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Research Paper

Stranding ahoy? Heterogeneous transition beliefs and capital investment choices ☆

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A B S T R A C T

Individuals have heterogeneous beliefs regarding the future speed and shape of the low-carbon transition. In this paper, we study to what extent opinion diversity matters for aggregate capital investment decisions. We develop a model where firms formulate heterogeneous expectations around a dominant narrative, or 'market norm', with their dispersion increasing over a finite planning horizon. Our analytical and numerical results suggest that belief heterogeneity can significantly affect the share of low-carbon investments, with the strength of its effects non-linearly correlated to market norms. We show that investment behaviour tends to be more sensitive to shocks to short-term, rather than long-term, belief heterogeneity, highlighting the importance of setting credible short-term targets. Finally, we find beliefs to interact strongly and in non-trivial ways with measures of short-termism, with increasing agents' farsightedness not necessarily leading to less carbon-intensive investments under high heterogeneity.

1. Introduction

How do we expect the low-carbon transition to unroll? This question is likely to be answered in radically different ways by different individuals. The answer depends on their information set, their degree of trust in policy-makers, their beliefs on future

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technological advancements, etc. Some might expect the transition to take place rapidly and in line with limiting global warming to 1.5 °C or 2 °C (IEA, 2021; IPCC, 2022). Others might expect a more gradual dynamics, either allowing carbon-intensive assets to exit the economy in an orderly fashion, or to remain in smaller proportion. Others might not even have well-formulated answers, as the transition timeline goes beyond the span of their planning horizon.

Disagreement over what lies in the future is common and found to be significant in several spheres of economic behaviour (Coibion et al., 2018; Hommes, 2021; Mankiw et al., 2003; Xiong and Yan, 2010). Similarly, some recent contributions have shown evidence of heterogeneous expectations for what concerns transition-related beliefs (*e.g.* Giglio et al., 2023; Nordeng et al., 2021). However, these insights have yet to be incorporated in suitable modelling frameworks. Does expectation heterogeneity matter for the low-carbon transition dynamics?

In this paper, we address this research question by developing a model of capital investment choices with heterogeneous beliefs.[1] Firms choose how to allocate investments between a high- and a low-carbon technology based on their relative expected profits, discounted over a finite planning horizon. Profit expectations are affected by how decision-makers perceive the future speed and shape of the low-carbon transition. We proxy transition-related beliefs by focusing on the expected degree of 'stranding' of the high-carbon technology, *i.e.* its expected utilisation rate. If the firm imagines a rapid low-carbon transition in the near future, it will expect the high-carbon technology to be used less than fully, and hence generate lower revenues and profits. If it expects instead a slow transition, it will anticipate full or close to full utilisation of carbon-intensive capital stocks. We then use a discrete choice model to aggregate the multiple decentralised individual investment choices and compute the overall share of low-carbon investments.

We introduce three main features of expectations in the attempt of capturing relevant real-world dimensions. First, a central transition projection exists, representing the dominant wisdom, or 'market norm', within the community of investors. Agents take this as a focal point when formulating their expectations and investment decisions (Beckert and Bronk, 2018; Schelling, 1960). This 'common wisdom' can take the form of a general narrative that most agents believe to be true and that guides their investment decisions, which might be more or less close to the government's stated policy objectives (Boyer, 2018; Campiglio et al., 2023). While we refrain from simulating co-existing conflicting narratives, we explore the implications of two distinct possible central projections: (i) a low-stranding scenario, roughly aligned with current policies and the expectation of a gradual transition; and (ii) a high-stranding scenario, entailing a more rapid transition and the achievement of net-zero emissions by mid-century.

Second, individual agents might drift from this dominant opinion, following their own beliefs. As exemplified by the wide range of possible decarbonisation pathways given by IPCC (2022) and other institutions (*e.g.* IEA, 2020c), the precise pace and shape of the transition is far from being well-established. Different combinations of production technologies, energy efficiency measures and societal changes may leave investors undecided as to what kind of business will be the most adequate for the future. Further uncertainties around the implementation of mitigation policies and technological developments cast doubt on the pace and steadiness of the low-carbon transition and force agents to formulate their own expectations around the market norm (Nemet et al., 2017). Hence, today's assessment of the profit prospects of available technological options is a distribution, rather than a point value, with its shape depending on the strength of transition-related belief diversity. Heterogeneity in beliefs may make aggregate investment decisions uncoordinated, possibly contradictory, ultimately hampering the good course of the transition (Acemoglu and Jensen, 2018; Fais et al., 2016).

Third, the degree of heterogeneity varies with the length of the time horizon considered. As shown by the literature on the term structure of expectations for key macroeconomic variables, diversity in expectations depends crucially on how far away in time agents are projecting (Binder et al., 2022; El Ouadghiri and Uctum, 2020; Patton and Timmermann, 2010). Fig. 1 confirms this evidence by showing how the dispersion of expectations concerning future carbon price levels increases if individuals are asked to provide estimates for periods further in time. We capture this stylised fact by letting the variance of expectation distribution increase along the planning horizon. We propose a novel logistic characterisation of this feature, building on the IPCC 6th Assessment Report decarbonisation scenarios (IPCC, 2022).

We then calibrate our model on 2019 data for the European Union, and derive both analytical and numerical results. We illustrate our findings with a sensitivity analysis based on sensible value ranges of our behavioural parameters. Our main results can be summarised as follows.

First, heterogeneity of transition expectations does matter, as it significantly affects firms' investment allocation decisions. We find the direction and strength of this effect to depend on the underlying market norm and its associated capital stranding dynamics. In general, stronger belief heterogeneity will decrease the share of low-carbon investment in presence of high-stranding central expectations, and increase it when central expectations forecast low stranding. However, we also find this relationship to be strongly non-linear. Market norms centred around expectations of either very low or very high stranding (*i.e.* very slow or very rapid transition) will lock in investment behaviours, while more balanced stranding expectations are exposed to large investment swings if belief dispersion moves.

Second, we show how, for our benchmark calibration and for a sizeable proportion of the parameter constellation we explore, investment behaviours are more sensitive to shocks to short-term, rather than long-term, belief heterogeneity. This situation only reverses if agents are strongly far-sighted. This result suggests that policy-makers should prioritise anchoring expectations for the earliest periods of the transition, even if there is no clear consensus about long-term outcomes. The introduction of credible *short-term*

[1] In what follows, we use the word 'beliefs' interchangeably with 'expectations' to insist on the idea that beliefs about the future are not model-consistent, following Acemoglu and Jensen (2018).

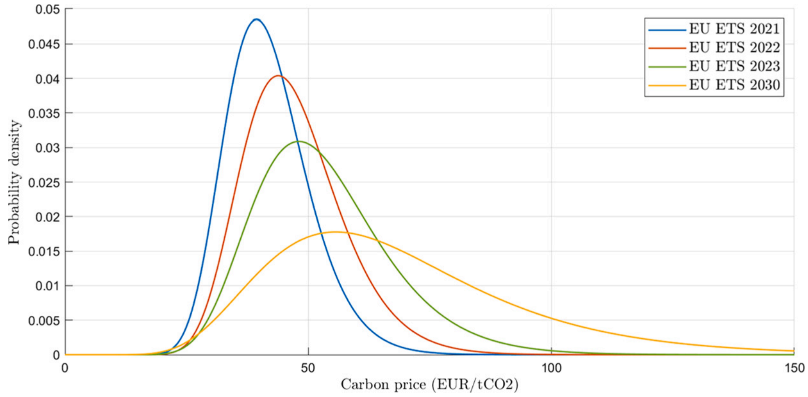


Fig. 1. Distribution of expected carbon price in the EU Emission Trading Scheme for different time horizons. Adapted from Nemet et al. (2017), using data from Nordeng et al. (2021). (For interpretation of the colours in the figure(s), the reader is referred to the web version of this article.)

targets hence appears crucial. In addition, policy-makers risk misinterpreting the drivers of investment allocation changes (*e.g.* an increase in low-carbon investment share might be due to shocks to short-run belief heterogeneity rather than a change in market norms). This warrants a thorough measurement and analysis of transition-related expectations, currently missing.

Third, we find belief heterogeneity to interact strongly with measures of short-termism (high discount rate or short planning horizon).[2] The effect of a higher discount rate on low-carbon investment share is exacerbated (mitigated) by higher heterogeneity if central expectations imply high (low) stranding. Belief heterogeneity can also negatively affect the impact of longer planning horizon, which generally increases low-carbon investment shares, by further widening the range of projections and expanding the diversity of opinions.

Our article contributes to better understanding the role of expectations and time preferences in defining the carbon intensity of capital investment choices. Several contributions rooted in neoclassical economic theory have investigated *optimal* investment decision-making in the context of the low-carbon transition, with or without uncertainty (Cai and Lontzek, 2018; Campiglio et al., 2022; Van den Bremer and Van der Ploeg, 2021; Vogt-Schilb et al., 2018, among others). Expectations in these models are usually homogeneous and model-consistent. Other contributions in the field of behavioural macroeconomics have studied transition dynamics allowing for belief/preference heterogeneity and stronger complexity in individual and systemic behaviours (*e.g* Dunz et al., 2021; Geisendorf, 2016; Knobloch and Mercure, 2016). A particularly relevant stream of work for us is the one studying the process of technological diffusion (Mercure, 2012; Mercure et al., 2016), which adopts a similar modelling approach rooted in discrete choice theory. However, these models tend to be governed by backward-looking (adaptive) expectations, making it difficult to analyse the effect of changes in longer-term thinking of economic agents. We opt for an in-between modelling strategy, able to capture expectations that are both forward-looking and (dynamically) heterogeneous. Our approach is similar in spirit to the literature developing logit/probit models of switching beliefs. This has been usually applied to issues linked to inflation expectations and monetary policy (De Grauwe and Macchiarelli, 2015; Franke and Westerhoff, 2018; Galanis et al., 2022; Hommes, 2021), but features recent applications to climate- and transition-related matters (Cafferata et al., 2021; Campiglio et al., 2023; Dávila-Fernández and Sordi, 2020; Guilmi et al., 2022; Zeppini, 2015).

Our treatment of transition expectations positions us close to the literature studying the 'stranding' of physical or financial assets along a low-carbon transition (Campiglio and van der Ploeg, 2022; Daumas, 2023; van der Ploeg and Rezai, 2020). To our knowledge, this paper is the first to incorporate capital stranding into a model with heterogeneous expectations, with most other contributions assuming homogeneity (see for instance Baldwin et al., 2020; Campiglio et al., 2022; Rozenberg et al., 2020). We also partly connect to the large field on the role of time preferences, discounting and planning horizons, in climate-related economic dynamics (see Groom et al. (2022) for a review). Finally, our joint representation of idiosyncratic beliefs and market norms calls out an emerging literature in economic sociology (Beckert and Bronk, 2018; Bronk, 2009) and macroeconomics (Andre et al., 2021; Barrero, 2022) that has emphasised the role of beliefs and narratives in driving economic outcomes.

The remainder of the article is structured as follows. Section 2 presents our modelling framework. Section 3 explains our calibration strategy. Section 4 discusses some analytical results and illustrates them numerically. Section 5 concludes and discusses future research avenues.

[2] Many companies extend the time horizon considered to adopt business decisions, including investments, only up to a few years into the future (Souder et al., 2021; Spiro, 2014). This tendency can be exacerbated by cognitive limitations, biases or norms, creating sets of incentives favouring myopia. While it has been shown that short-termist behaviour can slow down the development of relevant technologies and the pace of decarbonisation (Löffler et al., 2019; Nerini et al., 2017; Souder et al., 2016), it is yet unclear how different time preferences could interact with heterogeneous transition expectations in determining individual and aggregate capital investment choices.

2. The model

The model is populated by a continuum of firms producing electricity e in response to an exogenous level of electricity demand e^d, growing at a constant rate g_E. Electricity can be produced by two technologies: i) a stock of capital K_L running on renewable resources and producing low-carbon electricity, and ii) a stock of capital K_H running on fossil fuels and producing high-carbon electricity. The subscript $i \in \{H, L\}$ denotes the technology type. The electricity produced by the two technologies, e_i, $i \in \{H, L\}$, is identical. However, capital stocks have different productivities ξ_H and ξ_L.[3] Capacity utilisation $u_i = \frac{e_i}{\xi_i K_i} \in [0, 1]$, defines the extent to which capital stocks are used. We also define a full capacity utilisation level u_i^f, which can differ from one.

Firms decide how to allocate their investments in new physical capital between the two available technologies. To do so, they formulate expectations regarding their future profitability by exploring potential future transition scenarios. We define the space in which these calculations take place as 'psychological time' (s), which takes the form of a finite planning horizon $[|1; S|]$ to distinguish it from chronological time (t). In other words, psychological time is simply the mental projection of the future by individuals, extending for a finite number of periods. This representation of a finite planning horizon is how we represent our behavioural understanding of short-termism. This horizon is common to all firms. Expectations by a firm are denoted using the expectations operator $\mathbb{E}$. Chronological time t does not move in this paper, as we investigate only the impact of expectations about the future on present decision-making. We thus do not use a chronological time subscript t for convenience.

2.1. Technological return rates

We assume a continuum of small firms index by $j \in \mathbb{R}$. Firms compare the two available technologies $i \in \{L, H\}$ by calculating their unitary return rate r_i, *i.e.*, the sum of the discounted stream of expected profits $\pi_{i,j,s}$ that can be obtained from a unit of technology (in our case, a unit of installed generation capacity). Firms discount profit expectations over this planning horizon with the same discount factor $\beta = \frac{1}{1+\rho}$, with ρ the corporate discount rate our measure of 'rational' short-termism. For firm j, it writes:

$$\mathbb{E}_j(r_i) = \sum_{s=0}^{S} \beta^s \, \mathbb{E}(\pi_{i,j,s}). \tag{1}$$

Three components determine the unitary profit rate π_i: i) revenues; ii) capital costs; and iii) variable costs.

Revenues come from producing and selling electricity e_i. Electricity is sold on a wholesale market with a merit order structure. The energy produced by renewable sources usually comes first in the merit order, as these incur lower marginal costs than fossil-based technologies (Figueiredo and da Silva, 2019). It means that low-carbon electricity will be sold first and, assuming it is not enough by itself to satisfy the entire demand (*i.e.* $e^d > \xi_L K_L$), capacity utilisation u_L will be equal to u_L^f. The high-carbon capital stock will instead be used to the extent necessary to satisfy demand not already met by low-carbon electricity. That is,

$$u_H = \frac{e^d - e_L}{\xi_H K_H}. \tag{2}$$

The price of electricity p_E is also determined on the merit order, as the price offered by the marginal technology producing (the high-carbon one, typically). Hence, per-period revenues stemming from a unit of capital K_i can be computed as $p_E u_i \xi_i$.

Capital costs are incurred when installing a new capital unit. The cost of installing a unit of capital i is c_i. Firms require external finance to perform new investments. We define ψ_i as the debt-to-investment ratio, *i.e.* the proportion of investment expenditure funded via borrowed credit. Companies must pay back the debt over the course of the loan tenure LT, together with accrued interests. Firms spread repayment tranches equally throughout the loan tenure period. We thus calculate a capital recovery factor $\alpha_i = \frac{\iota_i (1+\iota_i)^{LT_i}}{1-(1+\iota_i)^{LT_i}}$, where ι is the fixed interest rate applied on the loan. α represents the ratio between the period repayments (inclusive of principal and interests) and the loan stock. Per-period capital costs for technology i can thus be computed as $\alpha_i \psi_i c_i$.

Variable costs in the model only arise from purchasing fossil fuels as intermediate inputs necessary to operate K_H (we abstract for simplicity from other variable costs such as labour). We name the price of fossil fuels p_F and the productivity of fossil fuels in producing electricity ξ_F. Variable costs can thus be computed as $\frac{p_F \xi_H u_H}{\xi_F}$.

At time t, we can treat most of the parameters above as constant in the expected future.[4] The price of electricity p_E is more and more determined by long-term power purchase agreements and is, therefore, less subjected to uncertainty over long horizons. Capital productivity parameters ξ_i are embodied in the specific vintage of capital available today. While productivity is likely to change in the future in more advanced capital vintages, we explicitly place ourselves in the context of an investor comparing current technologies and anticipating their payoffs. Sidestepping from simple productivity losses due to ageing and related maintenance costs, we assume investors to consider productivity parameters to be constant over their planning horizon. Finally, we treat the price of fossil fuels p_F as exogenous, as this allows us to disentangle the effect of stranding expectations.

[3] Since capital is the only production input in our model, productivities ξ_H and ξ_L can also be interpreted as Leontief production function coefficients.

[4] In Appendix B, we extend the model by allowing for heterogeneity in beliefs on the future profitability of both technologies, which include prices of both electricity and fossil fuels.

The proportion of investments covered by debt ψ_i is decided today and remains the same. Loan duration LT and interest rate ι are negotiated with the bank today and remain constant. In other words, firms choose a fixed interest rate and do not renegotiate financing conditions.

We can now define the expected unitary retained profit rates[5] for the two technologies as:

$$\mathbb{E}_j(\pi_{L,j,s}) = p_E \xi_L u_L^f - \alpha_L \psi_L c_L, \tag{3}$$

$$\mathbb{E}_j(\pi_{H,j,s}) = \left(p_E - \frac{p_F}{\xi_F} \right) \xi_H \, \mathbb{E}_j(u_{H,s}) - \alpha_H \psi_H c_H, \tag{4}$$

where the only variable subject to firms' expectations is the capacity utilisation rate of the high-carbon capital stock, u_H. We denote by $\mathbb{E}_j$ the fact that expectations are firm-specific.

After discounting and summing the stream of expected profits over the planning horizon S as shown in equation (1) and given a specific vector of expected high-carbon capacity utilisation rates $\{u_s\}_t^S$, an individual firm obtains values for the expected return rates of its two technological options, $\mathbb{E}_j(r_H)$ and $\mathbb{E}_j(r_L)$. Defining

$$\mathbb{E}_j(\varphi) = \mathbb{E}_j(r_L) - \mathbb{E}_j(r_H) \tag{5}$$

as the difference between the two expected return rates, firm j invests in a unit of K_L if $\mathbb{E}_j(\varphi) > 0$ or in a unit of K_H if $\mathbb{E}_j(\varphi) < 0$.

2.2. Stranding expectations

At the aggregate level, we assume stranding expectations to be heterogeneous across firms, normally distributed around a central expectation path and serially uncorrelated. This choice is motivated by the additive stability of independent normal distributions and the easy interpretation of parameters.[6]

Formally, this writes:

$$\mathbb{E}_j(u_{H,s}) = u_{H,s}^* + \varepsilon_{u,j,s}, \tag{6}$$

where $u_{i,s}^*$ identifies a benchmark 'central stranding' expected path and the error term $\varepsilon_{u,j,s}$ represents the idiosyncratic expectation of firm j. Its distribution $\varepsilon_{u,s}$ represents the diversity of expectations. It follows a normal distribution with mean 0 and variance σ^2, *i.e.* $\varepsilon_{u,s} \sim \mathcal{N}(0, \sigma_{u,s})$. We call this schedule 'central stranding' in that it would be the path expected if agents did not have idiosyncratic beliefs. This path can be considered the ongoing 'common wisdom' on the market that serves as a focal point for agents (Schelling, 1960). This 'common wisdom' can take the form of a general narrative that most agents believe to be true and that guides their investment decisions (Boyer, 2018). It can also be construed as the government's policy objective that agents use as an anchor for their beliefs. However, we refrain from adopting this definition, since we do not model the interactions between regulator credibility and investment behaviours, which may have critical implications (see Campiglio et al., 2023, on this topic). For instance, a very ambitious policy plan may be seen as non-credible, and increase belief heterogeneity. As a result, we interpret central expectations only as market norms.

2.3. Central stranding expectation

Three crucial factors contribute to determining firms' transition expectations: i) expected growth of demand; ii) expected speed of development of new technologies; iii) expected long-term share of the new technology in the mix. We analyse each of them in turn.

First, firms expect a constant and positive growth rate g_E of electricity demand within their planning horizon. This assumption is supported by energy demand forecasts, which argue that the increase in global population and the economic development of emerging economies require an expanding supply of electricity (Enerdata, 2021). An expansion of electricity production is also commonly perceived as a crucial component of decarbonisation strategies.

Second, firms expect the transition to follow an S-shaped curve, as technological transitions typically exhibit this pattern (Fouquet, 2010; Grubb et al., 2020). New technologies often first emerge as niches within a technological paradigm dominated by the incumbent technology (in this case: fossil-based capital stocks). After some early adoption, expansion can accelerate due to a number of factors, including the decline in production costs, the diffusion of information and the growing social legitimisation of the technology (Geels, 2002; Geroski, 2000). In the electricity sector, network effects also play a role in facilitating adoption, as complementary infrastructure and policy develop to better integrate renewable technology. This growth is however limited by factors such as market saturation and physical capacity and slows down as we approach the 'carrying capacity' of the system. Expectations of low-carbon energy share $\ell_E = \frac{e_L}{e_L + e_H}$ thus move logistically in psychological time s:

[5] For the sake of brevity, we conflate in what follows the profit rate and the retained profit rate.

[6] We also implement the model with another family of addition-stable distributions, Stable laws, whose skewness and kurtosis can be parameterised and of which the Normal distribution is a special case. The qualitative insights are similar. However, as Appendix A discusses, the properties of non-normal Stable distributions render the interpretation of results more uncertain. More general results could be found numerically using convolution products; however, we prefer to opt for addition-stable distributions for analytical clarity. See also Appendix B, where we extend the model by allowing for beliefs on the future profitability of both technologies.

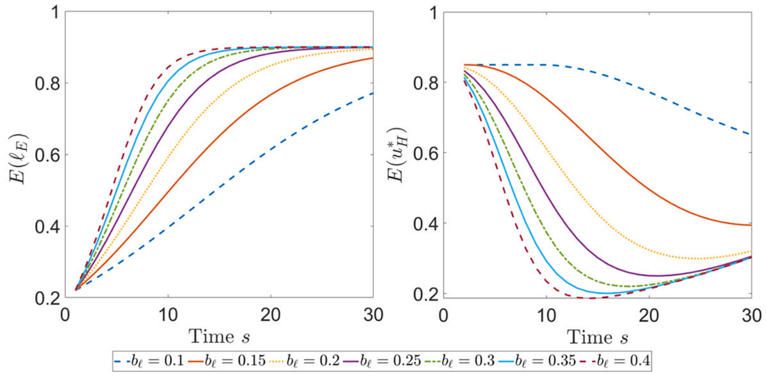


Fig. 2. Illustration of central expectations on future diffusion of low-carbon energy and the associated high-carbon capital utilisation rate. (The logistic function defined in equation (5) has a lower asymptote of zero. In the chart, we only show the portion of the curve to the right of our starting calibration value for the share of low-carbon energy, $\ell_{E,0} = 0.22$.)

$$\mathbb{E}(\ell_{E,s+1}) = \mathbb{E}(\ell_{E,s}) \left[1 + b_\ell \left(1 - \frac{\mathbb{E}(\ell_{E,s})}{\mathbb{E}(\bar{\ell})}\right)\right], \tag{7}$$

where b_ℓ represents the unconstrained expected speed of transition, *i.e.* the growth rate of ℓ_E when close to its lower asymptote and $\bar{\ell}$ represents the maximum expected share of low-carbon technologies.

Third, firms expect a less-than-full energy transition. Mainly due to the current lack of reliable large-scale energy storage technologies, some non-renewable generation capacities — able to adjust their output more rapidly than renewable technologies — will likely still be needed to deal with demand peaks. In addition, firms might also include radical technological breakthroughs in their mental scenarios (*e.g.* carbon capture and storage, direct air capture, geoengineering), which might result in an early deceleration of ℓ_E. Hence, $\mathbb{E}(\bar{\ell})$ is lower than 1.

Hence, given a set of expectation parameters g_E, b_ℓ and $\bar{\ell}$, the rational stranding path $\{u_s^*\}_t^S$ identifies the succession of expected capital utilisation rates for which: i) positive high-carbon investments I_H are expected to the amount necessary to provide the exact amount of K_H needed to satisfy demand $e_s^d - e_{L,s}$ at a full capacity utilisation rate u_H^f, which we call K_H^d; ii) no premature decommissioning or technological re-conversion of capital stocks is desired by firms; *i.e.* firms do not expect negative investments. We can thus define central stranding expectations of high-carbon investments $I_{H,s}^*$ as:

$$I_{H,s}^* = Max\left[K_{H,s}^d - (1-\delta)K_{H,s}^*; 0\right]. \tag{8}$$

Given (7) and the definition of u_H given in section 2.1, we can thus write the resulting rational stranding capacity utilisation u_H^* as:

$$u_{H,s+1}^* = \frac{(1+g_E)\left(e_s^d - e_{L,s}\left[1 + b_\ell\left(1 - \frac{e_{L,s}}{\bar{\ell} e_s^d}\right)\right]\right)}{\xi_H[(1-\delta)K_{H,s} + I_{H,s}^*]}. \tag{9}$$

Fig. 2 portrays how the expected share of low-carbon energy ℓ_E and the benchmark expected high-carbon capital utilisation rate u_H^* move in psychological time s for different values of expected intrinsic speed of renewable development b_ℓ.

It is worth noting that these expectations concern the whole of the high-carbon sector. We make the assumption that utilisation is homogeneous across high-carbon capital vintages, such that any future decrease in utilisation rates at the sector level will translate one-to-one to individual capital units to be installed today. Hence, if agents expect a lower utilisation rate at the sector level, they will expect a lower utilisation rate for their prospective new capacity.[7]

Stranding expectations are key in determining investment behaviours, as per Proposition 1 below:

Proposition 1. *For large enough values of b_ℓ, there exists an interval $T \subset [|0, S|]$ such that, $\forall s \in T$, $\pi_{L,s} - \pi_{H,s} > 0$.*

Proof. Demonstration given in Appendix F.1. □

In other words, if they suppose that the development of low-carbon energy will be fast, agents expect at least a period of psychological time over their planning horizon over which, in the future, low-carbon technologies will be more profitable than high-carbon technology, which could induce them to change their investment behaviour.

[7] This simplifying assumption could be challenged on the ground that older units will be under-utilised first. However, as noted by prospective studies (Grant and Coffin, 2020), high-carbon capital installed today will anyways have to suffer significant under-utilisation or premature decommissioning, even if older units stopped in priority.

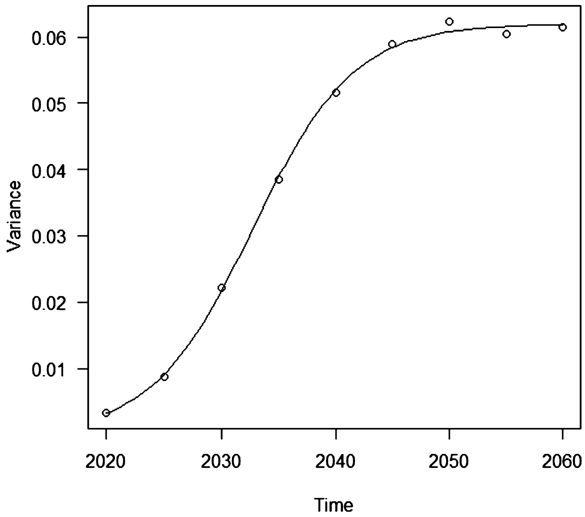


Fig. 3. Evolution of disagreement in psychological time - Source: AR6 Scenario Explorer and own calculations. Each point is the variance of the share of renewable energy across all scenarios provided by the AR6.

2.4. Heterogeneity of stranding expectations

Heterogeneity in expectations is represented by the error term $\varepsilon_{u,s} \sim \mathcal{N}(0, \sigma_{u,s}^2)$ of Equation (6), where $\sigma_{u,s}$ is a parameter indicating the strength of expectation diversity. The lower $\sigma_{u,s}$, the more stranding expectations are homogeneous and close to $u^*_{H,s}$. The higher $\sigma_{u,s}$, the more stranding expectations are diverse and possibly far away from $u^*_{H,s}$.

An important question is how this dispersion should change in time s. The literature on projection disagreements amongst economic forecasters provides inconclusive insights on the term structure of opinion diversity. Binder et al. (2022) show that disagreements largely depend on the variable at stake. The term structure for some variables (growth rate, inflation) show higher (lower) disagreement over short-run (long-run) forecasts. For other variables (unemployment, base rates), the disagreement's term structure is strictly increasing. Patton and Timmermann (2010) show a logistically increasing uncertainty disagreement for all the variables they consider. However, these studies focus on macroeconomic, short-run macroeconomic variables. Inter-model comparison exercises using Integrated Assessment Models (IAMs) focus instead on more relevant variables for our purposes, such as energy capacity shares. Kriegler et al. (2014) show that technology deployment schedules can vary importantly across models, which can be taken as a measure of disagreement along the term structure.

To build on this insight, we consider projections of the share of renewables in total electricity production across all IPCC (2022) scenarios[8] and compute their variance at each available simulation step over the 2020-2060 period.[9] We consider IPCC scenarios as a good proxy for expectations, in that they provide long-run projections that policymakers and economic agents can take as a benchmark in forming their own expectations. We assume further that the cross-scenario variance in the share of renewables reasonably proxies disagreement across agents, who can give more or less credence to one or the other IPCC projection. The result of this exercise is displayed in Fig. 3.

As can be seen, the variance follows a near-perfect sigmoid pattern, on which we fit a logistic function with an intrinsic growth rate of 0.28. Hence, we let σ increase in psychological time s following a logistic pattern:

$$\sigma_{u,s+1} = \sigma_{u,s}\left[b_\sigma\left(1 - \frac{\sigma_{u,s}}{\bar{\sigma}_u}\right)\right], \tag{10}$$

where b_σ is the unconstrained growth rate of $\sigma_{u,s}$, $\bar{\sigma}_u$ represents the maximum heterogeneity in the long run and $\sigma_u = \sigma_0$ at time t. Short-term views regarding the transition are roughly aligned, as agents observe the current state of things and recent trends. In other words, given the past evolution of low-carbon energy production shares up to time t, the expected low-carbon energy share for $t+1$ will be rather homogeneous across firms. However, transition expectations then diverge rapidly over the medium term, capturing the heterogeneity of opinions concerning technological and policy prospects. While some might be expecting decarbonisation to unravel rapidly in the course of the next decade, others might expect fossil fuels to remain the backbone of the global economy in the decades to come. In the longer run, the marginal divergence of expectations weakens, approaching a fixed maximum level $\bar{\sigma}_u$. In other words, the diversity of long-term opinions remains roughly constant once a certain beyond a certain threshold in psychological time.

[8] IPCC scenarios are available at https://data.ece.iiasa.ac.at/ar6.

[9] The picture over 2020-2100 is similar, with the variance of projections oscillating around a carrying capacity.

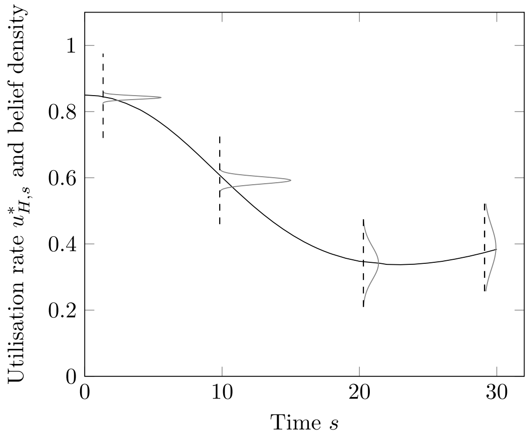


Fig. 4. Stylised representation of our approach to belief heterogeneity. To each time $s \in [|1, S|]$ corresponds a central utilisation expectation. Each bell curve represents the actual distribution of expectations (rotated 90°), with time-varying variances and means. Here displayed an example for $\bar{\ell} = 0.9$, $b_\ell = 0.2$, $\sigma_0 = 0.01$ and $\bar{\sigma} = 0.5$.

2.5. Aggregate investment decisions

We now want to calculate the share of aggregate investments flowing into each technology. We define $\ell_I = \frac{I_L}{I_H + I_L}$ as the share of total investments allocated to low-carbon capital stocks. In our setting, this is equivalent to the probability for an individual firm to obtain a positive φ; that is, to expect the low-carbon return rate r_L to be higher than the high-carbon return rate r_H.

Given our assumption of a normal distribution of the error term ε_u in equation (6) and considering that linear transformations maintain the normal distribution pattern, we can rewrite φ as the sum of a deterministic 'rational stranding' component φ^* and an error term $\varepsilon_\varphi \sim \mathcal{N}(0,1)$:

$$\varphi^* = \frac{R^*}{\Gamma}, \tag{11}$$

with:

$$R^* = \sum_{s=0}^{S} \beta^s \left\{ p_E \xi_L - \alpha_L \psi_L c_L - \left[\left(p_E - \frac{p_F}{\xi_F} \right) \xi_H u^*_{H,s} - \alpha_H \psi_H c_H \right] \right\} \tag{12}$$

$$\Gamma = \sqrt{\sum_{s=0}^{S} \beta^{2s} (p_E - \frac{p_F}{\xi_F})^2 \sigma^2_{u,s}}. \tag{13}$$

All details of the transformation are discussed in Appendix D. Fig. 4 schematises our representation of belief heterogeneity as a set of normal distributions with varying means and variances.

R^* can be thought of as a 'benchmark return rate', which would prevail in the absence of idiosyncratic beliefs ε, *i.e.*, when agents' expectations are aligned on the central projection. In the presence of belief dispersion, it represents the average return expectation. Γ is a measure of the extent of belief dispersion across the planning horizon. In the definition of φ^*, Γ can be taken as a belief-correction term used on R^* to account for the extent of belief dispersion. A high Γ implies that agents form beliefs that can be significantly different from the average expectations, making R^* less important for aggregate behaviour.

We can then derive ℓ_I, our main variable of interest, as the value of the cumulative distribution function $\Phi(\cdot)$ of the standard normal distribution at φ^*. That is,

$$\ell_I = Pr(\varepsilon_\varphi < \varphi^*) = Pr(r_L > r_H) = \Phi(\varphi^*) \tag{14}$$

To allow ourselves to explore large $\sigma_{u,s}$ values while keeping heterogeneous beliefs realistic, we censor the $\varepsilon_{u,s}$ distributions above 1 and below zero. After some transformations (see Appendix D and E), the final definition of ℓ_I is:

$$\ell_I = \frac{\delta_{\varphi_0 \varphi^*}(\Phi(\varphi^*) - \Phi(\varphi^*_0)) - \delta_{\varphi_1 \varphi^*}(\Phi(\varphi^*_1) - \Phi(\varphi^*))}{\Phi(\varphi^*_1) - \Phi(\varphi_1)}, \tag{15}$$

where $\delta_{uv} = \begin{cases} 1 & u < v \\ 0 & u \geq v \end{cases}$,

and φ^*_0 and φ^*_1 are the values φ would take if $\mu^*_{H,s} = 0\ \forall s$ or $\mu^*_{H,s} = 1\ \forall s$ respectively. For the values of φ^* we are exploring, we are always in a case in which $\varphi_0 \leq \varphi^* \leq \varphi_1$, such that the equation reduces to:

$$\ell_I = \frac{\Phi(\varphi^*) - \Phi(\varphi_0)}{\Phi(\varphi_1) - \Phi(\varphi_0)} \tag{16}$$

Table 1
Technological and financial parameters.

Symbol	Variable	Value	Source
Production			
e_d	Initial energy production	3243 GWh	European Commission (2019)
$K_{H,0}$; $K_{L,0}$	Initial capital stock	659 GW; 288 GW	European Commission (2019)
ξ_H; ξ_L	Capital productivity	4.5158; 2.9145	Eurostat (2022)
u_H^f; u_L^f	Full capacity utilisation rate	0.85	Eurostat (2022)
u_H, u_L	Initial utilisation rate	0.85	Eurostat (2022)
p_e	Price of electricity	0.2 bn$/TWh	Eurostat (2022)
ξ_f	Productivity of fossil fuels	0.114	EIA (2020)
p_f	Price of fossil fuels	0.0022 bn$/TWh	Eurostat (2022)
δ_H; δ_L	Capital depreciation rate	0.03; 0.04	IEA (2020d)
c_H^K; c_L^K	Capital cost	3.5 bn$/GW; 2.9 bn$/GW	IEA (2020d)
g_e	Energy demand growth	0.012	Enerdata (2021)
Finance			
ψ_H; ψ_L	Debt-to-investment ratio	0.7; 0.75	Baruya (2017); IRENA (2020)
ι_H; ι_L	Interest rate on loans	0.045; 0.0394	Kempa et al. (2021)
LT_H; LT_L	Loan tenor	15 years	Refinitiv (2022)
Belief heterogeneity			
b_σ	Intrinsic growth rate for $\sigma_{u,s}$	0.28	IPCC (2022)

3. Calibration

This section presents our calibration strategy. The model's time step in s-time is explicitly yearly. All monetary values are expressed in billion 2019$US; electricity production in terawatt-hours (TWh); electricity generation in gigawatts (GW); fossil energy in British thermal unit (Btu). We use the EU27 region in 2019 as our model economy. We can distinguish two categories of parameters. First, a set of technological or financial parameters calibrated to replicate empirical evidence and summarised in Table 1. Second, a set of behavioural parameters for which, in absence of solid empirical foundations, we perform a sensitivity analysis along reasonable value ranges in Section 4.

3.1. Technological and financial parameters

We include solar, wind and other minor renewable energy technologies in our low-carbon category and all other technologies in the high-carbon category. While hydropower and nuclear can be considered to be low-carbon considering their low emission intensity, additional environment-related issues (*e.g.* land use, waste treatment) usually lead them to be treated separately from wind, solar, geothermal and other renewable technologies. In addition, we take into consideration the fact that installing large hydro plants is now mostly infeasible in Europe, where generation of electricity from hydro has been stationary since 2000, nor strongly desired by policy-makers due its environmental footprint. Furthermore, across scenarios, uncertainty revolves mostly around the share of 'modern' renewables compared to other energy sources (Tsiropoulos et al., 2021). We thus focus on them and include nuclear and hydro in our 'high-carbon' category. We investigate alternative categorisations, with hydro and nuclear included as part of the low-carbon technology, in Appendix C.

We set the initial values of capital stocks following the European Commission (2019), which reports a total installed capacity of approximately 947 GW in 2019 for the EU-27 region, of which around 30% is made of solar, wind or geothermal plants. We thus set $K_{L,0} = 288$ GW and $K_{H,0} = 659$ GW, which implies that the share of low-carbon capital $\ell_{K,0} = \frac{288}{947} \approx 30\%$.

We further make a difference between utilisation rates and capacity factors. Utilisation rates are demand-driven and depend on economic factors. They refer to the degree to which the capital stock is used and are measured as the ratio between production and potential production at the best of technical possibilities. It is common for firms to maintain their available capital stocks operating on average at a rate lower than 100%, to be able to accommodate for peaks in demand. The normal capacity utilisation rate u^f is equal to 0.85 for both technologies, which is roughly in line with utilisation rates at the macro level in the European Union in 2019 given by Eurostat. We assume that the economy starts from a situation where both technologies operate at normal capacity and that firms expect the current-period utilisation to be equal to normal *i.e.*, we set $u_{L,0} = u_{H,0} = 0.85$.

On the other hand, capacity factors represent the technical limitations preventing an electricity-generation technology to operate at 100%. We assume them to be encapsulated in our productivity factors ξ_H and ξ_L, in the sense that they are purely defined by technology. Given our assumptions on utilisation rates, we calibrate our productivity parameters ξ_H and ξ_L to match energy production from high- and low-carbon technology in Europe. The share of wind, solar and geothermal technologies in total gross electricity production in Europe was around 22% in 2019. With a utilisation rate of 85% and a total energy demand equal to 3243 TWh this yields $\xi_L = \frac{0.22*3243}{0.85*288} = 2.9145$ and $\xi_L = \frac{0.78*3243}{0.85*659} = 4.5158$. Given that a GW of capacity would produce 8.76 TWh in a year at full capacity, this yields implicit capacity factors of $\frac{2.9145}{8.76} \approx 33\%$ and $\frac{4.5158}{8.76} \approx 51\%$, which are both roughly in line with 2018 capacity factors (*i.e.* uncorrected for utilisation rates in Europe) (IEA, 2019).

Table 2
Behavioural parameters.

Variable	Meaning	Reference value(s)	Sensitivity range
S	Length of planning horizon	20	[2, 40]
b_ℓ	Expected intrinsic growth rate for ℓ	0.15; 0.25	[0, 0.5]
$\bar{\ell}$	Maximum expected ℓ	0.85	[0.5, 0.95]
σ_0	Opinion diversity at time t	0.01	[0, 0.1]
$\bar{\sigma}$	Maximum opinion diversity	0.5	[0.01, 2]
ρ	Corporate discount rate	0.05	[0.01, 0.1]

The data on electricity prices for both households and non-household consumers is provided by Eurostat,[10] and shows values ranging from 0.005 to 0.27 €/KWh in 2019 for the EU27 region. We adopt a middle value by setting $p_E = 0.2$ bn$/TWh.

Fossil productivity parameter ξ_F transforms fossil fuels, expressed in trillion British thermal units (Btu), into electricity, expressed in TWh. 1 TWh physically corresponds to approximately 3.5 trillion British thermal units (Btu). We then need to adjust this number for the efficiency of thermal plants (heat rate), to account for energy losses arising from the conversion process. According to EIA (2020), the efficiency of thermal plants is around 0.33-0.45. Taking an intermediate value of 0.4, we calculate EU thermal plants to require 8.75 (=3.5/0.4) trillion Btu to produce 1 TWh of electricity. The ξ_F coefficient is then computed as the inverse of this number, that is $\frac{1}{8.75} \approx 0.114$.

The price of natural gas in 2019 for non-household consumers in the EU27 region was around 0.03€/KWh.[11] Rescaling to Btu and taking into consideration that the price of coal is usually lower than the one of gas, we set $p_F = 0.0025$ bn$/tnBtu.

We set depreciation rates δ_H and δ_L as the inverse of technology-specific asset lifetimes. IEA (2020a) reports expected lifetimes of 25 years for solar and wind plants and 30-40 years for fossil-fuelled plants. We thus set $\delta_H = 0.03 \approx 100/33$ and $\delta_L = 0.04 = 100/25$.

Capacity installation cost parameters c_i represent the cost of installing a unit of generating capacity (the 'overnight constructions costs'). IEA (2020a) describes the overnight cost for various technologies hypotheses made by the IEA in its projection exercises.[12] By taking a weighted average based on the European energy mix, we retain $c^k_H = 3.5$ bn$/GW and $c^k_L = 2.9$ bn$/GW.

Financing costs depend on the loan interest rate ι_i. Recent findings from Kempa et al. (2021) show an average 3.5% spread to Libor for high-carbon projects and that renewable projects face a 16% lesser markup. We then assume, for Europe, a 1% risk-free interest rate, resulting in $\iota_H = 0.01 + 0.035 = 0.045$ and $\iota_L = 0.01 + 0.035 \times 0.84 \approx 0.0394$ Debt-to-investment ratios (ψ_H, ψ_H) for renewable projects are taken from IRENA (2020), which reports a 75% rate. For high-carbon energy sources, sources are more conflicted (Baruya, 2017), with numbers ranging between 60 and 80% debt-financing. We thus adopt a middle-range assumption of a 70% rate. Regarding the loan term of debt financing, we rely on the Refinitiv project database. Albeit scarce, data shows a rough average of a 15-year loan term for all technologies ($LT = 15$).

Finally, we take energy demand growth from EnerData Enerblue scenario (Enerdata, 2021), which projects a 43% increase in final electricity consumption demand between 2020 and 2050. Assuming a constant growth rate over this period yields a yearly 1.2% growth.[13]

3.2. Behavioural parameters

Our model includes several parameters capturing the expectations and behavioural features of investment decision-makers. Despite the recent emergence of a stream of research contributions trying to assess climate-related expectations via surveys or financial econometrics (Bolton and Kacperczyk, 2020; Krueger et al., 2020), we currently do not have reliable data on which to calibrate these parameters. An exception is b_σ, which we calibrate to 0.28 based on our analysis of IPCC scenarios (see Section 2.4). However, since uncertainty acts on a different compact, we keep σ_0 and $\bar{\sigma}$ free.

For this reason, we illustrate our analytical results with sensitivity analyses on pairs of parameters while keeping the rest of the behavioural parameters fixed. We thus choose a reference value (to be kept constant while the parameter is not part of the sensitivity analysis) and a sensitivity range for each parameter. Since we are interested in exploring how these behavioural parameters could affect investment choices, we keep the sensitivity ranges large enough to capture all possible dynamics. In particular, we choose the sensitivity range for the maximum expected share of low-carbon technologies $\bar{\ell}$ and the intrinsic growth rate of the expected low-carbon energy share b_σ to match scenarios for the European Green New Deal (Tsiropoulos et al., 2021). Table 2 offers a summary of our choices.

3.3. High- and low-stranding projections

We conclude our calibration by specifying two representative central projection paths. In both of them, the long-run share of low-carbon energy is left fixed at 90%, in the upper distribution of the European Commission's scenarios (Tsiropoulos et al., 2021),

[10] See series nrg_pc_204 and nrg_pc_205 available at https://ec.europa.eu/eurostat/data/database.

[11] See Eurostat series nrg_pc_203_c.

[12] For hydro, the IEA does not provide data specific to Europe; we thus relied on a weighted average of costs across countries (IEA, 2020b).

[13] We follow most of the energy modelling literature in assuming that, while electricity demand can be affected by energy efficiency and other demand-side measures, the composition of its supply does not significantly affect the amount of power demanded by economic agents.

Table 3
Intrinsic growth rate values for low and high-stranding central expectations.

Scenario type	b_ℓ
Low stranding	0.15
High ambition	0.25

so to leave the intrinsic growth rate as the only degree of freedom. In formal terms, low-stranding projections can be defined as the set of b_ℓ such that $R^* < 0$ for our benchmark S and ρ. Reciprocally, high-stranding projections can be seen as the set of b_ℓ such that the benchmark return rate R^* is strictly positive. We choose $b_\ell = 0.15$ for a low-stranding central projection and $b_\ell = 0.25$ for a high-stranding central projection. We summarise this choice in Table 3. Whenever relevant, we will compare results from these two central projections.

We characterise a low-stranding scenario as a gradual transition, with a slow development of low-carbon technologies that does not result in much stranding. High-carbon energy sources remain operational for relatively long and be decommissioned gradually. By contrast, a high-stranding central expectation would feature a quicker deployment of low-carbon technology, resulting in larger stranding. This narrative implies a more disruptive transition, in which high-carbon technology is quickly replaced in the short run (Grubb et al., 2020). Our 'low-stranding' scenario can be roughly compared to the IEA's 'Announced Pledges' scenario (IEA, 2022a), in which fossil fuels are slowly replaced by alternative technologies. The IEA's 'Net Zero by 2050' scenario (IEA, 2022b) entailing a more rapid and intense low-carbon transition, could be compared instead to our 'high-stranding' path.

4. Results

This section expounds our main takeaways. We start by studying how belief heterogeneity affects aggregate investment decisions. To do so, we begin in Section 4.1 with a polar case without belief heterogeneity, corresponding to a benchmark in which agents' expectations are fully coordinated around the central expectation. We then lift the no-heterogeneity assumption to explore how our modelling proposal influences results compared to the benchmark. Subsequently, in Section 4.2, we explore how aggregate investment behaviours change with various levels of belief heterogeneity. We notably characterise the relative effect of short (σ_0) and long-run ($\bar{\sigma}$) belief heterogeneity and derive some properties in the case of hyperbolic heterogeneity. Sections 4.3 and 4.4 explore instead the interactions between belief heterogeneity and preference for the present: the discount rate ρ and the length of the planning horizon S.

4.1. Introducing belief heterogeneity

We start by assuming $\sigma_{u,s} = 0 \; \forall \; s \; \in [|1, S|]$, *i.e.*, we describe a situation in which all agents believe in the central projection. Being this a limit condition on our model, we can prove Proposition 2:

Proposition 2. *For $\sigma_{u,s} = 0 \; \forall s \in [|1, S|]$, ℓ_I tends towards a degenerate probability distribution function, whereby:*

$$\ell_I = \begin{cases} 0 & if \;\; R^* < 0 \\ 0.5 & if \;\; R^* = 0 \\ 1 & if \;\; R^* > 0 \end{cases} \tag{17}$$

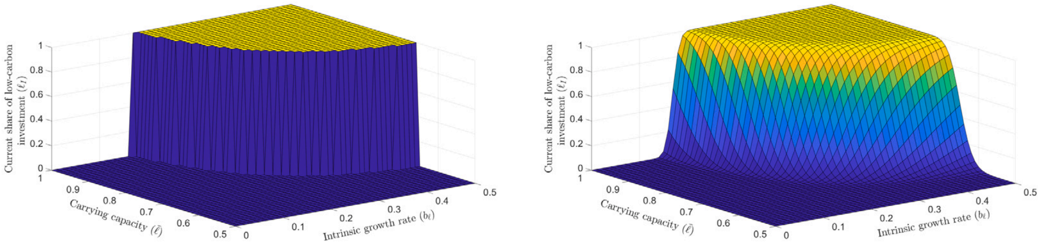
Proof. Demonstration is given in Appendix F.2. □

In other words, without belief heterogeneity the system can only achieve three outcomes: i) the whole populating invests in low-carbon energy ($\ell_I = 1$); ii) none of it does ($\ell_I = 0$); or iii) exactly half of the population does ($\ell_I = 0.5$). The interpretation is straightforward: absent belief heterogeneity, only the central projection, which rules the sign of R^*, matters. If this implies that low-carbon sources will be more profitable over the planning horizon according to this central projection ($R^* > 0$), then it is rational for all investors to invest in low-carbon energy. The intermediate case $R^* = 0$ would denote a 'total indecision' situation, in which agents are indifferent between the two technologies and therefore exhibit a 50-50 dispatch in aggregate. We illustrate these findings in Fig. 5, Panel (a).[14]

The value of R^* depends on the discount rate ρ, the planning horizon S and on the variables linked to the central expectations, *i.e.* the maximum expected share of low-carbon technologies $\bar{\ell}$ and the intrinsic growth rate b_ℓ. More precisely, we rewrite:

$$R^* = R^*(\rho, S, (u_{H,s})_{s \in [|1,S|]}) \tag{18}$$

[14] Note that the case $\ell_I = 0.5$ does not show because of the numerical simulation steps used for the chart.



(a) Without belief heterogeneity (b) With belief heterogeneity

Fig. 5. Effect of belief heterogeneity.

Based on the definition of Equation (12), it can be shown $\frac{\partial R^*}{\partial \rho} < 0$. This is a standard effect of increasing the discount rate. It leads agents to weigh less later periods over which stranding is expected to be strong enough to give an edge to low-carbon sources. For a high ρ, R^* can be negative.

Further, the lower the $(u_{H,s})_{s\in[|1,S|]}$ schedule, the lower R^*. The position of the $\left(u_{H,s}\right)_{s\in[|1,S|]}$ schedule depends directly on the $\left(\ell_{E,s}\right)_{s\in[|1,S|]}$ schedule, governed by $\bar{\ell}$ and b_ℓ, as per Proposition 3 below:

Proposition 3. *Consider a logistic sequence* $x_n = x_{n-1}\left(1 + b(1 - \frac{x_{n-1}}{K})\right)$ *where* K *is a carrying capacity and* b *an intrinsic growth rate. Consider then* x_0 *the first term of this sequence. It follows that,* $\forall n$ *such that* $x_n < K$ *and* $b \leq 1$*:*

$$\frac{\partial x_n}{\partial K} \geq 0 \tag{19}$$

$$\frac{\partial x_n}{\partial b} \geq 0 \tag{20}$$

$$\frac{\partial x_n}{\partial x_0} \geq 0 \tag{21}$$

With the last proposition holding for $x_0 < K$.

Proof. Demonstration is given in Appendix F.3. □

For what concerns the expected low-carbon share of energy, this implies that $\forall s$:

$$\frac{\partial \ell_{E,s}}{\partial \bar{\ell}} \geq 0 \tag{22}$$

$$\frac{\partial \ell_{E,s}}{\partial b_\ell} \geq 0 \tag{23}$$

The intrinsic growth rate b_ℓ rules the number of periods in time s needed to reach the maximum share $\bar{\ell}$ in expectations. If $\bar{\ell}$ is increased with b_ℓ held constant, agents will expect that a higher maximum share will be reached within the same amount of time. It requires ℓ_s to be higher or equal $\forall s$. Conversely, given a certain $\bar{\ell}$, a higher b_ℓ means that less time is required to reach $\bar{\ell}$. This entails a steeper growth and higher ℓ_s $\forall s$. Hence, a path with higher $\bar{\ell}$ or b_ℓ entails more stranding expectations due to a speedier increase of the share of low-carbon energy, which will result in higher low-carbon investment.

In economic terms, this proposition demonstrates that, under reasonable assumptions, if agents expect a higher long-term share of renewables $\bar{\ell}$ or a speedier transition b_ℓ, they will expect a higher share of renewables for all periods within their planning horizon. Given that stranding expectations are directly governed by the expected share of low-carbon investment, this implies that a higher ℓ or b_ℓ will imply higher stranding for all periods within the agents' planning horizon.

Finally, as per the definition of R^*, a minimum planning horizon is required for low-carbon investment to emerge. Indeed, if agents are so short-sighted to only account for early periods, over which stranding is low, they will expect a negative R^*. However, very long planning horizons are not necessarily improving. Given that stranding is transitory in our model — as high-carbon capital naturally depreciates — the period over which low-carbon capital becomes more profitable is finite. Once it is over, agents will expect an edge for high-carbon technologies again over subsequent periods, which may compensate for the positive payoff over the stranding period. Hence the following Proposition:

Proposition 4. *It is possible to define an interval* $\mathcal{S} = [|\underline{S}; \bar{S}|] \subset [|1, S|]$ *such that, for a given* ρ, b_ℓ *and* $\bar{\ell}$, $R^* > 0$ $\forall s \in \mathcal{S}$ *and* $R^* \leq 0$ *otherwise.* $\mathcal{S}$ *can be empty.*

Proof. Demonstration is given in Appendix F.4. □

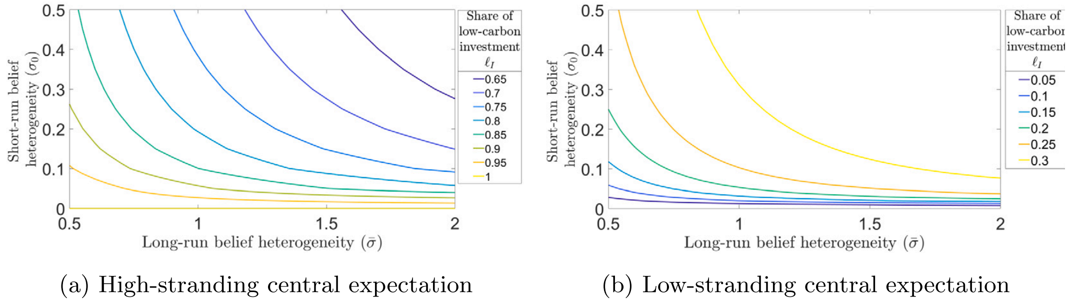


Fig. 6. Long-run and short-run belief heterogeneity. Panel (a) describes our high-stranding case, while Panel (b) shows our low-stranding case. The charts plot isovalue lines. For instance, the curve with legend "0.85" on Panel (a) corresponds to all $(\bar{\sigma}, \sigma_0)$ combinations for which the share of low-carbon investment ℓ_I is equal to 0.85 in the case of high stranding central expectation.

This proposition states that, over their planning horizon, agents will expect low-carbon energy sources to be more profitable than high-carbon technologies over a sub-period $\mathcal{S}$, typically the period over which the stock of high-carbon capital will suffer most from stranding.

We now introduce belief heterogeneity, by assuming the shape for the $\sigma_{u,s}$ schedule presented in Equation (10). Results are illustrated in Fig. 5, Panel (b).

As can be seen, the bang-bang solution disappears to give rise to a whole gradient of interior solutions ranging between 0 and 1 depending on the value of parameters b_ℓ and $\bar{\ell}$. The smoothness of the corresponding surface depends positively on belief heterogeneity.

Lifting the limit condition implies that the variables linked to relative return rates, φ^*, φ_0 and φ_1, take finite value and that the ℓ_I function takes value over the whole $[0, 1]$ interval. Intuitively, introducing belief heterogeneity allows for the existence of investors whose behaviour will drift from the central projection. Hence, for a projection entailing zero investment in the no-heterogeneity case, introducing idiosyncratic beliefs is equivalent to assuming that a part of the population will expect sufficient stranding to invest in low-carbon energy.[15] Reciprocally, for a high-stranding central projection, entailing 100% low-carbon investment in the absence of heterogeneity, allowing for a population of norm-contrarians will entail less low-carbon investment than in a no-heterogeneity case, since this share of the population will expect insufficient stranding.

Including a degree of belief heterogeneity increases significantly the indeterminacy of the model. This result is of important policy relevance, as the results implied by different degrees of belief heterogeneity can be very different from those flowing from an assumption of perfectly aligned expectations. We explore the impact of various levels of belief heterogeneity in the following and their policy consequences.

4.2. Belief heterogeneity, investment decisions and the central projection

To explore the role of belief heterogeneity, we let our parameters σ_0 (short-run belief dispersion) and $\bar{\sigma}$ (long-run belief dispersion) vary. Proposition 3 implies that:

$$\frac{\partial \sigma_{u,s}}{\partial \sigma_0} \geq 0 \tag{24}$$

$$\frac{\partial \sigma_{u,s}}{\partial \bar{\sigma}} \geq 0 \tag{25}$$

As a result, any increase in these two parameters will result in a higher $(\sigma_{u,s})_{s \in [|1, S|]}$ schedule, which will increase the belief-correction factor Γ defined in Equation (12). It is possible to demonstrate the following proposition:

Proposition 5. *The effect of a higher σ_0 or $\bar{\sigma}$ will depend on the sign of R^*. If $R^* < 0$, then $\frac{\partial \ell_I}{\partial \sigma_0} \geq 0$, $\frac{\partial \ell_I}{\partial \bar{\sigma}} \geq 0$. Furthermore, ℓ_I is concave in σ_0 and $\bar{\sigma}$. If $R^* > 0$, then $\frac{\partial \ell_I}{\partial \sigma_0} \leq 0$ and $\frac{\partial \ell_I}{\partial \bar{\sigma}} \leq 0$. Plus, ℓ_I is convex in σ_0 and $\bar{\sigma}$. Plus, there exists an $R' \in [R_0; R_1]$ such that $\frac{\partial \ell_I}{\partial \sigma_0}(R')$ and $\frac{\partial \ell_I}{\partial \bar{\sigma}}(R')$ equal to zero.*

Proof. Demonstration is given in Appendix F.5. □

We further illustrate the effect of belief heterogeneity on ℓ_I in Fig. 6. As a contour plot, it shows isovalue lines, *i.e.*, all the combinations within the $(\bar{\sigma}, \sigma_0)$ space that yield the same ℓ_I value. The space between the lines gives indication on how the value

[15] Due to the symmetry of belief heterogeneity, belief heterogeneity also entails that a population expects *less* stranding than with expectations aligned on the central projection. However, expecting even less stranding than on the central projection does not change the investment choice of these agents. As a result, only the population expecting more stranding has an impact on aggregate investment decisions.

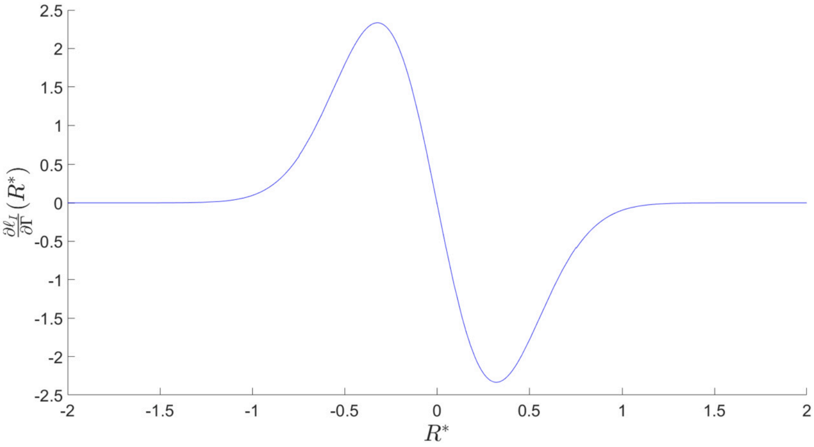


Fig. 7. Evolution of the sensitivity of the share of low-carbon investment ℓ_I to the belief correction factor Γ as a function of the central expectation return spread R^*.

of the outcome evolves when one of the two parameters is fixed. Typically, an increasing space across isovalue lines for increasing values of a parameter — like in Fig. 6 — would denote a decreasing marginal effect of the moving parameter. In the high-stranding scenario, increasing belief heterogeneity, either in the short or the long run, unambiguously decreases the low-carbon investment share. By contrast, increasing dispersion in the low-stranding case tends to increase low-carbon investment. In both cases, the effect of higher heterogeneity is bounded, as the low-carbon share tends towards a minimum (high stranding) or a maximum (low stranding) as dispersion increases. These results emerge because we define belief heterogeneity as deviations from the central projection or 'market norm'. Hence, the effects of belief heterogeneity on investment decisions also depend on the existing central projection. In the case of low-stranding expectations, 'transition believers' investing in low-carbon projects will be the 'norm contrarians'. Reciprocally, contrarians in the high-stranding case will be 'transition sceptics', who will invest more in high-carbon energy. As a result, belief heterogeneity will have a balancing effect on investment behaviour, the direction of which will depend on the existing norm.

We can also show that the (absolute) effect of more belief heterogeneity on investment allocation is higher when belief heterogeneity is lower. It shows on Fig. 6 through the increasing distance across isovalue lines. This is due to the concavity (in the low-stranding case) or convexity (in the high-stranding case) property of ℓ_I in Γ. Increasing belief heterogeneity from a low-dispersion situation will open a range of stranding expectations close to the cut-off point from which agents switch behaviours. Hence, many switches will occur. Conversely, if belief heterogeneity is high, most beliefs relevant for behaviour switch will already have a sizeable mass in the distribution. Hence a decreasing marginal (absolute) effect of belief heterogeneity.

The previous result, however, only holds for a fixed central projection. This begs studying how changes in belief heterogeneity will affect investment behaviours for various central expectation scenarios.

We first consider the expression of $\frac{\partial \ell_I}{\partial \Gamma}$ from the demonstration of Proposition 5 (see Appendix F.5, Equation (53)). Then, we fix the belief correction factor Γ (see (12)) to match our benchmark values ($\sigma_0 = 0.01$ and $\bar{\sigma} = 0.5$). Reducing $\frac{\partial \ell_I}{\partial \Gamma}$ to a function of R^*, the function takes the shape displayed in Fig. 7.

Fig. 7 shows that the higher (lower) the curve, the more positive (negative) a change in investment behaviour following a shift in Γ and *vice-versa*. A value of zero would denote that, for the corresponding central projection, moving belief heterogeneity has no effect on investment behaviour, which would be a case of 'perfect resilience'. However, norm resilience is non-monotonic. Sensitivity reaches two optima on each side of the y-axis. As can be seen in Fig. 7, sensitivity is zero for $R^* = 0$, *i.e.*, a perfect balance between profit rates at the benchmark. Moving from this point, (absolute) sensitivity increases to a maximum and decreases to perfect resilience.

Policy-wise, this implies that medium-stranding projections are fragile to belief heterogeneity shocks (*e.g.* shocks to confidence; decrease in policy credibility). As a result, policymakers should strive to measure the state of the central expectation to anticipate its resilience to possible shocks in belief dispersion. To reach a given penetration of renewable energy, the regulator may seek to anchor expectations towards higher stranding. It can do so by influencing the central expectation with policy announcements, while making sure to remain credible.

Regarding low-stranding projections, if the market norm is close to business-as-usual (very low stranding), the share of the population expecting enough stranding is so little that marginally increasing it will only affect aggregate investment decisions negligibly. This kind of 'low equilibrium' cannot be changed by a transition-believer minority but only by changing the ongoing market norm.

Another feature emerging from Fig. 6 is that the relative effects of short- (σ_0) and long-run heterogeneity ($\bar{\sigma}$) depend on the magnitude of one another:

Proposition 6. *For a given S and ρ, there exists a threshold ratio $\left(\frac{\bar{\sigma}}{\sigma_0}\right)^* = \sqrt{\frac{1-exp(-b_\sigma S)}{exp(-b_\sigma S)}}$ such that $\left|\frac{\partial \ell_I}{\partial \sigma_0}\right| > \left|\frac{\partial \ell_I}{\partial \bar{\sigma}}\right| \forall \frac{\bar{\sigma}}{\sigma_0} > \left(\frac{\bar{\sigma}}{\sigma_0}\right)^*$. In other words, the effect of increasing short-run belief dispersion σ_0 on investment behaviours is higher than that of increasing long-run dispersion $\bar{\sigma}$ if $\bar{\sigma}$ is sufficiently high relatively to σ_0.*

Proof. Demonstration is given in Appendix F.6. □

Whether the condition holds or not depends directly on the length of the planning horizon. Unsurprisingly, the more far-sighted agents are, the more the aggregate investment behaviour will be influenced by belief dispersion on long-run outcomes, unless belief dispersion on long-run developments is already very high.

It is possible to show that this condition holds true for a large proportion of the parameter space we explore. In particular, it holds for our benchmark calibration with $S = 20$ and $\sigma_0 = 0.01$ for $\bar{\sigma} > 0.16$. It accounts for the whole parameter space we explore in Fig. 6. We therefore focus on this case.

Let us first notice that long-run belief heterogeneity $\bar{\sigma}$ does not need to be very high for the condition to be fulfilled in our benchmark calibration. Because investment shares are more sensitive to belief heterogeneity for low values if σ_0 and $\bar{\sigma}$, it entails that, for reasonable values of $\bar{\sigma}$, an increase in σ_0 can have sizeable effects on aggregate investment behaviours. For high $\bar{\sigma}$ values, however an increase in σ_0, although it will bear larger effects than an increase in $\bar{\sigma}$, will have quantitatively small impacts on ℓ_I. It is due the concavity/convexity properties of ℓ_I in Γ (see above).

The policy implications are nonetheless clear. In the case of a high-stranding central expectation, the priority for policymakers should be to anchor expectations firmly for the earliest periods of the transition, if there is no clear consensus about long-run outcomes. If short-run belief heterogeneity is very low and long-run dispersion even moderately high, slightly higher short-run belief dispersion can have sizeable effects. Anchoring short-term expectations is all the more crucial considering that long-run belief dispersion is to some extent inevitable due to the many uncertainties surrounding the long-run future. Comparatively, aligning expectations on short-term outcomes seems more feasible. In the case of low-stranding expectations, policymakers should be cautious in interpreting positively a large tilt of investment behaviours towards low-carbon investment, as it may represent only a shock to short-run belief heterogeneity. These insights confirm the need for policymakers to carefully measure the state of expectations, in mean and in dispersion.

Fig. 6 further shows that the effect of higher belief heterogeneity dies down as σ_0 or $\bar{\sigma}$ increases, until seemingly reaching a finite value. What happens when the belief-dispersion term Γ tends towards infinity, describing a state of 'full dispersion' of beliefs?

Proposition 7. *As belief heterogeneity approaches infinity, ℓ_I will tend towards a finite value $\tilde{\ell}_I = \frac{R^*-R_0}{R_1-R_0}$, where R^*, R_0 and R_1 are the numerators of φ^*, φ_0 and φ_1 respectively. It defines a uniform distribution on R^* over $[R_0, R_1]$. We call $\tilde{\ell}_I$ 'full dispersion' equilibrium and it is a function of b_ℓ, $\bar{b}$ for a given S and ρ. Note that if we do not censor our distribution, the 'full-dispersion' equilibrium $\tilde{\ell}_I$ is always equal to 0.5.*

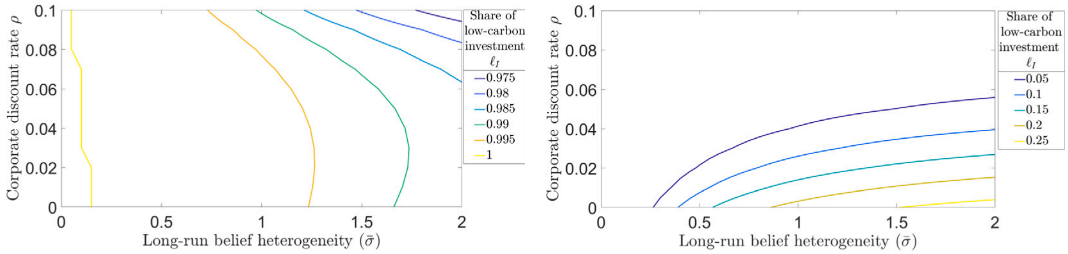
Proof. Demonstration is given in Appendix F.7. □

This result means that, if we ensure that expected utilisation rates remain between 0 and 1 (*i.e.*, agents have 'reasonable' beliefs), only the position of the central expectation within the realm of acceptable beliefs matters for aggregate investment behaviour when belief dispersion is very high. Because the distribution of beliefs converges towards a uniform distribution, so does the distribution of expected return rates. As a result, all expectations have the same weight in determining investment decisions as long as they remain within the boundaries of acceptable beliefs. It implies that the only determinant of investment shares will be the position of the central expectation relative to the boundaries defining acceptable beliefs.

This feature has several policy implications. First, it implies that, with high belief heterogeneity, 100% low-carbon investment can only be achieved if the central expectation entails maximum stranding ($u_{H,s} = 0\ \forall s \in [|1, S|]$), *i.e.* $R^* = R_1$. However, stranding the entire stock of high-carbon capital overnight is a hardly credible scenario. Hence, in the case of a full-dispersion equilibrium, low-carbon investment will always represent less than 100% of the total.

Second, low- and high-stranding projections are asymmetric. High belief heterogeneity for low-stranding projections will always yield *less* low-carbon investment than high belief heterogeneity with high-stranding expectations. This implies that a strong minority of 'high-stranding believers' will never be able to turn the tide of low-carbon investments and reach investment shares that would prevail for a high-stranding projection.

Finally, for a benchmark return rate R^* equal to zero, the limit is not equal to 0.5, unlike for the case $\Gamma = 0$. This is because, for Γ very high or close to infinity, the censoring of opinions becomes more relevant for aggregate investment behaviour. As a result, unless $-R_0 = 2(R_1 - R_0) \Longleftrightarrow R_0 = -R_1$, *i.e.* a case of perfect symmetry in censoring, high belief heterogeneity will introduce a distortion if beliefs are censored. Even in a situation of indifference ($R_0 = 0$), the aggregate investment behaviour will be biased. For our calibration, $\frac{-R_0}{R_1-R_0} \approx \frac{3.43}{6.59+3.43} = 0.3426$, which denotes a bias in disfavour of low-carbon technology.



(a) High-stranding central expectation (b) Low-stranding central expectation

Fig. 8. Interaction between long-run belief heterogeneity $\bar{\sigma}$ and the discount rate ρ. Panel (a) describes our high-stranding case, while Panel (b) shows our low-stranding case. The charts plot isovalue lines. For instance, the curve with legend "0.995" on Panel (a) corresponds to all $(\bar{\sigma}, \rho)$ combinations for which the share of low-carbon investment ℓ_I is equal to 0.995 in the case of high stranding central expectation.

4.3. The discount rate and belief heterogeneity

We now explore the effects of the discount rate ρ on investment behaviours and how it interacts with belief heterogeneity.[16] While the strong dependence on other parameters does not allow us to derive analytical results for the effect of discount rate ρ on aggregate investments, it is possible to draw some insights from numerical simulations.

As Fig. 8 shows, for high-stranding plans (Panel (a)), ρ and $\bar{\sigma}$ interact non-linearly. For sufficiently low levels of belief heterogeneity, the effect of the discount rate is negligible. In other words, when $\bar{\sigma}$ is low, an increase in ρ requires only a marginal change in $\bar{\sigma}$ to remain on the same isovalue curve. For higher levels of belief heterogeneity, instead, the relationship become strongly non-linear. When discount rate ρ is low, remaining on the same isovalue line requires a higher belief heterogeneity, *i.e.*, an equal level of belief uncertainty would yield a higher low-carbon investment share. When ρ becomes higher, its effect on low-carbon investments becomes unambiguously negative, as lower belief heterogeneity is now necessary to compensate for the increase in ρ and remain on the same isovalue line. This pattern emerges because of two opposite effects of the discount rate. On the one hand, the discount rate decreases the weight of periods over which agents expect a higher payoff for low-carbon energy in the central expectation. On the other hand, because longer-run beliefs are also discounted, agents tend to give less weight to opinions relevant for later periods. This suggests that the belief-discounting effect of ρ dominates the discounting of the central expectation for low values of ρ. The opposite is true for higher values of ρ. It also explains why belief heterogeneity and ρ should interact positively for high values of ρ. In the presence of high belief heterogeneity, discounting more those beliefs straying from the central expectation will tend to give even more weight to the central expectation, which yields less low-carbon investment due to higher discounting.

The low-stranding projection (Panel (b)), by contrast, entails an unambiguously negative impact of the discount rate on low-carbon investment shares. We can see that the interaction between belief heterogeneity and discounting is reversed compared to the high-stranding case. The mechanism is the same as in the above: discounting heterogeneity decreases the weight of norm-contrarian beliefs for investor behaviours which, with a low-stranding central expectation, will reduce low-carbon investment.

This interaction between belief heterogeneity and the discount rate shows that, regardless of their beliefs, agents exhibiting a higher discount rate will invest less in low-carbon technology. It suggests that anchoring expectations and striving to decrease socially inadequate preferences for the present (Steffen, 2020) should go hand in hand. For low-stranding projections, an optimal discount rate is zero. For high-stranding ones, our results show that a non-zero discount rate maximises low-carbon investment through the lower weighting of heterogeneous beliefs over later periods.

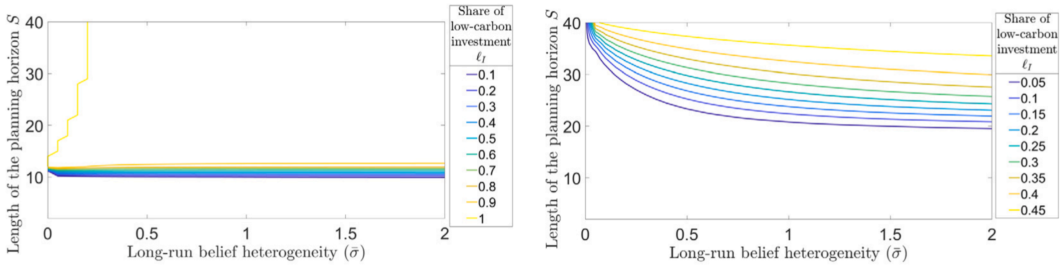
4.4. Farsightedness and belief heterogeneity

We now turn to the interactions between belief heterogeneity and farsightedness, denoted by the length of the planning horizon S. The general impact of increasing the planning horizon by one period is given by Proposition 8.

Proposition 8. *Let us define R^*_S the value of the benchmark return rate for a given length for the planning horizon S. An increase in the planning horizon S has a positive effect if $R^*_{S-1} + \pi_{L,S} - \pi_{H,S} > 0$. Based on Proposition 1, there exists an $s_1 \in [|1, S|]$ sufficiently large such that this condition holds (if $\pi_{L,1} - \pi_{H,1} > 0$, $s_1 = 1$). Still based on Proposition 1, there exists an $s_2 > s_1$ such that the condition reverses if $\pi_{L,1} - \pi_{H,1}$ is negative and low enough. s_2 increase with $\bar{\ell}$ and b_ℓ.*

Proof. Demonstration is given in Appendix F.8. ☐

[16] For the sake of brevity, we only allow $\bar{\sigma}$ to vary in modulating belief heterogeneity in our illustrations. Effects would be qualitatively similar if we changed the level of σ_0, as long as we keep $\sigma_0 < \bar{\sigma}$.



(a) High-stranding central expectation (b) Low-stranding central expectation

Fig. 9. Interaction between long-run belief heterogeneity $\bar{\sigma}$ and the planning horizon S. Panel (a) describes our high-stranding case, while Panel (b) shows our low-stranding case. The charts plot isovalue lines. For instance, the curve with legend "0.5" on Panel (a) corresponds to all $(\bar{\sigma}, S)$ combinations for which the share of low-carbon investment ℓ_I is equal to 0.5 in the case of high stranding central expectation.

Intuitively, agents with a longer planning horizon account for interval tend to include more periods s where low-carbon tech is expected to be more profitable. However, as shown in Proposition 8, this effect is compensated for by negative $\pi_{L,s} - \pi_{H,s}$ emerging once the stranding period ends. This latter effect is exacerbated by low discounting.

These figures illustrate the fact that a minimum planning horizon is required for low-carbon investment to emerge in the current period. This minimum planning horizon corresponds to the expectation horizon necessary for agents to account for enough s-time intervals so to tilt the expected profit rate in favour of low-carbon technologies.

Starting with the high-stranding central expectation (Panel (a)), increasing belief heterogeneity has two opposite effects. It increases low-carbon investment for low planning horizons, consistently with the discussion above. It can also decrease by a moderate amount ($\approx 10\%$) the share of low-carbon investment if the horizon of expectation is long and belief heterogeneity is high.[17] This feature is due to our assumption of time s-increasing opinion diversity. As the planning horizon increases, expectations will diverge more for later periods. Hence, agents will tend to exhibit a more balanced investment portfolio as their planning horizon increases. This highlights a trade-off between sufficient long-termism and the uncertainty linked to very late periods. Finally an increase in belief heterogeneity decreases the cutoff point from which the effect of a longer planning horizon entails lower low-carbon investment. This is because higher heterogeneity will tend to decrease the expected value of positive $\pi_{L,s} - \pi_{H,s}$ over $[|s_1, s_2|]$ in aggregate, resulting in negative φ^* if the planning horizon is sufficiently longer to include periods over which agents expect low-carbon technologies to be less profitable.

The low-stranding case (Panel (b)) shows a synergy between the length of the planning horizon and belief heterogeneity. It is because, with higher belief dispersion, including more periods into the planning horizon will lead a greater part of the investors' population believe that low-carbon investments will be profitable, and for longer. Conversely, if belief heterogeneity is low, increasing the planning horizon has only a very moderate impact low-carbon investment. It is because agents expect that the period of stranding over which low-carbon investments will be more profitable is only transitory. Because the central projection features low stranding, the stranding period will be short and too transitory to outweigh subsequent periods, over which the edge of the low-carbon technology is reduced. Quantitative implications are greater than in the high-stranding case and function of the length of the planning horizon. Intuitively, for a planning horizon maximising stranding expectation, allowing for greater belief heterogeneity pushes even farther the range of transition-prone expectations. Hence, the share of low-carbon investors will increase.

These results also show that a relatively high share of low-carbon investment (40-50%) can emerge for some planning horizons in the event of important belief heterogeneity, regardless of the underlying central expectation. As sketched in Sections 4.2 and 4.3, introducing belief heterogeneity introduces a whole gradient of interior solutions between 0 and 1. A same share of low-carbon investment can correspond to many parameter constellations. As a result, considering observed shares of low-carbon investment alone as an indicator of the good health of the transition can be misleading.

For instance, the share of renewable investment in Europe revolves around 40%, which may be seen as encouraging. Yet, policymakers should be cautious, in that this figure may correspond equally to a state of high central expectation, but short planning horizon (Fig. 9 Panel (a) or, conversely, to a state of long planning horizon, but high belief dispersion (Panel (b)). Given that both possibilities lead to different policy implications, regulators should consider surveying investors to gauge as much as possible to state of the market wisdom, how dispersed beliefs are, and how short-sighted agents are.

5. Conclusion

Transitioning to a carbon-free economy requires convincing a sufficiently relevant proportion of private decision-makers that investing in low-carbon technology is the most profitable strategy. High-carbon technologies still often represent the most convenient investment alternative due to higher productivity, better financing conditions, and other factors. However, firms might decide to invest in low-carbon technologies if they expect them to diffuse rapidly and, consequently, high-carbon capital units to become under-utilised ('stranded') and deliver lower profits in the future.

[17] This feature shows in Panel (a) through the upward-sloping shape of the "0.9" line.

Firms have diverse beliefs about what will happen in the future. We introduce heterogeneity by representing firms' opinions as normally distributed around a central expectation, which we take as an announced policy pathway or a common market norm, and increasing logistically in the length of their planning horizon. Our model allows us to explore the role of opinion diversity on investment behaviours, relaxing the hypothesis of coordinated expectations usually encountered in macroeconomic modelling.

Our analytical framework is not immune to limitations, paving the way for future research. The assumption of homogeneous time preferences could be relaxed by representing populations with heterogeneous planning horizons and discount rates. Including expectations for other variables than the utilisation rate, as we start exploring in Appendix B, would be equally relevant, possibly down to the conception of a full 'mental model' of the economy for the agents, close to Gabaix's (2014) endeavour. Our work could also include different and more complex distributions for opinion diversity, as suggested by Appendix A. Finally, exploring the dynamic implications of the model is likely to offer valuable insights. For instance, competing market norms across which agents could switch (in a way similar to Franke and Westerhoff, 2017; Hommes, 2021, among others) could be included; or climate policies and their implications could be explicitly represented. However, despite its limitations, we believe our paper offers a novel perspective on the low-carbon transition dynamics, with a framework that is close enough to reality to capture several key behavioural dimensions for the first time, while maintaining analytical tractability.

We find that the effects of belief heterogeneity on investment shares depend significantly on the existing market norm. If central market expectations entail a rapid transition and large high-carbon stranding, stronger belief heterogeneity reduce low-carbon investment. The opposite is true for central expectations implying low stranding expectations. The strength of this effect is strongly non-linear: in a context of both very polarised or fully balanced market expectations, investment shares will not react much to changes in belief heterogeneity; by contrast, milder central expectations in favour of either technology will be very sensitive to changes in heterogeneity. Another key finding is that high-stranding market norms will deliver higher low-carbon investment shares, even with high belief dispersion. Our main policy takeaway is that policymakers should strive to estimate the state of existing central expectations and of belief heterogeneity in the marketplace in order to best anticipate possible market reactions to real-world developments. They could also try to infuse high-stranding market norms within the business community, if their goal is to increase the share of low-carbon energy, with the caveat that such policy move should not endanger their credibility.

We also find that under our benchmark calibration, and for a sizeable proportion of the parameter constellation we explore, low-carbon investment shares are more sensitive to shocks to short-run belief heterogeneity than to long-run belief heterogeneity. For moderate overall belief dispersion, this implies that shocks to short-run belief dispersion can have disproportionate effects. In this respect, we suggest that policymakers should make sure that agents' expectations are aligned as much possible regarding short-run outcomes. This could be done, for instance, by adopting short-term planning involving all stakeholders to reach consensus, with regular evaluation from an independent authority. These findings finally suggest that policymakers should assess investors' views about the low-carbon transition — *e.g.* through surveys or expert auditions — to fully grasp whether the dynamics of today will keep going in the future.

Finally, we study how heterogeneous beliefs interact with agents' time preferences along two dimensions. Belief heterogeneity interacts with the discount rate in various ways. If the central expectation has high stranding content, higher belief heterogeneity exacerbates the effects of the discount rate. Reciprocally, higher belief heterogeneity tones down the impact of the discount rate if the central expectation has low stranding content. In that case, transition believers tend to expect more stranding in the early periods of their planning horizon. More importantly, we show that belief heterogeneity can thwart the positive effects of longer planning horizons. Indeed, while increasing the planning horizon augments expected stranding, it also increases the impact of opinion diversity by widening the range of projections. Again, the final result depends on the underlying central expectations. In particular, belief heterogeneity can have a highly detrimental effect if the central expectation has low stranding content by keeping low-carbon investment close to a 50-50 dispatch. Finally, we find that, in the presence of belief heterogeneity, simply looking at the share of low-carbon investment to assess the state of investor expectations is misleading, as the same share of low-carbon investment can correspond to many different states of investor opinion, lengths of the planning horizon, or levels of the market norm.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Emanuele Campiglio reports financial support was provided by European Research Council.

Data availability

Data will be made available on request.

Appendix A. Using a stable distribution for belief heterogeneity

We present here some insights on the use of alternative distributions to depict belief heterogeneity. The normal distribution has the important drawback of being symmetric, which does not allow for skewed distributions. It also puts great emphasis on values around the mean. The normal distribution, however, is a special case of a broader family of distributions, Stable laws. They are stable by addition and whose skewness and kurtosis can be parameterised.

Stable laws are not directly depicted by a density, but can be derived from their characteristic function. With $X \sim Stable(\alpha, \gamma, \beta, \delta)$, the characteristic function writes, with i the imaginary number and $\forall t \in \mathbb{R}$:

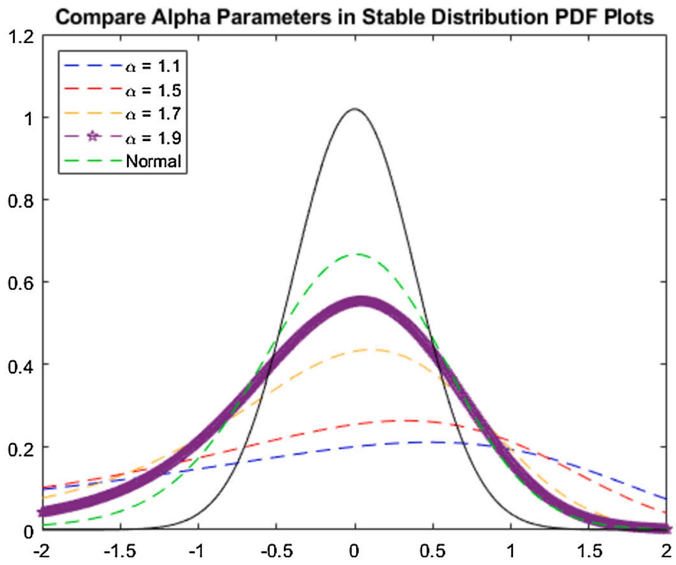


Fig. A1. Comparison of the Normal distribution benchmark to various Stable laws for the same $\sigma_{u,s}$ schedule.

$$\mathbb{E}(e^{itX}) = \begin{cases} \exp\left(-\gamma^{\alpha}|t|^{\alpha}\left[1 + i\beta sign(t)\tan(\frac{\pi\alpha}{2})((|\gamma|)^{1-\alpha} - 1)\right] + i\delta t\right) & if \ \alpha \neq 1 \\ \exp\left(-\gamma|t|\left[1 + i\beta sign(t)\frac{2}{\pi}\ln(\gamma|t|)\right] + i\delta t\right) & if \ \alpha = 1 \end{cases}$$

This function is parameterised by:

- $\alpha \in]0;2]$, named the 'stability parameter', which is a proxy for kurtosis. $\alpha = 2$ is a normal distribution.
- $\gamma \in \mathbb{R}^{+}$ is the scale parameter, which rules the range on which the distribution will take most of its values and is therefore a proxy for the variance.
- $\beta \in [-1;1]$ is the skewness parameter. $\beta = 1$ indicates rightward skewness and vice-versa.
- $\delta \in \mathbb{R}$ is a position parameter, which is an approximation for the mode for high αs.

The stable distribution is called α-stable, in the sense that the sum of stable distributions with the same αs is a stable distribution. More precisely, with $X_1 \sim Stable(\alpha, \gamma_1, \beta_1, \delta_1)$ and $X_2 \sim Stable(\alpha, \gamma_2, \beta_2, \delta_2)$, the sum $X_1 + X_2 \sim Stable(\alpha, \gamma, \beta, \delta)$, with:

$$\gamma = (\gamma_1^{\alpha} + \gamma_2^{\alpha})^{\frac{1}{\alpha}}$$

$$\beta = \frac{\beta_1\gamma_1^{\alpha} + \beta_2\gamma_2^{\alpha}}{\gamma_1^{\alpha} + \gamma_2^{\alpha}}$$

$$\delta = \delta_1 + \delta_2$$

This can be easily generalised to the sum of n stable distributions, which allows us to define our $\varepsilon_{u,s}$ much more generally than with a normal distribution while still being able to compute our aggregate profitability metric $\boldsymbol{R}^*$.

However, worth emphasising is that stable distributions are in general not as readily interpretable as the Gaussian special case. Typically, the variance is undefined for $\alpha < 2$ (*i.e.* any case that is not a normal distribution) and the mean value is undefined for $\alpha < 1$. As a result, the two parameters γ and δ are only proxies for respectively the variance and the mode of the distribution in the general case. Any result should therefore be taken with precaution given their lesser interpretability.

We nonetheless parameterise our $\varepsilon_{u,s}$, such that $\delta_{u,s} = 0$ and $\gamma_{u,s} = \sigma_{u,s}$, leaving β and α free. To keep an interpretable 0-mean, we modulate α to keep it within the $]1,2[$ interval. To study the impact of leftward-skewed beliefs (*i.e.*, a greater mass of agents believing in stranding), we set to start with $\beta = -1$. We illustrate how this constellation of parameters changes the distribution with respect to a Normal benchmark in Fig. A1, for a same scale ($\sigma_{u,s}$) schedule and various αs.

As can be seen, distributions are obviously more skewed leftward. Plus, the mode tends to shift away from the zero mean to make for the skewness. Finally, non-normal distributions tend to de-emphasise values around the mode and focus on 'rarer' events to the left. However, as can be seen, they also tend to include more events to the right of the zero-mean. As a result, especially for low αs, Stable distributions are useful in representing populations that are more polarised. We display results in Fig. A2 for the σ_0 and $\bar{\sigma}$, over a smaller compact than in Section 4 to make it more tractable and for various values of α.

As can be seen, changing the distribution has both qualitative and quantitative implications. Interestingly, more skewness leads most often to lower low-carbon investment, even if it makes a greater part of the population believing in high stranding. This is entirely attributable to the fact that skewness is compensated by a greater share of the population believing in higher stranding.

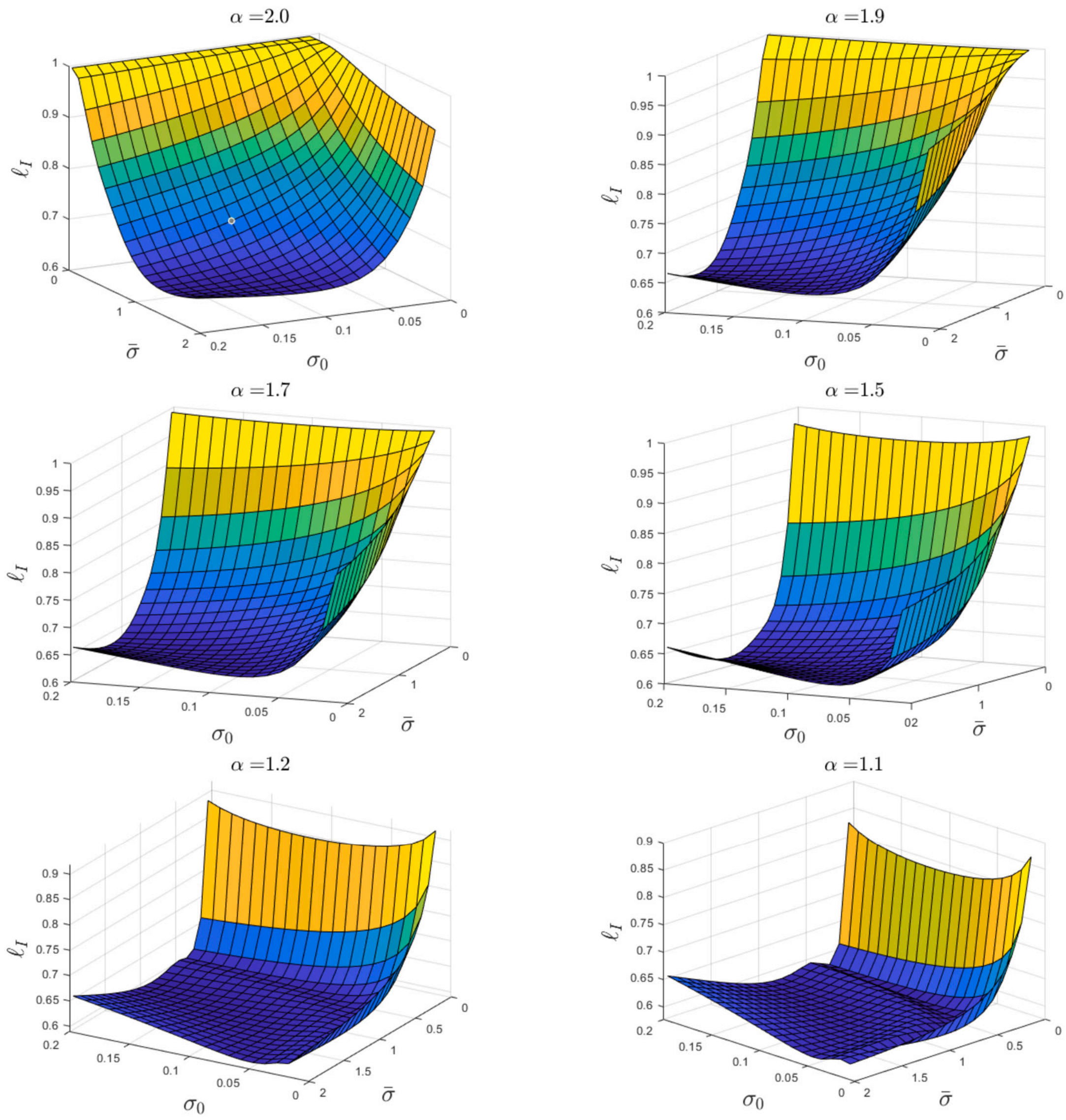


Fig. A2. Sensitivity figures on dissent parameters σ_0 and $\bar{\sigma}$.

Because of our censoring process, this share of the population will become more relevant as the central stranding projection hits lower values, resulting in lower low-carbon investment values. Interestingly, however, this logic gets reversed for low αs and high $\sigma_{u,s}$ schedules, as the population believing in high stranding is more important. These results suggest that a greater polarisation of beliefs acts in disfavour of the low-carbon transition, unless it is characterised by a very 'strong minority'. Note nonetheless that, within our parameter range, the impact of this strong minority seems reduced.

Appendix B. Expanding the realm of uncertainty

In this Appendix, we offer some insights on how our results would change if belief heterogeneity went beyond the utilisation rate of high-carbon capital to also affect the prices of both electricity and fossil fuels. We redefine the return rates for the two technologies as:

$$r_H = \sum_{s=t}^{S} \beta^s \left[\left(p_E - \frac{p_F}{\xi_F} + \varepsilon^H_{\pi,s} \right) \xi_H (u^*_{H,s} + \varepsilon_{u,s}) - \alpha_H \psi_H c_H \right] \tag{26}$$

$$r_L = \sum_{s=t}^{S} \beta^s \left[(p_E + \varepsilon^L_{\pi,s}) u^f_L \xi_L - \alpha_L c_L \right] \tag{27}$$

where $\epsilon_{\pi,s}^{(H,L)} \sim \mathcal{N}\left(0,(\sigma_{\pi,s}^{(H,L)})^2\right)$ is now the dispersion of beliefs around the normal expected unit profitability for both technologies. These terms include movements in intermediate fossil input prices p_F (including taxes) and changes in electricity prices p_E.

By recalling our investment rule for which $\ell_I = P\left(r_L - r_H > 0\right)$ and developing the expression, we can write:

$$\ell_I = P\left(\underbrace{\sum_{s=t}^{S}\beta^s\left[\left(p_E - \frac{p_F}{\xi_F}\right)\xi_H u^*_{H,s} - p_E\xi_L u_L^f - \alpha_H\psi_H c_H + \alpha_L c_L\right]}_{\text{“Mean belief”term}} + \underbrace{\sum_{s=t}^{S}\beta^s\left[\epsilon_{u,s}\xi_H\left(p_E - \frac{p_F}{\xi_F}\right) + \epsilon_{\pi,s}^H\xi_H u^*_{H,s} - \epsilon_{\pi,s}^L\xi_L\right]}_{\text{Normal distribution term}} + \underbrace{\sum_{s=t}^{S}\beta^s\left[\epsilon_{u,s}\epsilon_{\pi,s}^H\xi_H\right]}_{\text{Normal-Product Distribution Term}} \geq 0\right) \tag{28}$$

Equation (28) yields a product of Normal random variables (bottom term in the equation), which is known to be described by a Normal-Product distribution. The sum of such a distribution, which we need to derive our aggregate return rate, does not have a readily available functional form. However, if the random variables are assumed to be independent, the central-limit theorem allows us to approximate the whole distribution by a well-parametrised Normal distribution. Ware and Lad (2003) further show that for Normal-Product distribution, this approximation holds once we sum as few as five products of normal random variables. Hence, because we sum more than five random variables in our benchmark case with $S = 20$, all the random variables having a mean of zero, and since we assume independence between $\epsilon_{u,s}$ and $\epsilon_{\pi,s}^H$, products can be well approximated by a Normal distribution with mean zero and variance $\left(\epsilon_{u,s}\epsilon_{\pi,s}^H\xi_H\right)^2$.

As a result, waiving the censoring described in Appendix E for simplicity, we can write:

$$\ell_I \sim \mathcal{N}\left(\underbrace{\sum_{s=t}^{S}\beta^s\left[\left(p_E - \frac{p_F}{\xi_F}\right)\xi_H u^*_{H,s} - p_E\xi_L u_L^f - \alpha_H\psi_H c_H + \alpha_L c_L\right]}_{Mean}, \underbrace{\sqrt{\sum_{s=t}^{S}\beta^{2s}\left(\sigma_{u,s}^2\xi_H\left(p_E - \frac{p_F}{\xi_F}\right)^2 + \left(\sigma_{\pi,s}^H\xi_H u^*_{H,s}\right)^2 + \left(\sigma_{\pi,s}^L\xi_L u_L^f\right)^2 + \left(\sigma_{u,s}\sigma_{\pi,s}\xi_H\right)^2\right)}}_{Standard-Error}\right) \tag{29}$$

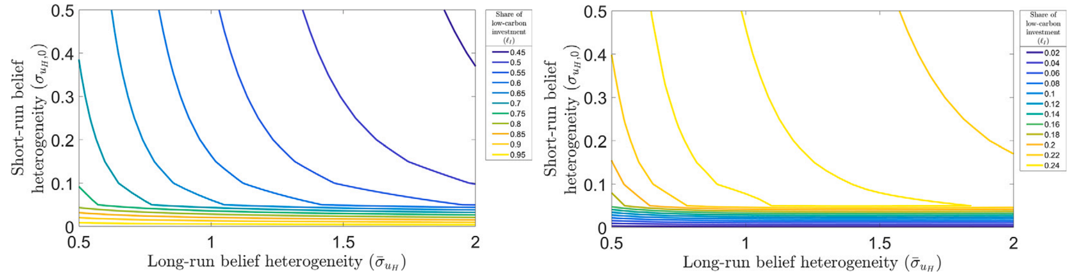
Hence, the Normal distribution above allows us to maintain the same Probit approach we use in the main text. Equation (29) is a direct extension of our basic formula described in Equations (11)-(16) and with three additional terms:

- $\left(\sigma_{\pi,s}^H\xi_H u^*_{H,s}\right)^2$, the belief dispersion on the profitability of high-carbon technology;
- $\left(\sigma_{\pi,s}^L\xi_L u_L^f\right)^2$, the belief dispersion on low-carbon profitability;
- $\left(\sigma_{u,s}\sigma_{\pi,s}\xi_H\right)^2$, the interaction between belief dispersion on the profitability of high-carbon technology and on the utilisation rate.

Notice that expanding the realm of uncertainty has, quantitatively, the same implications as shifting the $\sigma_{u,s}$ schedule in the case when there is only belief dispersion around future utilisation rates (asset stranding). We therefore expect this augmented model to yield lower values of ℓ_I, all other things left equal. Furthermore, increasing any σ would yield the same qualitative results as in the benchmark case with beliefs only on future utilisation rates.

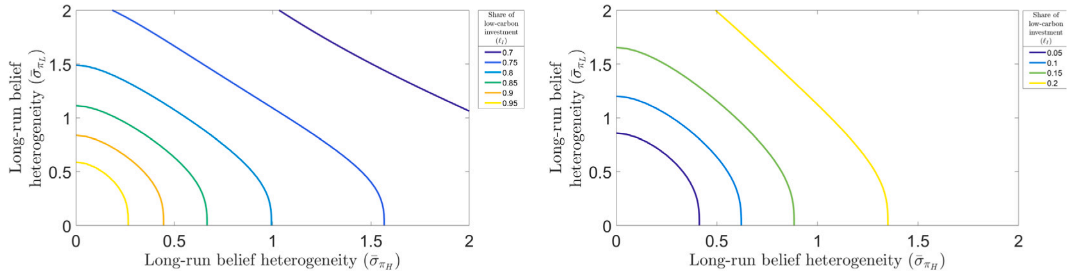
Without providing analytical proofs for brevity, we report some results along the line of Section 4 by supposing that belief dispersion on π_L and π_H (σ_{π_L} and σ_{π_H}) increases through time s following the same logistic behaviour identified for σ_{u_H} and with the same default minimum and maximum belief dispersion (*i.e.* $\sigma_{\pi_L,0} = \sigma_{\pi_H,0} = \sigma_{u_H,0} = 0.01$ and $\bar{\sigma}_{\pi_L,0} = \bar{\sigma}_{\pi_H,0} = \bar{\sigma}_{u_H,0} = 0.5$).

First, we study how the introduction of these new dimensions of belief uncertainty affects our results. For this purpose, we reproduce Fig. 6, including our new hypotheses on σ_{π_L} and σ_{π_H}. Results are reported in Fig. A3. For the ambitious scenario (high stranding), results are close to those in Fig. 6, qualitatively and quantitatively. However, effects are more in disfavour of low-carbon energy sources overall: a full low-carbon investment share is never reached, with a 95% maximum, and the lower values are reached for high belief dispersion. Furthermore, the effects of $\bar{\sigma}_{u_H}$ and $\sigma_{u_H,0}$ are much more non-linear, with sharper curvatures. This is



(a) High-stranding central expectation (b) Low-stranding central expectation

Fig. A3. Long-run and short-run belief heterogeneity (extended uncertainty). Panel (a) describes our high-stranding case, while Panel (b) shows our low-stranding case. The charts plot isovalue lines. For instance, the curve with legend "0.85" on Panel (a) corresponds to all $(\bar{\sigma}_{u_H}, \sigma_{u_H,0})$ combinations for which the share of low-carbon investment ℓ_I is equal to 0.85 in the case of high stranding central expectation.



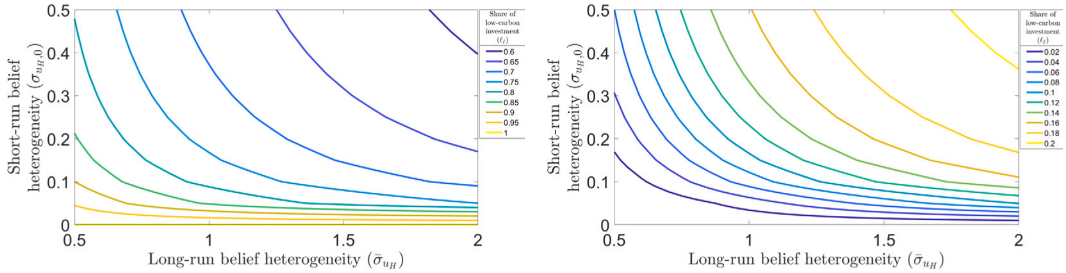
(a) High-stranding central expectation (b) Low-stranding central expectation

Fig. A4. Long-run belief heterogeneity on low- and high-carbon profitability (extended uncertainty). Panel (a) describes our high-stranding case, while Panel (b) shows our low-stranding case. The charts plot isovalue lines. For instance, the curve with legend "0.85" on Panel (a) corresponds to all $(\bar{\sigma}_{\pi_L}, \bar{\sigma}_{\pi_H})$ combinations for which the share of low-carbon investment ℓ_I is equal to 0.85 in the case of high stranding central expectation.

attributable to: (i) belief dispersion on low-carbon energy profitability, which tends to decrease low-carbon investment; and (ii) the interaction term $\left(\sigma_{u_H,s}\sigma_{\pi_H,s}\xi_H\right)^2$, which exacerbates the effects of uncertainty on asset stranding. In the unambitious case (low stranding), we find again effects to be in disfavour of low-carbon energy sources compared to our default case, due to the belief dispersion on low-carbon energy profitability. We also find a non-linear effect, with $\bar{\sigma}_{u_H}$ and $\sigma_{u_H,0}$ associated with *less* low-carbon investment than lower combinations, especially for high $\sigma_{u,0}$. This non-linearity emerges because of the interaction term $\sigma_{\pi_H}\sigma_{u_H}$, which amplifies the effect of high $\bar{\sigma}_{u_H}$ and $\sigma_{u_H,0}$ in late periods. In this context, agents hardly take into account the slow progresses of low-carbon energy in the long run prevailing under the central expectation, and consider, in the aggregate, low-carbon energy to be overall less profitable than for lower levels of belief dispersion. Hence a lower share of low-carbon energy for high belief dispersion levels in the unambitious case. Otherwise, results are qualitatively similar, albeit sharper due to the interaction between σ_{u_H} and $\sigma_{\pi_H,s}$.

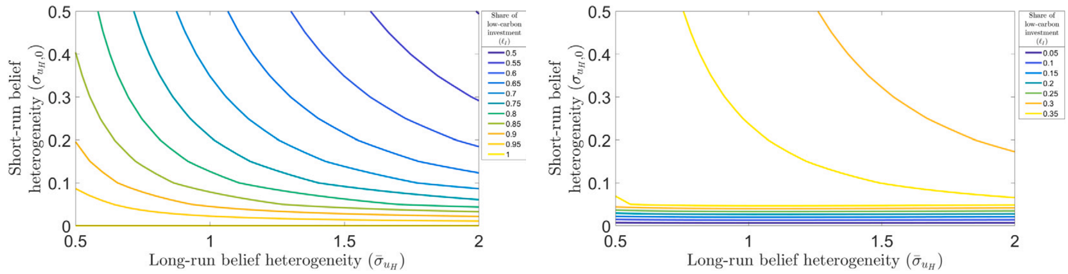
Second, we fix belief dispersion parameters on the utilisation rate to their benchmark values and modulate the maximum value of σ_{π_L} and σ_{π_H}. As above, we differentiate between an ambitious and an unambitious central expectation. Results are displayed in Fig. A4. The effects of higher belief dispersion on profitability are less pronounced than the ones associated to capacity utilisation belief dispersion, for both scenarios. This is because these beliefs apply to variables that do not move in time s, while we assume a moving central projection for stranding. However, we never reach a full investment in low-carbon technologies, the highest achieved value being 95% in the ambitious scenarios. We also find that the effects of both types of belief dispersion are non-linear, but not symmetrical. In the high-stranding scenarios, long-run belief heterogeneity on σ_{π_L} has relatively low effect on investment behaviour for low values, as figured by the flatness of the upper part of the curves in the bottom-left corner. These magnitudes are very close to the effects of σ_{u_H} shown in Fig. 6. Conversely, σ_{π_H} exhibits much larger effects. This is explained by the multiplicative term including σ_{π_H} and σ_{u_H}, which exacerbates the effects of any increase in σ_{π_H}. This, however, only holds true until a certain point, after which effects become relatively linear. Results are qualitatively similar, but reversed, in the non-ambitious case.

All in all, extending the realm of uncertainty bears similar qualitative results to the analysis provided in the main text. Quantitatively, it tends to reduce low-carbon investment shares due to uncertainty on future profitability. Most importantly, the effects of belief dispersion are sharper and more non-linear due to interactions between different belief items. This *compound* effect of belief dispersion suggests that several types of uncertainties can exacerbate each other and that regulators should aim to tackle various types of uncertainties simultaneously as much as possible.



(a) High-stranding central expectation (b) Low-stranding central expectation

Fig. A5. Long-run and short-run belief heterogeneity (hydro in low-carbon category). Panel (a) describes our high-stranding case, while Panel (b) shows our low-stranding case. The charts plot isovalue lines. For instance, the curve with legend "0.85" on Panel (a) corresponds to all $(\bar{\sigma}, \sigma_0)$ combinations for which the share of low-carbon investment ℓ_I is equal to 0.85 in the case of high stranding central expectation.



(a) High-stranding central expectation (b) Low-stranding central expectation

Fig. A6. Long-run and short-run belief heterogeneity (hydro and nuclear energy in low-carbon category). Panel (a) describes our high-stranding case, while Panel (b) shows our low-stranding case. The charts plot isovalue lines. For instance, the curve with legend "0.85" on Panel (a) corresponds to all $(\bar{\sigma}, \sigma_0)$ combinations for which the share of low-carbon investment ℓ_I is equal to 0.85 in the case of high stranding central expectation.

Appendix C. Alternative dispatch composition for low- and high-carbon technologies

In this Appendix, we consider alternative dispatch compositions for the definition of our 'low-carbon' category to address potentially misleading results linked to our choice of including hydropower and nuclear technologies in the 'high-carbon' category.

First, we include hydro in the low-carbon category. This brings the initial share of low-carbon energy production to 34%, and total low-carbon capacity to 438 GW, *i.e.* around 45% of total installed capacity (Eurostat, 2021). Productivity parameters are redefined accordingly to $\xi_H \approx 5.0221$ and $\xi_L \approx 2.8745$. To adjust for the change in the starting value of the low-carbon share, we recalibrate the intrinsic growth rate of our ambitious and unambitious scenarios to 0.2 and 0.1, respectively, while setting the long-term share to 95% after 30 years, consistently with the goals laid in the Fit for 55 package (EC, 2021). We reproduce here results displayed in Fig. 6, to compare the effect of short- and long-run belief heterogeneity. As shown in Fig. A5, results are qualitatively very close to the ones obtained with our default dispatch. The dichotomy between ambitious and unambitious scenarios remains, and we still find the decreasing marginal effect of increasing uncertainty in both cases. Our effects become slightly sharper than in the benchmark case due to the redefinition of our ambitious and unambitious scenarios, which tend to favour the incumbent.

Second, we also introduce nuclear power. Given the high weight of this energy source in the European mix, including nuclear brings the low-carbon share of energy to 53%, and total low-carbon capacity to around 550 GW, *i.e.* around 55% of total installed capacity Eurostat (2021). Productivity parameters are redefined as $\xi_H = 4.4942$ and $\xi_L = 3.69$. Given the large change to our energy shares, we redefine our ambitious and unambitious scenarios. The intrinsic growth rate b_ℓ for the ambitious scenario is decreased from 0.25 to 0.1; the carrying capacity $\bar{\ell}$ is moved from 0.9 to 0.95 as in the case above. For the unambitious scenario, while retaining the same carrying capacity of 0.95, we assume an intrinsic growth rate of 0.05. Results are displayed in Fig. A6.

In the ambitious scenario (high stranding), results are similar to the ones with the default dispatch composition, with similar gradients and effects. For the unambitious scenario (low stranding), the model yields a non-linearity in belief dispersion for low values, as shown by the outward orange line. Further, the overall pattern matches that of the ambitious scenario, with most cold-coloured line corresponding to low levels of low-carbon investments. Results differ due to the redefinition of productivity parameters. Although they still give an edge to the high-carbon sector for low levels of belief heterogeneity, this edge is very small due to the high productivity of nuclear power plants. As a result, for high level of belief dispersion, this edge is reversed (the spread between r_L and r_H becomes positive). This yields a behaviour similar to the ambitious scenario for high levels of belief dispersion. This result shows that, if the technologies are very close in terms of mean expected returns, non-linearities can emerge in the model. And, under certain conditions, such as those in the example above, belief uncertainty can diminish low-carbon investment even for otherwise unambitious scenarios.

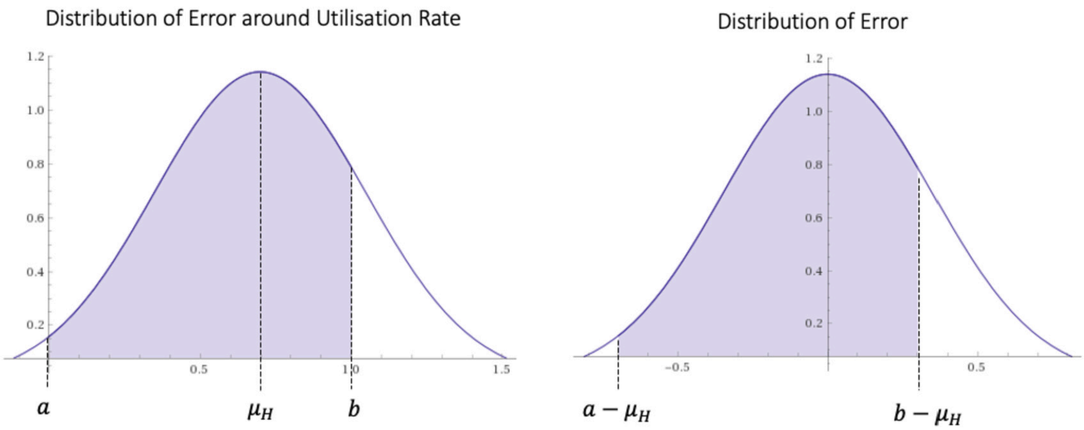


Fig. A7. Shifting bounds along with a change in variable.

Appendix D. Derivation of return rates

Heterogeneity in transition expectations creates heterogeneity in the expected return rates for the two technologies. Given equations (4) and (6), we can rewrite equation (1) for the high-carbon sector as

$$r_{H,t} = \sum_{s=t}^{S} \beta^s \left[\left(p_E - \frac{p_F}{\xi_F} \right) \xi_H (u^*_{H,s} + \varepsilon_{u,s}) - \alpha_H \psi_H c_H \right]. \tag{30}$$

Similarly to what was done with the expected capacity utilisation u_H, the expected return rate on a unit of K_H can be disaggregated into a 'rational stranding' deterministic part and an error term. Defining for convenience a new variable $\gamma_H = (p_E - \frac{p_F}{\xi_F})\xi_H$, equation (30) becomes $r_{H,t} = R^*_H + \varepsilon_r$, with $R^*_H = \sum_{s=t}^{S} \beta^s \left[\gamma_H u^*_H - \alpha_H \psi_H c_H\right]$ and $\varepsilon_r \sim \mathcal{N}(0, \sum_{s=t}^{S} \beta^{2s}\gamma^2\sigma^2_{u,s})$. The expected return rate on low-carbon capital r_H, on the other hand, lacks by assumption any random part. That is, $r_L = R^*_L = \sum_{s=t}^{S} \beta^s \left[p_E \xi_L - \alpha_L \psi_L c_L\right]$. This gives us the net present value of future technological investments but it now remains to find an expression ϑ such that Equation (14) is satisfied.

$$\Pr(r_L > r_H) = \Pr(r_L - r_H > 0) = \Pr(\vartheta > 0). \tag{31}$$

From the above we see that $\vartheta = R^*_L - R^*_H - \varepsilon_r$, but this expression must be scaled so the error term has a standard normal distribution. We thus divide the expression by the variance of ε_r to get our final expression φ:

$$\varphi = \frac{R^*_L - R^*_H}{\sum_{s=t}^{S} \beta^{2s}\gamma^2\sigma^2_{u,s}} - \frac{\varepsilon_r}{\sum_{s=t}^{S} \beta^{2s}\gamma^2\sigma^2_{u,s}} = \varphi^* - \varepsilon_\varphi, \tag{32}$$

where $\varepsilon_\varphi \sim \mathcal{N}(0, 1)$.

Furthermore, since the variance term $\sum_{s=t}^{S} \beta^{2s}\gamma^2\sigma^2_{u,s} > 0$,

$$\Pr(r_L > r_H) = \Pr(\vartheta > 0) = \Pr(\frac{\vartheta}{\sum_{s=t}^{S} \beta^{2s}\gamma^2\sigma^2_{u,s} > 0} > 0) = \Pr(\varphi > 0). \tag{33}$$

As a final step, using the symmetry of the normal distribution,

$$\Pr(\varphi > 0) = \Pr(\varphi^* - \varepsilon_\varphi > 0) = \Pr(\varepsilon_\varphi - \varphi^* < 0) = \Pr(\varepsilon_\varphi < \varphi^*) = \Phi(\varphi^*). \tag{34}$$

Appendix E. Censoring the bounds of the distribution

To deal with the caveat that the utilisation rate is clearly bounded, we have to find a way to factor in the clear technical constraints imposed on it. If u_H is between a and b we must find out what the bounds are for the error and associated latent variable and how we deal with it as a probability. By censoring the random part of u_H in the relevant bounds and shifting these bounds along with the variable, we get bounds for ε_φ. The final probability is then calculated conditionally on these bounds.

We begin by censoring the normal random variables in our given bounds. Given a utilisation rate constrained in the interval $]a, b[$, the error of $u_{H,s}$, $\varepsilon_{u,s}$, is constrained by the inequality in Equation (18). Pictured in Fig. A7, we may shift the distribution down to centre it on 0, simply by subtracting the central value μ_H from both bounds.

$$a - u^*_{H,s} < \varepsilon_{u,s} < b - u^*_{H,s}. \tag{35}$$

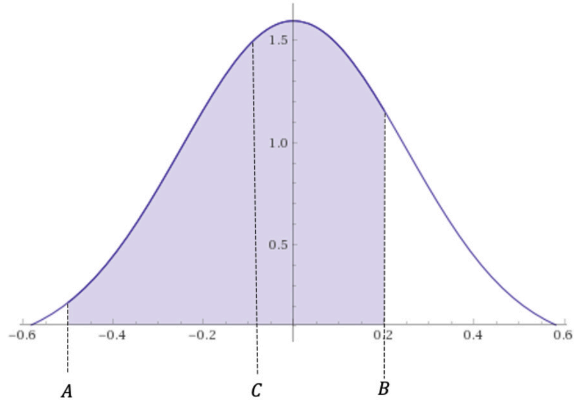


Fig. A8. Representation of possible values for bounds A and B and a value of interest C.

Likewise, the random variable derived from φ, $\varepsilon_\varphi = \frac{\sum_{s=t}^{S}\beta^s\gamma_s\varepsilon_{u,s}}{\sum_{s=t}^{S}\beta^{2s}\gamma^2\sigma_{u,s}^2}$, is hence constrained by the following bounds:

$$\frac{\sum_{s=t}^{S}\beta^s\gamma_s(a-u_{H,s}^*)}{\sum_{s=t}^{S}\beta^{2s}\gamma^2\sigma_{u,s}^2} < \varepsilon_\varphi < \frac{\sum_{s=t}^{S}\beta^s\gamma_s(b-u_{H,s}^*)}{\sum_{s=t}^{S}\beta^{2s}\gamma^2\sigma_{u,s}^2}. \tag{36}$$

Let A and B be the lower and upper bounds of ε_φ in Equation (36), respectively and let $C=\mu_\varphi$. We proceed with the probability as in Equation (16), but this time it is calculated as a conditional probability using the censored standard normal variable that we have derived. The situation is pictured in Fig. A8, with the value of interest C between bounds A and B. The probability that ε_φ is less than C is the area left of the value C, $\Phi(C)-\Phi(A)$. We must account for the limited values of possibility, so we divide by the shaded area representing all possible values, $\Phi(B)-\Phi(A)$, giving us Equation (37).

$$\ell_I = \Pr(\varepsilon_\varphi < C \mid A < \varepsilon_\varphi < B) = \frac{\Phi(C)-\Phi(A)}{\Phi(B)-\Phi(A)} \tag{37}$$

Extending this process, we must account for the fact that the value C may be taken out of the realm of possibility. Thus we make a further extension to say that if the value is less than the possible range the probability is 0 and if higher then it is 1.

$$\ell_i = \Pr(\varepsilon_\varphi < C \mid A < \varepsilon_\varphi < B) = \frac{\delta_{AC}(\Phi(C)-\Phi(A)) - \delta_{BC}(\Phi(B)-\Phi(C))}{\Phi(B)-\Phi(A)} \tag{38}$$

where $\delta_{ij} = \begin{cases} 1 & i<j \\ 0 & i\geq j \end{cases}$.

Appendix F. Proofs

F.1. Proof of Proposition 1

Proposition. *For b_ℓ large enough, $u_{H,s}^*$ is non-monotonic in $s \in [|t+1,S|]$ and reaches a minimum in $s_{min} \in [|1,S|]$.*

Proof. The proposition above is equivalent to showing that there exists an interval $[|v, s_{min}|] \subset [|t+1,S|]$ such that $\frac{u_{H,s+1}^*}{u_{H,s}^*} < 1$ $\forall s \in [|t+1, s_{min}|]$ and $\frac{u_{H,s+1}^*}{u_{H,s}^*} > 1$ $\forall s \notin [|v, s_{min}|]$. Let us first notice that $u_{H,s+1}^*$ is defined as:

$$u_{H,s+1}^* = \begin{cases} \frac{e_{H,s+1}}{(1-\delta)K_s\xi_H} & \text{if} \quad I_{H,s}^*=0 \\ \frac{e_{H,s+1}}{(1-\delta)K_{H,s}^d\xi_H} & \text{if} \quad I_{H,s}^*>0 \end{cases}$$

Hence that $\frac{u^*_{H,s+1}}{u^*_{H,s}}$ can take 4 possible values:

$$\frac{u^*_{H,s+1}}{u^*_{H,s}} = \begin{cases} \frac{e_{H,s+1}(1-\delta)K_{s-1}\xi_H}{(1-\delta)K_s\xi_H e_{H,s-1}} & \text{if} \quad I^*_{H,s}=0 \textit{ and } I^*_{H,s-1}=0 \quad (1) \\ \frac{e_{H,s+1}K^d_{H,s-1}\xi_H}{(1-\delta)K_s\xi_H e_{H,s-1}} & \text{if} \quad I^*_{H,s}=0 \textit{ and } I^*_{H,s-1}>0 \quad (2) \\ \frac{e_{H,s+1}(1-\delta)K_{H,s-1}\xi_H}{K^d_s\xi_H e_{H,s-1}} & \text{if} \quad I^*_{H,s}>0 \textit{ and } I^*_{H,s-1}=0 \quad (3) \\ \frac{e_{H,s+1}K^d_{H,s-1}\xi_H}{K^d_{H,s}\xi_H e_{H,s-1}} & \text{if} \quad I^*_{H,s}>0 \textit{ and } I^*_{H,s-1}>0 \quad (4) \end{cases}$$

We focus on cases (1) and (2), since cases (3) and (4) describe cases in which no stranding is expected and therefore on which $u_{H,s}$ is constant and equal to u^f.

Let us first notice that the condition for $I^*_{H,s}=0\ \forall s$ is:

$$\frac{u_{H,s-1}}{u^f} < \frac{(1-\delta)}{(1+g_{e_{H,s}})} \tag{39}$$

It is easy to show that:

$$(1-b_\ell)(1+g_e) < (1+g_{e_{H,s}}) < (1+g_e) \tag{40}$$

And that the sequence $\left((1+g_{e_{H,s}})\right)_{s\in[|t,S|]}$ is increasing and converges towards $(1+g_e)$.

Hence, it is possible to find a b large enough such that Condition (1) is fulfilled at a given $\bar{s}$. For instance, the condition for $\bar{s}=t+1$ supposing that $u_{H,t}=u^f$ yields:

$$1 < \frac{(1-\delta)}{(1+g_{e_{H,\bar{s}}})} \Leftrightarrow \left(1+g_e\right)\left(1-b\left(\frac{\bar{\ell}-\ell_{E,t}}{(1-\ell_{E,t})\bar{\ell}}\right)\right) < (1-\delta) \Leftrightarrow b > \frac{1-\frac{(1-\delta)}{(1+g_e)}}{\left(\frac{\bar{\ell}-\ell_{E,t}}{(1-\ell_{E,t})\bar{\ell}}\right)} \tag{41}$$

This condition can be generalised for any $s>t$ since, in expectations, as long as $I^*_{H,s}>0$, $u_{H,s}=u^f$.

The condition for $I^*_{H,\bar{s}+1}=0$ is:

$$\frac{u_{H,\bar{s}}}{u^f} < \frac{(1-\delta)}{(1+g_{e_{H,\bar{s}}})} \tag{42}$$

In that case, we can write $K_{H,\bar{s}+1}=(1-\delta)K_{H,\bar{s}}=(1-\delta)^2K_{H,\bar{s}-1}=(1-\delta)^2\frac{e_{H,\bar{s}-1}}{u_{\bar{s}-1}\xi_H}$ and Condition (1) can be rewritten as:

$$\frac{u_{H,\bar{s}-1}}{u^f} < \frac{(1-\delta)^2}{(1+g_{e_{H,\bar{s}}})(1+g_{e_{H,\bar{s}+1}})} \tag{43}$$

Which can again be fulfilled for b large enough. More generally, the condition for $I^*_{H,k}=0, k>\bar{s}$ writes:

$$\frac{u_{H,\bar{s}}}{u^f} < \frac{(1-\delta)^{k-\bar{s}}}{\Pi^k_{i=\bar{s}}(1+g_{e_{H,i}})} \tag{44}$$

As we saw above, the sequence $\left((1+g_{e_{H,s}})\right)_{s\in[|t,S|]}$ is increasing and converges towards $(1+g_e)>(1-\delta)$. Since g_e and δ are positive, based on the intermediate values theorem, there exists a s^* for which:

$$(1+g_{e_{H,s^*}}) < (1-\delta) < (1+g_{e_{H,s^*+1}})$$

Hence that, for $k>s^*$, we can write $\frac{(1-\delta)^{k-\bar{s}}}{\Pi^k_{i=\bar{s}}(1+g_{e_{H,i}})}$ as follows:

$$\frac{(1-\delta)^{k-\bar{s}}}{\Pi^k_{i=\bar{s}}(1+g_{e_{H,i}})} = \frac{1}{\Pi^{s^*}_{i=\bar{s}}(1+g_{e_{H,i}})}\frac{(1-\delta)^{k-\bar{s}}}{\Pi^k_{i=s^*+1}(1+g_{e_{H,i}})}$$

For S large enough, $k^*<S$. This result shows that there exists an interval $U\subset[|t,S|]$ on which $I^*_{H,s}=0$ and that, for S large enough, $k^*<S$. For $s>k^*$, $I^*_{H,s}>0$.

The right-hand term is decreasing in k and converges towards zero. As a result, there exists a k^* for which:

$$\frac{u_{H,\bar{s}}}{u^f} > \frac{(1-\delta)^{k^*-\bar{s}}}{\Pi^{k^*}_{i=\bar{s}}(1+g_{e_{H,i}})} \tag{45}$$

Cases (1) and (2) $I^*_{H,k}=0$ *and* $I^*_{H,k-1}=0\ \forall k\in U$ thus depict situations arising for b large enough.

Considering case (1) and simplifying the corresponding equation, we get:

$$\frac{u^*_{H,s+1}}{u^*_{H,s}} = \frac{e_{H,s+1}(1-\delta)K_{H,s-1}\xi_H}{(1-\delta)^2 K_{H,s-1}\xi_H e_{H,s}} = \frac{e_{H,s+1}}{(1-\delta)e_{H,s}}$$

Which is below 1 if and only if $\frac{e_{H,s+1}}{e_{H,s}} = (1+g_{e_{H,s}}) < (1-\delta)$, that is, the decrease rate in high-carbon energy demand is superior to the depreciation rate. Using the fact that $\left((1+g_{e_{H,s}})\right)_{s\in[|t,S|]}$ is increasing and converges towards $(1+g_e) > (1-\delta)$ and using again the intermediate value theorem, it follows that, for $s > s_{min} = s^*$, $\frac{e_{H,s+1}}{e_{H,s}} > 1$ and < 1 otherwise.

Considering now case (2) and noticing that in this instance $K_{H,s} = K^d_{H,s-1}$, we get:

$$\frac{u^*_{H,s+1}}{u^*_{H,s}} = \frac{e_{H,s+1}K^d_{H,s}\xi_H}{(1-\delta)^2 K^d_{H,s}\xi_H e_{H,s}} = \frac{e_{H,s+1}}{(1-\delta)e_{H,s}}$$

Which yields the same condition as above: for b_ℓ large enough, the utilisation rate will decrease. □

Lemma 1. *For b_ℓ large enough, there exists an interval $T \subset [|t,S|]$ such that, $\forall s \in T$, $\pi_{L,s} - \pi_{H,s} > 0$.*

Proof. The condition for $\pi_{L,s} - \pi_{H,s} > 0$ is:

$$u_{H,s} < \frac{1}{p_E - \frac{p_F}{f_F}}(p_E\xi_L - \alpha_K\psi_L c^k_L + \alpha_H\psi_H c^k_H)$$

As per Proposition 1, with b_ℓ large enough, it is possible to define a subset $U \subset [|t,S|]$ on which $u_{H,s}$ is decreasing, with the sequence $(u_{H,s})_{s\in[|t+1,S|]}$ hitting a minimum at the highest value of U: s_{min}. Now, we know that, $\forall s \in [|t+1,S|]$:

$$u^*_{H,s+1} = \frac{e^d_s(1+g_E) - e_{L,s}(1+g_E)\left[1 + b_\ell\left(1 - \frac{e_{L,s}}{\bar{\ell}e^d_s}\right)\right]}{\xi_H[(1-\delta)K_{H,s} + I^*_{H,s}]} \tag{46}$$

A fortiori,

$$u^*_{H,s_{min}} = \frac{e^d_{s_{min}-1}(1+g_E) - e_{L,s_{min}-1}(1+g_E)\left[1 + b_\ell\left(1 - \frac{e_{L,s_{min}-1}}{\bar{\ell}e^d_{s_{min}-1}}\right)\right]}{\xi_H[(1-\delta)K_{H,s_{min}-1} + I^*_{H,s_{min}-1}]} \tag{47}$$

Which is an obviously decreasing function of b_ℓ. Then, for b_ℓ large enough, $u^*_{H,s_{min}}$ will fulfil the condition above. It is further possible to define an interval $[|s_{min} - a; s_{min} + a|]$ on which this condition holds, again for b_ℓ large enough. □

F.2. Proof of Proposition 2

Proposition. *For $\sigma_{u,s} = 0\ \forall s \in [|1,S|]$, ℓ_I tends towards a degenerate probability distribution function, whereby:*

$$\ell_I = \begin{cases} 0 & if\ R^* < 0 \\ 0.5 & if\ R^* = 0 \\ 1 & if\ R^* > 0 \end{cases} \tag{48}$$

Proof. Starting from $\ell_I = \frac{\Phi(\varphi^*)-\Phi(\varphi_0)}{\Phi(\varphi_1)-\Phi(\varphi_0)}$ and noticing that $\varphi_0 = \frac{R_0}{\Gamma} < 0$ and $\varphi_1 = \frac{R_1}{\Gamma} > 0$ within our parameter space, we have:

$$\lim_{\Gamma\to 0^+}\Phi(\varphi_0) = \lim_{\Gamma\to 0^+}\Phi\left(\frac{R_0}{\Gamma}\right) = 0$$

$$\lim_{\Gamma\to 0^+}\Phi(\varphi_1) = \lim_{\Gamma\to 0^+}\Phi\left(\frac{R_1}{\Gamma}\right) = 1$$

For $R^* = 0$, the result flows from the definition of Φ. For any Γ, we have:

$$\ell_I = \frac{\Phi(0)-\Phi(\varphi_0)}{\Phi(\varphi_1)-\Phi(\varphi_0)} = \frac{0.5-\Phi(\varphi_0)}{\Phi(\varphi_1-\Phi(\varphi_0)}$$

Which, given the limits above, has $\Phi(0) = 0.5$ as limit for $\Gamma \to 0$.

All in all,

$$\lim_{\Gamma\to 0^+} \ell_I = \lim_{\Gamma\to 0^+} \Phi(\varphi^*) = \begin{cases} 0 & if\ R^* < 0 \\ 0.5 & if\ R^* = 0 \\ 1 & if\ R^* > 0 \end{cases} \quad \square \tag{49}$$

F.3. Proof of Proposition 3

Let us consider a logistic sequence $x_n = x_{n-1}\left(1 + b(1 - \frac{x_{n-1}}{K})\right)$ where K is a carrying capacity and b an intrinsic growth rate. Let us then consider x_0 the first term of this sequence. Then, $\forall n | x_n < K$:

$$\frac{\partial x_n}{\partial K} \geq 0 \tag{50}$$

$$\frac{\partial x_n}{\partial b} \geq 0 \tag{51}$$

$$\frac{\partial x_n}{\partial x_0} \geq 0 \tag{52}$$

With the last proposition holding for $x_0 < K$.

Proof. The first property can be shown by recurrence. Considering $\frac{\partial x_n}{\partial K}$, it is obvious, with x_0 given that $\frac{\partial x_1}{\partial K} > 0$. Supposing that $\frac{\partial x_n}{\partial K} \geq 0$, we can show that $\frac{\partial x_{n+1}}{\partial K} \geq 0$.

$$\begin{aligned} \frac{\partial x_{n+1}}{\partial K} &= \frac{\partial x_n}{\partial K}(1 + b(1 - \frac{x_n}{K})) - x_n b\left(\frac{\frac{\partial x_n}{\partial K}K - x_n}{K^2}\right) \\ &= \frac{\partial x_n}{\partial K}(1 + b(1 - \frac{x_n}{K})) - b\frac{x_n}{K}) + \frac{x_n}{K^2} \\ &= \frac{\partial x_n}{\partial K}(1 + b(1 - 2b\frac{x_n}{K})) + \frac{x_n}{K^2} \end{aligned}$$

The condition for this expression to be negative is:

$$1 + \frac{\partial x_n}{\partial K}\frac{K^2}{x_n^2} < b(\frac{x_n}{K} - 1)$$

$1 + \frac{K^2}{x_n^2}\frac{\partial K}{\partial x_n}$ is positive as per the assumption $\frac{\partial x_n}{\partial K} > 0$ and $\frac{x_n^2}{K^2} > 0$. Hence that the condition above cannot hold for $x_n \leq K$. We consider in the following only constellations of parameters for which $x_n \leq K$, without loss of generality for the purpose of the paper.

Regarding b, we can also proceed by recurrence. Defining:

$$\begin{aligned} x_n &= x_{n-1}(1 + b(1 - \frac{x_{n-1}}{K})) \\ x'_n &= x'_{n-1}(1 + (b + db)(1 - \frac{x'_{n-1}}{K})) \\ &= x'_{n-1}(1 + (b')(1 - \frac{x'_{n-1}}{K}))x_0 = x'_0 \end{aligned}$$

It is easy to check that, for x_0 given, $x'_1 - x_1 \geq 0$. Supposing that $x'_n - x_n \geq 0$, we write:

$$\begin{aligned} x'_{n+1} - x_{n+1} &= x'_n(1 + (b')(1 - \frac{x'_n}{K})) - x_n(1 + b(1 - \frac{x_n}{K})) \\ &= x'_n - x_n + b'(1 - \frac{x'_n}{K}) - b(1 - \frac{x_n}{K}) \\ &\geq x'_n - x_n + b'(1 - \frac{x'_n}{K}) - b'(1 - \frac{x_n}{K}) \\ &\geq x'_n - x_n + b'(\frac{x_n}{K} - \frac{x'_n}{K}) \\ &\geq (x'_n - x_n)\frac{(1 - b)}{K} \end{aligned}$$

Given that $(1 - \frac{b}{K}) > 0$ for $b < 1$ and null when $b = 1$, we can consider this condition to hold for reasonable values of b.

For x_0, we can use once again the same method. Defining:

$$x_n = x_{n-1}(1 + b(1 - \frac{x_{n-1}}{K}))\ ,\ x_0 = x_0$$

$$x'_n = x'_{n-1}(1+b)(1-\frac{x'_{n-1}}{K}))\ ,\ x_0 = x'_0$$
$$x_0 \le x'_0$$

Showing that $x'_1 \ge x_1$ and supposing that $x'_n \ge x_n$, we get the similar condition:

$$\begin{aligned} x'_{n+1} - x_{n+1} &= x'_n(1+b)(1-\frac{x'_n}{K})) - x_n(1+b(1-\frac{x_n}{K})) \\ &= x'_n - x_n + b'(1-\frac{x'_n}{K}) - b(1-\frac{x_n}{K}) \\ &= x'_n - x_n + b'(\frac{x_n}{K} - \frac{x'_n}{K}) \\ &= (x'_n - x_n)\frac{(1-b)}{K} \end{aligned}$$

Which again holds true for $b \le 1$. □

Lemma 2. *All else held equal, increasing $\bar{\ell}$ or b_ℓ will have a positive effect on low-carbon investment.*

Proof. This property follows from Proposition 2, Φ being a positive function of φ itself obviously a positive function of $\ell_{E,s}$. □

Lemma 3. *All else held equal, increasing σ_0, $si\bar{g}ma$, and b_σ will have a negative effect on low-carbon investment.*

Proof. This property follows from Proposition 2, $|\varphi_t^*|$ being a negative function of the $\sigma_{u,s}$ with a limit in zero. □

F.4. Proof of Proposition 4

Proposition. *It is possible to define an interval $\mathcal{S} = [|\underline{S}; \bar{S}|]$ such that, for a given ρ, b_ℓ and $\bar{\ell}$, $R^* > 0\ \forall S \in \mathcal{S}$ and $R^* \le 0$ otherwise. $\mathcal{S}$ can be empty.*

Proof. As per Proposition 1, $u_{H,s}$ gets back closer to u^f, if the profit rate spread between high and low technologies $\pi_{L,1} - \pi_{H,1}$ is low enough, a longer planning horizon may have a negative effect on low-carbon investment, as agents account for more time periods during which $\pi_{L,s} - \pi_{H,s} < 0$. □

F.5. Proof of Proposition 5

Proposition. *The effect of a higher σ_0 or $\bar{\sigma}$ will depend on the sign of R^*. If $R^* < 0$, $\frac{\partial \ell_I}{\partial \sigma_0} \ge 0$ and $\frac{\partial \ell_I}{\partial \bar{\sigma}} \ge 0$ and ℓ_I is concave in σ_0 and $\bar{\sigma}$. If $R^* > 0$, $\frac{\partial \ell_I}{\partial \sigma_0} \le 0$ and $\frac{\partial \ell_I}{\partial \bar{\sigma}} \le 0$ and ℓ_I is convex in σ_0 and $\bar{\sigma}$. Plus, there exists an $R' \in [R_0; R_1]$ such that $\frac{\partial \ell_I}{\partial \Gamma}(R')$ is equal to zero.*

Proof. Taking first the derivative of ℓ_I with respect to Γ, we find:

$$\frac{\partial \ell_I}{\partial \Gamma} = \frac{u_1 v^* - v_1 u^*}{2\Gamma^{\frac{3}{2}} v_1^2} \tag{53}$$

With:

$$\begin{aligned} u_1 &= R_1\phi(\varphi_1) - R_0\phi(\varphi_0) \\ u^* &= R^*\phi(\varphi^*) - R_0\phi(\varphi_0) \\ \phi(x) &= \frac{\partial \Phi}{\partial x}\ \forall x \\ v_1 &= \Phi(\varphi_1) - \Phi(\varphi_0) \\ v^* &= \Phi(\varphi^*) - \Phi(\varphi_0) \end{aligned}$$

Considering the cross-derivative $\frac{\partial \ell_I}{\partial \Gamma \partial R^*}$, we obtain:

$$\frac{\partial \ell_I}{\partial \Gamma \partial R^*} = (v_1(\varphi^*)^2 - v_1 - \frac{u_1}{\Gamma})\frac{e^{-\frac{x^2}{2}}}{2\pi}$$

Since $u_1 > 0$ and $v_1 > 0$, the determinant of $(v_1\varphi^* - v_1 - \frac{u_1}{\Gamma})$ is always positive. Hence, this function admits two roots in R^*, R_- and R_+, and is strictly negative between the two corresponding local optima. Noticing that $\frac{\partial \ell_I}{\partial \Gamma}(R_0) > 0$ and $\frac{\partial \ell_I}{\partial \Gamma}(R_1) < 0$, it follows that

$\frac{\partial \ell_I}{\partial \Gamma}(R_-) > 0$ and $\frac{\partial \ell_I}{\partial \Gamma}(R_+) < 0$. By the theorem of intermediate value, there exists a $R' \in [R_0; R_1]$ such that $\frac{\partial \ell_I}{\partial \Gamma}(R')$ is equal to zero. The concavity/convexity properties of ℓ_I follow from the definition of its second derivative. □

F.6. Proof of Proposition 6

Proposition. *For a given S and ρ, there exists a $\left(\frac{\bar{\sigma}}{\sigma_0}\right)^*$ ratio high enough such that $\left|\frac{\partial \ell_I}{\partial \bar{\sigma}}\right| > \left|\frac{\partial \ell_I}{\partial \bar{\sigma}}\right|$.*

Proof. Using the result of Proposition 3, suffices to prove that, for a $\left(\frac{\bar{\sigma}}{\sigma_0}\right)^*$ high enough, $\frac{\partial \Gamma}{\partial \sigma_0} > \frac{\partial \Gamma}{\partial \sigma_0}$.

Considering that the logistic sequence is well-approximated by a continuous counterpart, we write the following logistic function $l(x)\ \forall x \geq 0$, which includes a starting value σ_0 and a carrying capacity $\bar{\sigma}$:

$$l(x) = \frac{\bar{\sigma}}{1 + (\frac{\bar{\sigma}}{\sigma_0} - 1)e^{-b_\sigma x}}$$

Taking the corresponding derivatives:

$$\frac{\partial l}{\partial \bar{\sigma}} = \frac{1 - e^{-b_\sigma x}}{\left(1 + (\frac{\bar{\sigma}}{\sigma_0} - 1)e^{-b_\sigma x}\right)^2} \geq 0$$

$$\frac{\partial l}{\partial \sigma_0} = \frac{\left(\frac{\sigma_0}{\bar{\sigma}}\right)^2 e^{-b_\sigma x}}{\left(1 + (\frac{\bar{\sigma}}{\sigma_0} - 1)e^{-b_\sigma x}\right)^2} \geq 0$$

We consider the ratio $\frac{\frac{\partial l}{\partial \sigma_0}}{\frac{\partial l}{\partial \bar{\sigma}}}$ to determine the condition under which $\frac{\partial l}{\partial \sigma_0} > \frac{\partial l}{\partial \bar{\sigma}}$, which is a sufficient condition for $\frac{\partial \Gamma}{\partial \sigma_0} > \frac{\partial \Gamma}{\partial \sigma_0}$:

$$\frac{\bar{\sigma}}{\sigma_0} > \sqrt{\frac{1 - e^{-b_\sigma x}}{e^{-b_\sigma x}}}$$

Given that we only consider S-long logistic sequences and because $\frac{(1-\exp(-x))}{\exp(-x)}$ is a strictly increasing function of x, a sufficient condition is that:

$$\frac{\bar{\sigma}}{\sigma_0} > \max_x \sqrt{\frac{1 - e^{-b_\sigma x}}{e^{-b_\sigma x}}} = \sqrt{\frac{1 - e^{-b_\sigma S}}{e^{-b_\sigma S}}} \tag{54}$$

Given Proposition 3, this defines a $\frac{\bar{\sigma}}{\sigma_0}$ high enough for $\left|\frac{\partial \ell_I}{\partial \bar{\sigma}}\right| > \left|\frac{\partial \ell_I}{\partial \bar{\sigma}}\right|$.

Let us fix σ_0 to its benchmark value of 0.01. The value of the threshold for $S = 30$ is around 66, which implies that the condition would hold for this planning horizon for $\bar{\sigma} \geq 0.6$;, that is, for a sizeable range of our parameter constellation. The condition would hold for $\bar{\sigma} \geq 1$ with a planning horizon equal to 32, and $\bar{\sigma} \geq 1.5$ for a planning horizon of 35. Fig. A9 below gives the range of $\bar{\sigma}$ values for which the condition holds true for each length of the planning horizon. □

F.7. Proof of Proposition 7

Proposition. *As belief heterogeneity approaches infinity, ℓ_I will tend towards a finite value $\tilde{\ell_I} = \frac{R^* - R_0}{R_1 - R_0}$, where R^*, R_0 and R_1 are the numerators of φ^*, φ_0 and φ_1 respectively. We call $\tilde{\ell_I}$ 'full dispersion' equilibrium and it is a function of b_ℓ, $\bar{b}$ for a given S and ρ.*

Proof. Using l'Hôpital's Rule, we have:

$$\lim_{\Gamma \to +\infty} \ell_I = \lim_{\Gamma \to +\infty} \frac{\Phi(\varphi^*) - \Phi(\varphi_0)}{\Phi(\varphi_1) - \Phi(\varphi_0)} = \lim_{\Gamma \to +\infty} \frac{\frac{\partial \Phi(\varphi^*) - \Phi(\varphi_0)}{\partial \Gamma}}{\frac{\partial \Phi(\varphi_1) - \Phi(\varphi_0)}{\partial \Gamma}}$$

Differentiating, we obtain:

$$\frac{\frac{\partial \Phi(\varphi^*) - \Phi(\varphi_0)}{\partial \Gamma}}{\frac{\partial \Phi(\varphi_1) - \Phi(\varphi_0)}{\partial \Gamma}} = \frac{\frac{-R^*}{2\Gamma^{\frac{3}{2}}}\phi(\varphi^*) - \frac{-R_0}{2\Gamma^{\frac{3}{2}}}\phi(\varphi_0)}{\frac{-R_1}{2\Gamma^{\frac{3}{2}}}\phi(\varphi_1) - \frac{-R_0}{2\Gamma^{\frac{3}{2}}}\phi(\varphi_0)}$$

Where $\phi(x) = \frac{\partial \Phi}{\partial x}\ \forall x$, the probability density function of a $\mathcal{N}(0,1)$. Simplifying, we get:

$$\frac{\frac{\partial \Phi(\varphi^*) - \Phi(\varphi_0)}{\partial \Gamma}}{\frac{\partial \Phi(\varphi_1) - \Phi(\varphi_0)}{\partial \Gamma}} = \frac{R^* \phi(\varphi^*) - R_0 \phi(\varphi_0)}{R_1 \phi(\varphi_1) - R_0 \phi(\varphi_0)}$$

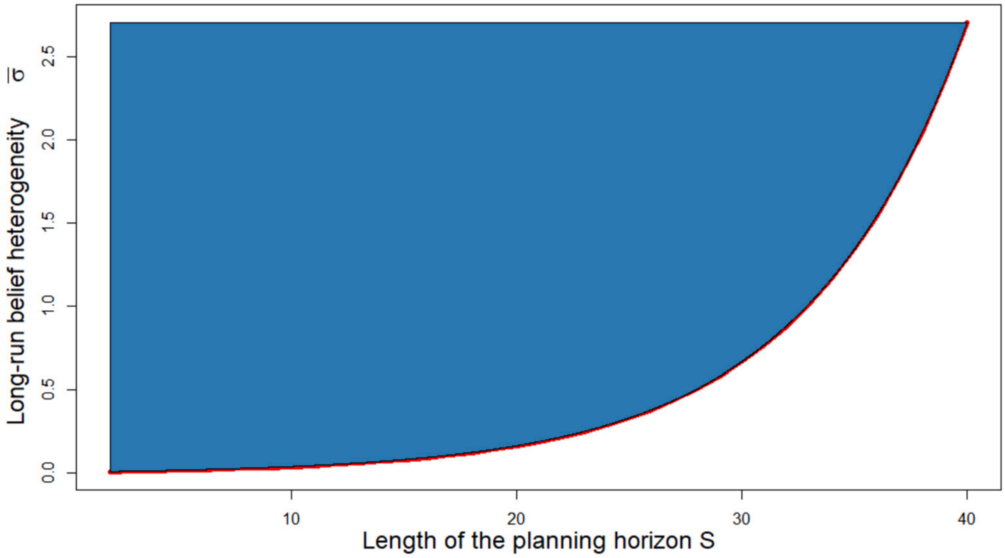


Fig. A9. Range of $\bar{\sigma}$ values for which Condition (54) holds true for each length of the planning horizon. The shaded area gives the range of acceptable value, while the red line gives the value of the threshold as defined in Equation (54).

Since $\phi(x) = \frac{1}{2\sqrt{\pi}} \exp(-\frac{x^2}{2})$, it is easy to see that, for any R, $\lim_{\Gamma\to+\infty} \phi(\frac{R}{\Gamma}) = \lim_{x\to 0^+} \phi(x)$ for $x = \Gamma$, which is equal to 1. Hence, we get the results

$$\lim_{\Gamma\to+\infty} \ell_I = \frac{R^* - R_0}{R_1 - R_0}.$$

Which indeed belongs to $[0,1]$ for $R_0 \leq R^* \leq R_1$. □

If $\ell_I = \Phi(\varphi^*)$, (*i.e.* the distribution is not censored), it is straightforward that, the limit of φ^* being zero, that of $\Phi(\varphi^*)$ is $\Phi(0) = 0.5$.

F.8. Proof of Proposition 8

Proposition. *An increase in the planning horizon S will have a positive effect if $R^*_{S-1} + \pi_{L,S} - \pi_{H,S} > 0$. For b_ℓ There exists an $s_1 \in [|1, S|]$ sufficiently large such that this condition holds. If $\pi_{L,t} - \pi_{H,t} > 0$, $S = 1$. There also exists an $s_2 > s_1$ such that the condition reverses if $\pi_{L,S_2} - \pi_{H,S_2}$ is negative and low enough. s_2 increases with $\bar{\ell}$ and b_ℓ.*

Proof. Let us assume that agents have a sufficiently large planning horizon S. In all generality, from Proposition 1, it is possible to decompose $\sum_1^S \beta^s(\pi_{L,s} - \pi_{H,s})$ as follows:

$$\sum_s^S (\pi_{L,s} - \pi_{H,s}) = \underbrace{\sum_1^{s_1} \beta^s(\pi_{L,s} - \pi_{H,s})}_{<0} + \underbrace{\sum_{s_1+1}^{s_2} \beta^s(\pi_{L,s} - \pi_{H,s})}_{>0} + \underbrace{\sum_{s_2+1}^{S} \beta^s(\pi_{L,s} - \pi_{H,s})}_{<0}$$

Where s_1 and s_2 are the thresholds derived from Proposition 1. It is obvious from this decomposition that, because from $s_2 + 1$, only negative terms are added, a sufficiently large S will yield $\sum_0^{S-1} \beta^s(\pi_{L,s} - \pi_{H,s}) + \beta^s(\pi_{L,S} - \pi_{H,S})$ if $(\pi_{L,S} - \pi_{H,S})$ sufficiently negative.

Let us now assume that the planning horizon is equal to $s_1 \leq S' \leq s_2$. From Proposition 1, increasing the planning horizon to $S' + 1$ will have a positive effect on φ^*_t if $(\pi_{L,S'} - \pi_{H,S'})$ sufficiently high, which is true for b_ℓ (or $\bar{\ell}$) high enough. It follows immediately that S_2 is a positive function of b_ℓ and $\bar{\ell}$, the term $\underbrace{\sum_{s_1+1}^{s_2} \beta^s(\pi_{L,s} - \pi_{H,s})}_{>0}$ increasing in b_ℓ and $\bar{\ell}$. □

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