LETTER

Carbon price dynamics in ambitious climate mitigation scenarios: an analysis based on the IAMC 1.5 °C scenario explorer

Mark Meyer1,∗, Andreas Löschel2 and Christian Lutz3
1 The Institute of Economic Structures Research—Gesellschaft für Wirtschaftliche Strukturforschung (GWS), Heinrichstraße 30, 49080 Osnabrück, Germany
2 Ruhr-Universität Bochum, Faculty of Management and Economics, Universitätsstraße 150, 44801 Bochum, Germany
3 The Institute of Economic Structures Research—Gesellschaft für Wirtschaftliche Strukturforschung (GWS), Heinrichstraße 30, 49080 Osnabrück, Germany
∗ Author to whom any correspondence should be addressed.
E-mail: m.meyer@gws-os.com, loeschel@uni-muenster.de and lutz@gws-os.com

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Abstract
We analyse global carbon price trajectories from integrated assessment studies of 2 °C and below-compatible emission pathways based on a new scenario ensemble that has been made publicly available together with other relevant data sets in the IAMC 1.5 °C Scenario Explorer. We complement and extend the findings of the initial study on carbon price variations in integrated assessment models of (Guivarch and Rogelji 2017 Carbon price variations in 2 °C scenarios explored, Carbon Pricing Leadership Coalition) by providing a broader and more robust empirical assessment based on a comprehensive statistical analysis. We discuss the prospects and challenges of in-depth bivariate econometric analyses of key impact factors in data sets from integrated assessment models. We show that the amount of meta-information reported for individual models differs significantly across all variables where a large part of all recorded scenario explorer variables can be attributed to only a small number of applied models. We analyse the trend patterns emerging from the analysed global carbon price trajectories based on a statistical trend identification procedure. About half of the analysed carbon price projections seem to be best characterised by long run exponential growth patterns in carbon prices. Moreover, we break down the explanatory contribution of individual components on global carbon prices by the Kaya identity, i.e. global GDP, primary energy intensity and emission intensity. We show that the price of carbon is lower in baseline scenarios with faster economic growth per capita, low-energy consumption patterns and high potentials for low carbon technologies compared to fossil fuels. In contrast to previous findings, the observed carbon price developments are impacted much more strongly by scenario-specific than by model-specific influences. Next to the diagnostic indicators for models, further indicators for the categorization of scenarios describing key context and policy parameterisations applied in individual model runs should be developed and included in descriptions of integrated assessment studies.

1. Introduction

Integrated assessment models (IAM) derive global scenarios consistent with different global temperature goals. Out of the wealth of assumptions going into the models and the respective results, carbon price trajectories necessary to achieve the climate objectives have spurred the public and scientific debate. In 2017 the High-Level Commission on Carbon Prices (HLCCP) concluded that, ‘… in a supportive policy environment, the explicit carbon-price level consistent with the Paris temperature target is at least US$40–80/tCO2 by 2020 and US$50–100/tCO2 by 2030.’ (HLCCP 2017, p. 50). However, the price span is regarded as high. It also should be noted that the HLCCP conclusion looks at 2 °C scenarios. Carbon price levels for more ambitions climate mitigation scenarios will have to be higher and the price span likely to be higher. It remains open how different integrated assessment modelling
philosophies, assumptions regarding agents’ expectations of the future as well as the other differences in baseline scenarios (like trends in population, GDP, technology), climate policy assumptions (implementation, complementary policies, timing) and model characteristics (socioeconomic and technological factors) are correlated to different carbon price trajectories.

A first assessment of this correlation was presented by Guivarch and Rogelj (2017) who analysed simulation results from 18 ambitious integrated assessment studies from the Shared Socioeconomic Pathways (SSP) database that limit global warming to below 2 °C with a probability greater than 66%. However, the data situation improved significantly thereafter with the publication of the IPCC special report on 1.5 °C global warming (IPCC 2018). 222 CO₂ price trajectories from integrated assessment studies of 2 °C and below-compatible emission pathways have been made publicly available together with other relevant data sets in the IAMC 1.5 °C Scenario Explorer (Huppmann et al 2018, Huppmann et al 2019).

In this paper we analyse this new scenario ensemble that has been published alongside the IPCC 1.5 °C Special Report and provides a unique quantitative basis for further analyses of price trajectories observable in ambitious climate mitigation scenarios. We complement and extend the findings of the initial study of Guivarch and Rogelj (2017) by providing a broader and more robust empirical assessment based on the newly available database by means of a comprehensive statistical analysis. We review and analyse characteristic trend dynamics of global carbon price projections from ambitious climate mitigation scenario simulations and discuss the prospects and challenges of in-depth bivariate econometric analyses of key impact factors. The explanatory contribution of individual components on global carbon prices is broken down by the Kaya identity, i.e. global GDP, primary energy intensity and emission intensity (Kaya and Yokobory 2018).

## 2. IAMC 1.5 °C scenario explorer

### 2.1. Models and scenarios

We use scenarios from the IAMC 1.5 °C Scenario Explorer release 1.1 as of February 2019 (Huppmann et al 2018, Huppmann et al 2019). This comprehensive database includes scenario-specific CO₂ price projections for global aggregates. We focus on ambitious climate protection scenarios, i.e. ‘Below 1.5 °C’ scenarios, ‘Low-Overshoot’ scenarios, ‘High-Overshoot’ scenarios, ‘Lower 2 °C’ scenarios and ‘Higher 2 °C’ scenarios (see table 2.1 in Rogelj et al 2018a). All subsequent statistical findings are based on a sample of simulation results from 204 ambitious climate mitigation studies. Our dataset covers all 222 scenario datasets analysed by Rogelj et al (2018a). However, 18 scenarios with global carbon prices below 5 US$/t CO₂ were excluded from the analyses. Figure A1 in the appendix shows the
distribution of analysed simulation results categorized by median values of expected year 2100 warming levels across all considered ambitious warming categories.

Figure 1 gives an overview of the distribution of individual model results among considered warming categories for the respective models in the IAMC 1.5 °C Scenario Explorer. Different models provide results for different year 2100 median warming levels and thus map different causes relevant for the global carbon price projections.

2.2. Global carbon price time series

The global CO₂ prices observed in our sample for the years 2030 (upper graphs), 2050 (middle graphs) and 2100 (lower graphs) are shown in figure 2 (left part). The boxplots give median values of the observed annual carbon prices per warming category individually marked by a horizontal line; corresponding mean values are indicated by a triangle. Coloured boxes indicate the range of carbon prices between the first and the third quartile per warming category. Associated sample sizes are designated as n. Descriptive statistics for all 204 global carbon price projections are shown in table A1 in the appendix. All projected price paths feature long-term upward trending dynamics. The sample is considerably influenced by individual observations with exceptionally high values: Whereas 75% of the 2100 global carbon price observations remain under a threshold value of US$ 3,135 the maximum carbon price observed exceeds US$43,300. The descriptive statistics for individual pathway classes confirm the right-skewed distribution patterns especially for the ‘Lower 2 °C’ class. The lowest reported maximum values for global carbon prices can be found in the ‘Higher 2 °C’ pathway class with the least ambitious scenarios. For reporting years 2030, 2050 and 2070 the highest reported carbon prices are assigned to the most ambitious pathways category ‘Below 1.5 °C’.

Overall, the statistics and the visual observation indicate that these aggregated findings could possibly be significantly influenced by individual outliers. There are six extreme outliers described in table A2 in the appendix, which are excluded from the analysis. The right section of figure 2 shows respective boxplots for the adjusted sample.

Economic theory tells us that the price of carbon should grow at the interest rate under a carbon budget when future marginal abatement costs are known (Gollier 2018a). We focus on model scenarios with exponential price series that are consistent with intertemporal optimization under the assumptions most common to the simulation models in the sample (a total of 104 analysed carbon price projections). Detailed information on the applied statistical trend identification procedure, the observed trend patterns of global carbon price trajectories and the selected carbon price projections is given in the appendix.

2.3. Further explaining variables and characteristics

For the statistical analyses of the CO₂ price dynamics in alternative climate mitigation scenarios, additional scenario components must be considered. For a comprehensive analysis of additional explanatory factors, of course all explaining variables need to be available to the same extent in the sample. To illustrate data availability in the IAMC 1.5 °C Scenario Explorer, figure 3 shows available observations for the entire set of 598 variables recorded in the database from the 204 ambitious climate mitigation studies with a positive CO₂ price as coloured grid cells. The variables from the scenario explorer are sorted in descending order of total available observations across all models from left to right on the x-axis and the 19 assessment models in descending order of total available observations following a colour key. A large part of all recorded scenario explorer variables can be attributed to only a small number of applied models (REMIND-MAGPIE_1.7–3.0, AIM/CGE_2.0, IMAGE_3.0.1, AIM/CGE_2.1 as well as REMIND_1.7), simulation studies are not evenly distributed across individual models, and reporting frequencies vary between models. In addition we categorised all 598 variables reported in the Scenario Explorer thematically to represent key research areas of applied climate impact research. The amount of meta-information reported for individual models differs significantly across all

4 For reporting years 2030 and 2050, one striking outlier can be observed for each of the ‘Below 1.5 °C’ boxes referring to a single simulation of the POLES model (EMF33_1.3C_LIMBIO) for the Stanford Energy Modeling Forum (EMF 33, see Bauer et al 2018). These model runs generate also a significant outlier amongst all observed year 2100 global carbon price simulations. Other extreme carbon prices come from WITCH-GLOBIOM (see Rogelj et al 2018a) and from the MESSAGE model (see Rogelj et al 2013a, 2013b).

5 Models in this category include IMAGE 3.0.2, MERGE-ETL 6.0, POLES ADVANCE, POLES CD-LINKS, WITCH-GLOBIOM 3.1 and WITCH-GLOBIOM 4.2. This finding is at least insofar interesting as WITCH-GLOBIOM is usually classified as an intertemporal optimization framework (see for example Guivarch and Rogelj 2017 in this regard). The same applies in case of the MERGE-ETL model (see, for example, also Kriegler et al 2015 for respective model classifications). Tables A3 and A4 in the appendix summarise descriptive statistics for reporting years 2020, 2050 and 2100 for this subset of 104 global carbon price series with pre-dominant exponential growth patterns. Roughly every second identified exponential carbon price series (50 out of 104) refers to simulation results from the REMIND-MAGPIE_1.7–3.0 framework (26 series) or the MESSAGE-Globiom 1.0 framework (16 series). Further 16 price paths can be assigned to standalone REMIND applications (9 series from REMIND_1.7 simulations, 7 series from REMIND_1.5 simulations), and further 8 price trajectories can be assigned to standalone MESSAGE V.3 simulation results. Overall, our set of identified exponential price trajectories is thus heavily dominated by results from applications of the models REMIND and MESSAGE, which are generally classified as intertemporal optimization models.
variables. Our applied assignments of individual Scenario Explorer variables to thematic categories as well as details concerning measurement units and the total amount of available observations per variable is given in figures A2–A5 in the appendix.

3. Drivers of global carbon prices

To understand the drivers of global CO₂ prices, we study observable correlations between global CO₂ prices and relevant other variables from the IAMC 1.5 °C Scenario Explorer. The selection of the indicators used here to categorize the price observations (primary energy per capita, freight transportation, livestock demand) is based on a structured stock taking of the entire information content of the IAMC 1.5 °C Scenario Explore and general data availability (figure 3 plus figures A2–A5 in the appendix).

This bivariate analysis is constrained by the availability of data in the different models as described above. Thus, a selection of individual scenario variables may already result in severe limitations of the analysed sample as is illustrated below for, e.g., freight transport volumes and meat consumption. Moreover, if the scenario sample is further reduced, e.g., to only those CO₂ price projections from 1.5 °C-compatible simulation studies, the number of scenarios is reduced substantially, and any robust conclusions are difficult. Despite these limitations, the results still extend existing analyses and contribute to an improved picture of the drivers of the carbon price range across different model results.

The observable correlations between global CO₂ prices and other selected global indicators of the IAMC 1.5 °C Scenario Explorer are illustrated with uniformly structured box plots. Figure 4 shows global carbon prices and their correlation with key elements of the Kaya identity, i.e. global GDP (left panels), primary energy intensity (middle panels) and emission intensity (right panel), for the years 2030 (upper panels), 2050 (middle panels) and 2100 (lower panels). Global carbon prices for individually selected categorizing variables are arranged in columns where the first column considers all overall 2 °C-compatible scenarios with positive CO₂ prices in the selected reporting year and excluding outliers as discussed before (figure 1'). The supplementary figures (figures 2–4) show corresponding findings when the original sample is stepwise restricted considering
only exponential growth scenarios ('figure 2'), 1.5 °C-compatible scenarios ('figure 3') and 'below 1.5 °C' and 'return 1.5 °C with low overshoot' scenarios ('figure 4') with exponential price dynamics. The analysed sample sizes in the respective individual graphs thus continuously decrease from left to right (see ‘n’ = number).

Median values of the global CO₂ prices are marked by a dash and mean values with a triangle. In the boxplots, a green / blue / red area marks the range between the 1st and 3rd quartile of the CO₂ price observations if only those scenarios are considered in which the categorizing variable is below its 33-percentile / is between its 33-percentile and its 66-percentile / is larger than its 66-percentile ('Low' / 'Medium' / 'High').

Scenarios with relatively low GDP values (left column) tend to be characterized by relatively high CO₂ prices: For all 2 °C-compatible scenarios analysed in 'figure 1', the median CO₂ price value for low GDP values in the years 2030, 2050 and 2100 exceeds the median values of middle and high GDP scenarios. This is due to the specifications of the SSPs. High GDP is (assumed to be) correlated with high technological progress, which reduces the costs of low or zero carbon technologies. This finding is confirmed for 2 °C-compatible scenarios with exponential price paths ('figure 2'). For the small number of 1.5 °C-compatible scenarios ('figures 3' and '4') there is no clear pattern visible, probably as these categories are less robust to the influences of individual extreme observations.

A similar pattern can be observed for the relationship of global carbon prices and primary energy intensity (middle column): 2 °C-compatible scenarios with low primary energy intensity tend to be characterized by relatively high CO₂ prices, at least in 2030 (upper panel) which seems to level off towards the end of the observable simulation period (middle and lower panel). In the short term up to 2030 the availability of low or zero carbon technologies at low costs is limited. Low primary energy intensity can just be reached with high carbon prices. In the longer run, zero carbon technologies such as CCUS will be available at lower costs, offering alternatives to reduction of energy intensity.

If CO₂ prices are considered in connection with the development of the emission intensity (right column), there is a clear change of the correlation patterns over time. Scenarios with lower emission intensities (Low) are characterized by lower CO₂ prices for the reporting year 2030, but in 2100 scenarios with relatively low emission intensities (Low) tend to show higher CO₂ prices compared to scenarios with medium and higher emission intensities. This has to be related to total emissions, which are still high in 2030, when fossil fuels will represent a large part of the energy mix, whereas most energy sources will be free of carbon in 2100. A tiny amount of unavoidable emissions will then not have a large cost effect, even if carbon prices are extremely high. The higher the emission intensity, the larger will this cost effect be. Sectors will increase their abatement efforts in the case of high carbon prices.

In order to better understand the interplay of simulated CO₂ prices with the central variables of the Kaya identity, especially with global emission intensity, CO₂ price observations are related to characteristics of the energy system in the scenarios (figure 5). Obviously, one of the key factors behind these correlations are the different developments of technology costs for biomass, nuclear and carbon capture and sequestration (CCS) in the respective model scenarios (Gambhir et al 2019, Krey et al 2019). The clearest findings are detectable for primary energy supply based on biomass, with a share of around 25% in global energy supply in 2050 (left column) (Rogelj et al 2018a). Scenarios with a relatively high primary energy supply based on biomass (High) show higher simulated (median) carbon prices compared to scenarios with a relatively low primary energy supply based on biomass (Low). Butnar et al (2020) show that bioenergy with carbon capture and storage is envisaged as a critical element of most deep decarbonisation
pathways compatible with the Paris Agreement. Its usage depends among others on assumptions about biomass availability, technology costs, and wider system conditions.

High electricity production based on nuclear energy in 2030 (middle column, upper panel, High) is characterized by higher (median) carbon prices, that induce the installation of available low carbon technologies. The findings for the reporting year 2050 do not contradict this, even if no clear patterns can be identified for individual smaller subsamples. At the end of the simulation period (lower panel), however, the total group of all 2 °C-compatible scenarios analysed (‘figure 1’) and scenarios with exponential price dynamics (‘figure 2’) show a lower (median) carbon price for scenarios with relatively high nuclear power production levels (High) compared to the other scenarios. Similar patterns can be observed for the relationship between simulated global CO2 prices and CCS deployment. As costs of CCS are decreasing over time and with technology upscaling, lower CO2 prices are compatible with high shares of CCS in ambitious climate scenarios. Nuclear energy is mainly relevant in parts of Asia and in regulated energy markets, where there has been a built-out in the 2015–2025 decade and O&M costs are low. The share of nuclear in global energy supply is by a factor 6 lower in 2050 compared to biomass (Rogelj et al 2018a).

Finally, figure 6 presents correlations between simulated CO2 prices and lifestyle patterns in our sample. Based on plausibility considerations and general data availability, the CO2 price observations are categorized for the level of primary energy per capita, freight transportation and livestock demand. In scenarios with relatively low per capita primary energy consumption (left column, Low) the simulated CO2 prices are usually higher than in scenarios with relatively high per capita primary energy consumption (High, red bars). Extensive additional energy efficiency measures are quite expensive compared to other (technological) mitigation options. The differences between categories seem to level off over time. Similarly, in scenarios with relatively low freight transport volumes (middle column, Low, green bars) the simulated CO2 prices are usually higher than in scenarios with relatively high freight transport volumes (red bars). As CO2 mitigation in freight transport is rather costly, reducing CO2 emissions in this area must be accompanied by high CO2 prices or abatement costs have to decrease due to fast technological progress. If freight transport volumes continue to be high in the simulated scenarios, other mitigation options might be available at lower costs—and hence with lower CO2 prices - to meet the emission target. The findings regarding food demand are less clear. For the total group of all 2 °C-compatible scenarios analysed (right column, ‘figure 1’), the simulated CO2 prices in scenarios with relatively low meat consumption (Low, green bars) are generally higher than in scenarios with relatively high meat consumption (High, red bars). This result is in line with Hasegawa et al (2018): They conclude that stringent climate mitigation policy would have a significant negative impact on global hunger and food consumption in 2050. However, the observation range of this sample is already relatively small. The scaling of the ordinate also makes it clear that, compared to the CO2 price levels available in other analyses, only relatively low carbon prices have been considered here.
4. Conclusions

Based on a unique dataset of ambitious carbon price trajectories we can reinforce the judgement of the High-Level Commission on Carbon Prices (HLCCP 2017). The price of carbon is lower in scenarios with faster economic growth per capita, low-energy consumption patterns and high potentials for low carbon technologies compared to fossil fuels. Carbon price trajectories in IAMs differ substantially and any interpretation of these price paths proves to be extremely challenging. Based on our findings, we advise policy makers not to rely simply on any given Integrated Assessment study as a reference to ‘the’ necessary CO₂ price for reaching specific climate targets. To avoid serious misunderstandings, modellers should clearly communicate whether and under which assumptions the CO₂ price paths of their simulation studies can act as reference points for concrete policy measures.

Various scenario projections have been created under different combinations of policy options. In the context of the so-called Shared Socioeconomic Pathways (SSPs; O’Neill et al 2014), Kriegler et al (2014), for
example, provide a detailed presentation of relevant aspects in this regard. In doing so, they stress the need to develop so-called Shared Climate Policy Assumptions (SPAs) for a systematic mapping of individual policy approaches. The conceptual point raised by them is that both, sufficiently harmonised framework conditions (SSPs) as well as sufficiently harmonised climate policy measures (SPAs), represent necessary requirements for any meaningful comparison of the result sets from individual modelling exercises. Single model applications may be best categorised according to their underlying SSP-SPA parameterisations. Interdependent causal relationships of complex simulation models play a less important role.

It should be highlighted that our analysis rests on a decidedly large dataset. Prior to the publication of the IAMC 1.5 °C Scenario Explorer, only a limited number of simulation results from 2-degree compatible (or even more ambitious) scenario projections could be analysed. Based on a much smaller set of scenarios and models, Guivarch and Rogelj (2017), for example, concluded that the largest part of the carbon price variation (90%) is due to inter-model differences and only a small fraction of carbon price differentiation can be attributed to socioeconomic variations as represented by the different SSPs. The descriptive overview of the information ranges for the 19 models observed in our sample clearly shows that there are significant differences in causal relationships covered by individual models. These differences in the information sets of individual models should further be carefully reflected. However, our empirical findings indicate that the observed price developments are impacted much more strongly by scenario-specific than by model-specific influences. These findings can only be derived by a comparison of numerous different scenario projections for individual models. As the evidence base of previous studies appears to be relatively narrow in this respect, it is statistically plausible why predominant influence had been previously attributed to model-specific effects.

One salient policy-relevant insight that emerges from our analyses is that in complex climate policy model simulations, global CO2 prices represent only one of many instruments that can be mapped by the models. The systematic review by Peñasco et al. (2021) of different types of decarbonization policy instruments show the differences in environmental, technological, innovation, competitiveness and distributional outcomes. Sustainability scholars urge policymakers to apply comprehensive policy mixes which, besides carbon taxation, also rely on standards, incentives or subsidies to address global sustainability challenges by radical systems transitions (see, for example Markard et al. 2020). Extensive parameterisation capacities hence increase the policy relevance of respective models significantly. Ambitious climate policy simulations parametrised for political consulting will therefore, in addition to carbon prices, usually also incorporate other ‘sustainability transition policy’ instruments (Rosenbloom et al. 2020). Considering this, we identify the issue of whether and how the interplay of various sustainability transition policy instruments differs between individual scenarios and models as a compelling question that should be analysed in more detail by future research activities.

Historically, observable evidence becomes continuously better documented through individual statistical ex post studies. See, for example, the literature review on the effects of applied carbon pricing mechanisms on emissions by Green (2021), the review of empirical ex-post evidence on effect of carbon pricing on technological change by Lilliestam et al. (2021), the meta-analysis to assess the effectiveness of a range of monetary and behavioral interventions on energy demand and emission reduction by Khanna et al. (2020) or the study by Greene et al. (2020) on the effectiveness of US fuel economy standards as well as the regression analyses on the effectiveness of carbon pricing and renewables subsidisation in power sectors by Gugler et al. (2021) as more recent references in this regard. From a methodological point of view, multivariate regression analyses are also perfectly suited for analysing how respective findings are mapped by individual models in different scenarios. This would require the scenario descriptions, which are currently only available in narrative form, to be coded in a harmonised classification scheme. Due to the extent of information included in the IAM Scenario Explorer, we decided not to address this labour-intensive process as part of the work documented here. However, we are convinced that this should be addressed in the future. Next to the diagnostic indicators for models as proposed in Kriegler et al. (2015), scenario-specific indicators of effective sustainability policies should be developed and included in the IAM Scenario Explorer. These additional indicators should enable researchers to classify key context and policy parameterisations applied in individual model runs in a harmonised way. Assumptions about complementary policies next to carbon pricing such as energy efficiency, renewable energy policies and about behavioural change have to be clearly stated. It is important to understand these key scenario and policy assumptions as they drive the simulation results and the variables that are endogenously determined by the models applied.

General critique of the lack of transparency in integrated assessment models and the current information content of the IAM Scenario Explorer has already been published by other authors (Robertson 2021). Our contribution substantiates this criticism by means of a comprehensive descriptive statistical analysis. This enables us to provide clear indications of how to increase the potentials for scientific applications of the IAM scenarios and especially the Scenario Explorer significantly. If researchers are not enabled to control in a harmonised way for the effects of complementary policy instruments, future statistical analyses of this database will also tend to remain restricted to an examination of bivariate correlation patterns. Some of our findings
already indicate the limitations of such a reduced approach. While we can observe quite robust correlation structures for the interaction of CO₂-prices and core elements of the Kaya identity across different sample sizes, supplementary analyses of further variables tend to result in ambiguous bivariate findings. Concerning the later, an interesting example is given by meat consumption: Altogether, the observable correlation patterns indicate that simulated consumption levels are likely to be significantly influenced by other scenario parameters in addition to carbon prices. We consider it very likely that, at least in some model runs, specific changes in dietary preferences have been rather exogenously determined by scenario specific lifestyle assumptions. Therefore, it would be natural to identify respective model runs and to exclude these cases from further analyses. However, such an approach is not immediately feasible given the currently available scenario classifications.

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Data availability statement

All data that support the findings of this study are included within the article (and any supplementary files).

Appendix

Notes on the trend identification routine

The price of carbon should grow at the interest rate under a carbon budget when future marginal abatement costs are known (Gollier 2018a): An investment in a (marginal) reduction of carbon emissions undertaken today costs today’s marginal abatement cost and saves future marginal abatement cost. The return is equal to the growth rates of marginal abatement costs or the growth rate of carbon prices. Other investments yield the interest rate and, accordingly, a cost-efficient carbon price schedule is characterized by a growth rate of carbon prices that equals the interest rate (following Hotelling’s rule) (Hotelling 1931). Under uncertainty the growth rate of carbon prices might be larger than the interest rate (Gollier 2018b). Carbon price trajectories which are not following this exponential growth paths hint to carbon abatement that is intertemporally not optimal.

We analyse the trend patterns based on a statistical trend identification procedure. Our applied trend identification routine is based on individual trend regression specifications as illustrated by the equation.

\[ p_t^s = \beta_0^s + \beta_1^s t + \beta_2^s t^2 + \varepsilon_t^s. \]  

(A1)

Letting \( p_t^s \) denote the observed global carbon price for an individual model simulation \( s \) at time \( t \), we fitted a two-dimensional trend polynomial to the observed time series over the time-period 2030 to 2100. Based on these regression results, we first checked whether the t-statistic associated with parameter estimate \( \beta_1^s \) exceeded a threshold value of two and whether this t-statistic exceeded the absolute value of the corresponding t-statistic for parameter estimate \( \beta_1^1 \). For all series which passed these initial t-Tests we then analysed the distribution of the implied residuals \( \varepsilon_t^s \) like follows: To decide whether observed carbon price deviations from equation (1) appeared to be normally distributed we computed respective test statistics for the Lilliefors tests, the Cramer-von Mises test, the Watson test, and the Anderson-Darling test. See for example D’Agostino and Stephens (1986) for a general description of the underlying principles of respective distribution tests.

Given this battery of diagnostic test results, we then decided from the minimum of all calculated marginal significance levels, whether the null hypothesis of normally distributed error terms was significantly violated. If the minimum significance level did not exceed a value of 0.05, we considered these results to be indicative of more complex trend dynamics. Therefore, only global carbon price series which passed all applied distribution tests at a 5% significance level were considered to inhibit exponential trend patterns.

It is important to note that the results from this testing procedure benefit from the availability of carbon price series with regular (and preferably similar) observation frequencies. Unfortunately, this requirement is not fulfilled by all IAMC 1.5 °C Scenario Explorer carbon price series: Whereas many models do, for example, report carbon price observations in regular ten year time periods until 2100, some models do also feature a regular five-year reporting scheme. Additionally, from other models, carbon price observations are available at five years frequency until 2050, but with ten years frequency after 2050. Therefore, we decided to harmonise our analysed dataset by the decision to include only carbon price series in our sample which met the condition that the largest observed time period between two subsequent observations remained restricted to a maximum of ten years.
The highest reporting frequency available from all IAMC 1.5 °C Scenario Explorer carbon prices equals five years. To achieve a harmonised panel dataset, all selected carbon price observations with lower or infrequent reporting periods were adjusted to this reporting pattern by linear interpolations of any missing observations.

Overall, a total of 104 analysed carbon price projections seem to be best characterised by long run exponential growth patterns in carbon prices. The other 100 global CO2 price projections appear to feature non-exponential trend dynamics, mainly linear trends, but also complex non-monotonous CO2 price dynamics. Guivarch and Rogelji (2017) note that optimizing models tend to have exponentially increasing carbon prices with relatively lower prices in the short term and relatively high prices later. However, our analyses highlights the fact that conclusions about the dynamic properties of the CO2 prices projected in individual model simulations are difficult to derive from a single general model property (like intertemporal optimization models compared to models with recursive dynamics). More additional factors drive the respective results.

### Table A1. Sample statistics for the analysed IAMC 1.5 °C Scenario Explorer global carbon price projections per reporting year.

| Pathway class | 2020 | 2030 | 2050 | 2070 | 2100 |
|---------------|------|------|------|------|------|
| All           |    |      |      |      |      |
| Obs           | 201 | 204  | 204  | 204  | 204  |
| Min           | 0.00 | 14.25 | 45.02 | 119.46 | 153.72 |
| 1. Quart      | 0.72 | 52.29 | 157.73 | 378.42 | 870.09 |
| 2. Quart      | 4.66 | 105.95 | 318.75 | 747.64 | 1483.32 |
| 3. Quart      | 13.56 | 220.00 | 805.06 | 1321.35 | 3134.26 |
| Max           | 172.03 | 6050.00 | 14300.00 | 19260.03 | 43323.21 |
| Mean          | 17.07 | 216.43 | 675.26 | 1304.29 | 3127.30 |
| S. D.         | 29.18 | 471.60 | 1247.23 | 2000.63 | 5102.79 |
| Below-1.5 °C  |    |      |      |      |      |
| Obs           | 7   | 7    | 7    | 7    | 7    |
| Min           | 0.00 | 135.69 | 245.07 | 419.83 | 691.35 |
| 1. Quart      | 0.53 | 166.29 | 300.33 | 514.51 | 847.19 |
| 2. Quart      | 0.72 | 717.52 | 2085.12 | 3237.49 | 6557.19 |
| 3. Quart      | 25.78 | 1204.50 | 4127.75 | 5897.51 | 10071.69 |
| Max           | 131.32 | 6050.00 | 14300.00 | 19260.03 | 30104.97 |
| Mean          | 33.59 | 1472.17 | 3977.87 | 5612.80 | 9472.66 |
| S. D.         | 52.84 | 1919.55 | 4534.97 | 6035.67 | 9273.60 |
| 1.5 °C-low-OS |    |      |      |      |      |
| Obs           | 42  | 43   | 43   | 43   | 43   |
| Min           | 0.00 | 56.87 | 125.55 | 215.10 | 262.70 |
| 1. Quart      | 0.72 | 176.47 | 467.19 | 832.76 | 1208.44 |
| 2. Quart      | 7.26 | 217.70 | 729.82 | 1261.41 | 2696.10 |
| 3. Quart      | 78.48 | 478.21 | 1914.79 | 5620.19 |         |
| Max           | 172.03 | 1275.24 | 4303.97 | 11124.41 | 35037.73 |
| Mean          | 37.23 | 333.60 | 1026.42 | 1896.64 | 4995.24 |
| S. D.         | 34.10 | 261.26 | 971.10 | 2052.22 | 6260.03 |
| 1.5 °C-High-OS |    |      |      |      |      |
| Obs           | 42  | 43   | 43   | 43   | 43   |
| Min           | 0.00 | 14.25 | 112.78 | 263.25 | 501.87 |
| 1. Quart      | 1.25 | 40.08 | 296.08 | 731.04 | 1349.60 |
| 2. Quart      | 2.71 | 83.49 | 362.13 | 857.59 | 1900.26 |
| 3. Quart      | 8.55 | 138.06 | 611.82 | 1135.94 | 3519.48 |
| Max           | 82.66 | 672.86 | 3725.30 | 7635.18 | 13500.00 |
| Mean          | 10.11 | 132.62 | 603.46 | 1274.16 | 3214.41 |
| S. D.         | 29.24 | 395.55 | 1220.08 | 2334.67 | 4995.24 |
| lower-2 °C    |    |      |      |      |      |
| Obs           | 68  | 69   | 69   | 69   | 69   |
| Min           | 0.00 | 14.25 | 75.25 | 146.87 | 153.72 |
| 1. Quart      | 0.72 | 54.41 | 176.99 | 376.41 | 801.18 |
| 2. Quart      | 4.49 | 118.54 | 343.39 | 816.93 | 1505.71 |
| 3. Quart      | 10.24 | 240.56 | 832.35 | 1642.44 | 2526.11 |
| Max           | 96.22 | 1423.87 | 3777.95 | 10024.01 | 43323.21 |
| Mean          | 11.04 | 171.51 | 525.78 | 1205.96 | 2854.07 |
| S. D.         | 18.67 | 188.98 | 529.10 | 1352.35 | 5445.89 |
| higher-2 °C   |    |      |      |      |      |
| Obs           | 50  | 51   | 51   | 51   | 51   |
| Min           | 0.00 | 14.25 | 45.02 | 119.46 | 173.85 |
| 1. Quart      | 0.47 | 30.71 | 98.22 | 219.57 | 585.67 |
| 2. Quart      | 6.39 | 53.68 | 142.63 | 368.54 | 932.33 |
| 3. Quart      | 14.37 | 71.07 | 183.79 | 419.02 | 1430.28 |
| Max           | 46.66 | 218.41 | 1057.00 | 1988.29 | 2339.60 |
| Mean          | 10.77 | 61.94 | 176.00 | 366.60 | 993.04 |
| S. D.         | 12.57 | 43.26 | 157.51 | 190.64 | 530.17 |
Table A2. Sample statistics, apparent outliers of global carbon price series.

| Year | Carbon price | Warming category | Median warming in 2100 | Model | Scenario          |
|------|--------------|------------------|------------------------|-------|-------------------|
| 2030 | 6050         | Below 1.5 °C     | 1.247                  | POLES_EMF33 | EMF33_1.5C_LIMBIO |
| 2050 | 14300        | Below 1.5 °C     | 1.247                  | POLES_EMF33 | EMF33_1.5C_LIMBIO |
| 2100 | 30105        | Below 1.5 °C     | 1.247                  | POLES_EMF33 | EMF33_1.5C_LIMBIO |
| 2100 | 24036        | 1.5 °C return with low overshoot | 1.270 | WITCH-GLOBIOM_3.1 | SSP4-19 |
| 2100 | 35038        | 1.5 °C return with low overshoot | 1.277 | WITCH-GLOBIOM_3.1 | SSP1-19 |
| 2100 | 43323        | Lower 2.0 °C     | 1.604                  | MESSAGE_V.3 | GEA_MIX_1P5C_ADVNCO2_PARTIALDELAY2020 |
Figure A1. Year 2100 median warming levels from the ambitious mitigation scenarios of the IAMC Scenario Explorer.

Figure A2. Model coverage; meta data, population and macroeconomic variables.
Figure A3. Model coverage; energy sector.

Figure A4. Model coverage; agriculture, land use, water use & transport sector.

Figure A5. Model coverage, cost & price variables.
Table A3. Distribution of analysed exponential carbon price trajectories across models and warming categories.

| Sequential Number | Below-1.5°C | 1.5°C-1.5°C-low-OS | 1.5°C-1.5°C-High-OS | lower-2°C | higher-2°C | Total |
|-------------------|-------------|---------------------|---------------------|-----------|------------|-------|
| 1 AIM/CGE_2.0     | 0           | 0                   | 0                   | 2         | 1          | 3     |
| 2 AIM/CGE_2.1     | 0           | 2                   | 0                   | 2         | 0          | 4     |
| 3 GCAM_4.2        | 0           | 1                   | 2                   | 1         | 1          | 5     |
| 4 IMAGE_3.0.1     | 0           | 0                   | 0                   | 0         | 1          | 1     |
| 5 MESSAGE_V.3     | 0           | 0                   | 0                   | 5         | 3          | 8     |
| 6 MESSAGE-GLOBIOM_1.0 | 0     | 5                   | 5                   | 5         | 9          | 24    |
| 7 MESSAGEIX-GLOBIOM_1.0 | 0 | 1                   | 1                   | 1         | 1          | 4     |
| 8 POLES_EMF33     | 0           | 1                   | 0                   | 2         | 2          | 5     |
| 9 REMIND_1.5      | 0           | 4                   | 0                   | 0         | 3          | 7     |
| 10 REMIND_1.7     | 0           | 2                   | 2                   | 3         | 2          | 9     |
| 11 REMIND-MAGPIE_1.5 | 0   | 0                   | 3                   | 0         | 2          | 5     |
| 12 REMIND-MAGPIE_1.7-3.0 | 0 | 4                   | 7                   | 9         | 6          | 26    |
| 13 WITCH-GLOBIOM_4.4 | 1   | 1                   | 0                   | 1         | 0          | 3     |
| Total             | 1           | 21                  | 20                  | 31        | 31         | 104   |
Table A4. Descriptive statistics for the sample of identified exponential price dynamics.

| Model   | Obs | 2020     | 2050     | 2100     |
|---------|-----|----------|----------|----------|
|         |     | Total    | AIM/CGE 2.0 | AIM/CGE 2.1 | GCAM 4.2 | IMAGE 3.0.1 |
|         |     |          | 2.0 | 2.1 | 4.2 | 3.0.1 |
|         | Min | 0.00    | 45.02 | 325.74 | 0.00 | 106.87 |
|         | 1. Quart | 0.19 | 120.46 | 945.20 | 0.00 | 106.87 |
|         | 2. Quart | 4.98 | 181.25 | 1635.53 | 6.51 | 186.05 |
|         | 3. Quart | 17.17 | 387.88 | 3498.98 | 13.03 | 2991.90 |
|         | Max | 172.03 | 5777.95 | 43323.21 | 13.03 | 2991.90 |
|         | Mean | 17.63 | 331.99 | 3113.89 | 7.85 | 164.89 |
|         | S. D. | 30.43 | 430.65 | 4780.47 | 7.82 | 74.23 |
|         |     | 104      | 104     | 104      | 5  | 5  |
|         |     | 45.02    | 325.74 | 945.20   | 6.51 | 186.05 |
|         |     | 120.46   | 387.88 | 1635.53  | 13.03 | 2991.90 |
|         |     | 172.03   | 3498.98 | 43323.21 | 13.03 | 2991.90 |
|         |     | 17.63    | 3113.89 | 4780.47  | 7.85 | 4780.47 |
|         |     | 30.43    | 4780.47 | 4780.47  | 7.82 | 4780.47 |
|         | AIM/CGE 2.0 | 3 | 3 | 3 | 3 | 3 |
|         | AIM/CGE 2.1 | 4 | 4 | 4 | 4 | 4 |
|         | GCAM 4.2 | 5 | 5 | 5 | 5 | 5 |
|         | IMAGE 3.0.1 | 1 | 1 | 1 | 1 | 1 |
Table A4. (Continued.)

|                | 2020   | 2050   | 2100   |
|----------------|--------|--------|--------|
|                | 2020   | 2050   | 2100   |
|                | 2. Quart | 3. Quart | Max | 106.87 | 699.01 |
|                | Mean | 0.00 | 106.87 | 699.01 |
|                | S. D. | 0.00 | 0.00 | 539.35 |
| Obs | 24 | 24 | 24 |
| Min | 48.78 | 48.78 | 559.35 |
| 1. Quart | 67.66 | 775.93 |
| 2. Quart | 114.55 | 1313.59 |
| 3. Quart | 18.89 | 192.41 | 2206.45 |
| Max | 172.03 | 743.51 | 8526.08 |
| Mean | 18.00 | 209.88 | 2406.83 |
| S. D. | 37.14 | 211.28 | 2422.82 |
| MESSAGE V.3 | Obs | 8 | 8 | 8 |
| Min | 0.00 | 83.13 | 953.23 |
| 1. Quart | 0.00 | 113.68 | 1303.58 |
| 2. Quart | 46.62 | 161.71 | 1854.38 |
| 3. Quart | 46.66 | 867.03 | 9942.53 |
| Max | 96.22 | 3777.95 | 43323.21 |
| Mean | 40.02 | 801.83 | 9194.90 |
| S. D. | 28.60 | 1165.88 | 13369.66 |
| MESSAGEix-GLOBIOM 1.0 | Obs | 4 | 4 | 4 |
| Min | 0.23 | 45.02 | 516.31 |
| 1. Quart | 0.23 | 45.02 | 516.31 |
| 2. Quart | 0.23 | 87.80 | 704.03 |
| 3. Quart | 0.23 | 160.59 | 1008.78 |
| Max | 0.23 | 290.98 | 3336.74 |
| Mean | 0.23 | 146.10 | 1390.97 |
| S. D. | 0.09 | 93.29 | 1136.94 |
| POLES EMF33 | Obs | 5 | 5 | 5 |
| Min | 0.00 | 142.62 | 945.20 |
| 1. Quart | 0.00 | 142.62 | 1092.59 |
| 2. Quart | 0.36 | 208.81 | 1585.13 |
| 3. Quart | 0.72 | 456.50 | 1635.53 |
| Max | 0.72 | 880.00 | 3024.66 |
| Mean | 0.43 | 391.45 | 1755.13 |
| Table A4. (Continued.) | 2020       | 2050       | 2100       |
|-------------------------|------------|------------|------------|
| REMIND-MAgPIE 1.5       |            |            |            |
| S. D.                   | 0.35       | 279.94     | 684.81     |
| Obs                     | 5          | 5          | 5          |
| Min                     | 8.07       | 80.96      | 928.40     |
| 1. Quart                | 8.07       | 113.60     | 1205.88    |
| 2. Quart                | 8.07       | 305.75     | 3312.10    |
| 3. Quart                | 8.07       | 618.59     | 7304.28    |
| Max                     | 8.07       | 1033.45    | 10149.70   |
| Mean                    | 8.07       | 483.47     | 5182.54    |
| S. D.                   | 0.00       | 343.13     | 3526.49    |
| REMIND-MAgPIE 1.7-3.0   |            |            |            |
| Obs                     | 26         | 26         | 26         |
| Min                     | 0.00       | 107.90     | 480.14     |
| 1. Quart                | 3.11       | 158.47     | 802.89     |
| 2. Quart                | 9.03       | 195.53     | 1429.06    |
| 3. Quart                | 9.03       | 315.33     | 2577.59    |
| Max                     | 74.30      | 1170.26    | 11011.74   |
| Mean                    | 15.33      | 310.35     | 2257.81    |
| S. D.                   | 18.92      | 264.62     | 2266.75    |
| REMIND 1.5              |            |            |            |
| Obs                     | 7          | 7          | 7          |
| Min                     | 33.00      | 142.62     | 1635.53    |
| 1. Quart                | 33.00      | 142.62     | 1635.53    |
| 2. Quart                | 71.50      | 309.02     | 3543.65    |
| 3. Quart                | 110.00     | 475.41     | 5451.76    |
| Max                     | 110.00     | 475.41     | 5451.76    |
| Mean                    | 77.00      | 332.79     | 3816.23    |
| S. D.                   | 38.11      | 164.69     | 1888.55    |
| REMIND 1.7              |            |            |            |
| Obs                     | 9          | 9          | 9          |
| Min                     | 1.80       | 99.89      | 444.50     |
| 1. Quart                | 1.80       | 162.33     | 940.28     |
| 2. Quart                | 1.80       | 251.71     | 2107.52    |
| 3. Quart                | 1.80       | 313.93     | 3465.93    |
| Max                     | 1.80       | 1205.33    | 13821.96   |
| Mean                    | 1.80       | 370.67     | 3788.35    |
| S. D.                   | 0.00       | 321.89     | 3947.97    |
| WITCH-GLOBIOM 4.4       |            |            |            |
| Obs                     | 3          | 3          | 3          |
| Min                     | 0.000000   | 232.6466   | 1189.181   |
| 1. Quart                |            |            |            |
|            | 2020     | 2050    | 2100    |
|------------|----------|---------|---------|
| 2. Quart   | 0.000000 | 344.3551| 1745.399|
| 3. Quart   | 0.000000 | 616.8093| 3131.378|
| Max        | 0.000000 | 1099.046| 5620.665|
| Mean       | 0.000000 | 595.9189| 3037.154|
| S. D.      | 0.000000 | 367.2708| 1882.423|
ORCID iDs

Mark Meyer  https://orcid.org/0000-0001-7637-2925
Andreas Löschel  https://orcid.org/0000-0002-3366-8053
Christian Lutz  https://orcid.org/0000-0001-8849-8197

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