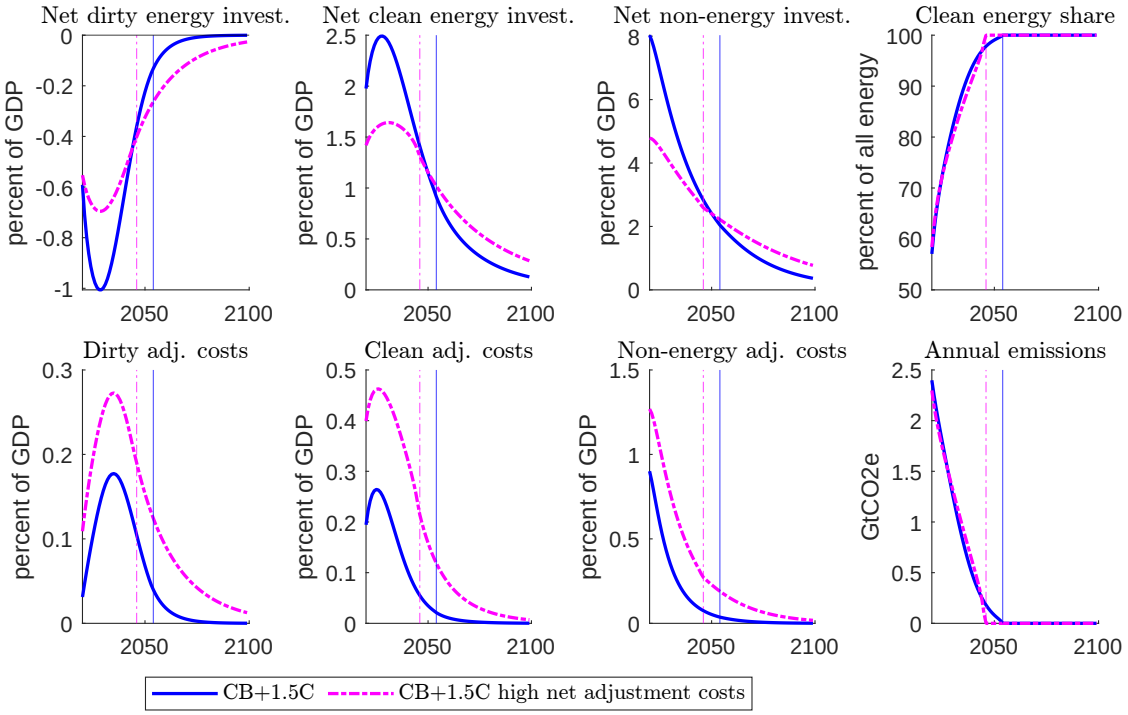
6 Conclusion

Energy-related capital will play a crucial role in the green transition. Fossil-fueled energy needs to be phased out over time. Although carbon-dependent energy sources currently enjoy a cost advantage, the clean energy premium is rapidly declining, and for major technologies is expected to converge by 2030. Since much energy-related capital is long-lived and costly to adjust, investment decisions in anticipation of these needs have already brought the transition underway. We calculate that clean energy investments have been outpacing dirty energy investments in advanced and emerging economies alike. However, these economies face some different challenges for the transition.

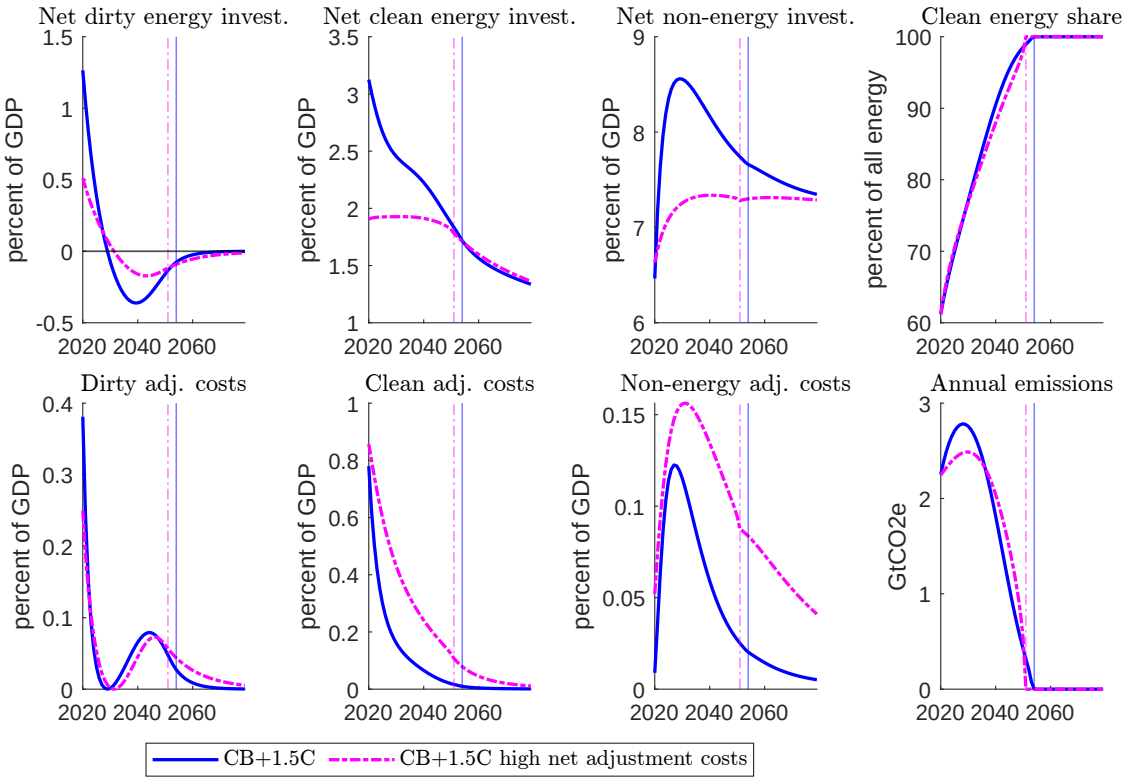
An advanced economy like the EU has a larger share of legacy capital that is associated with dirty energy, as well as a larger historical responsibility to reduce its emissions. Its challenge is how to phase down its productive dirty capital stocks and more rapidly replace them with clean energy, while managing the adjustment costs of both in a moderate-growth environment. An emerging economy like India, which is growing more quickly, has relatively less legacy capital, and can take advantage of technological improvements to build up its energy capital biased towards clean. Excess investments in dirty capital would lead to higher adjustment costs from a future phaseout, even without stringent climate policy, due to the rapidly evolving technological landscape and longevity of energy based infrastructure.

Our best estimates indicate that, for either an advanced economy like the EU or an emerging one like India, more ambitious climate policy consistent with remaining within

Figure 5: Transition paths for CB 1.5°C scenario under baseline ($c_i = 5$) and high ($c_i = 20$) adjustment cost parameters



(a) EU



(b) India

Source: Own estimation. By net investment we refer to the change in the respective capital stock $(K_t - K_{it-1})/Y_t$ for i $\in [c, d, n]$. Energy based adjustment costs refer to the share in overall adjustment costs contributed to changes in the clean and dirty energy capital stock $(\Omega_c + \Omega_d)/Y_t$.

the 1.5°C target seems to entail only modest welfare costs, given anticipated technological progress and capital adjustment horizons. This suggests that a well-designed transition strategy can balance economic stability with ambitious climate objectives, ensuring both environmental sustainability and economic resilience.

Underestimating adjustment costs has larger implications for business-as-usual welfare than for the incremental costs of greater ambition for a quicker transition. The larger adjustment costs turn out to be, the higher is the required carbon price to meet the cumulative budget and to accelerate the phaseout. Greater clarity from the empirical macroeconomics literature on the form and magnitude of adjustment costs would help inform energy transition strategies.

With the detailed new estimates of energy-related capital stocks and clean technology premiums we have built, future research could advance macroeconomic modeling of the transition by further disaggregating the relevant capital stocks by sector. Evidence suggests that clean technologies already have a productivity advantage in the power sector and will also soon dominate for heating. However, the major transportation technologies are expected to have a slower productivity convergence, and dirty energy will have a more enduring advantage in industrial applications. Our investment data indicate that the clean transition is particularly lagging in the transportation sector. Industrial capital stocks, by value, are composed largely of clean assets compatible with electrification. However, within these categories, certain forms of dirty capital may be harder to replace with clean applications. Future research could shed light on the role of hard-to-abate sectors on transition costs and strategies.

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A Model equations

This section provides an overview of the most relevant features for our analyis, a complete version of the model can be found in Burda et al. (2025).

Environment. The dirty technology causes greenhouse gas emissions, which accumulate in the atmosphere according to:

$$G_t = G_{t-1} + \mu Y_{dt},$$

where μY_{dt} is the flow of emissions at time t and G_t is the stock of accumulated emissions. The parameter μ represents the emissions intensity of dirty energy output. The cumulative carbon budget is $\bar{G}$, measured in $G_t CO_2 e$. In the numerical model, the carbon budget will be scaled such that the constraint is that cumulative emissions, relative to the carbon budget, do not exceed one:

$$\frac{G_T}{\bar{G}} \leq 1$$

and emissions accumulate as follows:

$$\frac{G_t}{\bar{G}} = \frac{G_{t-1}}{\bar{G}} + \frac{\mu}{\bar{G}} Y_{dt}$$

The parameterization of μ should equate

$$\mu = \frac{Y_{e,2020}}{Y_{2020}} \frac{Y_{2020}}{Y_{d,2020}}$$

where E is annual energy related emissions of $CO_2 e$.

Technological Progress. Total factor productivity of technology i grows at exogenous rate m_i:

$$M_{it} = M_{it-1}(1 + m_i). \tag{5}$$

Because of the different production technologies, growth is unbalanced in this economy. Following Acemoglu and Guerrieri (2008) and Burda et al. (2025), we assume that $\frac{m_N}{\alpha_N} < \frac{m_C}{\alpha_C}$ and $\epsilon < 1$. Under these assumptions, the long-run growth path takes the shape described in Section Burda et al. (2025).

Clean catch-up growth. For our baseline scenario we choose the scenario of Burda et al. (2025) including catch-up growth in the clean technology. Many technologies which produce energy without greenhouse gas emissions relatively recent and thus not as mature as conventional energy production technologies. As a result, they are not currently cost competitive but they improve at much faster rates. As shown in Table 1 from about 2030 on clean energy has caught up with dirty energy production. However, we assume that clean technology does not overtake dirty technology but both technologies stay equally productive until the end of the simulation. We model catch-up growth in a simple manner, by assuming that TFP in the clean sector approaches a long-run path with a constant rate. During the

transition the distance to this path shrinks at a constant rate. In particular we define the catch-up factor

$$a_{ct} = 1 - \frac{b_M}{(1+\kappa_M)^t}$$

where $\lim_{t\to\infty} a_{ct} \to 1$, κ_M is the catch-up rate and b_M determines the initial distance to the long-run constant-rate growth path. The level of TFP then follows

$$M_{ct} = a_{ct}\tilde{M}_{ct} \tag{6}$$

with

$$\tilde{M}_{ct} = (1+m_C)\tilde{M}_{ct-1}.$$

This economy still approaches the unbalanced growth path. We calibrate the model to the EU and India capturing their different path of clean technological catch up.

B Calculation Details Scenario Comparison Table

B.1 Calculation of energy-technology parameters

We measure the relative performance of "dirty" and "clean" technologies by the ratio

$$\frac{M_d}{M_c} \equiv \frac{\text{unit–cost proxy for dirty}}{\text{unit–cost proxy for clean}},$$

so that values above (below) one indicate a dirty (clean) productivity advantage. Across four sectors—electricity generation, heating, transport, and industry—dirty technologies are, on average, $26-37\%$ more productive than clean ones in the EU and $18-23\%$ in India in 2021/22. By 2030, this dirty advantage largely disappears in both economies (see Table 1). For each sector we compute $\frac{M_d}{M_c}$ in two ways. First, we form simple dirty–to–clean ratios using one of the most prevalent clean and dirty technologies in that sector (see Table 5). Second, we aggregate sectoral ratios to an economy-wide index using weights given by each sector's share in total energy-related greenhouse-gas emissions. See Table 8 for the respective shares.

Table 5: Summary of clean and dirty technologies used for productivity comparisons across sectors

Sector	Clean technologies	Dirty technologies
Electricity	Nuclear; solar PV; onshore wind; offshore wind	Coal; gas CCGT
Heating	Air-source heat pumps	Gas boilers
Transport	Battery-electric vehicles (BEV); hydrogen fuel-cell vehicles (down-weighted)	Gasoline ICEV; diesel ICEV; hybrids
Industry (steel)	Hydrogen-based DRI with VRE/grid electricity and storage	Fossil-based crude steel

Electricity. In power generation the unit–cost proxy is the *value-adjusted levelised cost of electricity* (VALCOE, USD/MWh) from the IEA's Stated Policies Scenario (CBSTEPS) (International Energy Agency, 2023b). VALCOE augments LCOE with estimates of energy, capacity, and flexibility value, yielding a system-value metric of competitiveness. The clean cluster comprises nuclear, solar PV, onshore wind, and offshore wind; the dirty cluster comprises coal and gas CCGT. We construct weighted average VALCOEs for each cluster using each technology's share in electricity generation (EU: Council of the EU and IRENA; India: Ember).[19] Comparing the cluster means yields a *clean* advantage already in 2021/22: dirty electricity is only 0.57× as productive as clean in the EU and 0.89× in India. Because we work with CBSTEPS (which assumes no new climate policies beyond those in place), the relative cost of gas CCGT in India falls faster than that of clean options, narrowing the clean advantage by 2030 in the electricity sector alone. For details on the calculation see Table 6. However, when weighting by sectoral emission shares from Climate Watch (2023)—which aggregates electricity and heating sector emissions—the clean technology advantage increases as well until 2030.

Heating. We compare the levelised cost of heating (LCOH) for air-source heat pumps (clean) with gas boilers (dirty). For 2022 we use IEA data on unsubsidised annual costs for households in advanced economies under CBSTEPS (see Fig. 1.22 in International Energy Agency (2023c)). For 2030 we apply the European Heat Pump Association's projected 34%

[19]For the EU, electricity-generation shares are taken from the Council of the EU; to split onshore and offshore wind we use IRENA (`https://www.irena.org/Energy-Transition/Technology/Wind-energy`). For India we use Ember (`https://ember-climate.org/countries-and-regions/countries/india/`). Shares observed in 2022 are used to weight technologies in both 2021/22 and 2030.

Table 6: Calculation of dirty technology advantage in the electricity sector in the EU and India

	EU 2022				**EU 2030**			
Technology	VALCOE (USD/MWh)	Share (%)	Weighted VALCOE	$\text{VALCOE}_i \in$ (c,d)	VALCOE (USD/MWh)	Share (%)	Weighted VALCOE	$\text{VALCOE}_i \in$ (c,d)
Clean								
Nuclear	160	22	77	114	130	22	63	99
Solar PV	80	8	13		85	8	14	
Wind onshore	65	14	20		65	14	20	
Wind offshore	75	2	4		55	2	3	
	Clean share	**45**				**45**		
Dirty								
Coal	190	16	85	198		16	0	190
Gas CCGT	205	20	114		190	20	37	
	Dirty share	**35**				**35**		
VALCOE_c/ VALCOE_d		**0.57**				**0.52**		
	India 2022				**India 2030**			
Technology	VALCOE (USD/MWh)	Share (%)	Weighted VALCOE	$\text{VALCOE}_i \in$ (c,d)	VALCOE (USD/MWh)	Share (%)	Weighted VALCOE	$\text{VALCOE}_i \in$ (c,d)
Clean								
Nuclear	70	3	15	55	70	3	15	50
Solar PV	45	5	20		40	5	18	
Wind onshore	60	4	20		50	4	17	
Wind offshore	135				90			
	Clean share	**11**				**11**		
Dirty								
Coal	60	74	58	62	50	74	48	51
Gas CCGT	120	3	4		70	3	2	
	Dirty share	**77**				**77**		
VALCOE_c/ VALCOE_d		**0.89**				**0.98**		

Notes: Lower VALCOE indicates improved competitiveness; ratios below 1 imply a clean advantage. "Share" is each technology's share in overall electricity generation of EU or India.
Sources: VALCOE—International Energy Agency (2023), *Global Energy and Climate Model Documentation 2023*, IEA, Paris. Electricity shares: EU—IRENA and Council of the EU infographic; India—Ember.

decline in heat-pump costs to LCOH, holding gas-boiler LCOH constant.[20] This implies a dirty disadvantage of 0.78 in 2030. Owing to limited data, we apply the same heating ratios to India in both periods.

Transport. The unit–cost proxy is the *levelised cost of driving* (LCOD) from National Renewable Energy Laboratory (NREL)'s Transportation ATB (2020, mid-range trajectory). Dirty technologies include gasoline and diesel ICEV (including hybrids); clean technologies include battery electric and hydrogen fuel-cell vehicles. The latter only has a niche market share. Averaging light-duty and medium/heavy-duty categories yields a dirty advantage of 1.73 in 2020, falling to 1.25 by 2030 as clean vehicles improve under the mid range scenario. We weight the average index to reflect the substantially larger market share of light-duty vehicles—98 percent of all vehicle sales—compared with only 2 percent for medium- and heavy-duty vehicles ACEA (2023). Light-duty vehicles also account for a smaller share of transport emissions (66 percent) relative to medium/heavy vehicles (34 percent) Fleck (2023). When weighting the average productivity index by these respective emission shares, we find that dirty transport retains a significant cost advantage: 46 percent in 2023, declining to 18 percent by 2030.

[20] EHPA market-conditions statistics: `https://stats.ehpa.org/home/market-conditions/`.

Table 7: Levelized Cost of Driving (2022$/mi): Mid-range vs Conservative Scenarios

Category	Duty	Technology	Mid range			Conservative		
			2023	2030	2050	2023	2030	2050
Dirty								
	Light duty	Gasoline	0.48	0.47	0.45	0.48	0.48	0.49
		Diesel	0.52	0.50	0.48	0.52	0.52	0.54
		Gasoline hybrid	0.47	0.45	0.42	0.47	0.47	0.48
	Medium/heavy duty	Diesel	1.20	1.10	0.95	1.20	1.12	1.11
		Diesel hybrid	1.22	1.12	0.95	1.22	1.20	1.15
		Total Average	0.78	0.73	0.65	0.78	0.76	0.75
		Total Average Weighted	0.74	0.69	0.62	0.74	0.72	0.72
Clean								
	Light duty	Battery Electric	0.42	0.37	0.32	0.42	0.37	0.36
		Hydrogen fuel cell	0.55	0.51	0.46	0.55	0.515	0.48
	Medium/heavy duty	Battery Electric	2.15	1.40	1.00	2.15	1.75	1.60
		Hydrogen fuel cell	2.25	1.70	1.47	2.25	2.15	2.05
		Total Average	1.34	0.99	0.81	1.34	1.20	1.12
		Total Average Weighted	1.07	0.82	0.68	1.07	0.96	0.90
Index unweighted (clean/dirty)			1.73	1.37	1.25	1.73	1.58	1.49
Index weighted (clean/dirty)			1.46	1.18	1.10	1.46	1.33	1.26

Notes: The data on levelized costs of driving is based on National Renewable Energy Laboratory (NREL). For the weighted total average we assume emission shares of 66 percent for light duty vehicles and 34 percent for medium/heavy vehicles based on Fleck (2023).

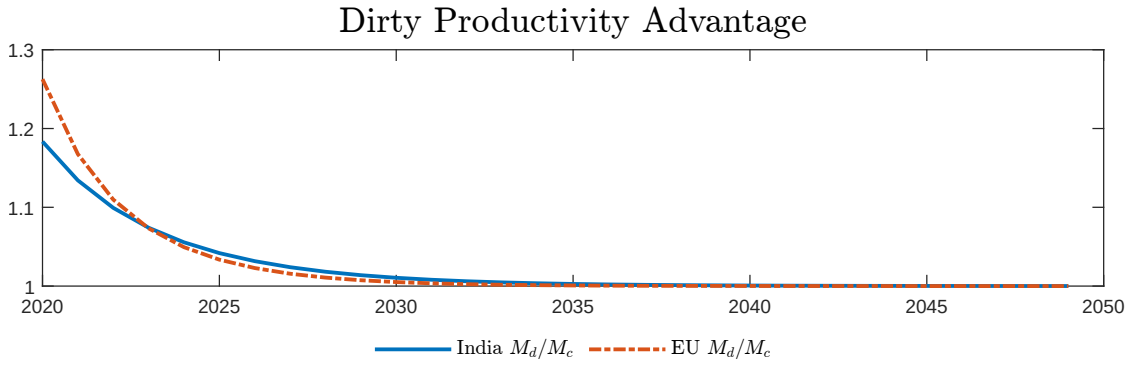
Industry (steel). We compare indicative production costs for crude steel via electrolytic hydrogen-based DRI (clean) with the current unabated fossil reference (dirty) using International Energy Agency (2023a) data. Clean-steel costs are constructed using the average of VRE and recent grid electricity prices, with additional hydrogen-storage costs to ensure an 80% minimum load. For the EU we use the Western Europe average whereas for India we proxy by China due to data limitations. Dirty costs use the "current reference" with recent fuel and electricity prices and a 5% cost of capital. In 2021/22 this implies dirty advantages of 2.27 (EU) and 1.39 (India). For 2030 we use IEA APS (Announced Pledges Scenario) cost projections for clean steel and compare them with the current reference for dirty steel, which reduces the dirty advantage to 1.50 (EU) and 1.10 (India).

Figure 6 illustrates how clean energy technology catches up with dirty energy technology but does not overtake it until the end of the simulation. Taken together, the sectoral evidence shows sizeable dirty advantages in transport and industry in 2021/22 that dominate the clean advantage already visible in power and (partly) in heating. Under baseline (CBSTEPS) technology progress, these dirty advantages shrink materially by 2030. The use of CBSTEPS scenario is conservative: stronger climate policies (carbon pricing, faster learning and deployment of clean technologies) would further tilt the ratios toward clean, particularly in electricity.[21]

Table 8: Energy sector CO_2-equivalent emissions by sector in 2020: India vs. EU

	India		**EU**	
Sector	**MtCO₂e**	**%**	**MtCO₂e**	**%**
Building	162	8	438	18
Electricity/Heat	1122	54	864	36
Manufacturing/Construction	509	25	351	15
Transportation	276	13	720	30
All sectors	2070		2373	

Figure 6: Development of the dirty productivity advantage in the EU and India



Note: The figure illustrates the evolution of the productivity advantage of dirty energy relative to clean energy in the EU and India under the stated policy scenario.

[21] See International Energy Agency (2023b), which reports substantially larger clean advantages in net-zero-compatible pathways.

B.2 Energy related capital stocks

B.2.1 Energy related investment in industry, transport and residential

Estimating the distribution of new investments in clean versus dirty energy technologies presents a significant challenge due to the limited availability of direct data sources. In order to approximate clean and dirty energy-related investment, annual industrial production data combined with export and import data is used as a proxy. We classify all products into clean and dirty energy according to the energy source they need to function. We use the AI tools MAi and ChatGPT to provide descriptions of each good's typical use and the type of energy it utilizes. To ensure a robust categorization into clean and dirty, we combine automated insights with human reasoning. Clean and dirty energy-related products can then be further classified into industrial, residential, heating, power and transport-related energy capital.

All products that require fossil fuel-related energy like diesel, gasoline, natural gas, fuel oil, or LPG are classified as dirty. All products that require the use of electricity or any direct use of renewable energy (solarthermal energy) are classified as clean. For electricity-based capital goods to become clean, only the electricity needs to be produced in an emission free way, but the capital goods themselves can still be used. For some product, the product description does not allow to determine whether the product is run on e.g. gasoline, natural gas, or electricity because from a technological standpoint both options are possible. For example, "Condensers for steam or other vapor power units" or "Pneumatic elevators and conveyors specially designed for agricultural use" could be run by fossil fuel or by electricity. In these cases we assume that a certain share of it is clean and dirty. Shares of clean and dirty of these double use goods are again classified with the help of AI tools MAi and ChatGPT combined with human reasoning.

In order to approximate investment into each technology taken within the EU and India we subtract exported and add imported energy related capital goods. Exports are not part of the domestic energy related capital stock but imported ones are. Therefore, the following calculation is carried out for each product in India and the EU in each year

$$\text{Investment}_{it} = \text{Sold production value}_{it} - \text{Exports value}_{it} + \text{Imports value}_{it} \tag{7}$$

All products are summed up for each year and clustered into clean and dirty at sectoral levels including industry, residential, power generation, transport and heating. Table 9 provides an overview on the classifications of different items.

Sector	Clean Examples	Dirty Examples
Transport	EVs, metro/rail (electrified), non-fossil fuels (e.g., green hydrogen); rail-related infrastructure	ICE vehicles using petrol/diesel/CNG/LPG
Heating	Electric heat pumps, solar thermal, district heat (non-fossil); electrified boilers and furnaces	LPG, biomass, coal, diesel, kerosene heaters; fossil-fuel-based boilers and furnaces
Power	Renewable and nuclear generation; distribution; battery-powered backup	Fossil-fired generation (coal, gas, oil); gas-related pipelines
Industry	Electrified machines, green hydrogen, biomass residues (high-efficiency systems)	Coal/gas-fired systems, diesel generators for backup power
Residential	Household appliances tied to electricity/batteries	Household appliances tied to coal, kerosene, LPG, biomass

Table 9: Examples of Clean vs. Dirty Technologies by Sector

In the PRODCOM dataset Eurostat provides data on industrial production data together with related external trade data for EU27 Eurostat (2025). We use the value of production sold during the survey period. The Prodcom data is obtained by the National Statistical Institutes (NSIs) who conduct a survey of enterprises. Eurostat calculates EU totals for $EU-27$ level from the national data at each year. The products included in the PRODCOM data set are based on national survey data and clustered around approximately 4000 headings representing manufactured products and some industrial services following NACE Rev.2 sectors categories. Prodcom data is available for the period of 2003-2024.

A similar procedure was applied to India. For India's domestic production data we use the Annual Survey of Industries (ASI) of the Ministry of Statistics & Programme Implementation (MOSPI) which provides product level output data based on ASICC (Annual Survey of Industries Commodity Classification) and after 2011 on NPCMS (National Product Classification for Manufacturing Sector). For India we use the Annual Survey of Industries (ASI) get an estimate of all energy related production value in India. To account for exported and imported energy capital goods we use COMTRADE data of the United Nations (2025). COMTRADE data uses the HS product classification system, which differs from the classifications NPCMS and ASICC used in the industrial survey. According to our knowledge,

no concordance table exists, therefore we classify the product categories separately and calculate investment not at the product level but only at the sectoral level.

We suggest that using the formula production plus imports minus exports offers a practical estimate for domestic energy investment. However, this methodology has several notable shortcomings. One key limitation is the ambiguous treatment of spare parts and intermediate goods. We include both in the calculation, but this is an ambiguous assumption. On the one hand, spare parts and intermediate goods may be used to repair and maintain existing capital stock, but they can also be used to produce another good. Since we cannot trace the value chains our measure of energy related investment does not completely align with value-added measures such as GDP. There are also challenges specific to measuring energy-related capital stocks. The term "capital" in macroeconomics lacks a precise definition, which means that we may not capture certain components of capital for example our way of constructing energy related capital may not reflect the full value of e.g. existing energy producing capital such as power plants, pipelines or industrial boilers. Furthermore, the time series data available for energy-related production, exports, and imports are short, which poses well known challenges for the perpetual inventory method. This method is also sensitive to assumptions about depreciation rates and the choice of starting points, introducing additional uncertainty into the results.

B.3 Energy related capital stocks based on the perpetual inventory method

To produce a time series for the energy-related capital stock we use the perpetual inventory method. The Perpetual Inventory Method (PIM) conceptualizes an economy's capital stock as an inventory. This inventory grows through investments forming the capital stock.[22] Once an investment is added to the inventory, it remains indefinitely, providing services to the owner. The service quantity is highest immediately after the investment and diminishes over time. The depreciation rate represents the reduction in capital stock per period. Although the investment's value decreases over time, it never reaches zero, implying that the investment has a perpetual utility. The main equation for the PIM is:

$$K_{it} = (1 - \delta_i) \times K_{i,t-1} + I_{it} \tag{8}$$

where

- K_{it} = capital stock at time t for category i (or asset)
- δ_i depreciation rate

[22]For these definitions we rely heavily on Berlemann and Wesselhoft (2012).

- I_{it}= investment at time t for category i

with i including the investment series described above.

- Industry/residential: clean, dirty
- Transport: clean, dirty
- Power: clean, dirty

Since equation 10 can be iterated backwards obtaining the following equation

$$K_{it} = \sum_{t=2000}^{2020} (1 - \delta_i)^{(2020-t)} \times I_{it} \tag{9}$$

it can be said that the capital stock in period t is a depreciated sum of the history of previous investments.[23]

We choose the "disequilibrium approach" to estimate an initial capital stock, which is the most common method used in the literature. Proponents of this approach contend that an economy is usually not in its long-term equilibrium. Hence, it is more realistic to assume that economies are generally on their adjustment path towards equilibrium. During this adjustment process, investment and capital accumulation typically follow a systematic pattern. Consequently, the growth rate of the capital stock can be approximated by the growth rate of investments (g_i).

$$K_{i,0} = \frac{I_{i,1}}{g_i + \delta_i} \tag{10}$$

In most cases, authors employing this approach use a 10 to 20-year average of investment growth. However, there are several approaches on how to estimate the initial capital stock see Barrot (2016). We determine the capital stock for each of the described categories i, assuming common depreciation rate taken from the literature: Depreciation rates for transport and industry are based on official BEA deprecation rates of Fraumeni (1997) (Also see Appendix in Feenstra et al. (2015)). Power sector depreciation rates are taken from Arkolakis and Walsh (2023)

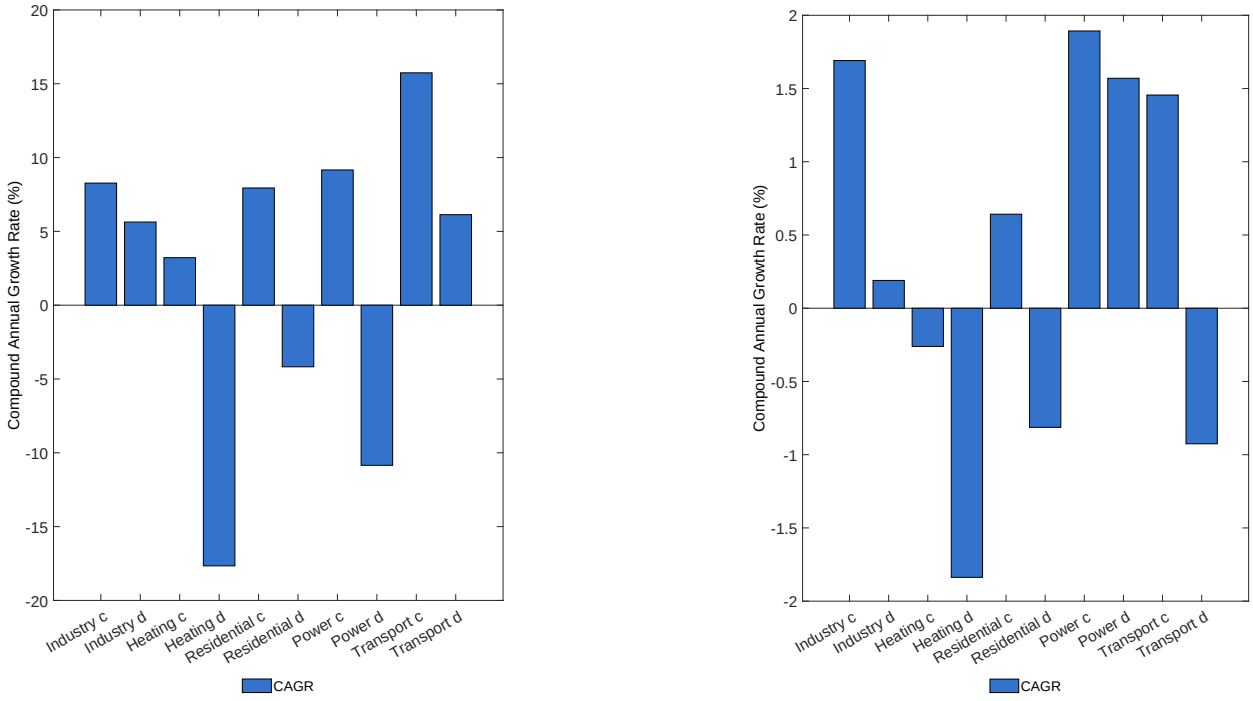
[23]For the EU data is only available from 2003 onwards.

Table 10: Geometric Depreciation Rates assumed for different categories

Asset	Depreciation Rate (%)	Energy Category	Source
Power sector	3.1	Power	Arkolakis and Walsh (2023)
Transport equipment	18.9	Transport	Fraumeni (1997)
Other machinery and assets	12.6	Industry	Fraumeni (1997)

We make the assumption that the growth rate of investment g_i of each category is the compound annual growth rate between 1990-2023 (see Figure 7).

Figure 7: Growth rates of energy-related investment



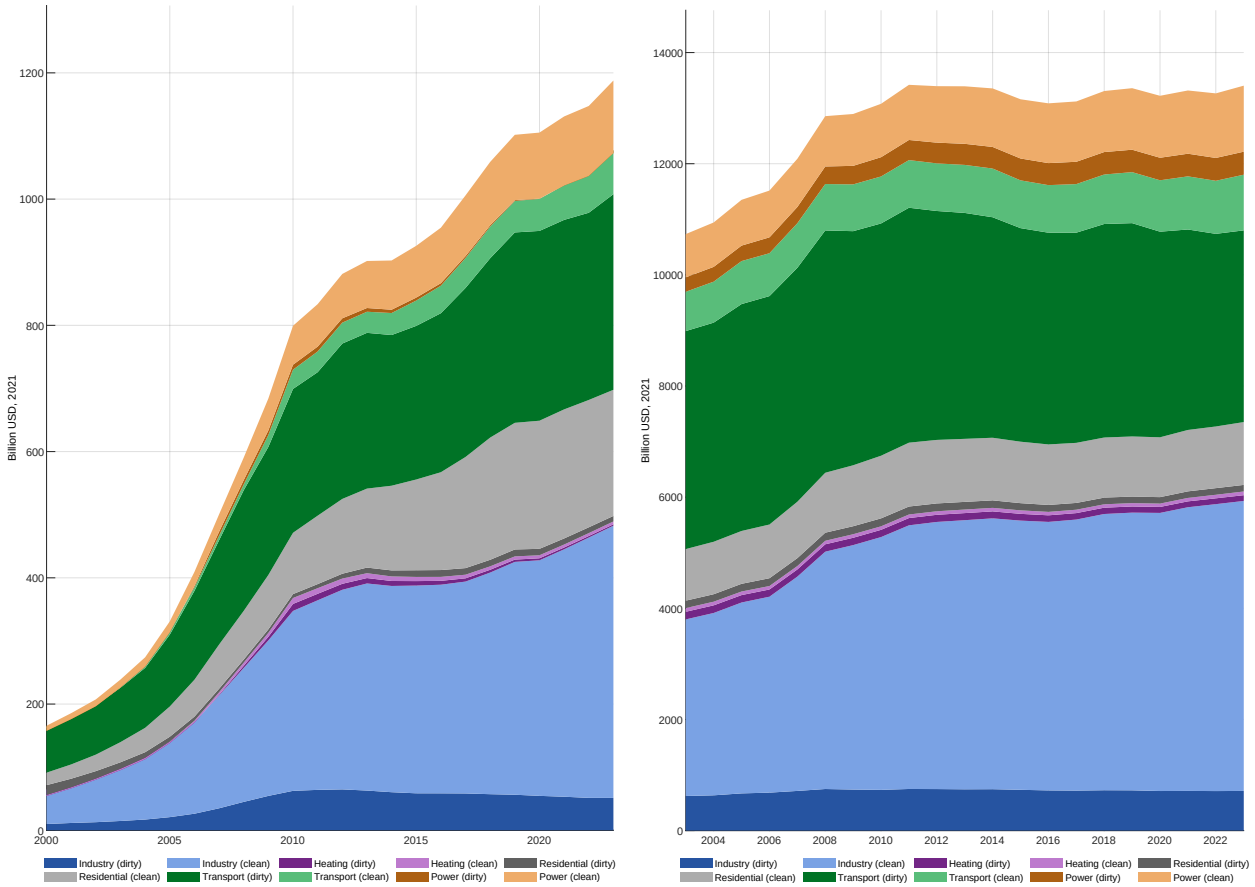
(a) India **(b)** EU

Note: The panels compare the growth rates of energy-related investment in India and the EU.

To get the share of clean and dirty energy capital in total capital we use the International Monetary Fund (2021) Investment and Capital Stock Data as an estimate for the total capital stock in India and the EU 27. Since the data is only until 2019 we extrapolate the data until 2023 using the average capital stock growth rate since 2000. The capital stock estimates are provided in constant 2017 international dollars. We convert them into constant US 2021 dollars via the procedure in Section B.3.1. Based on the proxy investment data used as

an input for the perpetual inventory method, Figure 8 displays the results for the sectoral capital stocks.

Figure 8: Sectoral capital stocks in India and the EU



(a) India **(b)** EU

Note: The panels compare sectoral capital stocks in India and the EU.

B.3.1 Conversion Formulas to yield estimates for total capital stock in USD 2021

1. US GDP Deflator (2021 Constant Prices)

$$\text{US_Deflator}_t^{2021} = \frac{\text{GDPDefl}_{2021}^{2017}}{\text{GDPDefl}_t^{2017}} \tag{11}$$

Source: WEO 2024

Note: GDP deflator for base year 2017.

2. Deflator for Constant 2017 to Constant 2021 Prices

$$\text{Defl}^{2017\to2021} = \frac{\text{GDPDefl}^{2017}_{2021}}{\text{GDPDefl}^{2017}_{2017}} = 1.1 \tag{12}$$

Note: Fixed across all years.

3. EU GDP in Constant 2021 US Dollars

$$\text{EUGDP}_t^{2021,\text{US\$}} = \text{EUGDP}_t^{\text{current US\$}} \cdot \text{US_Deflator}_t^{2021} \tag{13}$$

Source: WDI 2024

4. US$ to PPP Conversion Factor

$$\frac{n_t}{\text{ppp}_t} = \frac{\text{EUGDP}_t^{2021,\text{US\$}}}{\text{EUGDP}_t^{2021,\text{PPP}}} \tag{14}$$

Note: Converts international dollars to constant 2021 US dollars. *Source:* WDI 2024

5. Capital Stock in Constant 2021 International Dollars

$$K_t^{2021,\text{int}} = K_t^{2017,\text{int}} \times \text{Defl}^{2017\to2021} \tag{15}$$

Source: IMF Capital Stock Estimates (constant 2017 international $)

6. Capital Stock in Constant 2021 US Dollars

$$K_t^{2021,\text{US\$}} = K_t^{2021,\text{int}} \times \frac{n_t}{\text{ppp}_t} \tag{16}$$

Note: Converts capital from international $ to US $ using exchange rate from step 4.

B.4 Welfare measure

As the measure to compare welfare across two scenarios A and B, we use the percentage variation in consumption between 2023 and 2060 that compensates agents in scenario B for living in scenario A permanently, following Burda and Zessner-Spitzenberg (2022).

Specifically, we define Λ as

$$\sum_{t=2023}^{2060} \beta^t U\left(\left(1+\frac{\Lambda}{100}\right) C_t^B\right) + \sum_{t=2061}^{2273} \beta^t U(C_t^B) = \sum_{t=2023}^{2273} \beta^t U(C_t^A),$$

where 2273 is the last period in our simulation. The choice of the year 2060 only affects scaling of welfare effects, not their sign. We choose 2060, in order to relate transition costs to consumption during the time the transition occurs. If we were to choose a later point as the cutoff, welfare effects would be scaled down, as losses would be distributed over more periods. Importantly, we include the utility stream after 2060 in the comparison to ensure that differences in capital accumulation up to this point are reflected in the welfare measure. At the end of the simulation horizon, all paths have reached the same terminal capital stocks which makes the comparison meaningful. By letting the interval on which the variation is computed approach infinity along with the simulation horizon, one recovers the standard measure of welfare in terms of permanent consumption (see Lucas (1987) for example).

C Calibration Strategy Details

C.1 Calculation of the carbon budget in different scenarios

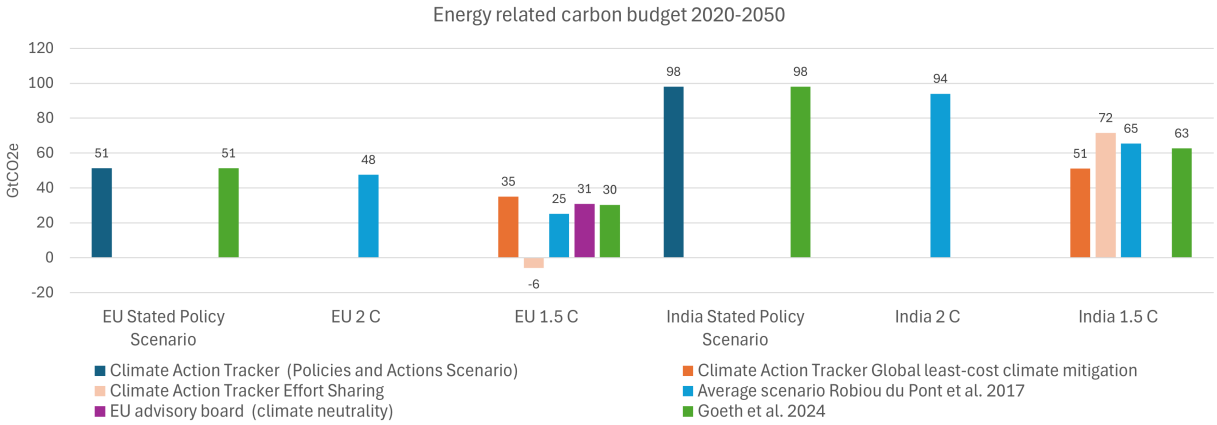
For the overview chart we calculate the carbon budget implied by different policy scenarios. Taking the EU as an example, we derive the Stated Policies Scenario (CBSTEPS) from Climate Action Tracker (CAT) data, using the average of their "Policies and actions" projections until 2030 and extending them linearly to 2050. Summing emissions over 2020–2050 yields a carbon budget of 68 $GtCO_2$, of which about 80 percent are energy-related according to Climate Watch (2023) sectoral emission data, leaving an energy budget of 51 $GtCO_2e$. For India, we apply the same procedure. CAT's "Policies and actions" pathway to 2030, extrapolated to 2050, results in a total budget of 137 $GtCO_2$. With energy emissions accounting for 74 percent of the total, the implied energy-related budget is 98 $GtCO_2$.

We apply the same procedure to derive energy-related carbon budgets for India and the EU under the Climate Action Tracker's effort-sharing scenario and its global least cost scenario. The CAT evaluates countries' mitigation commitments and policies by comparing them to both their fair share and the domestic requirements for full decarbonisation. Its "Effort Sharing" methodology uses state-of-the-art research to assess the fairness of government efforts and NDCs relative to Paris Agreement–consistent emission reduction pathways. CAT's global least-cost scenario downscales the global least-cost mitigation pathway to a national level to assess whether a country is on track for full decarbonization domestically. Du Robiou Pont et al. (2017) examine five burden-sharing principles for allocating global

mitigation efforts consistent with the 1.5°C target. For the EU we use the average remaining emission budget across these scenarios (80 $GtCO_2e$ for the 1.5°C goal and 114 $GtCO_2e$ for the 2°C goal). Since these budgets cover 2010–2050 and include the UK, we subtract cumulative EU+UK emissions of 41.7 $GtCO_2e$ for 2010–2019 using data from Climate Watch (2023). This leaves a carbon budget of 38.3 $GtCO_2e$ for the 1.5°C goal. Assuming that about 80% of emissions are energy-related, this corresponds to roughly 33.5 $GtCO_2e$ for energy-related emissions. We apply the same procedure for the 2°C goal leaving a remaining carbon budget of 48 $GtCO_2e$. Similarly, we proceed with the carbon budget data provided by Du Robiou Pont et al. (2017) for India resulting in remaining carbon budgets of 65 $GtCO_2e$ and 94 $GtCO_2e$ for 1.5°C and 2.0°C respectively.

For the EU and India, the CB+1.5°C carbon budget is closest to the carbon budget size estimated by the average scenario of Du Robiou Pont et al. (2017). India's CB+1.5°C carbon budget is very close to the carbon budget based on CAT's modeling assumptions for global least-cost mitigation efforts. The following figure compares the carbon budgets used in our analysis to those reported in the literature.

Figure 9: Comparison of remaining energy-related carbon budgets (2020–2050) for the EU and India using different sources



Source: Authors' calculations based on Climate Action Tracker (2024), European Scientific Advisory Board on Climate Change (2023) and Du Robiou Pont et al. (2017).

C.2 Externally calibrated parameters

The relative capital intensity of clean and dirty energy is an important determinant of their relative costs, but unlike productivity it is assumed to remain constant over time. Capital intensity, defined as $1-\alpha_i$ for energy type i, can be calibrated from data on labor cost shares. We set the capital intensity of both dirty and clean energy to 0.7 ($\alpha_{d,c} = 0.3$). These values are assumed to be identical across our two economies and are calibrated using technology-

specific data available for the EU. In 2017, the average labor share in the electricity, gas, steam, and air conditioning supply sector of the EU was 29% (EU KLEMS, 2023), consistent with earlier findings by Acemoglu and Guerrieri (2008) who report a capital share of 77% for mining and utilities.

Fried et al. (2022) report labor shares of 0.28 in the fossil energy sector and 0.09 in the green energy sector, implying that the capital share in green energy may exceed that in fossil energy. However, these sectoral definitions are not fully aligned with the construction of our energy capital stocks, which also include energy-related assets in transport, storage, housing, electricity, manufacturing, and construction. It is therefore plausible that the capital share in clean energy is higher, but the precise magnitude is uncertain. For this reason, we set the labor share at 0.3 for both clean and dirty energy. There is broad consensus, however, that capital intensity in the energy sector is substantially higher than in the general economy. For the non-energy sector, we calibrate the capital share internally, yielding 0.37 for the EU and 0.43 for India (see Section C.3).

For the elasticity between the capital–labor composite and energy, we follow Bretschger and Ara (2022), who use French firm-level manufacturing data and estimate values between 0.45 and 0.80, implying that labor and energy are strong complements in most firms. Airaudo et al. (2023) assume a slightly lower elasticity (0.35) between physical capital and energy. [24]

We calibrate the adjustment parameter $c_{n,d,c}$ to 5 in the baseline following Goeth (2025) who finds that this is a common parameter. Since our model captures structural change within the energy sector for which precise empirical estimates are scarce, we test robustness by setting $c_{n,d,c} = 20$, which lies at the upper end of values typically used for quadratic adjustment costs (Hall, 2004; Bloom, 2009; Goeth, 2025). Standard assumptions from the literature are used for the depreciation rate, the intertemporal elasticity of substitution, and the discount factor.

[24] Labandeira et al. (2017) review empirical evidence on elasticities of substitution, which in this context correspond to the own-price elasticity of energy demand. They summarize existing estimates of own-price elasticities for energy consumption, distinguishing between the short run (less than one year) and the long run (beyond one year). The average short-run elasticity for aggregate energy is estimated at –0.22, for natural gas at –0.18, while heating oil is found to be least elastic at –0.02. Differences between residential and industrial consumers are relatively small. In the long run, average own-price elasticities for energy products reported in the literature range between –0.584 and –0.608. Dissou and Karnizova (2016) highlight that there is no consensus on the interaction between capital, labor, and energy in production functions, nor on their degree of substitutability. Kim and Loungani (1992), Carlstrom and Fuerst (2006), and Leduc and Sill (2004) provide examples of alternative approaches to incorporating energy into production functions in business cycle models.

Table 11: Common Parameter Values: External calibration

Parameter	Value	Source
Elasticity of substitution ϵ btw. intermediate inputs Y_n & Y_e	0.45	Bretschger and Ara (2022)
Output elasticity wrt labor α_d	0.3	EU KLEMS (2023); Acemoglu and Guerrieri (2008)
Output elasticity wrt labor α_c	0.3	EU KLEMS (2023); Acemoglu and Guerrieri (2008)
Depreciation rate δ_n	0.07	Arkolakis and Walsh (2023)
Depreciation rate δ_c	0.03	Arkolakis and Walsh (2023)
Depreciation rate δ_d	0.02	Arkolakis and Walsh (2023)
Inverse of intertemporal substitution elasticity θ	2	common in literature
Discount factor β	0.98	common in literature
Adjustment cost parameter $c_{n,d,c}$	5; 20	Goeth (2025)

Parameter	Value EU	Value India
Exogenous growth rate of TFP $m_{n,c,d}$ *	0.00015	0.018
Share of initial dirty energy capital $\frac{K_{D0}}{K_0}$	0.11	0.05
Share of initial clean energy capital $\frac{K_{C0}}{K_0}$	0.195	0.1
Rel. prod. of dirty energy tech. $\frac{M_{d0}}{M_{c0}}$ **	1.25	1.18
Clean initial disad. b_m ***	0.208	0.155
Clean catch up rate κ_m ***	0.45	0.31
CO_2 intensity of dirty energy μ $(\frac{tCO_2}{1000EUR\ or\ USD})$****	3.05	11.68
CO_2 intensity of GDP $(\frac{tCO_2}{1000EUR\ or\ USD})$*****	0.18	0.82

Table 12: Differentiated Parameter Values: External calibration for EU and India

Note: * set to meet the initial growth rate of the EU and India ** IEA & own calculation (India & EU) *** set to match $\frac{M_{dt}}{M_{ct}}$ for India & EU **** based on model outcome ***** Calculation of μ exemplified for the EU: $\mu_{EU} = \frac{2.47\ GtCO_2e}{0.06*13.5\ trEUR} = 0.18\frac{tCO_2}{1000\ EUR}$

C.3 Internally calibrated parameters and empirical targets

To compute the quantitative predictions of the model we set the four remaining structural parameters $\{\gamma, K_0, \sigma, \alpha_n\}$[25] to match the following four empirical moments: (i) the initial

[25]For the calibration of K_0 in the code we set a parameter K_f. Instead of μ we set σ since in the code we assume $\mu = \frac{1}{\sigma}$.

dirty energy share in GDP, (ii) the initial capital output ratio, (iii) the initial emissions as a share of remaining carbon budget as well as (iv) the initial labor share.

European Union. First, the model needs to match the initial dirty energy share in GDP, which we assume to be 6%. We base this guess on the fact that the energy sector, covering extraction, production and distribution, directly corresponds to 4% of value added of the non-financial EU business economy EUCloudEdgeIoT (2025). This 4% share of fossil energy in GDP is widely assumed in the literature (e.g., Golosov et al. (2014); Fried et al. (2022)), but we argue this underestimates the dirty energy share, which we define as consisting of the energy-related production in the sectors of transport storage, housing, electricity, manufacturing, and construction. Therefore, we add roughly 2% of GDP to account for all transport services that use fossil fuel-based energy like combustion engines, the service of warming a house done by gas, and all machinery in the industry sector that runs using fossil based energy.[26]

Second, based on the IMF Investment and Capital Stock Dataset (International Monetary Fund, 2021)we calibrate the capital to output ratio to 2.55 corresponding to the EU capital output ratio in 2019. To match the second target we adjust K_0 accordingly.

Third, we match the initial flow of energy related emission in t = 2020 of 2.47 $GtCO_2e$ (Climate Watch, 2023) for the EU to be 4.8% of the remaining energy emission related carbon budget of 51 $GtCO_2e$ (see Section C.1) for the calculation of the remaining carbon budget).

The last empirical target we match the model with, is the initial share of labour compensation in GDP at current national prices ($\frac{wL}{Y}$) of the economy. For the EU this is 58 % which is the GDP weighted average of the share of labor compensation within the EU based on Penn World Table version 10.01.

India. For India we assume the initial dirty energy share in GDP to be 7%, slightly higher than in the EU. We arrive at this estimate by weighting the EU share by the dirty share of total primary energy consumption of India and the EU.[27] We take the data moment for the initial capital output ratio from the International Monetary Fund (2021) Investment and Capital Stock Dataset. This data shows a capital to output ratio of 2.1 in 2019. For the calculation of the share of the initial emissions in the remaining carbon budget we use the energy related emissions flow data of Climate Watch (2023). India used about 2.22

[26] A possible approximation could be to use the energy expenditure share for end use-energy like in U.S. Energy Information Administration (2022) U.S. energy expenditures accounted for 4.8 % of gross domestic product (GDP) in 2020) (lowest share since 1970)).

[27] The data on Primary energy consumption of the U.S. Energy Information Administration (2023) shows that the dirty share in energy consumption is 89 percent and for the EU it is 72 percent ($6*\frac{89}{72}$=7 percent).

$GtCO_2e$ in 2020. This amounts to a share of 2.3 percent of the remaining carbon budget of 98 $GtCO_2e$. For the labor share in India we use the 'Share of Labour Compensation in GDP at Current National Prices for India, Ratio, Annual, Not Seasonally Adjusted' from Penn World Tables (version 10.01), showing that the labor share in 2019 was about 52 percent.

We use a nonlinear least-squares solver to find the combination of optimal parameter values that matches empirical with model moments (see Table 13).

Parameter	**Value EU**	**Value India**
Weight on non-energy input in production γ	0.9663	0.9751
Determining level of init. capital stock K_0	0.4241	0.3579
CO_2 efficiency of dirty energy production σ	3.2351	3.6119
Non-energy technology output elasticity wrt labor α_n	0.6279	0.5709

Table 13: Parameter Values: Internal calibration