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Comparing future patterns of energy system change in 2°C scenarios with historically observed rates of change

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***Highlights ((without author details, acknowledgements or affiliations)**

This paper systematically compares modeled rates of change to historical references

The indicators tested vary in terms of system focus, timeframe and normalization

Indicators that look into absolute change reach unprecedented levels by 2030

Indicators that account for overall system growth remain within historical records

The indicators provide no conclusive insights into the achievability of 2°C scenarios

Comparing future patterns of energy system change in 2°C scenarios with historically observed rates of change

Abstract

This paper systematically compares modeled rates of change provided by global integrated assessment models aiming for the 2°C objective to historically observed rates of change. Such a comparison can provide insights into the difficulty of achieving such stringent climate stabilization scenarios. The analysis focuses specifically on the rates of change for technology expansion and diffusion, emissions and energy supply investments. The associated indicators vary in terms of system focus (technology-specific or energy system wide), temporal scale (timescale or lifetime), spatial scale (regional or global) and normalization (accounting for entire system growth or not). Although none of the indicators provide conclusive insights as to the achievability of scenarios, this study finds that indicators that look into absolute change remain within the range of historical growth frontiers for the next decade, but increase to unprecedented levels before mid-century. If overall system growth is taken into account the study finds that monetary-based normalization metrics (GDP, investments and to some degree capacity) result in less conservative outcomes than energy-based normalization metrics (primary energy). This is in particular true for indicators that experience rapid rates of change (for both technology-specify and system-focus indicators). By applying a diverse set of indicators alternative, complementary insights into how scenarios compare with historical observations are acquired but they do not provide further insights on the possibility of achieving rates of change that are beyond current day practice.

Keywords: *integrated assessment modeling; energy system change; technological change; model validation; 2 degrees; feasibility*

1 Introduction

Keeping temperature increase to less than 2˚C with a high likelihood will require substantial changes in energy and land use. Integrated assessment model (IAM) studies on mitigation scenarios can provide insights into the level of the required change over time. IAM-based studies often conclude that the required transition for reaching the 2˚C target is 'technically feasible', depending on the model set-up and assumptions. In the past, such studies generally considered rather idealised conditions such as full participation of all regions and sectors in climate policy. However, more recently, models have also studied the achievability of the 2˚C target under less idealized circumstances assuming limits in technology availability or reduced participation in international climate policy (Clarke et al., 2009; Kriegler et al., 2013b; Riahi et al., 2015; Weyant and Kriegler, 2014). Even in those cases, most models still identify scenarios that reduce emissions in line with the 2˚C target. It should, however, be noted that in their assessment, IAMs mostly account for technological and economic factors that can be easily included in the models. This, for instance, includes constraints like mitigation potentials, capital stock turnover rates, mitigation costs and inertia in investments patterns. Several other factors are not included such as the role of international negotiations, societal inertia or the time associated with decision-making processes on the one hand and behaviour changes on the other. Clearly, such factors can have a substantial influence on the probable (future) rate of change..

Historically observed rates of change can be important reference points for assessing the difficulty associated with future rates of change – providing possibly also insights in real world factors not covered in the models. In fact, several studies have already tried to compare model results and historical data using different indicators (Kramer and Haigh, 2009; Loftus et al., 2014; Riahi et al., 2015; Tavoni and van der Zwaan, 2009; Van Der Zwaan et al., 2013; Van Vuuren et al., 2013; Wilson et al., 2012). In these studies different methods and data sets have been used to confront existing scenarios with historical evidence, meaning that their results and conclusions cannot be easily compared. For instance, Van Vuuren et al. and Riahi et al. looked at overall change in emissions or emission intensity. In contrast, the studies of Van der Zwaan et al. and Wilson et al. look at absolute and relative changes in the deployment of particular energy technologies. It should also be noted that model comparison projects have shown that models select different pathways in achieving similar goals, and that models can be 'diagnosed' as being more or less responsive to climate policy (Kriegler et al., 2015). In order to represent model uncertainty, it is therefore important to compare the results of a diverse set of IAMs against a standardized set of historical indicators.

In this light, the goal of this study is 1) to systematically compare several methods that use historical evidence as a basis for analyzing the difficulty associated with future energy transitions and 2) to use these methods for evaluating model results. We use the results of a multi-model study to provide insight into the uncertainty resulting from a wide diversity of technology trajectories that are consistent with the 2ºC target. Questions that are addressed are:

- How do historical rates of change compare to future rates of change required under the 2°C climate objective?
- Do various indicators of technology change depict a coherent storyline?

2 Methodology

2.1 Comparing historical and future rates of change

Historical observations provide an important reference point for the required level of effort to achieve future energy system changes associated with ambitious climate policy objectives. To date, different indicators have been used to compare historical trends with future rates of change, varying in terms of system focus (technology-specific or energy system wide), temporal scale (timescale or lifetime), spatial scale (regional or global) and normalization (accounting for entire system growth). In order to gain a more holistic insight from these analyses we combine and harmonize the methods to encompass an overall similar scope of research. In the following paragraphs the various methods are described first followed by how they are interpreted in the current study. Table 1 and Table 2 provide summaries of the metrics used and scope of study. Figure 1 provides a visual example of the introduced methods.

2.1.1 Indicator a): Annual capacity addition

Van der Zwaan et al. investigated historical and future capacity growth by comparing the average annual capacity additions (in GW/yr) in a multi-model context for low-carbon technologies for the short-term (2010-2030) and medium-term (2030-2050) (Van Der Zwaan et al., 2013). The study focused on the *absolute* rate of change required to reach the 2°C target compared to rates experienced during historical periods of rapid expansion for established technologies (e.g. natural gas power) and newer technologies (e.g., solar power). The comparison provided easy interpretable insights into the expansion rate for future deployment versus historical figures published in literature and online databases (e.g. EPIA, 2014; Platt's, 2013; US EIA, 2014).

$$\text{Annual capacity addition} = \frac{\sum_{t_0 \to t}^{t} (\text{newly installed capacity})}{\text{t-t}_0} = GW/_{yr}$$

Using this approach, Van der Zwaan et al. concluded that future global expansion rates need to increase significantly, reaching expansion rates well beyond those observed historically in order to stay below the 2°C target. In particular, the expansion of renewable energy technologies would need to be several times larger than the historical rate (Van Der Zwaan et al., 2013).

However, the comparison of *absolute* future rates with historical rates does not correct for the stage of development for specific technologies nor the general growth in the size of the energy or electricity system. In this study we account for overall system growth by normalizing *absolute* indicators with metrics representing system growth, such as global GDP (in T$), global primary energy demand (in EJ), total electricity generation capacity (in GW) or total capital investments in the energy system (in billion USD$).

$$\text{Normalized annual capacity addition} = \frac{\sum_{t_0 \to t}^{t} \left(\frac{\text{Newly installed capacity}}{\text{Normalization metric}} \right)}{\text{t-t}_0} = {}^{GW}\!/\!_{\text{metric unit}}\Big/_{\text{year}}$$

A similar analysis has been done by Loftus et al. (2014), who normalized electricity capacity deployment rates in various global decarbonization scenarios using global GDP. In their study they found that the rates of change are broadly consistent with historical experience. Only specific decarbonization scenarios with imposed restrictions on the implementation of clean and carbon sequestration technologies would lead to unprecedented rates of change for the remaining eligable low-carbon energy technologies (Loftus et al. 2014).

2.1.2 Indicator b): Technology diffusion

Technology growth dynamics are generally characterized by S-shaped curves that show an initial 'formative' phase, then rapid diffusion through an 'upscaling' phase and into a mature 'growth' phase which eventually slows to saturation (Grübler et al., 1999; Wilson, 2012). Growth rates vary over this technology lifecycle, beginning slowly until a lift-off point is reached and growth accelerates. After some time, an inflection point is passed and growth rates level off and eventually saturate, reducing growth to zero.

Wilson et al. (2012) compared historical and future dynamics of technological diffusion in the energy system by fitting logistic growth curves (with a R-squared fit of 98% or higher) to cumulative capacity time series describing technologies' full lifecycle from formative phase to saturation. The advantage of using cumulative capacity over the technology lifecycle, as opposed to installed capacity or growth rates during particular time periods, is that short-term volatility and potential selection biases towards specific periods of growth are avoided. From the logistic growth function various parameters can be extracted that respectively represent the duration of diffusion (Δt, between 10% to 90% of saturation) and the extent of growth or saturation point of a technology (the theoretical asymptote denoted as K). To account for the growing size of the energy system, Wilson et al. (2012) normalized the extent of diffusion by the size of the energy system (expressed in primary energy) at the midway point of each technology's lifecycle (Tm, inflection point). The normalized K and Δt create the extent-duration relationship for the number of technologies included.

$$\text{Technology diffusion} = \frac{\dfrac{\text{Extent (K)}}{\text{PE}_{(Tm)}}}{(1+e^{-\text{diffusion rate*duration of diffusion}(\Delta t)}}$$

The main disadvantage of this methodology is that it is not readily comparable to recent observations or to maximum or frontier growth rates over short time periods. Moreover, only historical and future technologies for which diffusion approximates logistic growth can be included in the analysis. This excludes, for example, wind and solar power whose growth to-date is still broadly exponential with no evidence of a slowdown towards saturation. The results from the methodology applied by Wilson et al. (2012) showed that the full lifecycles of advanced power generation technologies as modelled in many future scenarios have longer durations than the full lifecycles of energy technologies that have diffused historically. In other words, there is evidence that deep decarbonization scenarios may be somewhat conservative in their long-term technology growth dynamics. However, the authors acknowledged several caveats, including the possibility that comparing long-run historical growth with long-run future growth in this way is problematic. This was specifically the case for the analysis of coal or nuclear power, which combined historical and future growth dynamics in the logistic fitting procedure.

2.1.3 Indicator c): Annual emission (intensity) decline rate

Two indicators often used to gain insight into economy-wide changes are (1) annual emissions decline rate and 2) annual emission intensity decline rate (decarbonization rate) (Riahi et al., 2015; Van Vuuren et al., 2013).

Annual emission decline rate = $$\left(\left(\frac{Emissions_t}{Emissions_{t_0}}\right)^{\frac{1}{t-t_0}}-1\right)*100=\%/yr$$

Annual emission intensity decline rate = $$\left(\left(\frac{\left(\frac{Emissions_t}{GDP_t}\right)}{\left(\frac{Emissions_{t_0}}{GDP_{t_0}}\right)}\right)^{\frac{1}{t-t_0}}-1\right)*100=\%/yr$$

The disadvantage of this generic descriptive indicator is that details on underlying drivers of emissions are not visible. Moreover, as emission reduction and emission intensity decline rates have not been major policy goals in the more distant past, a comparison against the long-term historical record can be regarded as having limited relevance. Nevertheless, the study by Van Vuuren et al. (2013) used historical comparisons to conclude that emission reductions as well as decarbonization rates for scenarios consistent with the 2°C target can be regarded as extremely rapid compared to historical rates of change.

2.1.4 Indicator d): Required supply-side investments

Structural changes in the energy system are associated with increasing supply-side investments. As investments are also needed to achieve other social and economic goals there could be constraints in the required pace of change. Therefore, we look into the global investments into electricity generation and supply (including electricity storage and transmission and distribution, but not investments into the fossil fuel extraction sector nor the bio-energy fuel supply costs) to assess the efforts needed to mobilize an energy system transformation that is in line with the 2˚C objective. Demand-side investments are not taken into account as such estimates are subject to considerable uncertainty due to a lack of reliable statistics and definitional issues (McCollum et al. 2013).

Annual required supply-side investments $\dfrac{\text{Investments}_t - \text{Investments}_{t_0}}{t - t_0} = \$/yr$

As the total amount of investments is coupled to the size of the economy, we normalize the annual investments using global GDP, creating an indicator reflecting investments as percentage in total GDP.

Annual required supply-side investments as share of GDP = $\dfrac{\text{Investments}_t - \text{Investments}_{t_0}}{GDP_t - GDP_{t_0}} = \%$

McCollum et al. (2013) examined absolute rates of change for investments in more detail, concluding that future investment levels remain consistent on the short term although significant increases in investments in both developed and developing countries will be necessary over the next decades under the 2°C objective.

Table 1- overview of technology change indicators included for study

Indicator	Variations	Metric
a) Annual capacity addition	Average annual capacity addition	GW/yr
	Normalized annual capacity addition	GW/yr/ $
b) Technology diffusion	Normalized extent (K) and duration Δt	GW/EJ/year
c)_Annual emission (intensity) decline rates	Annual emission decline rate	%/yr
	Annual emission intensity decline rates	%//yr
d) Required supply-side investments	Annual required investments	$/yr
	Annual required investments as share of GDP	%-share

Table 2- overview of methodologies and the scope of this study

Indicator	System focus	Temporal scale	Spatial scale	Normalization (Metric)[2]
a) Annual capacity addition	Technology specific	Annual[1]	Global	No
	Technology specific	Annual[1]	Global	Yes (GDP)
b) Technology diffusion	Technology specific	Lifetime	Global	Yes (Primary Energy)
c) Annual emission (intensity) decline rates	Energy system	Annual[1]	Global / National	Yes (GDP)
d) Required supply-side investments	Energy system	Annual[1]	Global	No
	Energy system	Annual[1]	Global	Yes (GDP)

[1] on average over a selected period of time

[2] This study depicts GDP throughout the results as the measure of growth, other metrics of growth are further discussed in the discussion

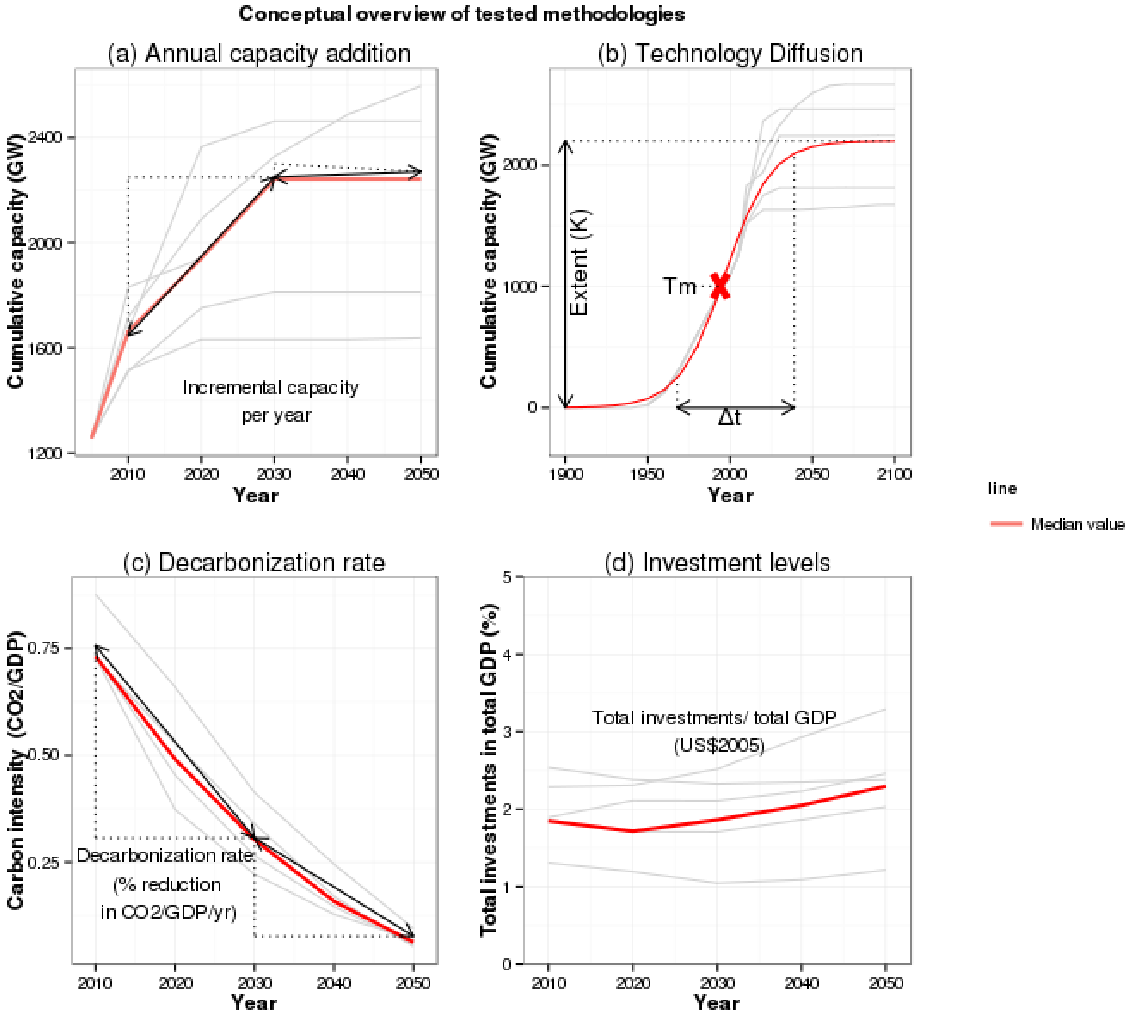

Figure 1 – Conceptual overview of the methodologies and key indicators. Panel (a) and (b) represent cumulative capacity of coal without CCS. Although the figure demonstrates future (modeled) trends the analysis is similar for historical trends.

2.2 Comparing future technological change to historical references

2.2.1 Future rates of change

We demonstrate the indicators by using three scenarios from a five-model study with varying assumptions on long-term international climate policy. A marked advantage of the multi-model approach is that it inherently accounts for technology biases and preferences among individual models. The study here, however, is not a model comparison: we only include the model range as an indication of the uncertainty in model results. We therefore do not discuss the results of individual models in any detail. The focus in the figures is also on the median of the range of model results.

Five global energy-environment models are included in this study: REMIND:(Bauer et al., 2013; Luderer et al., 2013); MESSAGE: (Messner and Strubegger, 1995); IMAGE: (Bouwman et al., 2006); WITCH: (Bosetti et al., 2006) and TIAM-ECN: (Keppo and Zwaan, 2011)) (see table 3). These five models represent a diverse array of different solution frameworks (general equilibrium, partial equilibrium, dynamic recursive, perfect foresight and systems engineering) and differ in a variety of model characteristics, such as coverage of sectors and their disaggregation and in technological and socio-economic assumptions that determine technology diffusion.

Table 3 - key model characteristics

Name	Time horizon	Model category	Intertemporal Solution Methodology
IMAGE	2100	Partial equilibrium	Recursive dynamic
MESSAGE	2100	General equilibrium	Intertemporal optimization
REMIND	2100	General equilibrium	Intertemporal optimization
TIAM-ECN	2100	Partial equilibrium	Intertemporal optimization
WITCH	2100	General equilibrium	Intertemporal optimization

The three scenarios that are used in this study are based on different policy assumptions for long-term international climate policy and have been developed as part of the LIMITS project (Kriegler et al., 2013a).

(1) The baseline (*Baseline*) scenario addresses the future energy system and emission developments in the absence of climate policy. This scenario is a best reference for historical rates of change as no climate policy is involved.

(2) The second (*Reference*) scenario reflects current (unilateral) climate policy implementation based on national energy and climate targets for 2020 formulated as unconditional Copenhagen pledges. These targets are then extrapolated post-2020 by assuming similar levels of stringency in the subsequent decades. This scenario represents the current day situation and imposes no additional (technological) restrictions.

(3) The third (*2 Degrees*) scenario is a cost-optimal mitigation scenario that assumes immediate global cooperation toward the long-term target of 2°C. This scenario represents the most optimistic view on technology availability, availability of carbon sinks and (bio-) resources to attain the 2°C climate target.

Differences are created due to the varying assumptions on long-term international climate policy, all other factors, such as the penetration and expansion rates of technologies, are treated the same across all scenarios.

The methods and indicators set out in Section 2.1 are comparatively applied on this set of three scenarios. As timing of change is important this study has restricted the analysis to the time period between 2010 and 2050 because it is considered most relevant for current policy and decision making.

2.2.2 Historical references

For the annual capacity addition indicator, we reconstruct a similar analysis to that of Van Der Zwaan et al. (2013) by comparing modeled average annual rates of change in total new installed capacity to historical average annual rates of change. Several databases provided historical data on various technologies (see Table 4) of which the decade with the largest absolute growth in capacity is selected for further analysis.

For the technology diffusion indicator, similar logistic growth curves are constructed as in Wilson et al. (2012) on both historical (if applicable) and future time series. The historical time series begin as far back as the early 1900s (natural gas and coal power), the 1950s (nuclear power), the 1970s (wind power and solar PV), or start no sooner than the 2020s or later (CCS).

For the emission (intensity) decline rate indicator, we depict average CO_2 emission and carbon intensity reduction rates and compare them to historical national events that led to emission (intensity) reductions (such as oil crises, collapse of political regime) (Riahi et al., 2015; Van Vuuren et al., 2013).

For the required investments indicator, we show the average annual investments or the share in GDP over the 2010–2050 timeframe and compare them to the historical investments (or share in GDP) over the 2000-2013 timeframe (IEA, 2014).

In order to normalize the *absolute* indicators to take into account relative changes in the size of the energy system or economy, we use GDP, primary energy, total energy system investments and total capacity as normalization metrics. The historical period taken into consideration is the 1980-2012 period as most metrics have annual data available in public sources with investments as an exception (see Table 5).

Table 4 - Overview of selected historical timeframes per indicator and the used databases

Indicator	Technology	Historical reference	Source
a) Annual capacity addition	PV	2003-2013	EPIA (2014
	Wind	2003-2013	GWEC (2014)
	Nuclear	1980-1990	Platts (2013)
	Biomass	2005-2011	(US EIA, 2014)
	Fossil	2003-2012	Platts (2013)
	CCS	-	-
b) Technology diffusion	PV	1970s	Wilson et al. (2012)
	Wind	1970s	
	Nuclear	1950s	
	Fossil	Early 1900s	
c) Annual emission intensity decline rates	System	1970s-2000	Riahi et al. (2015)
d) Required supply-side investments	System	2000-2013	IEA (2014a)

Table 5 - Overview of normalization metrics, available historical timeframe and source

Method	Metric	(Historical) timeframe	Source
Normalization	GDP	1980-2012	The World Bank (2015)
	Primary Energy	1980-2012	US EIA (2014)
	Investments	2000-2013	IEA (2014a)
	Capacity|Electricity	1980-2012	US EIA (2014)

3 Results

In the results below, we show the results of each of the indicators presented in Section 2 for the three LIMITS scenarios and all 5 models as well as the historical reference period.

3.1 Annual capacity addition

The modeled annual capacity additions (in GW) for the 2010-2030 period are on average consistent with the historical reference across all three scenarios. In the *Baseline* scenario, the expansion rates from 2010-2030 are broadly consistent with historical observations (see Figure 2). Coal without CCS maintains a constant annual expansion rate whereas gas without CCS will nearly double its current annual expansion rate, matching and overtaking coal without CCS. Under climate constraints, we find a shift away from fossil fuels either shifting to a less carbon-intense substitute (gas) or shifting to non-fossil resources. For solar PV, wind and biomass the expansion rates stay within historical peak observations. The projections of nuclear power capacity growth are also consistent with historically observed expansion rates. However, currently planned additional nuclear capacity between 2015-2019 (World Nuclear Association, 2014) indicates that the expansion rate of nuclear energy will most likely not exceed the 3GW/yr. Hence, given the long inertia in nuclear power plant planning and construction process, the actual expansion rates of nuclear power might continue to be below the deployment rates as depicted in some of the high scenarios.

In the 2030-2050 timeframe, the modeled rates of annual capacity additions for non-fossil technologies increase beyond analogous technology-specific expansion rates observed historically. Some even exceed the maximum rates observed historically for any technology. Under *Baseline* assumptions, both coal and gas without CCS will expand their growth to unprecedented levels as fossil fuels remain the fuel of choice. Under the 2°C objective (*2 Degrees*) the use of fossil fuel without CCS will gradually decrease or be substituted by CCS facilities. Moreover, the growth of solar and wind capacity will become particularly rapid, showing deployment rates above the historical peak value in the stringent climate policy (*2 Degrees*) scenario.

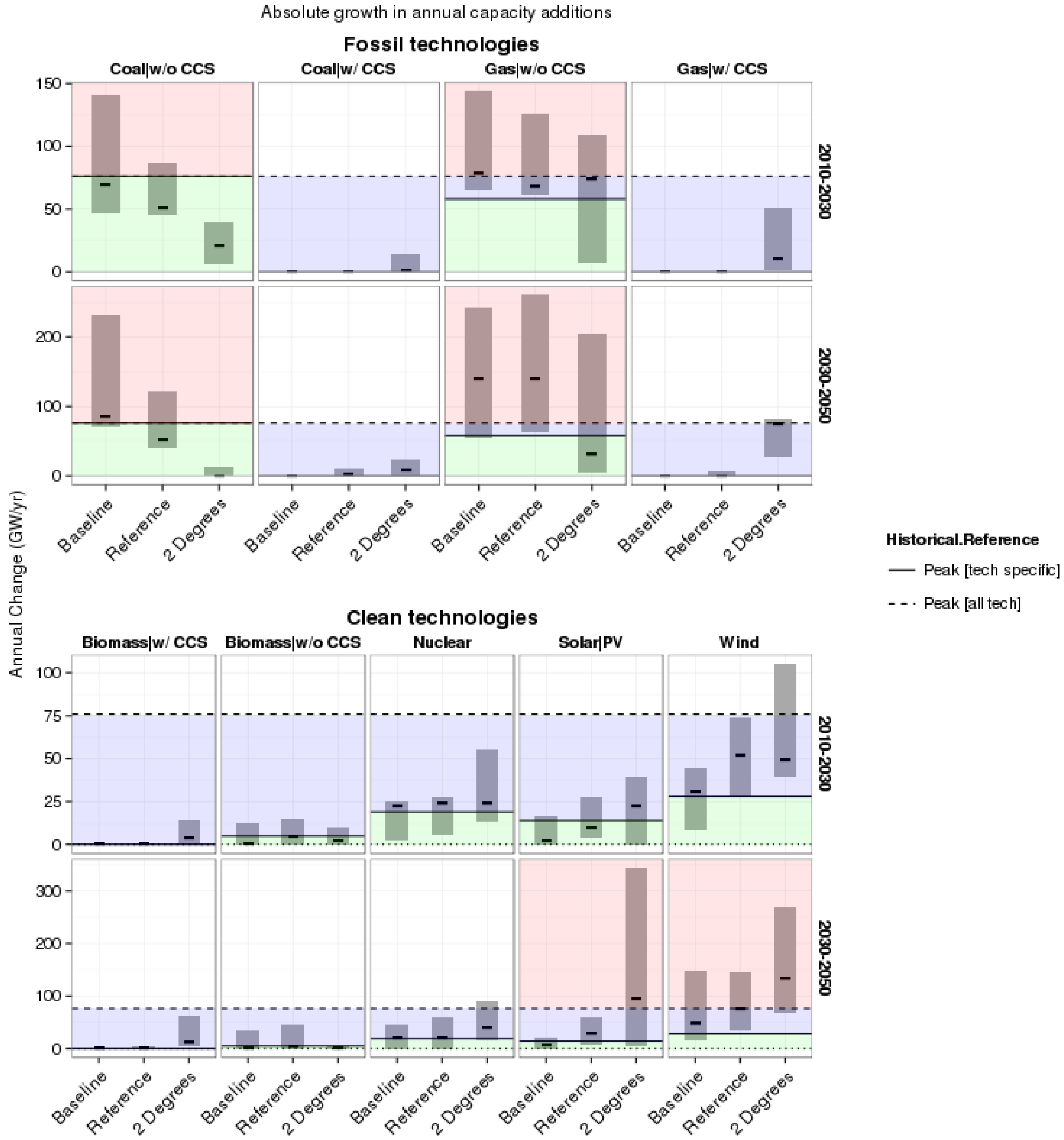

Figure 2 - Average annual capacity additions (over the 2010-2030 and 2030-2050 period) for various electricity-generation technologies under different climate policy assumptions. The horizontal lines indicate the technology-specific peak or maximum value observed historically (solid lines) and the peak value across all technologies which is given by coal without CCS (dotted lines). The green, blue and red areas indicate whether a historical benchmark has been exceeded (red for all-technology peak, blue for technology-specific peak) or not (green). The bars indicate the range of modeled rates of change with the median value highlighted in black inside the bars.

By accounting for system growth between historical and future periods (normalizing the annual capacity indicator using GDP growth), we find that future capacity additions are overall consistent with maximum expansion rates of the most succesful technologies in the past (see Figure 3). On the short-term most outcomes remain within historical observation, whereas over the mid-term several technologies (wind and solar in particular) venture into territory that goes beyond the overall best system achievement from the past.

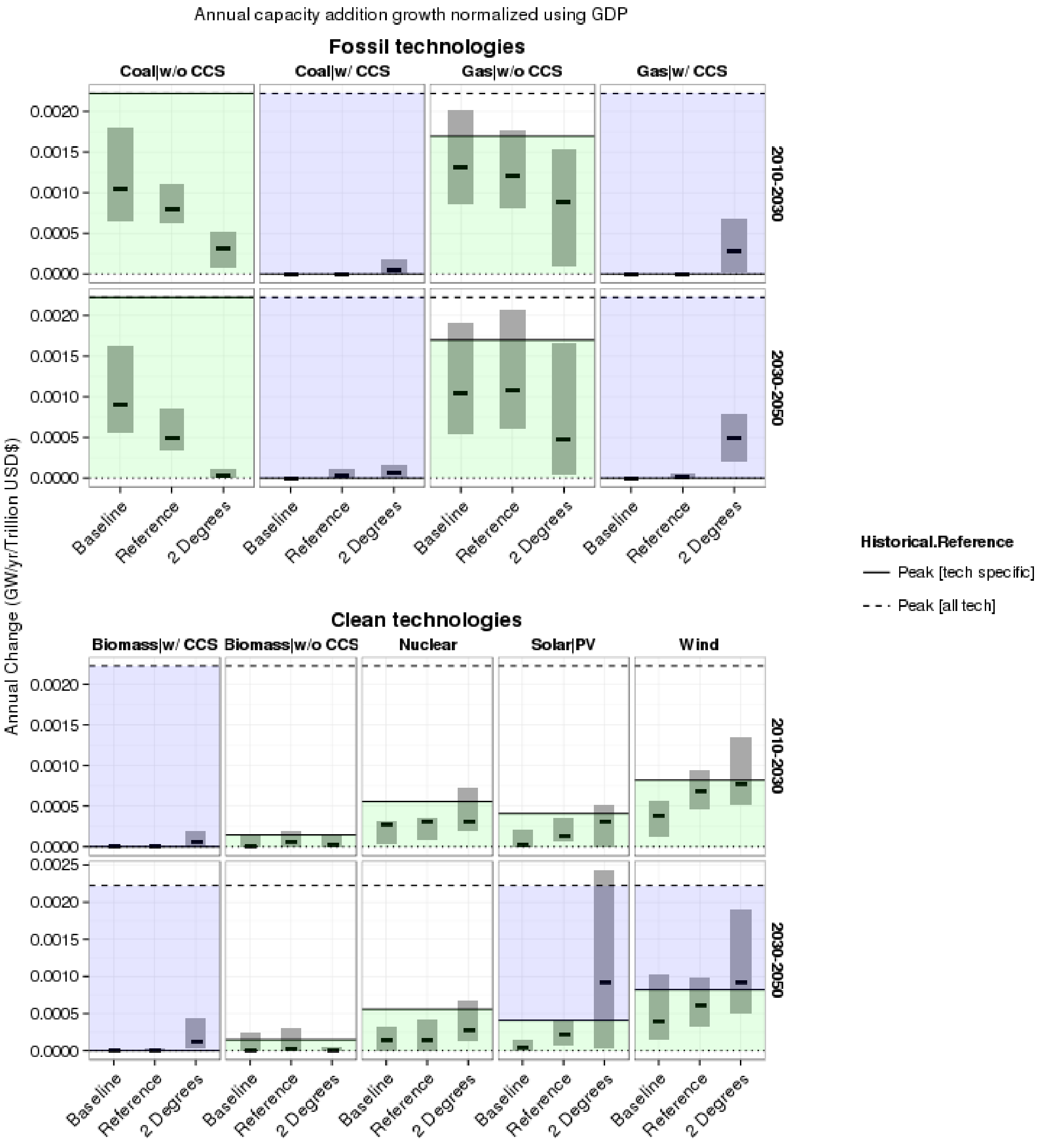

Figure 3 - Average annual capacity additions (GW/yr), normalized using GDP (in trillion US$2005) for both historical data as well as scenario projections. The horizontal lines indicate the technology specific maximum value and the maximum value of any technology in the past. The green, blue and red areas indicate whether a historical benchmark has been exceeded (green below technology specific rate; blue above technology specific rate; red above the historical rate of any technology). The bars indicate the range of modeled rates of change with the median value highlighted in black inside the bars.

3.2 Technology diffusion

The modeled technology diffusion rates over the full technology lifecycle are analyzed using a methodology similar to that of Wilson et al. (2012). An extent-duration relationship (normalized K vs. Δt, normalized with the total energy produced at the inflection point Tm) is constructed of all electricity generation technologies for three scenarios (see Figure 4). The extent-duration relationship depicts the extent to which technologies penetrate into the energy system and the time period until saturation is reached.

In the *Baseline* scenario, fossil technologies mostly follow the historically observed patterns (i.e., the historical relationship between normalized K vs. Δt data points across all technologies are in line with the relationship from modeled data points). However, the time periods to saturation are generally longer (further to the right) with the eventual saturation point often occurring beyond 2100.

If climate policy is introduced, the extent-duration relationships change (*Reference* and *2 Degrees* scenarios). Although all technologies shift to the left (shorter diffusion durations) the differences are the greatest for fossil without CCS technologies which show a lower capacity saturation level, a shorter lifecycle, and some capacity reduction in the year in which maximum growth is achieved (see the supplementary material online). For clean technologies (fossil with CCS, CO_2 neutral and renewable energy technologies), the *2 Degrees* scenario shows more a greater extent of growth and shorter diffusion durations. It would still require nearly a century of capacity growth and development to fully utilize the technological potential of clean technologies under the 2°C objective. This means that the expansion rates are very near to those of the most successful technologies in the past, yet the durations of full technology lifecycles remain above the historically observed pattern. In that sense this study is in agreement with Wilson et al. (2012) concluding that the modeled diffusion rates appear to be conservative compared to historically successful technologies.

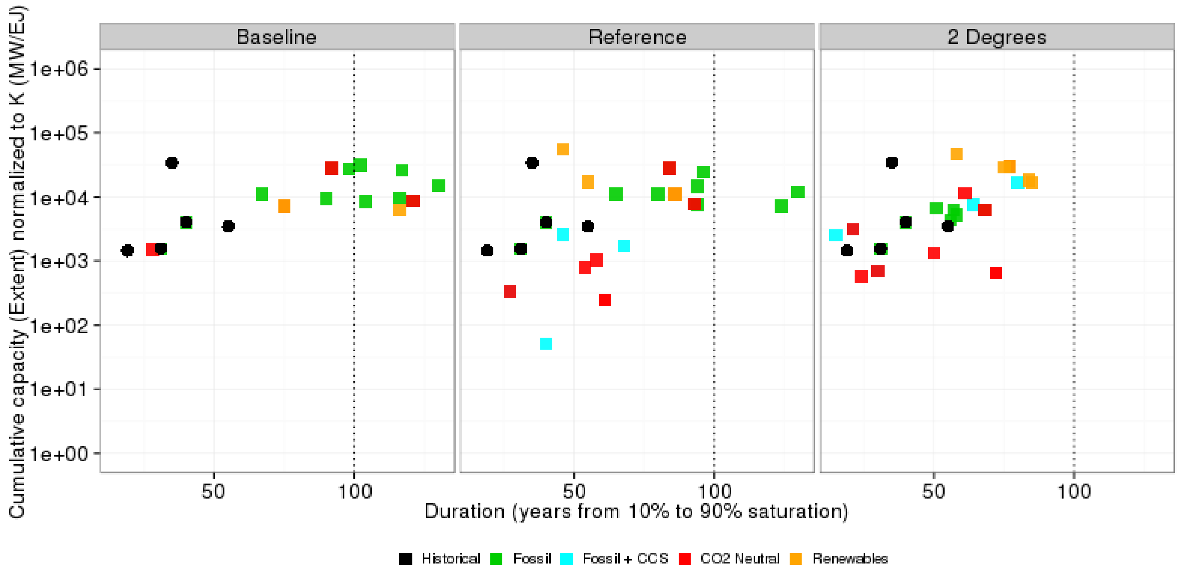

Figure 4 - Capacity growth of energy technologies in 3 future scenarios of the 21st century: extent vs. duration of growth using fitted logistic function parameters. Black dots represent historical extent-duration relationships of various energy-supply technologies (such as nuclear, coal and gas without CCS, hydro and refineries (FCC).

3.3 Decarbonization rates

Figure 5 shows the average annual emission decline rate and the decline rate normalized using GDP (creating a carbon intensity decline rate or decarbonization rate). Up till today, only rare historical occurrences on a national level have led to significantly higher reduction rates than the global average, which have been negative (-0,8% per year on average throughout the 1970-2010 period) owing to continuously growing emissions worldwide. For example, fairly swift emissions reduction rates were observed in Sweden from 1974 to 2000 as a result of policy impulses on greening the Swedish energy system after the oil crisis in 1973 (2-3% per year). Another example is the emission decline rate of 2-4% per year for Eastern European and former Soviet Union countries after the collapse of the Soviet Union (Riahi et al., 2015). To stay in line with the 2°C objective a sustained global carbon emission reduction rate of about 1% till 2030 is required, remaining within the earlier discussed regional historical boundaries. However, after 2030 the models depict a sustained global carbon emission reduction rate of 5% which goes beyond both global and regional historical achievements.

Similarly, the global decarbonization rate has been around 0.5% over the period 1900–2010 and around 1% over the 1970–2010 (driven by technological change and sectoral shifts) (Van Vuuren et al., 2013). If compared to the modeled decarbonization rates, we find ranges of 2-3% under *Reference* scenario assumptions whereas the margins expand to 6-10% by 2050 if 2°C is to be attained at the end of the century. These rates are considerably higher than the global average rate experienced in the past. At the regional level, historically faster rates can be observed than the global average: some Asian regions have managed to achieve decarbonization rates of 3–5% per year during the late 1980s and early 1990s. This would imply that the global rate would need to increase significantly, but also go beyond the most rapid (local) decarbonization rates experienced in the recent past and maintain this rate (globally) for several decades.

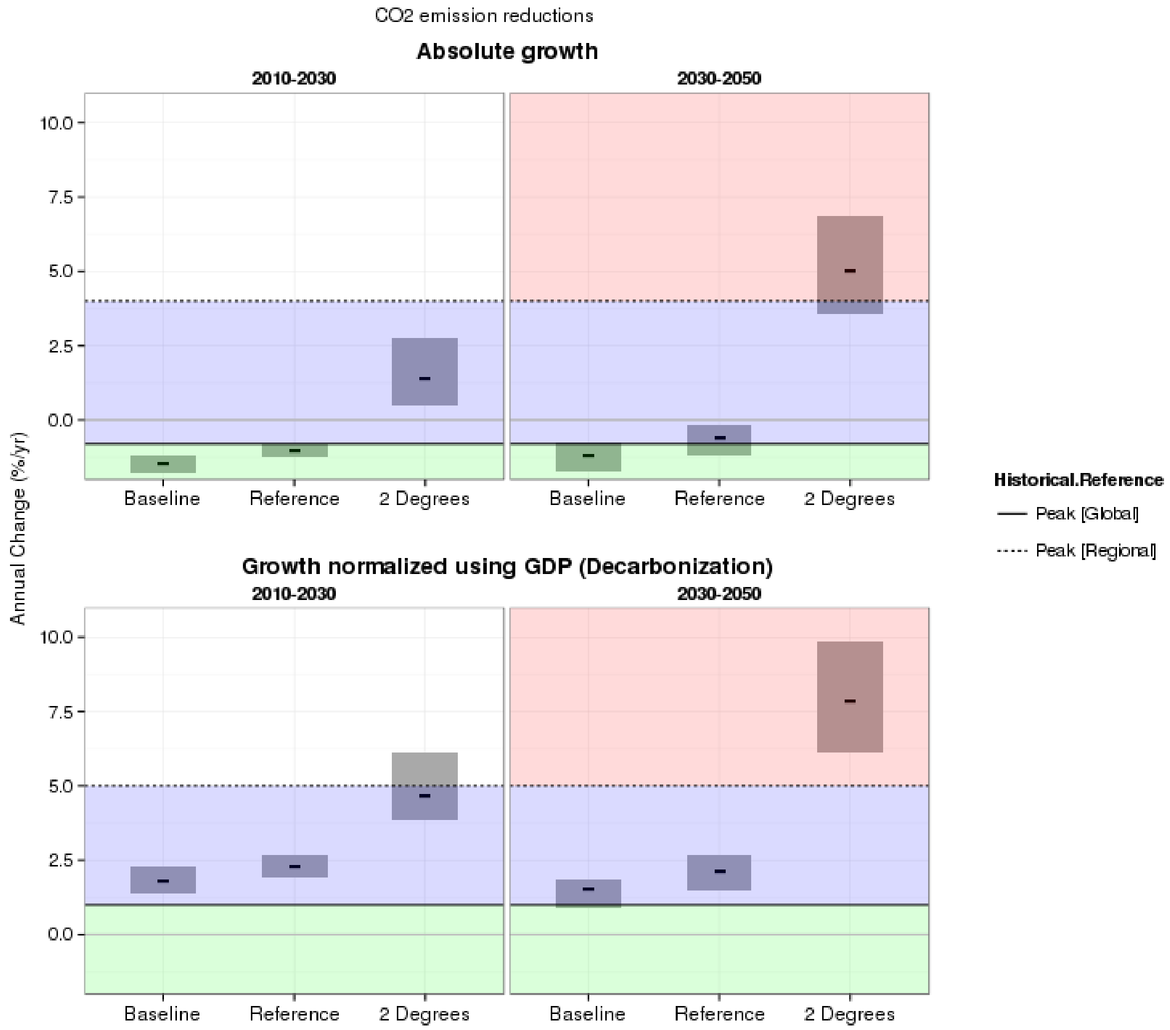

Figure 5 – Average annual emissions decline rates (top) and average annual emission intensity decline rates (bottom). Negative numbers indicate emissions increase. Green area implies consistency with historical evidence for global rates, blue represents values within historical bounds of the fastest regional reduction addressed and red implies beyond historical reference for either considered spatial scale. The bars indicate the range of modeled rates of change with the median value highlighted in black inside the bars.

3.4 Required supply-side investments

Rapid transitions in the energy system are associated with increasing investment flows compared to the status quo, which is reflected in Figure 6. Both current climate policy (*Reference*) as well as the 2°C pathway (*2 Degrees)* would require greater investments than the business-as-usual case (*Baseline*), climbing up on the short term to about 1.5 trillion USD per year which is slightly greater than observed historically. Under 2°C ambitions these investment levels are modeled to nearly double for the subsequent decade, increasing up to 2.5 trillion USD per year on average. Upscaling investments to these levels might pose several difficulties as two-third of the total sum is levied by developing areas (McCollum et al., 2013) which require finance mechanisms other than their own domestic funds (BOWEN et al., 2014).

If total supply-side investments are expressed as a share in global GDP, it shows that the ratio remains within the bounds of historical experience. However, by looking into global rates it potentially masks the large differences between regions. The average investment intensity of developing economies was around 3.5%, whereas it was just 1.3% in industrialized countries (McColumn et al., 2014).

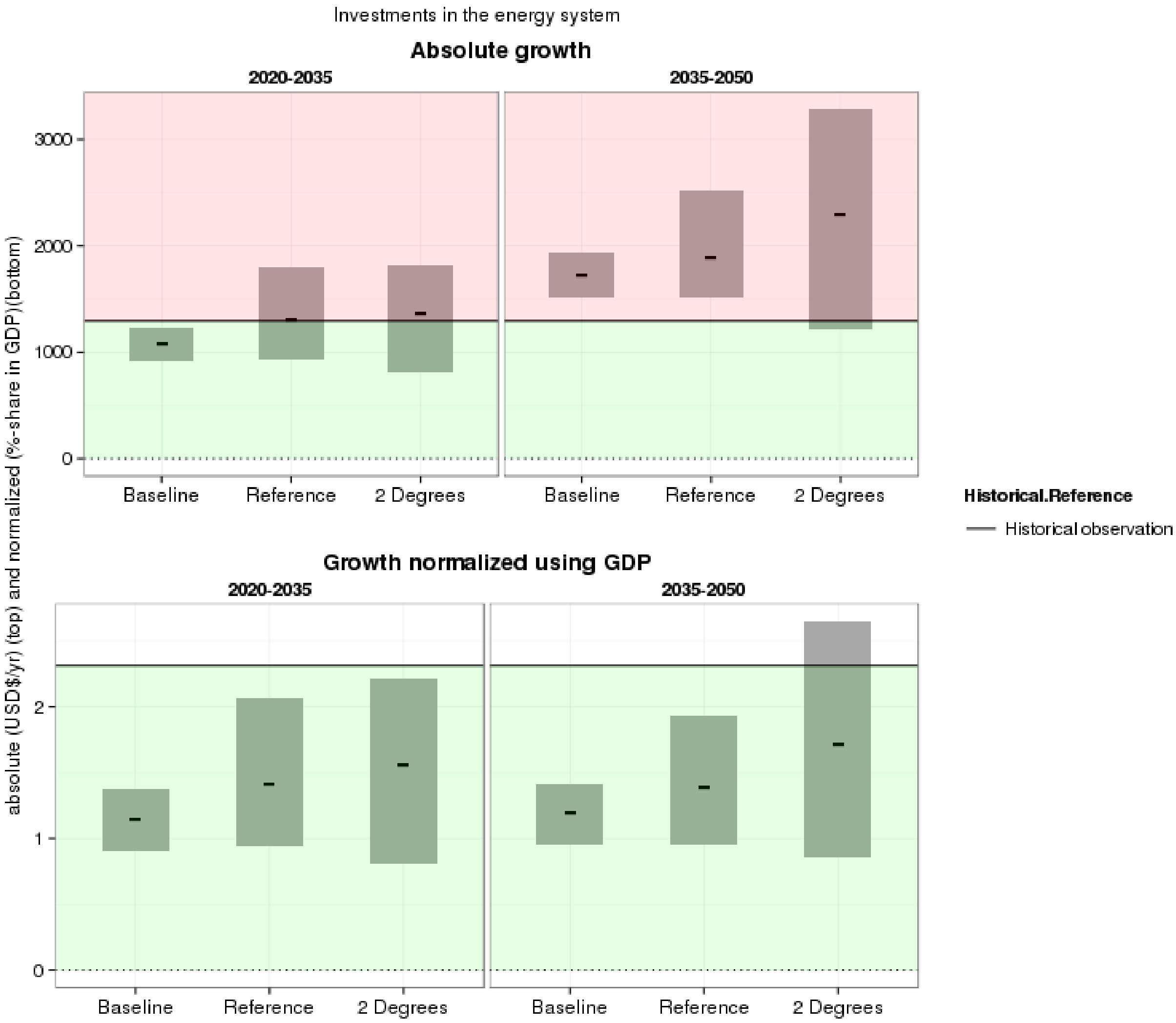

Figure 6 – Average annual supply-side investments (top) and average annual supply-side investments in GDP (bottom). Bars represent the range of model outcomes of respectively *Baseline*, *Reference* and *2 Degrees*[1]. The bars indicate the range of modeled rates of change with the median value highlighted in black inside the bars.

4 Discussion

4.1 Comparative overview of indicators and results

This study uses a diverse set of indicators that assesses the consistency of modeled future energy transitions with the historical record. The study yields ambiguous insights into the consistency of modeled rates of change with historical observations (see Table 5). Absolute and near-term (2010-2030) rates of change vary in their consistency with historical observations for the three scenarios, although these are mostly within the range of overall system achievements (blue shaded areas on the graphs). By normalizing the indicators to account for system growth shows an overall consistency with historical records is found. Over the longer term the indicators create a near similar picture for the

[1] For the *Baseline* scenario, the numbers are recalculated, as they were not included in the study of McCollum et al. (2013). Due to data availability, only results for IMAGE and MESSAGE are shown here. The *2 Degrees* scenario includes unilateral climate policy targets till 2020, suspending immediate global action, and therefore deviating from the *2 Degrees* scenario as presented in other graphs. As the *Reference* and *2 Degrees* scenario start to deviate only after 2020 the time periods are amended to 2020-2035 and 2035-2050. The historical observation consists of cumulative energy supply investments and cumulative total GDP from 2000-2013.

Baseline and *Reference* scenarios. However various significant differences emerge under the 2-degree objective (*2 Degrees*), specifically in terms of (absolute) capacity expansion rates, (absolute) total energy-supply investments and (absolute and normalized) decarbonization rates.

Table 6 - Summary of comparisons between historical observations and three modeled scenarios using a diverse set of indicators. For plotting convenience the fossil and renewable technologies are grouped - the table considers the highest rate of change in the group per scenario

			Absolute growth			Normalized growth		
			Baseline	Reference	2 Degrees	Baseline	Reference	2 Degrees
2010-2030	Average annual capacity additions	Fossil						
		Renewables						
	Annual emission (intensity) decline rates	System						
	Required supply-side investments	System						
2030-2050	Average annual capacity additions	Fossil						
		Renewables						
	Annual emission (intensity) decline rates	System						
	Required supply-side investments	System						
	Technology diffusion	Tech-specific						

	Not applicable
	Below historical growth frontier for corresponding technology
	Below historical growth frontier for any technology
	Above historical growth frontier for any technology

4.2 *Methodological diversity and issues*

The indicators used vary in focus and scope. In this section we further discuss the influences and sensitivities of the study design on the outcome.

(1) **System focus:** Models are inherently limited in their representation of energy-economy dynamics, and are highly dependent on their technological resolution (number of technologies included), underlying assumptions (on e.g. capital replacement or learning rates) as well as model structure and solution frameworks. In that respect technology-specific indicators are potentially more sensitive to specific model behavior than system-wide indicators. However, in a multi-model set-up these sensitivities are more-or-less balanced out and in that case, as depicted in Table 5, system indicators are not consistently more or less likely to remain consistent with historical observations;

(2) **Temporal scale:** Indicators that focus on a specific timeframe (e.g. the average annual capacity additions or decarbonization rates) can be sensitive to the selected time period. This is especially the case if rapid expansion or declines rates are nested in certain periods of time, which can be either highlighted or numbed down in the longer-term average.

Focusing on the full technology lifecycle, however, can also influence the results. For example, the Wilson et al (2012) methodology is sensitive to technology projections with a clear logistic growth profile, such as mature historical technologies for which long time-series data are available. As renewable technologies are generally still in their early deployment phase these are not expected to saturate in the timeframe of the model, and will therefore not appear as logistic growth profiles in the Wilson et al. methodology. Hence, some modeled rates of change will not find application in the extent-duration analysis. The conservatism in the extent-duration curves could thus be an outcome of the overrepresentation of incumbent technologies;

(3) **Spatial scale:** By focusing on global outcomes an indicator may potentially mask the large differences between regions. In this light the indicator provides only limited insights into the actual challenges that are faced to reach such rates of change.

In the case where a global benchmark is absent (such is the case for emission and decarbonization decline rates) we selected a more local (contemporary) achieved peak value. Such a comparison inherently includes selection bias as frontier reduction rates have specifically been selected. However although these regional benchmarks only lasted for a short period of time and emerged under rare circumstances (such as oil crises and regime changes), these specifically underline the difficulty of achieving the needed rates of change;

(4) **Normalization:** The normalization approach is visibly sensitive to the type of system growth metric used (see Figure 7). Monetary-based normalization metrics (GDP, investments and capacity to some degree as well) result in more conservative rates of change than energy-based normalization metrics (primary energy). As a result, rates of change that are normalized by using monetary-based normalization metrics are less likely to exceed historical rates than those normalized using energy-based metrics. This is in particular true for indicators that experience rapid rates of change (for both technology-specify and system-focus indicators).

Choosing the appropriate normalization metric is important – as the choice for a specific metric could render future rates of change (in)consistent with historical rates. The choice depends according to the authors on (a) the variable being normalized, and (b) the question being asked. For example, if the modeled variable is annual capacity additions, then (a) suggests using historical primary energy or capacity as the normalization metric, unless (b) the specific question is whether investment requirements in new capacity are in line with historical observations.

In sum, the results of the indicators discussed in this study are associated with several methodological considerations. Applying a wide set of indicators therefore offers alternative, complementary insights into how scenarios compare with historical observations on two different scales (e.g. technology-specific and system-wide indicators and the choice for normalization). Although none of the indicators provide conclusive insights as to the achievability of scenarios they are useful ways to contribute to scenario evaluation and provoke critical interpretation of results.

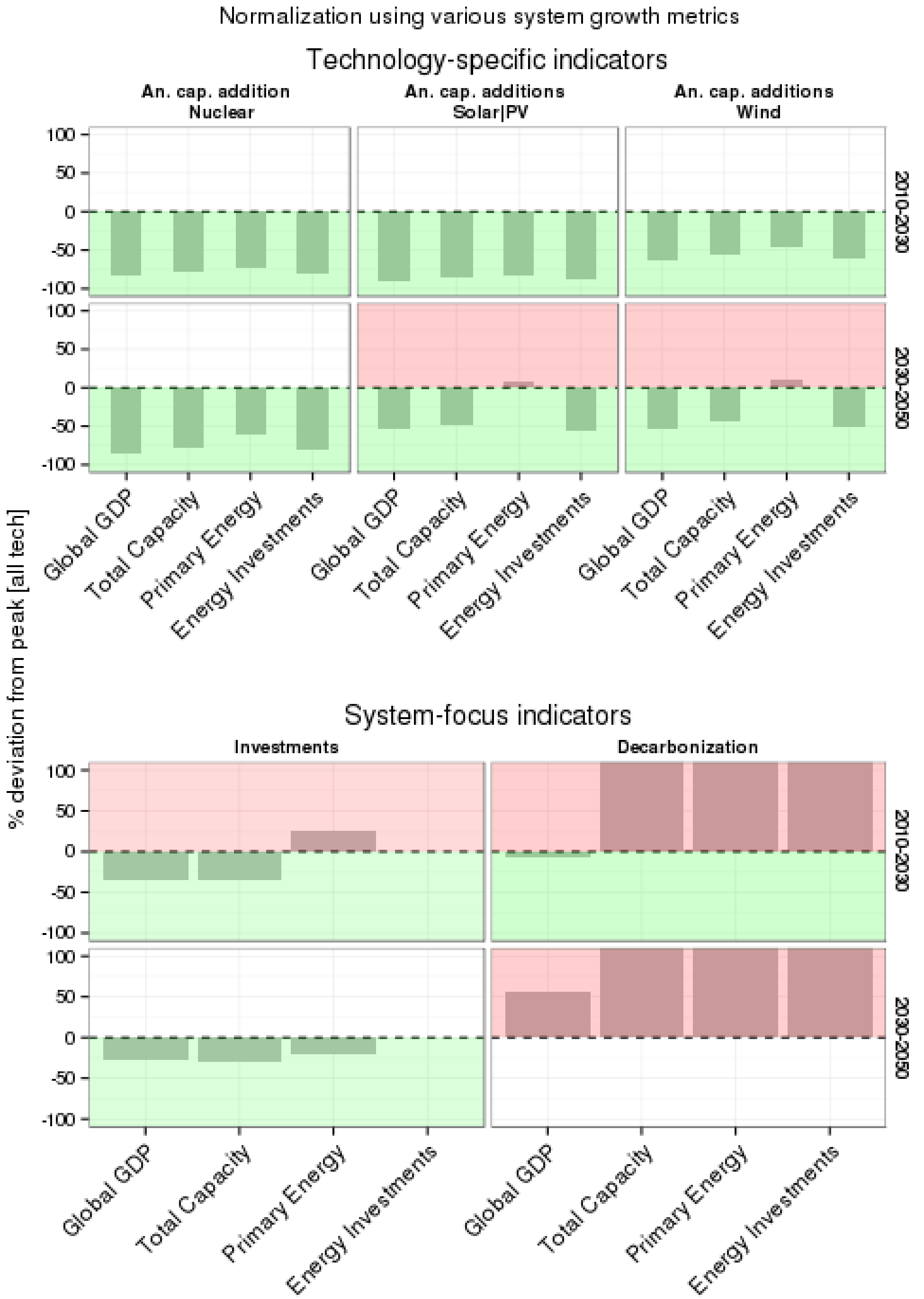

Figure 7 - Deviation of the median model value from the maximum peak benchmark per indicator for each considered normalization metric. Positive values indicate that the indicator exceeded historical experience whereas negative values imply consistency with historical observations. For plotting convenience the annual capacity additions are limited to nuclear, solar PV and wind technologies. Moreover, the investments indicator is plotted on the 2010-2030 and 2030-2050 timeframe but these represent the timeframes as depicted in paragraph 3.4. The picture focuses on the 2ºC objective.

4.3 Expanding the scope of research

By applying a diverse set of indicators one can gain more holistic insights into how scenarios compare with historical observations. Further research in line with this study could focus on:

(1) **Fine-tuning and extending the scope of current indicators:** Two fundamental regularities of successful technology diffusion patterns are described in Kramer and Haigh (2009). According to their study, the build rate of new and existing energy technologies follow two 'laws' which have been fairly consistent across energy technologies in the past. The first law describes how technologies grow quickly for the first two decades at exponential rates (+/-26%/yr) until 'materiality' is reached, defined as a +/-1% share of the global energy system. The second law states that after materiality, growth rates level down to an eventual equilibrium or constant market share. Although the expansion phase and the maturing growth phase characterized by Wilson et al. (2012) broadly correspond with these 'fundamental laws', this could be embedded more clearly within the historical comparison methods. Moreover, additional insights may also be acquired by distinguishing between expanding systems (adding new capacity) and stabilizing systems (substituting existing capacity);

(2) **Introducing additional comparison methods:** Modeled rates of change could be compared against actual trends over the same period of time, for instance a decade after the original projection was made. An example of such an exercise is found in van Vuuren and O'Neill (2006). If short-term model trajectories are significantly inconsistent with historical trajectories, it could expose conservatism in the long-term scenario logic and the assumptions on the driving forces. This methodology is, however, only useful if historical trends include similar climate policies as included in the model projections;

(3) **Including demand-side indicators:** Historical and future emissions and their driving forces have also previously been studied by applying the Kaya-identity (Kaya, 1990). The Kaya-decomposition analysis is applied in numerous studies (i.e. Steckel et al., 2011; Zhang et al., 2009) to examine the implications of changes in total CO_2 emissions on affluence (representing growth of economic activities), change in energy intensity (i.e. total primary energy over GPD reflecting efficiency and consumption patterns) and the carbon intensity (i.e. total CO_2 emissions over total primary energy). The three components could be assessed in tandem or as separate indicators in comparative work of prospective studies and historical records. This study has a greater energy supply orientation as all indicators focus on either energy supply technologies, investments or the carbon intensity of energy supply but future work could also include demand side indicators such as energy intensity and affluence;

(4) **Going beyond the historical benchmark:** This study considers history as an important benchmark, though history provides only limited information when looking at innovation. For example the results provide no further information about, amongst others, the drivers of technological change, (perceived) risks, scalability, structure of the industry or role of institutions. Expert elicitation could expand the knowledge on critical implementation barriers and further test the feasibility of prospective studies. Several prospective studies on technology development use expert elicitation protocols as a research tool to assess the feasibility of emerging (carbon-free) energy technologies (see for example Bosetti et al. 2012, Jenni et al. 2013, Fiorese et al. 2014). Experts can go beyond the historical benchmark by providing probabilistic information on the likelihood that technologies will overcome particular hurdles and estimate the overall probability of success for each technology (Baker et al., 2009).

5 Conclusions

In this study we have compared indicators of change in future scenarios to historical trends for various degrees of climate policy. The analysis confronts scenario data from the LIMITS project to four methodologies that focus on different indicators of technology change, such as capacity expansion, technology diffusion and changes in emission trends or investments. The main conclusions of this analysis are:

The achievability of future rates of change depends on the indicator used. In this study, we assessed a variety of indicators to look at the rate of future change versus historically achieved rates of change. This comparison provides some insight into the effort involved in achieving these scenarios but is highly dependent on: (1) selecting the historical benchmark, (2) normalization, (3) data availability as well as the (4) underlying economic and technological assumptions, model structures and the included level of technological detail in the models. Although none of the indicators provide conclusive insights as to the achievability of scenarios they are useful ways to contribute to scenario evaluation and provoke critical interpretation of results.

Indicators highlight that absolute rates of change in scenarios achieving the 2 degree target are rapid in the medium term compared to historically achieved rates of change. In absolute terms we have observed that projections are more-or-less in line with reported achievements on the short-term, but these increase to unprecedented levels by mid-century. Specifically the capacity expansion rates for solar and wind and required energy-supply investments are particularly strong under 2°C constraints, showing rates above the historical peak value of overall system achievements by 2030.

Methods that look at relative rates of change by comparing the change to overall growth in the system conclude that future rates of change are generally within the range of successful transitions in the past. Indicators that account for the growth in the overall system show that the modeled rates of change in the scenarios are lower compared to the rates of change in the past. We find that monetary-based normalization metrics (GDP, investments and to some degree capacity) result in less conservative normalization than energy-based normalization metrics (primary energy). This is in particular true for indicators that experience rapid rates of change (for both technology-specify and system-focus indicators)

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Figure

Conceptual overview of tested methodologies

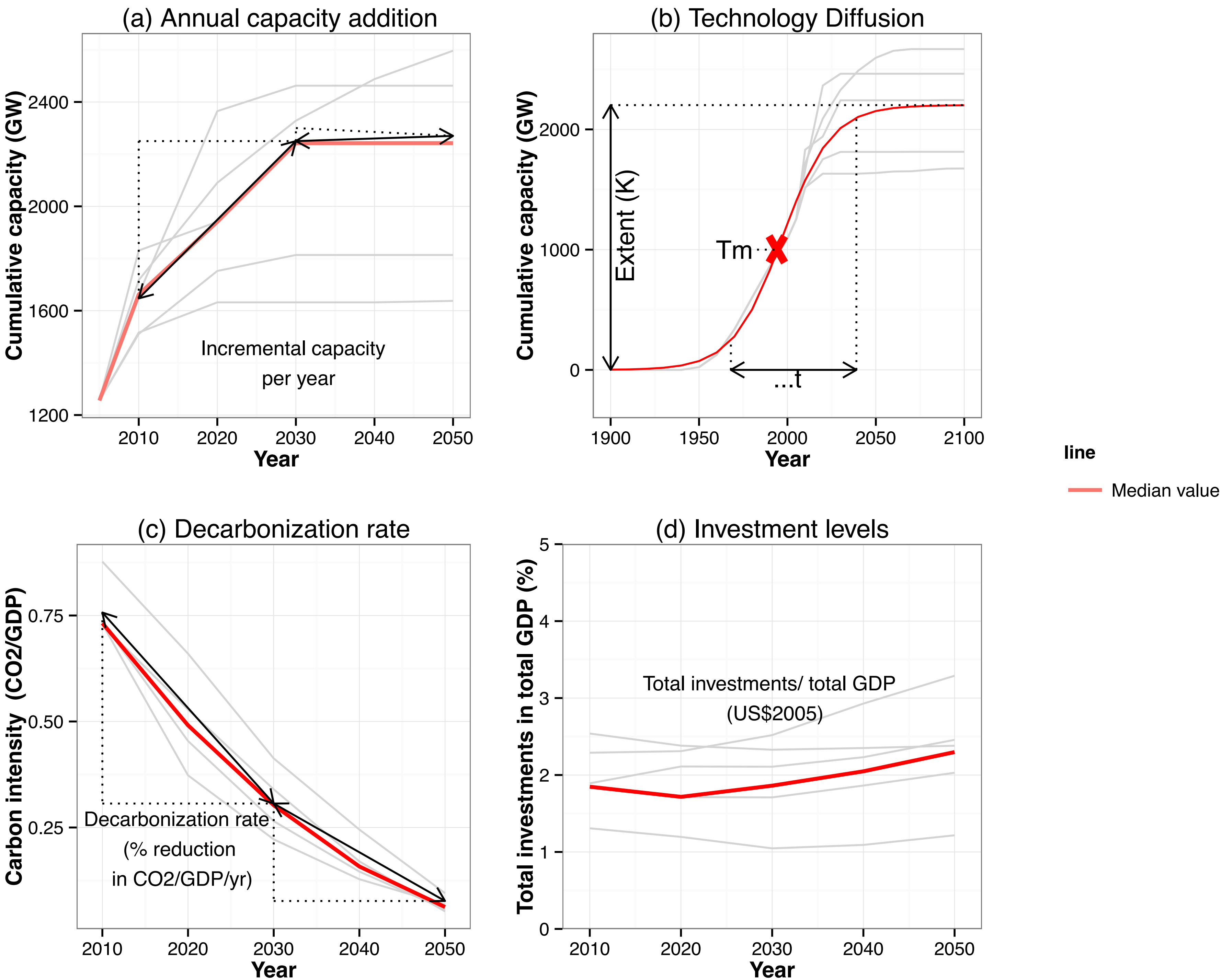


Figure Absolute growth in annual capacity additions

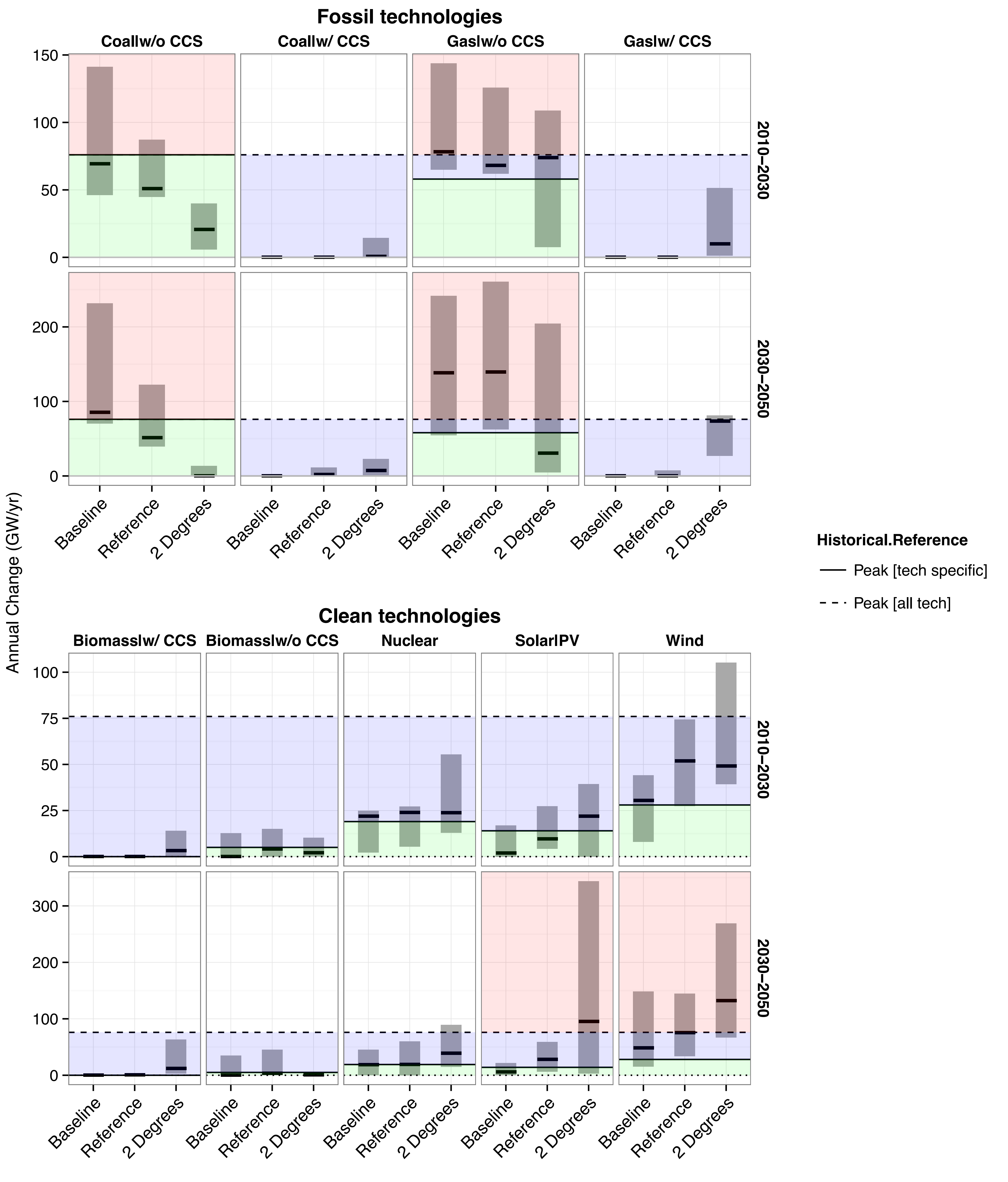
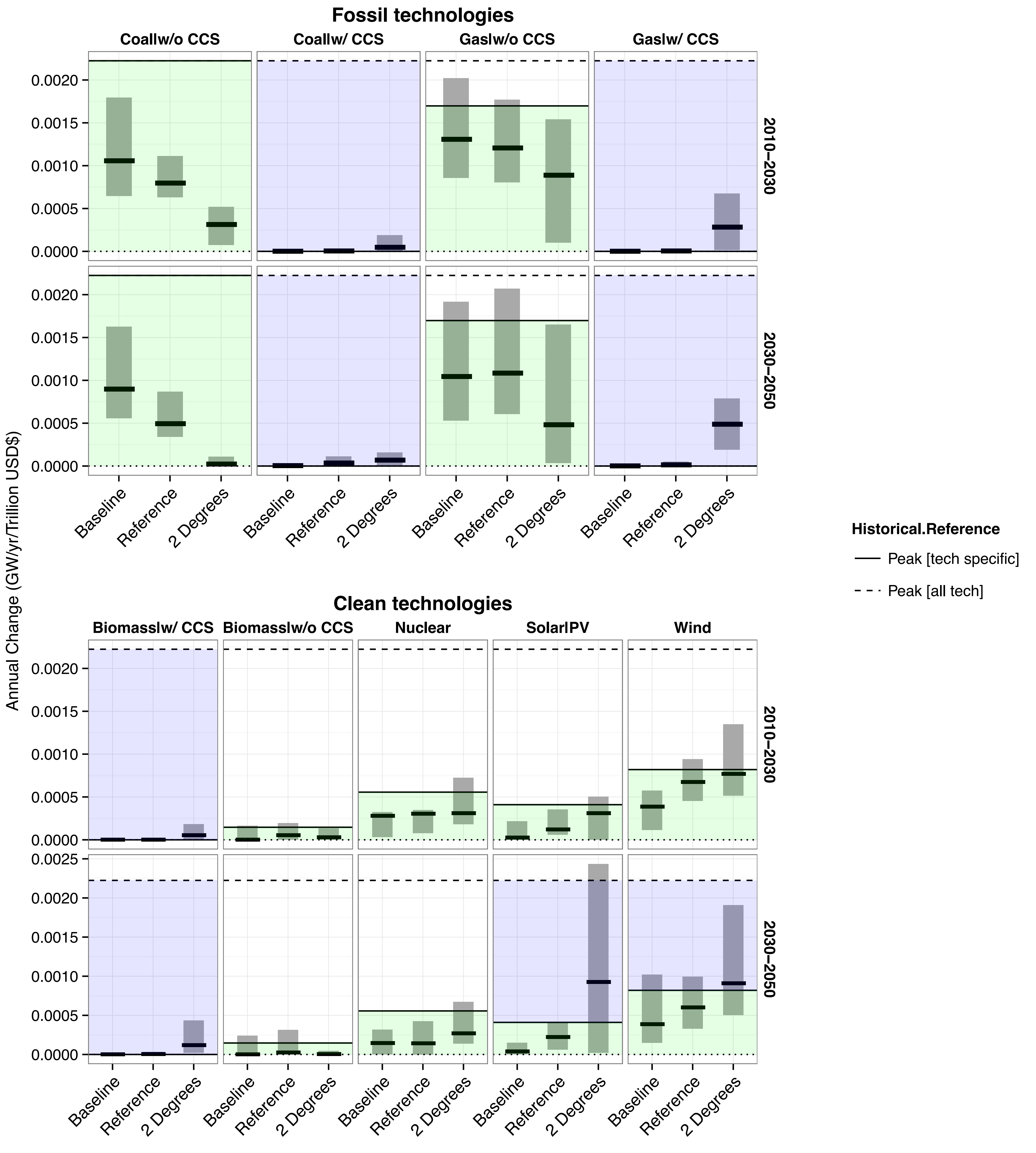
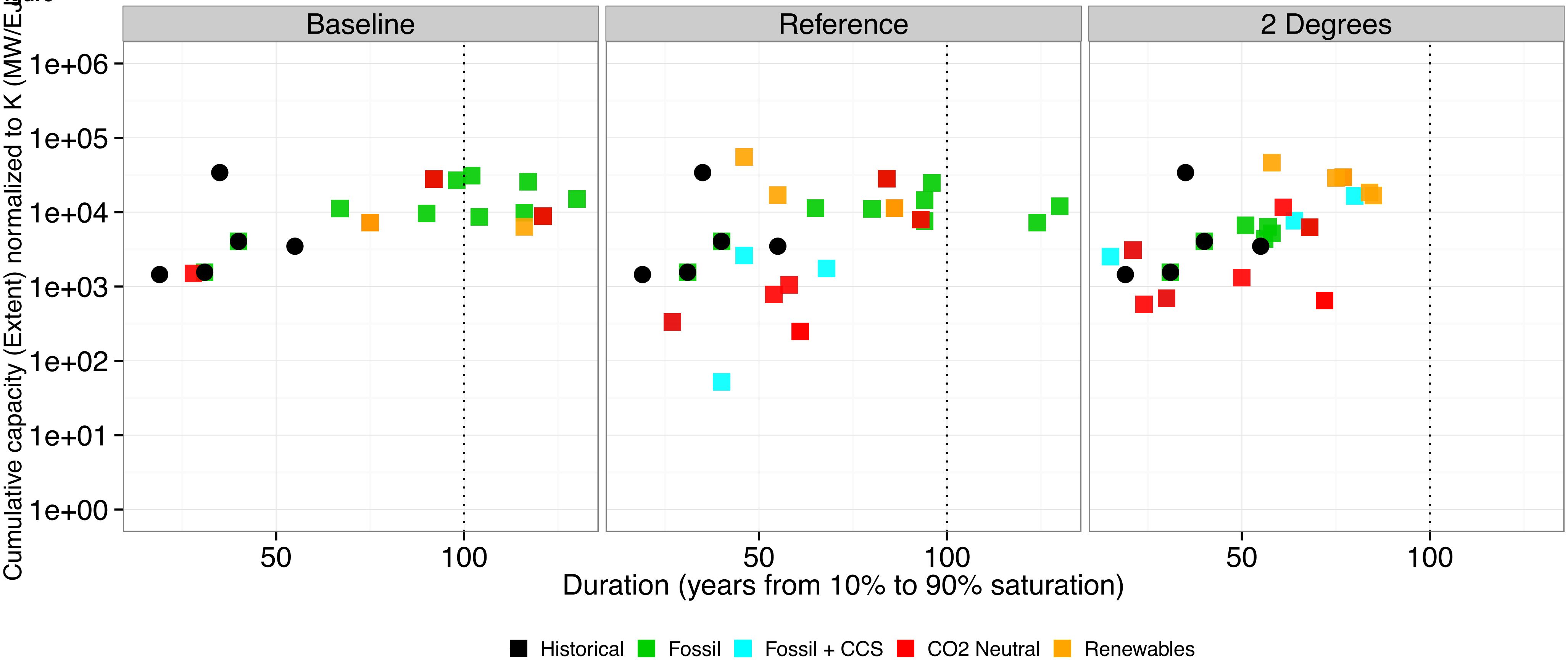


Figure Annual capacity addition growth normalized using GDP

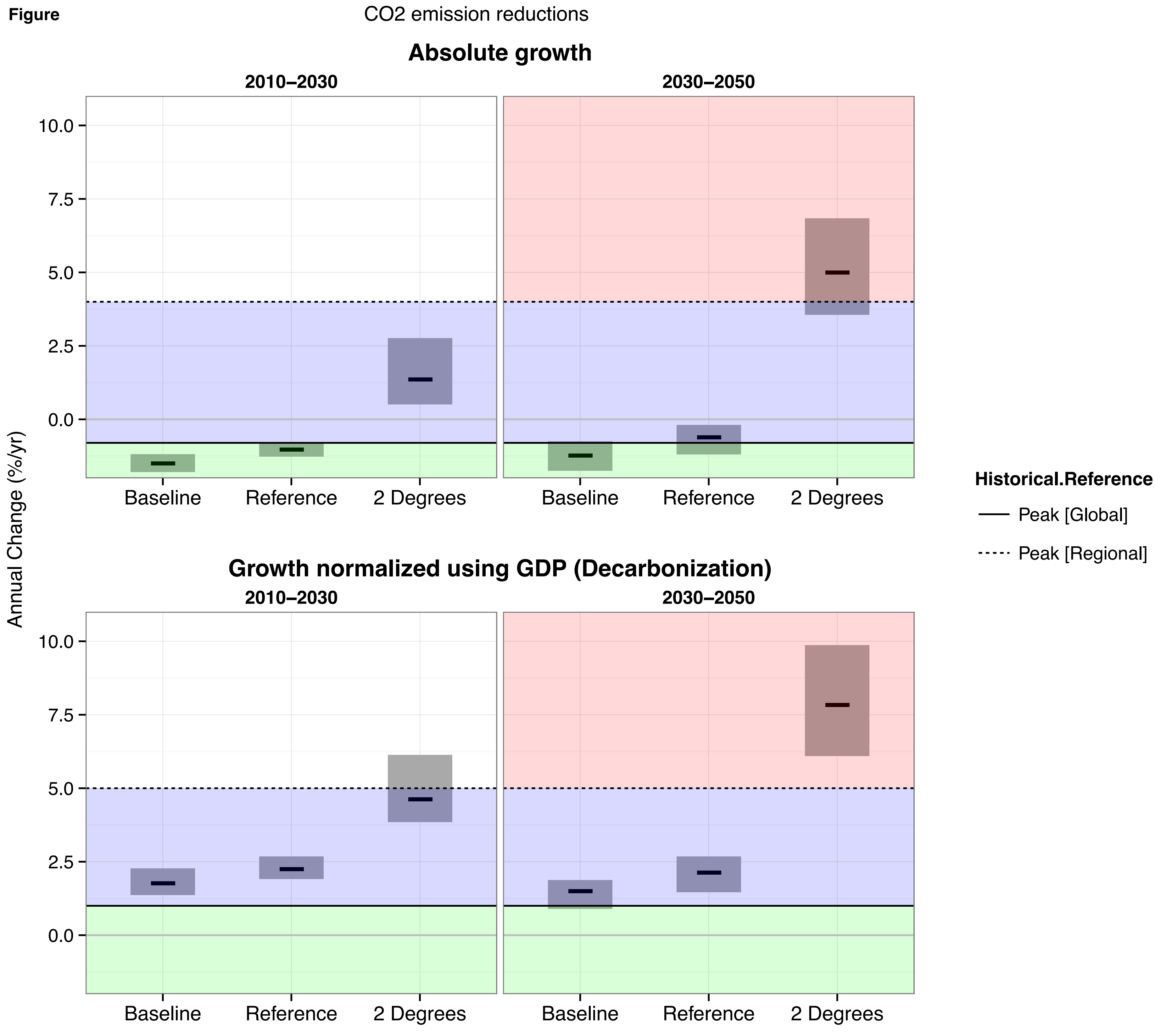


Figure

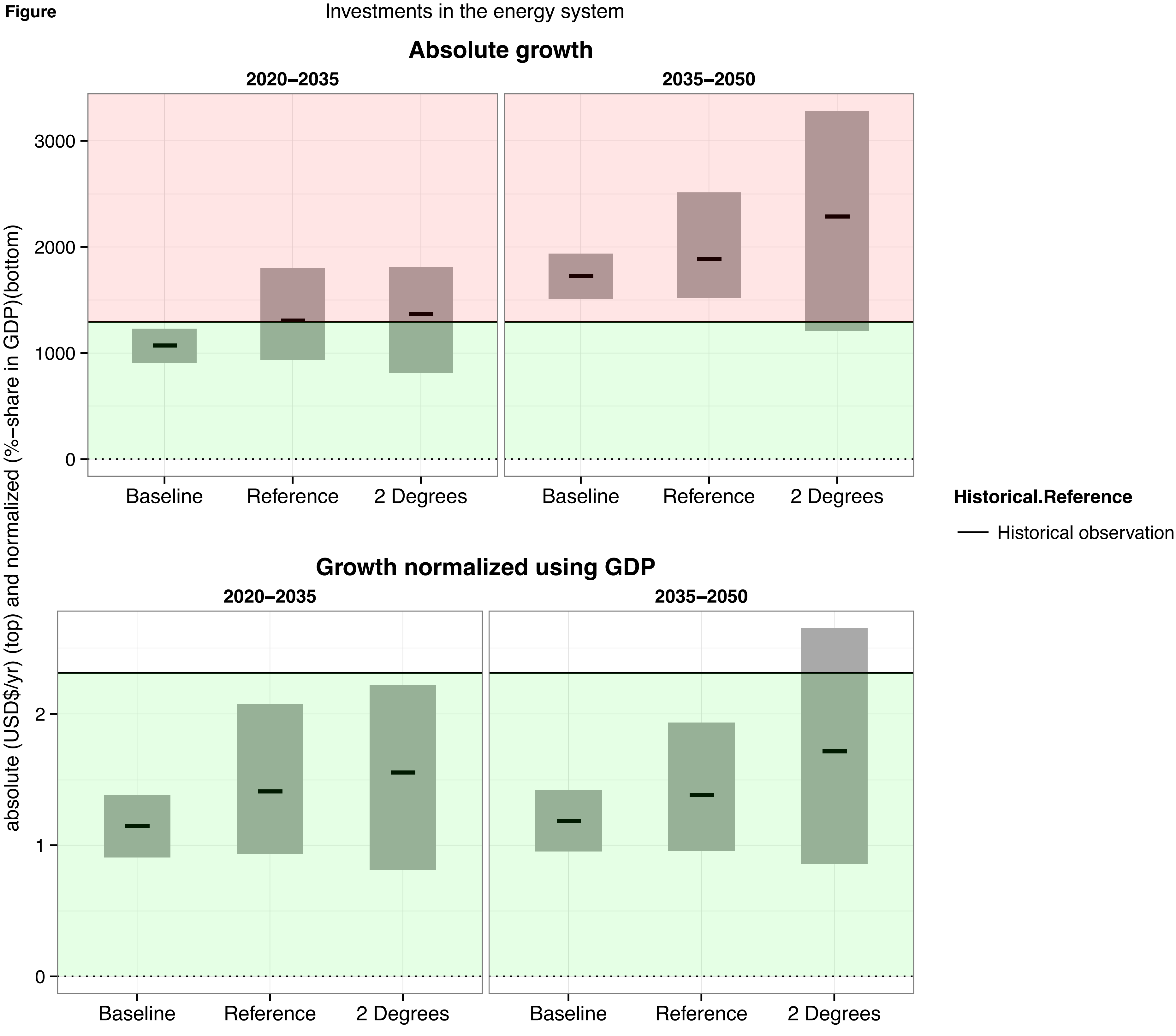


Baseline
Reference
2 Degrees
1e+06
1e+05
1e+04
1e+03
1e+02
1e+01
1e+00
Cumulative capacity (Extent) normalized to K (MW/EJ)
50
100
Duration (years from 10% to 90% saturation)
Historical
Fossil
Fossil + CCS
CO2 Neutral
Renewables

Figure


CO2 emission reductions
Absolute growth
2010–2030
2030–2050
10.0
7.5
5.0
2.5
0.0
Baseline
Reference
2 Degrees
Annual Change (%/yr)
Growth normalized using GDP (Decarbonization)
Historical.Reference
Peak [Global]
Peak [Regional]

Figure



Investments in the energy system
Absolute growth
2020–2035
2035–2050
3000
2000
1000
0
Baseline
Reference
2 Degrees
Baseline
Reference
2 Degrees
Historical.Reference
Historical observation
Growth normalized using GDP
2020–2035
2035–2050
2
1
0
Baseline
Reference
2 Degrees
Baseline
Reference
2 Degrees
absolute (USD$/yr) (top) and normalized (%–share in GDP)(bottom)

Figure Normalization using various system growth metrics