Playing with progress: the implications of a technological slowdown for climate policy

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Abstract

This research investigates the implications of low technological progress for a well-known climate-economy model. This research is valuable as current models that form the basis of climate policies often assume a highly simplistic influence of technology that seems to be too optimistic when looking at recent growth statistics. This research can be divided into three broad parts, the first is an overview of important determinants of technological change, the second an overview of technology in contemporary theory and models and the third presents a number of modelling changes applied to one of these models. I found that while there is ample evidence for a technological slowdown, there is also considerable debate about its severity, causes and duration. In current theory and models, a few distinct approaches were covered but none of these seemed to pay explicit attention to quickly decreasing technological progress. The alternative modelling efforts showed that lower technological progress resulted in faster abatement at higher carbon prices for the first years, but their intensity and duration differed per approach. This indicates the need for stronger environmental policies in the short term in the case of a technological slowdown. An immediate increase in carbon prices of €10 to €20 should be the priority.

Keywords: Technological slowdown, climate-economy models, DICE, abatement, environmental policy.

Preface

I wrote this thesis to fulfil the graduation requirements for the master Management, Economics and Consumer studies. The topic of technological change in models has been an interesting and challenging subject and it has given me a better understanding of the issues around growth statistics and climate models. I want to thank my supervisor dr.ir. R.A. Groeneveld for his continued support, frequent feedback and availability. I would also like to thank the members of my thesis ring. Although I was sceptic at first, I truly think that these weekly meetings were valuable. The opportunity to receive feedback on written pieces by other students and additional clarifications by the acting supervisor helped me improve my writing style. Aside from that, they were a welcome break in the otherwise monotonous days of the COVID-19 pandemic.

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1 Introduction

The world currently faces many great challenges with the most prominent being climate change, environmental pollution, depleting natural resources and a still growing population. The differences in living standards between populations are still large and while we want these differences to disappear, they present a problem. Catching up to first world countries means adopting technologies to raise production. This in turn further strains the carrying capacity of the earth and forces us to a choice. Either continue and see the inevitable end of human growth and welfare or create new technologies that lessen our strain upon resources and environment while still being able to uphold good living standards for all. The well-known book, "The limits to growth", published in 1972, describes this problem and presents rough predictions on what the planetary limits are and when these are expected to be exceeded. It predicted a global collapse around the end of the 21st century (Meadows, Meadows, Randers, & Behrens, 1972). With 30 years of data, Turner (2008) finds that the reality closely matches the standard scenario predicted in the book.

Given this dilemma, it is especially worrying that the rate of technological progress seems to be slowing down. New technology should someday be able to resolve these issues of climate change, pollution and resource depletion. The slower rate of technological change has been under considerable attention already and it seems that the most obvious reason for a decrease in innovation, lower investments and research efforts, is not at the core of this problem. The best example for this must be Moore's law, a law that refers to the observation that the number of transistors in a computer chip doubles every two year. It turns out that this has been possible by greatly increasing the number of researchers and investments over the years (Bloom, Jones, Van Reenen, & Webb, 2020). Bloom et al. (2020) also show that this is only one of the areas in which technological progress is slowing down.

For the actual cause of decreasing technological change, a wide variety of options can be mentioned. One possibility is that we are simply running out of ideas and that it takes increasingly more efforts and knowledge to come up with something new (Bloom et al., 2020). Another is that no general-purpose-technologies or breakthrough technologies have been developed lately (Cowen & Southwood, 2019) while others mention that ICT developments belong to this class but their true value has yet to be discovered (Bersch, Diekhof, Krieger, Licht, & Murmann, 2019). Other possible explanations with seemingly lower impact are the influence of high and low population growth rates (Coccia, 2014) and influences of environmental pollution (Lin, Xiao, & Wang, 2020). Unfortunately, there is no consensus on what the most important cause is, and it seems that a combination of all those factors best resembles reality.

The degree of uncertainty also has a big impact on current economic models. These models cannot ignore the importance of technological change and several different approaches have been constructed to properly incorporate technological change. It can be modelled as exogenous or endogenous with multiple variations in both options (Löschel, 2002). All of these differ in their application and usefulness and some are easier to use than others. As models and simulations form the backbone of important policies, a certain amount of realism and certainty is necessary to provide trustworthy data that can be of actual use.

One of the most well-known models is the Dynamic Integrated Climate-Economy (DICE) model made by William Nordhaus, which sets out the optimal trajectories for emissions, temperature and carbon taxes (Hänsel et al., 2020). This model is relatively straightforward and treats technological change as an exogenous parameter that slightly decreases but never turns negative. The numerous scenarios that have been simulated with DICE cover a number of important situations but seem to ignore the possibility of an actual technological slowdown. For all its prominence in present-day science, little attention seems to have been paid to technological change. In fact, it somewhat contradicts the results from Meadows et al. (1972) as the DICE model does not have an upper limit for growth. Technological change does not seem to be related to the level of capital either, nor does it take the previously mentioned aspects of technological change into account. It is possible that this method no longer properly represents current events anymore and one can wonder what better options are available.

This research aims to investigate the implications of the current technological slowdown for climate policy. I aim to do so by performing an extensive literature review and adapting a well-known climate model to compare results. The following research questions will make up the core of this work.

Main research question
What are the implications of a technological slowdown for the abatement trajectory?

Sub questions
1. How is technological change represented in the DICE model?
2. What alternative methods to model technological change are used in current economic theories and models?
3. How does alternative modelling of technological change influence the abatement trajectory?

This thesis is structured as follows. Chapter 2 covers the methodology used for this research. Chapter 3 covers the most recent research on the topic of the technological slowdown and discusses several important determinants and arguments that make up the core of the debate. Chapter 4 goes over the DICE model, explaining the model background, structure and parameter development. Chapter 5 discusses the more recent approaches to technological change in contemporary theory and models. Chapter 6 then gives an overview of the alternative modelling choices applied to DICE and chapter 7 presents the results from these alternatives. Chapter 8 revisits the scenarios in a sensitivity analysis. Finally, chapter 9 presents the discussion after which chapter 10 presents the conclusion.

2 Methods

2.1 Literature

I performed a systematic literature search to acquire the information required to answer research questions one and two. The primary database was Scopus as it offers a wide range of peer-reviewed articles. Due to the relatively recent developments, not all articles are published yet. I occasionally used other options like google scholar or a regular google search to find these unpublished working or discussion papers. In addition, I scanned the authors' other works and the article references to discover relevant articles that did not show up in the search results.

Keywords are an important topic here as there is no single term for a technological slowdown. Similar terms had to be found to both capture the relevant articles and leave out the others. An example of a Scopus query aimed at finding articles discussing the slowdown of technological progress is the following:
TITLE-ABS-KEY ((innovation OR "technological change" OR "technological progress") AND (slowdown OR "slowing down" OR decreas)).*

Due to the large amount of literature on the topic of technological change, some manual selection was important as not all returned articles are relevant. On the other hand, the number of relevant articles is large and could not be included entirely due to time and size restrictions.

2.2 Modelling

To answer the third research question, I made use of the modelling software GAMS to run and adjust the DICE 2016R model by William Nordhaus (Nordhaus, 2020). I changed the model code to better resemble the slowdown of technological change in the following ways.

First I adjusted the value of Total Factor Productivity (TFP) growth rates to better resemble the latest global data. The growth rates in the model are consistently high and are no longer in line with the most recent economic estimates. I looked at both the most recent estimates and the averages for the past two decades. As the model presents a global aggregate, differentiation between growth rates was not possible. Suitable estimates require information on all countries and not only the most developed countries.

The second adjustment was the implementation of an economic limit. Due to the approach Nordhaus took to modelling technological change, TFP growth is set equal to technological growth. This limit results in an economy that barely increases after a certain point in time. The underlying idea is that technological growth either no longer produces productivity gains and thus does not contribute to TFP or that the advantages of new technology no longer outweigh the costs of development. This requires an adjusted functional form that introduces an exogenously set TFP limit.

Finally, I adjusted the decline rate of growth to simulate the faster decline in technological progress. More elaborate explanations of chosen values and functions can be found in chapter 6 and 8.

2.3 Comparison

The results from the modelling efforts must be compared to the original model results. To do so, I specified a number of variables that are of primary importance. First, the growth path of technological progress and the resulting level of TFP were compared to the baseline. Secondly, I looked at a few different climate parameters that are of importance to climate policy. First of those has to be the development of temperature as it is one of the central predictions of the model. Then, I looked at the trajectory for abatement, carbon price and the emissions control rate. These parameters give insights into the pace of decarbonisation as well as the optimal tax levels at a point in time.

Apart from the environmental variables, economic indicators are valuable as well. Consumption per capita for example, is used to calculate utility and the objective function. The model only provides discounted values for the first year in a period however, requiring a different approach to calculate the discounted values for all other years.

First, I calculate the growth in consumption per capita between one period and the next using the formula $\frac{(new-o\quad)}{old}$, to get the growth percentage pg. I then converted this growth percentage to an annual growth percentage ag as follows:

$$1 + pg = (1 + ag)^n$$

where n is the number of years per period. From this follows that:

$$1 + ag = (1 + pg)^{1/n} => ag = (1 + pg)^{1/n}\text{-}1$$

The model determines the value for the first year in the first period (2015) which is used as the initial value for the calculations. I multiplied this value with the annual growth factor for that period to find the value for the second year. Afterwards, I used the value for the second year multiplied by the growth factor to find the third year and so on. As a period consists of only five years, the theoretical sixth year therefore becomes the first year of the next period. For each period, the growth rate is different so the process must be repeated with its own unique growth factor. I repeated this process for each year until 2100. An example of how this looks in practice can be seen in Table 2.1.

Table 2-1
An example of the calculation of yearly consumption per capita for the first periods.

Growth per period (from 1 to 2, 2 to 3 etc.)	/	0.16	0.16
Annual growth factor: $\sqrt[5]{(1 + growth\ per\ period)}$	/	1.03 (multiplier for P1)	1.03 (multiplier for P2)
Period	1	2	3
Year			
1	10.74	12.49	14.53
2	11.07	12.87	14.95
3	11.41	13.27	15.38
4	11.76	13.68	15.82
5	12.12	14.10	16.27
6	12.49	14.54	16.74

Note: This table is for illustrative purposes and as such, shows only two decimals. The only values that are seen in the model output are the values for year 1 in their period. Years 2-5 do not show up in the output. The value for year 1 of period 1 is determined by the model and cannot be calculated like the other values. The value for a year is calculated by multiplying the value for the previous year with the corresponding multiplier.

Finally, I multiplied these values with their corresponding discount factor and summed the individual results. To find the correct discount factors for each year, I adjusted the model equation that calculated the discount factor for the first year of each period to produce a discount factor for each year. I checked their validity by comparing these values to the values produced by the model and found that these are the same.

3 Determinants of technological change

This chapter presents the most recent evidence of slowing technological change and covers the literature on the determinants of technological change. Paragraphs 3.1 and 3.2 discuss the most important indicators of technology and how these are used to estimate technological and economic growth. Paragraphs 3.3 and 3.4 discuss the most important determinants of slowing technological change and reasons for optimism.

3.1 How we measure technological progress

Productivity growth is highly related to technology and innovation (Brynjolfsson & Yang, 1996; Carlaw & Lipsey, 2003). New technologies make jobs easier and their processes more efficient, leading to a higher output per capita. Technological growth can be a somewhat abstract concept and we have developed several indicators to measure it. A combination of two indicators is often necessary to make the link between the inputs and outputs of the innovation process. To truly grasp how technology is progressing, we need to know how much effort and resources go into producing a unit of output.

The most important indicator for the inputs of the innovation process is the level of R&D spending by companies, countries and research institutes. They give insights in the efforts that have gone into new innovations and technologies. R&D data is not flawless unfortunately, comprehensive overviews are not readily available and often come in aggregate forms, meaning that there is no distinction between technology groups (De Vries & Withagen, 2005).

While the term R&D can encompass many different factors, the majority of the costs will likely be the wages for researchers (OECD, 2015). When talking about the inputs for the innovation process, some researchers therefore choose to calculate the idea output per effective researcher instead of the output per dollar of R&D for example. An effective researcher will be determined by the wage for a high-skilled worker adjusted for inflation (Bloom et al., 2020). This approach also allows for differentiation between researchers based on academic rank for example (Abramo & D'Angelo, 2014).

A widely used indicator for the outputs of the innovation process is the number and quality of patents. The extensive administration of patent data can be used to calculate the number of new ideas, valuable and non-valuable innovations, their country of origin and which sector or industry they affect (Cowen & Southwood, 2019). Although there are problems with the validity of patent data, it remains one of the most widely-used indicators of technological progress. An example of such a problem is that the value of a patent might differ for the patentee and the public as a patent might grant a monopoly position with high profits but no real benefits for the public and technological progress. Over the last few decades, patenting has become increasingly bureaucratic as well, increasing the ability and incentive to patent, leading to high patent numbers with low innovative value (Cowen & Southwood, 2019; De Vries & Withagen, 2005).

The most important indicator for the outputs of the innovation process might be the increase in TFP. TFP is a measure of output growth that is unexplained by increases in capital and labour. TFP is primarily seen as a measure of innovation, as output can only grow with a more effective and efficient production process when capital and labour remain the same (Byrne, Fernald, & Reinsdorf, 2016). Unfortunately, TFP can also pick up impacts of other forces and unjustly classify these as technological progress. Even though TFP sees such wide use, its existence and interpretation are highly debated. For the same concept, there are at least 3 different interpretations of what it actually measures and whether it does so accurately (Carlaw & Lipsey, 2003; Lipsey & Carlaw, 2004).

Lately, other attempts have been made to measure the true progress of technology more accurately. The most prominent of them is the use of book data which shows promising results (Alexopoulos & Cohen, 2019) but is still a long way from becoming a mainstream indicator. First and foremost because this approach will need time to further develop and be adopted by researchers. It will be interesting to see how researchers will adopt these indicators because they present different information. Compared to an indicator as TFP-based research productivity, technology patents and books show vastly different returns. The patent indicator shows a half-life of 114 years instead of 13 years for research productivity and in the case of books, there are no diminishing returns at all (Crafts, 2018). One indicator would make it reasonable to conclude that technological progress is getting harder to achieve while the other concludes that progress is not slowing down at all, or at least to a smaller degree.

3.2 Decreasing research productivity

The combination of effective researchers as an input and the growth in TFP as an output to measure technological progress forms the basis of a very recent article that discusses the notion of a technological slowdown. This paper by Bloom et al. (2020) investigates this notion for a number of research areas. They find convincing evidence that progress is indeed slowing down. They graphed R&D spending, in the form of effective researchers, against research productivity and TFP growth in the US. Figure 3.1 shows the course of TFP growth and research efforts from the 1930s to the 2000s. Figure 3.2 shows the research productivity against research efforts for the same time period.

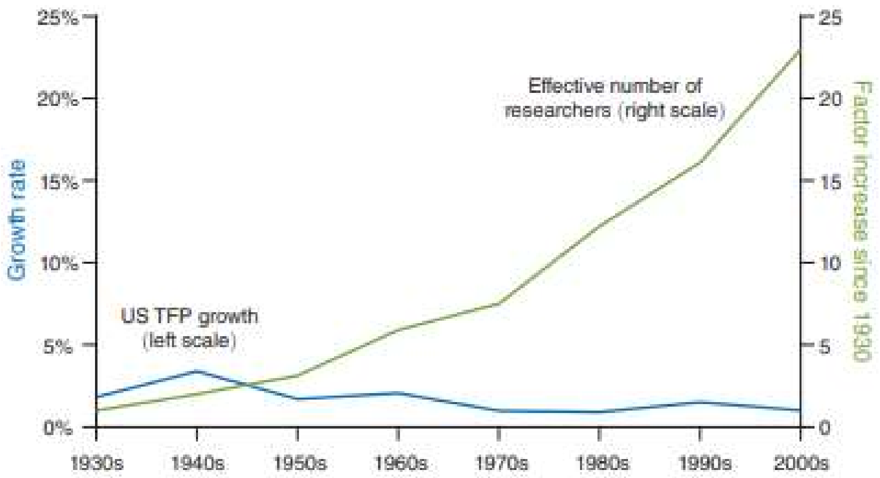

Figure 3-1 Aggregate data on growth and research effort

Notes: The idea output measure is TFP growth by decade. The idea input measure, effective number of researchers, is gross domestic investment in intellectual property products deflated by a measure of the nominal wage for high-skilled workers. Adapted from *Are ideas getting harder to find?,* by Bloom, N., Jones, C,I., Van Reenen, J., & Webb, M. (2020). *American Economic Review, 110(4),* p.1111.

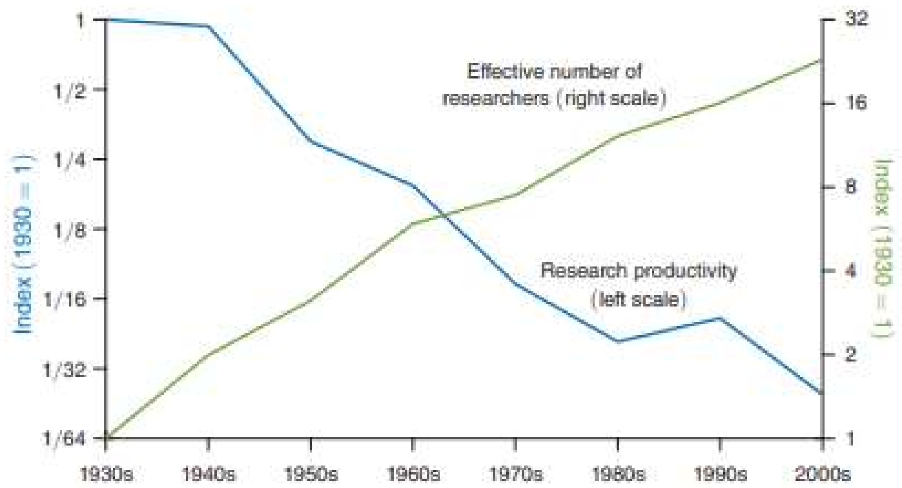

Figure 3-2 Aggregate evidence on research productivity

Notes: Research productivity is the ratio of idea output, measured as TFP growth, to the effective number of researchers. Both research productivity and research effort are normalized to the value of 1 in the 1930s. Adapted from *Are ideas getting harder to find?,* by Bloom, N., Jones, C,I., Van Reenen, J., & Webb, M. (2020). *American Economic Review, 110(4),* p.1111.

Perhaps the most showing example of the increasing difficulty of innovation is Moore's law. This law states that the number of transistors on an integrated circuit doubles roughly every 2 years which implies an exponential growth rate of 35% per year. Bloom et al. (2020) found that these developments have only been made possible by a large increase in research efforts which have increased by a factor of 18 since 1971. This increase in research efforts indicates a decrease in research productivity of 6.8% per year (Bloom et al., 2020).

Bloom et al. (2020) find similar patterns in other sectors. Research productivity in US agriculture shows an annual decline rate of 3.7% in the period 1970-2008. US medical research produces similar numbers, general cancer research productivity declines with 5.1% and breast cancer research with 10.1% annually, both for the period 1975-2006. Research productivity in the research on heart diseases declines with 7.2% annually for the period 1986-2011 (Bloom et al., 2020).

3.3 Explanations for a technological slowdown

A process as complicated as technological change can be affected by many different determinants. The following 7 paragraphs each cover a determinant that is mentioned as an important influence or possible cause of decreasing technological change. These determinants are (1) a limited amount of ideas; (2) a rapidly expanding knowledge frontier; (3) technological heterogeneity; (4) population growth; (5) adoption issues; (6) pollution; (7) policy.

3.3.1 A limited amount of ideas

The first possible explanation is also subject to considerable debate which receives further attention in chapter 3.4. It states that there might be a fixed stock of ideas from which we can develop new technologies and that we have taken out the easiest. This would leave the technologies that are harder to develop and require far more knowledge and resources than previous innovations, thus slowing down the rate of technological progress (Bersch et al., 2019; Nordhaus, 2002). This particular statement is also referred to as the low-hanging fruit hypothesis and is a core argument for the literature on the topic (Cowen, 2011).

3.3.2 Knowledge frontier

A second reason is that the knowledge frontier has increased over the years. Through the accumulation of knowledge and development of new technologies, the knowledge frontier has shifted noticeably. New researchers spend more time and effort on reaching the knowledge stock needed to further enhance existing technologies or come up with something new entirely. Not only does it take longer to reach the required level of knowledge, researchers are also increasingly occupied with preparing the new generation of researchers, further limiting their time to make new discoveries (Cowen & Southwood, 2019; Jones, 2009).

A related point is that team size has increased over time, requiring a larger number of researchers to develop a single innovation. Team size increases even further in research areas where the level of knowledge is already very high (Jones, 2009). This is not surprising if we consider that each individual needs to specialize further than ever before to reach the required knowledge on a single topic of research. A new technology often consists of numerous parts which now each require their own specialist to be developed.

3.3.3 Technological heterogeneity

The third possible explanation is the difference in circumstances between research areas which can affect growth rates (Castellacci, 2007; Klevorick, Levin, Nelson, & Winter, 1995). Not every industry or research area faces the same technological opportunities and economic situations. The same amount of money invested in one area may result in more or less innovation in another area (Castellacci, 2007). This on itself does not explain how technological progress might have slowed down as these differences have always been there and will continue to exist. It might be that investments have shifted to areas that have a low level of technological opportunities.

The area of energy technology presents a good example for this argument. Even though the development of energy technology is vital for solving the issues mentioned in the introduction, the rate of energy technological change develops at a far slower pace than IT-technologies. This is partly caused by the homogenous nature of the end products from the energy sector. As energy as an end product is largely the same, there is less interest in new technologies that produce the same end products in a different way. The sector cannot meet the love for variety among households as ITs do with their large number of different apps and programmes (Jin & Zhang, 2017). Another important point is that energy sectors use heavy-asset technologies. Investments are high for these technologies as they require large amounts of expensive and large machinery and are often bound to a specific geographical area. This further limits the ease with which they can be transported and used, contrary to ITs that are far less dependent on area and capital (Jin & Zhang, 2017).

3.3.4 Population and technology

The relation between population size, population growth and innovation has been a much-discussed topic (Bucci, 2008; Coccia, 2014). One often-used explanation for the relation between population and technology is that a larger population means more researchers and geniuses, thus leading to higher technological change (Kremer, 1993). A larger population also creates new problems like pollution, food availability and others that push the need for innovation even further (Meadows, Randers, & Meadows, 2004). Recent research revisits the relation between population and technology. Instead of focusing on population levels, Coccia (2014) investigates the optimal population growth rates for a steady technological growth rate. Coccia looks at this issue for the OECD countries and finds that an annual population growth rate between 0.21-0.75% is optimal for technological change. When growth rates are outside of this interval, innovation output may start declining (Coccia, 2014). With the use of population projections from the United Nations (United

Nations Department of Economic and Social Affairs Population Division, 2019), I calculated the annual growth rates for the OECD countries and plotted their course as can be seen in figure 3.3. We currently find the OECD growth rates hanging around 0.4% per annum but according to the population projections, we might reach an annual population growth of 0.21% around 2035 which rapidly declines afterward (United Nations Department of Economic and Social Affairs Population Division, 2019).

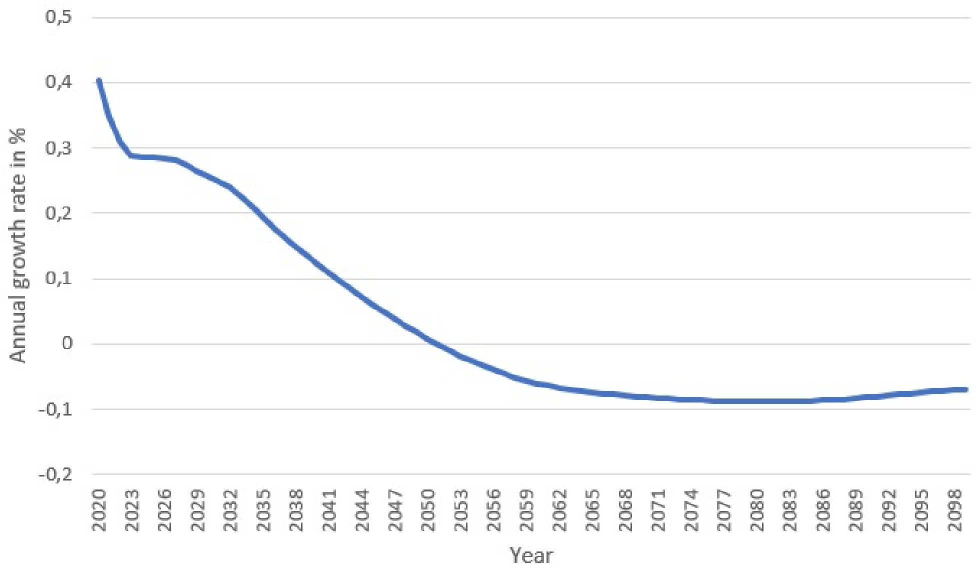

Figure 3-3 Annual OECD population growth rates
Note: Growth percentages are based on the sum of annual population predictions of the OECD countries by the Population Division of the United Nations Department of Economics and Social Affairs (2019).

3.3.5 Adoption issues

The adoption of new technologies can be hindered by the spread of said technology across companies and industries. New users have to be convinced of their reliability and added value which is not always easy. Haapala (2013) investigates the adoption of precision farming and found several problems that slowed down the spread of technology which can likely be generalized to other areas of technology. Users are usually not included in the design process of a new technology and developers have little knowledge of what the end-users want. In addition, those that market the product do not have enough knowledge to explain the benefits and are not included in the development process either (Haapala, 2013).

To follow up on this, diffusion simply takes time. Even if users decide to adopt a new technology, they will need time to get used to it and make the necessary investments to make use of their full potential. New technologies are often expensive in their early stages and it takes time and sufficient demand to change this (Goldin, Koutroumpis, Lafond, & Winkler, 2020). In contrast, adoption rates have been decreasing for some types of technology. The internet had a mean adoption lag of 6 years compared to previous developments like the telegraph with a lag of 46 years (Cowen & Southwood, 2019). Comin and Hobijn (2010) develop a new framework for the diffusion of technology. They find that adoption lags are large, vary a lot and that they have been decreasing for the past two centuries. Their results closely match empirical data and are able to partly explain the breakthroughs of the Asian tigers (Comin & Hobijn, 2010).

On the contrary, some discuss the possibility that diffusion has actually slowed down (Criscuolo, Andrews, & Gal, 2016; ECB Economic Bulletin, 2017). The main reason put forward by Criscuolo, Andrews & Gal (2016) is that new technologies are more complex and need complementary investments in infrastructure and other technologies to reach their true value. Case in point, there is little benefit to placing solar panels on each house when the energy grid cannot handle the supply. The European Central Banks also mentions lower investments in intangibles by laggard firms and a decrease in business dynamism (ECB Economic Bulletin, 2017).

3.3.6 Pollution

Increased pollution has clear negative effects on human welfare and society which in turn might affect our ability to innovate. Higher pollution appears to be one of the determinants that can work two ways. One the one hand, higher pollution can lead to increased innovation. Evidence from China suggests that higher carbon emissions create new opportunities for innovators and simultaneously have a positive effect on environmental regulation, making it either more stringent or more favourable to those who want to change (Wang et al., 2020). At the same time, other Chinese researchers find that air pollution in the form of sulphur dioxide, smoke, dust and industrial waste emissions have a negative effect on innovation as they crowd out innovation funds (Lin et al., 2020). Whether pollution also leads to researchers moving away from the polluted area is still up for debate as they found no significant evidence for this statement.

This provides an interesting parallel with the Porter hypothesis which states that strict regulation might benefit innovation and the economy by adopting different approaches. This hypothesis suggests that the benefits from reduced pollution could exceed the costs of compliance and innovation (Wagner, 2003). Van Leeuwen and Mohnen (2017) tested for the presence of both the weak and strong version of this hypothesis in a Dutch case. They find strong evidence for the presence of the weak version which suggests that environmental regulation positively affects eco-innovation. They also find weaker evidence for the strong version which states that environmental regulation boosts TFP. Only under specific circumstances is there a strong relation between regulation and TFP growth (Van Leeuwen & Mohnen, 2017). This might explain some of the apparent decrease in technological progress. Since the conditions for the strong Porter hypothesis are often not present, actual technological progress still happens but does not show up in TFP statistics. We then incorrectly conclude that innovation did not take place.

3.3.7 Policy

Finally, I discuss the importance of policy for the development of technology. Policy has numerable forms and can make or break the development of a particular sector or process. The different forms of policy have different effects on investment decisions and its suitability depends on several factors, the political and economic situation in a country being the most important of which.

Policy can be divided into two main categories being command-and-control and market-based (Jaffe, Newell, & Stavins, 2002; Perman, Ma, McGilvray, & Common, 2011, p. 182). Command-and-control in the field of technology is often shaped as performance or technology standards. While this approach would theoretically be suited to achieving the set requirements, it often fails in reality and produces some negative effects. First of all, standards must be unambitious as the majority of companies will not be able to achieve stricter measures. Secondly, it forces companies to adopt technology that they might not use otherwise. Some have to adopt technology that does not fit the business while others might downgrade in the presence of lax requirements. Finally, it hinders the development of technology that could have larger positive effects. The incentive to innovate is taken away from companies as their only requirement is complying with regulations (Jaffe et al., 2002).

Market-based instruments achieve their goal by presenting financial incentives to companies. This usually takes the form of either a subsidy or a tax. The subsidy creates a financial incentive to undertake innovation efforts that a firm normally would not be able to. The money supplied to the firm is used to adopt a new technology or to directly develop new technology. Taxes on the other hand make production less profitable by charging a firm for their produced pollutants. Contrary to the subsidy, the tax will most likely push firms to produce less instead of adopting or developing cleaner and more modern technology (Jaffe et al., 2002).

Greaker, Heggedal and Rosendahl (2018) discuss the impact of market-based instruments on the development of clean technologies. They mention that both the growth rates and spill-overs coming from investments in clean technology are larger than those in dirty technology. Their own model indicates that a subsidy might outperform and potentially replace a tax policy when the elasticity of substitution between clean and dirty inputs is relatively high. They also discuss the situations where the government should actively direct R&D towards clean technology (Greaker, Heggedal, & Rosendahl, 2018).

These instruments are mainly used in domestic policy but can also be used in certain international covenants. The fact that trade is often international increases the influence of foreign policies on domestic production decisions. Leading countries in environmental policy stringency may benefit by attracting foreign innovators which increase the innovativeness of home clean-tech industries by incorporating a larger variety of innovations from home and foreign markets (Herman & Xiang, 2019). Policy can also have a big impact on production decisions of international firms that deal with multiple production facilities and markets in different countries. Stringent policies in a firm's main market might influence the choice in production technology for other markets as well.

Finally, as was already mentioned in 3.3.6, policy can also influence the direction of technological progress. Creating incentives to improve certain desired technologies can have large environmental effects. Acemoglu, Aghion, Bursztyn and Hemous (2012) even argue that policy is only needed for a limited period of time. When clean technologies have caught up to dirty technologies, intervention is not as necessary anymore as further innovation will focus on the field that is most developed. Their analysis also implies that policy should always combine both taxes and subsidies but it must do so in a proportion that relies less heavily on taxes (Acemoglu, Aghion, Bursztyn, & Hemous, 2012).

3.4 The technological slowdown might not be so severe

While a large amount of evidence presents itself in favour of the techno-pessimists, some non-negligible evidence is presented by their more positive colleagues. The three arguments that form the core of their reasoning are (1) increasing measurement problems; (2) untapped potential of ICT; (3) human ingenuity knows no bounds.

3.4.1 Measurement problems

The link between economic growth and technology is mainly captured by the TFP indicator. Unfortunately, this concept suffers from a number of issues including measurement issues. The mismeasurement of technological progress can be roughly divided into three arguments being (1) uncaptured value from ICTs; (2) varying rates of technological diffusion; (3) increased R&D spending by entrepreneurs.

The first issue relates to uncaptured value of ICTs. Mismeasurement has been an issue for quite some time already but the emergence, development and spread of ICTs has added to the problem (Grillo & Nanetti, 2020). This class of technologies has made products easier to produce and increased the quality of many. The prices of these products have remained largely the same though, which results in lower productivity growth as the actual value of these products is not properly adjusted (Bersch et al., 2019). The large number of services provided by the internet is also difficult to fully capture and value.

Secondly, lags between the creation and adoption of new technologies can influence measurements. As there is no consensus on whether diffusion has slowed down or sped up, it would be best to assume that it can take a variable and undeterminable amount of time for a technology to reach the masses and have an impact on productivity. Productivity growth rates therefore still measure technological progress but might do so for the technology developed years ago instead of current technological developments (Cowen & Southwood, 2019).

Finally, an increasing number of scientific advances do not come from what we call a researcher, but rather by large tech-entrepreneurs. This means that part of the perceived slowdown is attributed to researchers alone while it should have been divided among both academic research and non-academic research. In addition, as was discussed in chapter 3, many of these researcher no longer devote all of their time to research as they perform a number of other tasks or functions on modern-day universities (Cowen & Southwood, 2019).

These three issues distort our view on technological progress but not necessarily in a bad way. Inability to capture the gains from ICTs for example, means that the actual progress is larger than presented in the statistics. The same goes for the increased spending by entrepreneurs as the decreased research productivity is unfairly attributed to only a small part of the total researchers.

3.4.2 ICTs need more time

It is no secret that the digitalization of the economy as a result of ICTs has had a major impact on everyday life and productivity, especially in the early years of its development. Their development has seemingly slowed down after the financial crisis as productivity numbers show lower growth rates. While this can partly be explained by the previously mentioned measurement problems that plague productivity statistics, it is likely not the whole reason. According to some, the development of ICT has not yet reached its full potential (Bartelsman, 2013; Bersch et al., 2019; Brynjolfsson & McAfee, 2014; Goldin et al., 2020; Grillo & Nanetti, 2020). It is estimated that another 20 or so years will be needed for these technologies to fully develop. This is partly caused by the idea that ICT will have to be accepted and properly used by other industries and combined with other technologies to reach their full potential (Bersch et al., 2019; Goldin et al., 2020). When successful, they should be able to give a tremendous boost to productivity and further technological innovation (Crafts, 2017).

Alexopoulos and Cohen (2019) think that technological change has already begun increasing. They develop a new measure of technology not based on patent data but on book data. They derive a new indicator of technological change based on the sales of books across multiple topics, assuming that larger sales indicate more knowledge and interest in using and developing a technology. They conclude that expected productivity boost as a result of improvements in the fields of AI, robotics and cloud computing might already have started (Alexopoulos & Cohen, 2019).

The positive attitude towards the possibilities of ICT often obscures the accompanying problems. One of these issues is privacy and data safety. While larger amounts of data can probably produce larger benefits, there is a limit to how much we want to share. This could mean that the ICTs do not perform at the best of their ability as they are limited by data restraints. In addition to this comes the issue of data safety. Protecting gathered data from outside parties is becoming more important and difficult. Data theft can have substantial consequences for the parties involved and in severe cases might even influence the development of new technology. When the parties involved are countries, data theft might put significant pressure on international relations.

Even though there are still a few problems that might dampen the impact of technological development in the fields of robotics, ICTs and AI, the prospects are still very positive. So much so that the benefits in labour productivity and TFP might be substantial. Bartelsman (2013) estimates labour productivity growth in Europe of 2.5% for a period of 20-30 years, while Brynjolfsson and McAfee estimate TFP growth percentages of at least 2% (Bartelsman, 2013; Brynjolfsson & McAfee, 2014).

3.4.3 Human ingenuity knows no bounds

While some emphasize the slower pace of innovation due to a lack of new ideas or a limit on ideas, others note that this might just be a temporary state based on outdated indicators (Pyka, Bogner, & Urmetzer, 2019). Pyka et al. (2019) cover a number of considerations that speak in favour of a more optimistic viewpoint.

First of all, a breakthrough technology is never really expected and is often an impossibility until it has been made possible. It can build upon other ideas and technologies or arise out of seemingly nowhere and the paradigm shift resulting from such developments may become the foundation for new ideas. Just because we have not seen a breakthrough like the combustion engine these last years does not mean that we will never see one again.

A second important point is the Mass University Effect which refers to the change from education for the elite to education for the masses. With education becoming more widespread than ever and the quality improving thanks to our growing stock of knowledge, the amount of educated people keeps rising and with it the opportunities for new ideas do too.

Finally, we must realise that ideas are non-rival (Romer, 1990). Once a design or idea is created, it can be used as often as required and the use by one does not limit the availability for another. One implication of this is that knowledge created in the development of a certain product can then also be used to develop and create other products.

3.5 Concluding remarks

The overview above presented a few the most important determinants of technological change. Some, like depleting ideas and increased knowledge requirements, present relatively pessimistic prospects in the case that they are true while others like pollution and policy might have positive influences. While there is certainly some reason for pessimism, there might also be a valid reason for optimism. Measurement problems understate the value and growth rate of new ICTs and the unpredictable nature of innovation can present new breakthroughs at unexpected times. Finally, some economists think that ICTs have yet to reach their full potential and predict a new breakthrough in the coming decades that could give a tremendous boost to TFP.

4 Technological change in DICE

DICE belongs to the class of models we call 'integrated assessment models' or IAMs, which aim to connect the most important characteristics of society, economy, biosphere and atmosphere. The model follows the view of neoclassical economic growth theory where economies make investments in capital, education and technologies, thereby reducing consumption today, in order to increase consumption in the future (Nordhaus & Sztorc, 2013). DICE belongs to the type of IAMs that optimize an objective or welfare function. This makes it suited to evaluate and compare different policies within the model. The model follows a global-aggregate approach meaning that there are no different regions incorporated in the model.

I will describe three distinct parts of the DICE model that are most important for understanding technology in the model. The first is the objective function. The second describes the equations for general technology. The third part covers the environmental aspect of technological change, explaining how this technology differs from the general technology and how it influences the rest of the model.

This chapter will not discuss the equations for the climate and carbon cycle. While important to the model, it does not directly mention any of the technological determinants and understanding its working is not necessary for this research.

The model is completely free and a full description of the DICE model in both text and GAMS code as well as an overview of model changes over time can be found online (Nordhaus, 2018; Nordhaus, 2020; Nordhaus & Sztorc, 2013; Nordhaus, 1992).

4.1 Objective function

The model aims to maximize the utility function which represents the discounted sum of population-weighted utility of per capita consumption.

$$\max \left\{ \tau * \sigma_1 * (\sum_t V_t) + \sigma_2 \right\} \tag{1}$$

Where τ is the number of years per period, σ_1 a multiplicative scaling coefficient and σ_2 an additive scaling coefficient. V_t is the total utility in period t, with t being a time index starting at 1.

Period utility V_t depends on the per-capita utility, labour force and the average utility social discount rate.

$$V_t = U_t * L_t * \rho_t \tag{2}$$

Where U_t is the per capita utility, L_t the labour force and ρ_t the average utility social discount rate. Per capital utility depends on labour force and consumption

$$U_t = ((C_t * \frac{1000}{L_t})^{(1-\gamma)} - 1)/(1-\gamma) - 1 \tag{3}$$

Where C_t is consumption and γ the elasticity of marginal utility of consumption.

4.2 General technology

This part discusses the development of general technology. In DICE, this means the technology that raises the general level of productivity and which is not related to the environment and more specifically, the environmental technology that decreases CO2.

DICE assumes that the growth rate of productivity is the same as technological progress. In this model this means that growth in TFP is synonymous to technological progress. It is defined by the following set of parameters and equations. The growth rate of the technology is defined as G_t, with an initial growth rate of 0.076 (7.6%) per 5 years. The decline rate of technological growth is defined as θ, with a decline of 0.005 (0.5%) per 5 years. t represents the time period, the model assumes 100 periods starting in 2015 where each period represents 5 years. Only the first 18 periods (2015-2100) will be discussed though. The G_t parameter function is:

$$G_t = G_0 * e^{-\theta*5*(t-1)} \tag{4}$$

The development of this parameter can be seen in Figure 4.1. It shows a gradual decline, but it still has a growth of 5% at the end of 2100.

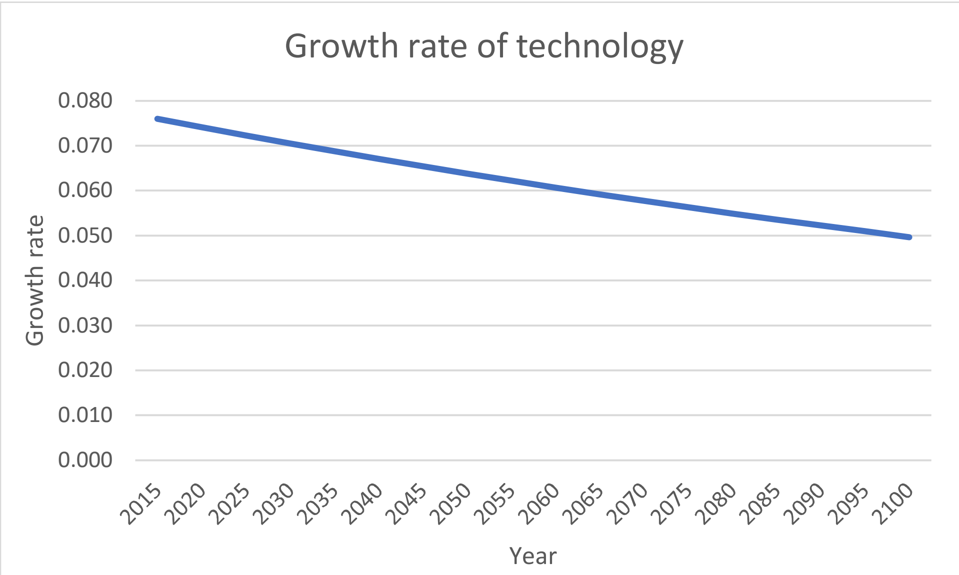

Figure 4.1 Development of Technological Growth Rate
Note: The graph shows the development of technological growth G_t, or more accurate, the growth rate of total factor productivity.

The level of total factor productivity is defined as A with the following parameter function:

$$A_{+1} = A_t/(1 - G_t) \tag{5}$$

A_t is then added to the equation for the gross world product gross of abatement and damages or Y_t. This function is a standard Cobb-Douglas production function and is determined as follows:

$$Y_t = A_t * (\frac{L_t}{1000})^{(1-\beta)} * K_t{}^{\beta} \tag{6}$$

Where K_t is the level of capital and β is the capital elasticity valued at 0.3

Output net of damages N_t is then calculated as follows:

$$N_t = Y_t * (1 - \epsilon_t) \tag{7}$$

Where ϵ_t is the damages as a fraction of gross output. Y_t forms the basis of several other economic variables among which consumption, investments, capital and the interest rate.

4.3 Environmental technology

DICE has a clear division between an economic module and an environmental module. Both modules influence each other directly. For example, Y_t is directly mentioned in the climate part in the equations for industrial emissions, damages and the cost of emissions reductions. The development of the general technology explained in the first part thus has an indirect influence on the climate part as well. I will leave this influence for what it is now and focus on the technological development that directly influences the climate part of the model.

In this part, the development of technology is exogenously determined as well, and it follows the following intuition. A backstop technology forms the basis of technological development. A backstop technology is often defined as an energy source that is already known but not yet commercial. They often represent the substitution of dirty energy for clean energy where the backstop technology might be capable of providing infinite amounts of a clean energy (Nordhaus & Sztorc, 2013). This concept will receive a more elaborate explanation in the next chapter. Given that it is not yet commercial, this must mean that the price of this technology is too high to be used in production. Technological progress can then be simulated by reducing the price of this technology per period of time. We learn and become able to produce and use this technology at lower prices. The model presents this approach as follows. DICE defines the backstop technology as a technology that can replace all fossil fuels. In the full model, it replaces 100% of CO2 emissions at a decreasing price per ton CO2.

First, the model determines how S_t changes, which is defined as the CO2-equivalent-emissions output ratio. In simpler terms, this means the amount of energy needed for a unit of production, also known as energy efficiency. The change in S_t is defined as i which is the cumulative improvement in energy efficiency or simply the decline rate of energy efficiency improvements. This approach is comparable to the Autonomous Energy Efficiency Improvement (AEEI) parameter, which gets more attention in the next chapter. It is exogenously determined and declines over time to simulate technical progress that reduces the need for energy per unit of output. The main result is a decrease in damages as most energy comes from fossil fuel sources. As for the actual source of this progress, it could be a result of a general improvement in technology, an improving backstop technology or a substitution to other fuels.

$$i_{t+1} = i_t * (1 + d)^{\tau} \tag{8}$$

Where d is the decline rate of decarbonization per period valued at -0.001 and τ the number of years per period which is 5. Its development can be seen in Figure 4.2. We see that i_t increases.

which is expected as improving technology and decreasing energy intensity reduces the possibility for further improvement.

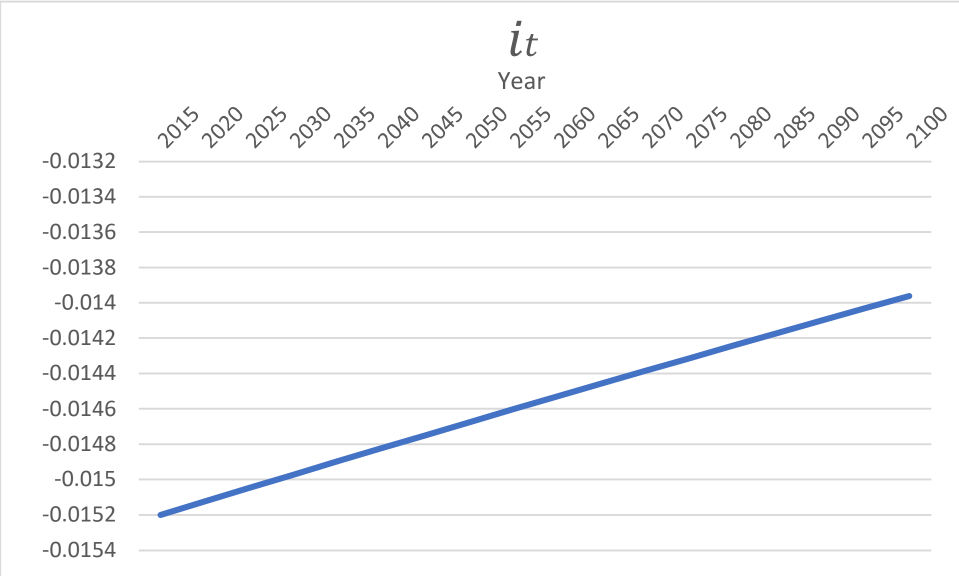

Figure 4.2 The development of the decline rate of energy efficiency

Next, we are able to define $sigma$ whose development is shown in Figure 4.3.

$$S_{t+1} = (S_t * e^{i_t * \tau}) \tag{9}$$

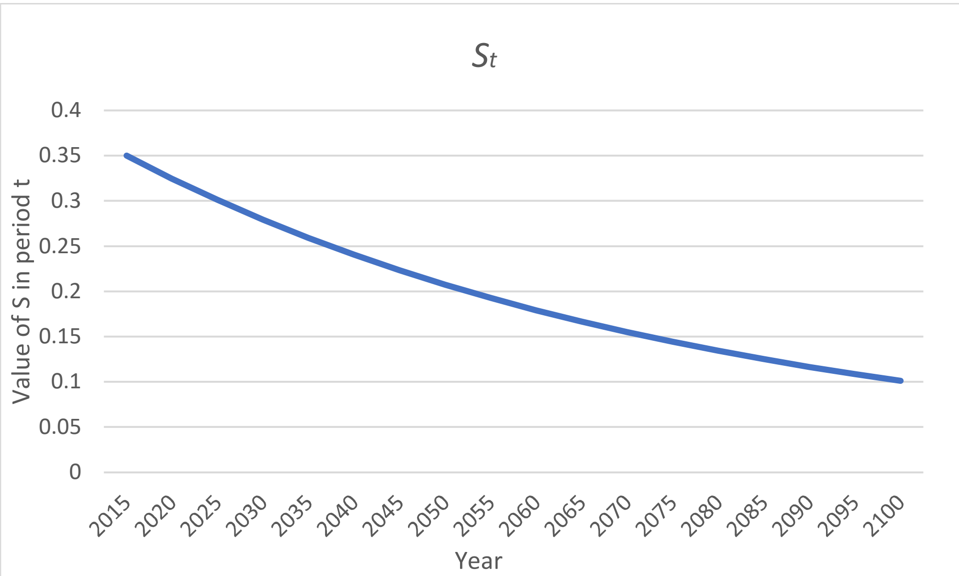

Figure 4.3 Development of the CO2-equivalent-emissioins output rate S_t over time

The parameter P_t indicates the price of the backstop technology in a certain period. η represents the initial price of the backstop. The parameter o valued at 0.025, then lowers the price of the backstop technology as follows.

$$P_t = \eta * (1 - o)^{(t-1)} \tag{10}$$

A lower backstop price indicates that technology has improved, as it becomes cheaper to use this technology to reduce emissions. Its development can be seen in Figure 4.4. The costs of this backstop technology gradually decrease from \$550 in 2015 to \$357 per ton CO2 in 2100.

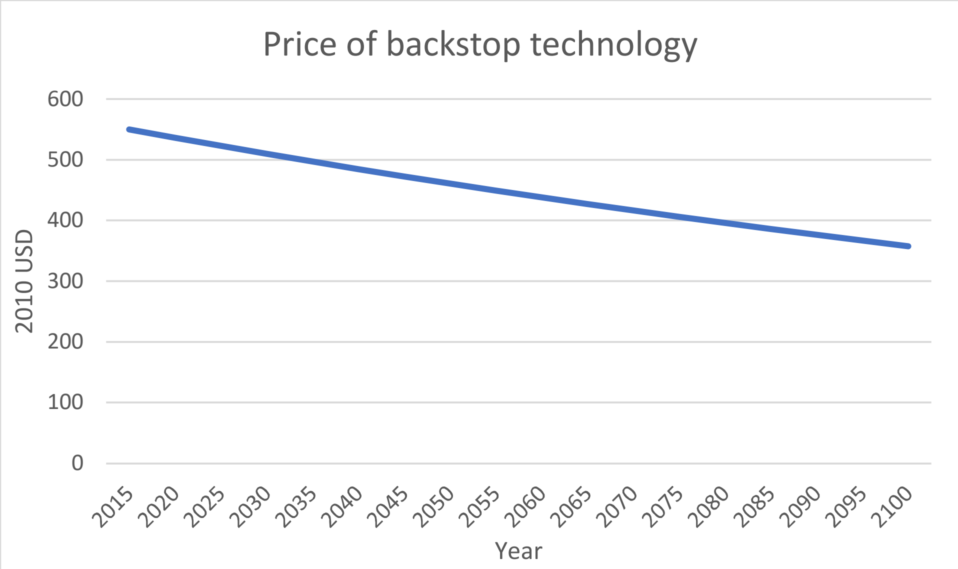

Figure 4.4 The costs of completely removing a ton of CO2 in 2010 USD over time

Afterwards, the new value of P_t is incorporated in the carbon price equation and the adjusted cost of backstop technology, λ_t, which is defined as follows.

$$\lambda_t = P_t * S_t / x / 1000 \tag{11}$$

where x is the exponent of the control cost function which is valued at 2.6. λ_t then influences the amount of abatement.

4.4 Comparing TFP in DICE to reality

This section will compare the TFP growth as represented in DICE to recent growth statistics. Equation 5 in chapter 4.2 defined the TFP level whose development can be seen in figure 4.5.

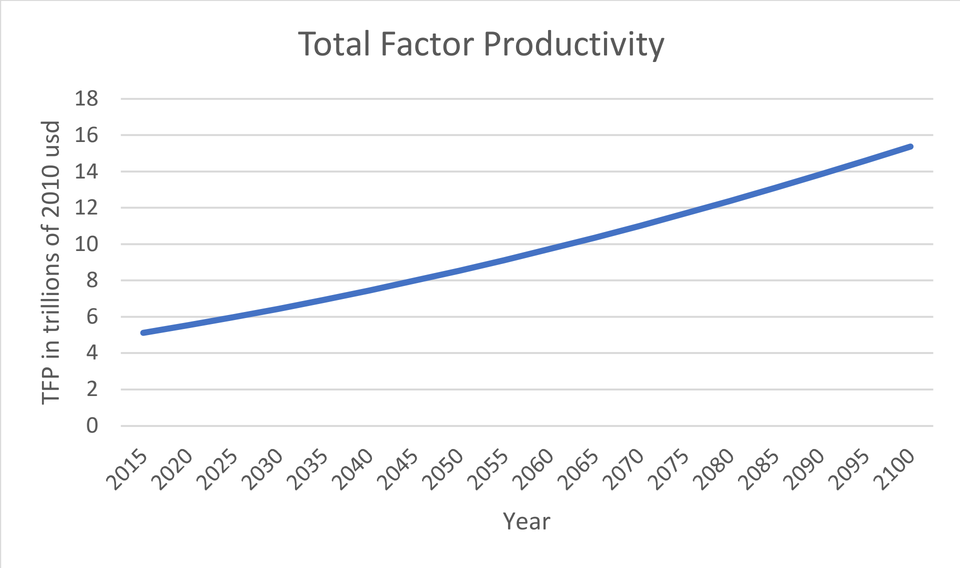

Figure 4.5 Level of Total Factor Productivity

We can take a couple of things from this. First of all, since this is a global aggregate model, there is no clear distinction between technological growth rates in separate regions. Because an aggregate shows the sum of parts, it must represent the total amount of technological change in the model.

In a sense, the growth of TFP mainly comes from the developing countries that have not yet reached the technology frontier. TFP growth then comes from an improvement in the average level of technology in use. True technological progress, which would be innovation that pushes the technological frontier, mainly comes from the developed regions. The importance of this distinction is also emphasized by Haider, Kunst and Wirl (2020), who give some consequences of not distinguishing between catching-up and innovation. The developed regions on average, show TFP growth percentages that are far lower and lately even negative. This should not come as a surprise as we already found in Chapter 3 that research productivity seems to be declining with around 6% annually. Evidence of declining productivity growth turns up more frequently with the latest data showing a trend towards 0 or negative growth.

The Conference Board (2019) estimates that global TFP growth has rarely been above 1% since the start of 2000 and turned negative again in 2018. The Euro area shows TFP growth of -0.1% and the US sees rapidly declining TFP growth in the same year. Japan stands out with a TFP growth of -1.4% in 2018. These results are mostly in line with OECD data, showing similar trends for the majority of countries with slight differences in severity (OECD, 2020). This trend is worrying because we assume that developed countries are at the front of the technology frontier and the main driving force behind innovation. Developed countries possess the resources and opportunities to devote to research.

In emerging countries, TFP growth has been decreasing as well and seems to be stalling. In contrast to the mature economies, these are still primarily positive (International Finance Corporation, 2016; The Conference Board, 2019). It makes sense to assume that these growth rates will remain positive for some years to come. These countries still have numerous possibilities to raise TFP by adopting existing and more advanced technology to catch up to the technological frontier. Research suggests however that innovation in these countries cannot simply increase by spending more on R&D (Haider, Kunst, & Wirl, 2020).

Compare this to the predicted growth by DICE which is closer to an annual growth rate of 1.5% in 2015. The difference at the global level of TFP growth is substantial. If we take a growth rate more in line with recent data like 0.2%, it would result in a growth rate per period of only 1.004%. The closest value we find for this in the model is in period 80, a good 400 years from now. Up until then, TFP growth is systematically high.

Secondly, even after almost 500 years, TFP still does not reach a limit and is only slowly approaching a 0% growth rate. In no way does it look to be approaching a collapse in growth around 2100 as predicted by meadows et al (1972).

The simplification of technological change in the model is not necessarily wrong as it avoids many uncertainties, but it does require an adjustment to its growth values to keep them in line with recent measurements.

5 Technological change in contemporary theories and models.

For a long time models were based on the assumption by Solow (1957), that technological growth was the reason for unexplained economic growth (Köhler, Grubb, Popp, & Edenhofer, 2006). In the past few decades however, economists realised that the exogenous representation of technological change did not suffice. The efforts of Romer (1986) inspired numerous efforts to endogenize technological change in economic and climate models (Grubb, Köhler, & Anderson, 2002). Within the endogenous technological change track, several different assumptions and approaches have been developed that all affect the models in their own way. Some are directed only at the energy sector or environmental technology while others address technology throughout the whole economy. This chapter will cover the most-used exogenous and endogenous approaches to model technological change in climate-economy models.

The modelling approaches treated below are in no ways exhaustive. There is a large number of models and adaptations that attempt to correctly model technological change, each in their own way. Within the body of related literature, most agree that there is no best approach yet and probably not for many years to come (Gillingham, Newell, & Pizer, 2008). The large number of factors and inherent uncertainties in the area of technological change make it difficult to specify one approach that includes all factors of importance. Even in the act of modelling the factors that are widely regarded as the most important, discussion is present concerning model specification, used values and calibration.

Appendix A consolidates several different overview tables from different articles. It is non-exhaustive but presents a fair number of models in use. Note that some of these models still see frequent revisions and updates that range from parameter calibrations to new equations and functional forms. The references in this table therefore might not lead to the most recent versions.

5.1 Exogenous approaches

5.1.1 Solow production function

The most basic approach to exogenous technological change is to assume that technological progress is the driving force for the growth of TFP. The growth rate of technology directly influences the growth of TFP and the general economy. This approach is also used by DICE.

$$Y = AL^{\beta}K^{\alpha} \tag{12}$$

where A presents Hicks-neutral technical change, which grows at some exogenously determined rate (Nordhaus & Sztorc, 2013).

This approach, though widespread, is subject to considerable criticism. The view that any and all increases in Y can be explained by technological progress ignores several important factors like the innovation process and the development of a technology over its lifetime. Lipsey and Carlaw (2004) are sceptical about TFP's ability to properly measure technological change and even argue that it is conceptually possible to have sustained economic growth, driven by technological changes without any changes to TFP (Lipsey & Carlaw, 2004). Even more pessimistic is the stance taken by Felipe and McCombie (2020) who state that "The growth literature has to evolve and abandon the conceptualization of growth through a production function and through the TFP research program." (Felipe & McCombie, 2020, p. 29).

5.1.2 AEEI parameter

The Autonomous Energy Efficiency Improvement parameter (AEEI) presents a decoupling of economic growth and energy use. In simple terms, this parameter represents the reduced energy requirements for a unit of economic output (Richels & Blanford, 2008). The AEEI is one of three energy efficiency improvement parameters, the other two are based on price-driven changes in demand and income-driven changes in demand (Kaufmann, 2004). This change in energy efficiency is considered to be the only scientifically valid definition of TFP by some (Beaudreau & Lightfoot, 2015). Beaudreau and Lightfoot (2015) find that energy efficiency has almost reached its theoretical limit in a number of processes. From this follows that a further increase in R&D might no longer bring about efficiency improvements. Shanker and Stern (2018) find that energy intensity never declines faster than output grows, meaning that gains in energy efficiency are negated by higher usage which is in line with the Jevons paradox.

The approach itself is relatively straightforward and consists of an added parameter to a cost, production or demand function. The AEEI parameter is often combined with a backstop technology and can be easily implemented in models with endogenous technological change. The parameter is declining over time, indicating the decreasing room for improvement in energy efficiency.

Löschel and Schymura (2013) give an example of how this can be written in a neoclassical production function:

$$Y_t = F(A_t, C_t, D_t) \tag{13}$$

where A_t is technological progress, C_t output from a clean input and D_t output from a dirty input. The AEEI parameter is characterized as:

$$AEEI_t = \frac{\frac{\partial A_t}{\partial t}}{A_t} > 0 \tag{14}$$

One example of a practical use is the IMAGE3.0 model, which introduces an AEEI parameter in the equation for the demand of final energy.

$$FE_{R,S,F} = \frac{POP_R * \left(\frac{ACT_{R,S}}{POP_R}\right) * SC_{R,S,F} * AEEI_{R,S,F} * PIEEI_{R,S,F}}{\sum_F \eta_{R,S,F} * MS_{R,s,F}} \tag{15}$$

where FE is final energy demand in region R, sector S and energy form F. POP is population, $\frac{ACT_{R,S}}{POP_R}$ is sectoral activity per capita, SC a factor capturing intra-sectoral structural change, $AEEI$ the autonomous energy efficiency improvement, $PIEEI$ the price-induced energy efficiency improvement, η the end-use efficiency of energy carriers and MS the share of each carrier (Stehfest et al., 2014).

Though it is used in several different models, it has some important issues. One problem with the use of an AEEI parameter is the difficulty of distinguishing between long-term price effects and technological progress. Changes in relative price influence energy demand and energy intensity resulting in a substitution away from certain inputs.

A second problem is the wide variety of factors that can influence energy consumption over time, which leads to difficulties in capturing the appropriate value. This can be seen in the wide range of AEEI estimates which can range from 0.4% to 1.5% (Löschel, 2002). Beaudreau and Lighfoot (2015) investigated the limits on economic growth induced by R&D expenditures and find that the upper bound of changes in energy efficiency is around 0.68% per year.

A third problem is the stochastic nature of the parameter. Kaufmann (2004) argues that the deterministic trend often used by modellers results in econometric results that are difficult to interpret or just wrong (Kaufmann, 2004).

Last, Dowlatabadi (1998) found that some models that specify the AEEI parameter as a constant are not able to replicate historic trends. He transforms the parameter to an endogenous formulation that works with a base energy efficiency as a function of per capita income and adds a new value that is a function of average energy price multiplied by a lagged coefficient for price-induced energy efficiency (Dowlatabadi, 1998).

5.1.3 Backstop technology

A backstop technology is often given as an exogenous impact on the model. In climate models it is often an energy source that is known but not yet commercial or a way to capture emissions (Löschel & Schymura, 2013). These technologies become more important as they spread and their costs decline while at the same time, conventional technology becomes more expensive due to depleting resources and policies for example. Most models assume that the decrease in backstop prices is solely dependent on the passing of time, decreasing at its own autonomous rate (Gillingham et al., 2008; Löschel, 2002). One can include fossil and non-fossil backstop technologies which can be in the form of existing technologies or possible future technologies. It is also possible to add more than one backstop technology to present multiple energy sources and emissions for example.

Continuing from equation 13, the production function changes to:

$$Y_t = F(A_t, C_t, B_t) \tag{16}$$

where B_t is the backstop input. This only happens under the condition that the time of implementation has passed and the price of the backstop is now lower than the price of the dirty production technology (Löschel & Schymura, 2013).

Exogenous approaches like the backstop technology are useful for scenario analysis with existing technology but are not suited to future predictions as they cannot properly model innovation and diffusion (Löschel, 2002). As is the case in the DICE model, the price of the backstop often decreases with a constant rate in each period. This ignores a number of aspects like the diffusion of technology, which usually starts slow and then undergoes a rapid increase only to slow down again afterwards. Because the DICE model assumes 100% removal in the first periods, it also does not pay attention to the improvement of this technology which is questionable. The technology is already perfect, but the producers are not yet capable of creating or using the technology efficiently. Normally, it would make more sense to start with an imperfect technology that improves rapidly and after some time shows slower improvements as it approaches maximum efficiency.

Even when the backstop technology reaches a price that is profitable enough for producers to adopt it, one must take care to include a transition period. When the backstop technology is commercially available and viable, there will still be a period of time where the original energy source is used (Löschel & Schymura, 2013). Producers might lack the resources to invest in something new and policy that could provide incentives to invest can take a long time to be realised.

The MIT-EPPA6 model takes a different approach to backstop technologies. Chen, Paltsev, Reilly, Moris and Babiker (2015) define the mark-up as ''the ratio of the backstop technology's production cost to that of the technology that currently produces the same output'' (Chen, Paltsev, Reilly, Morris, & Babiker, 2015, p. 17). This means that a mark-up of 1.2 indicates that the backstop is 20% more expensive than the current technology. This approach requires a decent amount of data to determine the mark-up costs for each sector and one must be careful in determining the technology used as the baseline technology. Old coal-fired power plants that are still in use are likely to be easier and cheaper to use than the new coal-fired power plants due to changes in technology and regulation (Chen et al., 2015).

5.2 Endogenous approaches

5.2.1 Price-induced energy efficiency improvement (PIEEI)

Innovation is the result of a change in relative prices aimed at better use of the relatively expensive factor. In climate models, this usually refers to the energy prices where fossil fuel sources become smaller, thus raising the price (Richels & Blanford, 2008). This provides an increasingly bigger incentive to look for and develop other energy sources. A change in relative prices can thus push innovation into a certain direction. Dowlatabadi (1998) uses this approach in the ICAM-3 model, his formulation for the change in energy technology is as follows:

$$\pi_{tj} = k(y_j) + \sum_{i=1}^{3} \beta_i (p_{j,t} - p_{j,t-5i}) * p_{j,t-5i} \tag{17}$$

where k is the base energy efficiency which is a function of income per capita y, per region j. $p_{j,t}$ is the average price of energy in region j at time t. β_i is the coefficient for price induced energy efficiency with a 5 year time lag.

This concept is closely related to that of the innovation-possibility-frontier, which is a production function for producing new knowledge that improves the productivity of the different inputs. There is a trade-off between improving the use of one input compared to the others. Changing relative prices can thus push innovation towards a certain direction (Gillingham et al., 2008).

5.2.2 Learning-by-doing

The concept of learning-by-doing can usually be split into two parts, being the producer and consumer side. Learning-by-doing which decreases costs to manufacturers as a function of cumulative output, or learning-by-using in which the decrease in costs to consumers comes as a function of the use of a technology (Gillingham et al., 2008). The increasing use of a new technology can be a major contribution to its development as users figure out new and better uses and become more adept at using a technology. This approach often assumes that there are no additional costs needed to advance technology. It simply improves as a function of increased use and time (Clarke, Weyant, & Edmonds, 2008).

As such, it is not a completely accurate representation of the real-life development of a technology. No new technology is introduced and adopted by the masses on the same day. Diffusion takes time and so do the learning processes connected to something new. The basic approach expresses technological progress in the form of decreasing costs of a technology as a function of installed capacity. A certain learning elasticity influences the decrease of technological costs after an increase in capacity (Löschel, 2002).

A disadvantage is its reduced-form nature. Learning-by-doing can be inserted into many models but it is difficult to identify the mechanisms behind it. Finding out what causes or speeds up the learning process is arguably one of the most important pieces of knowledge that is required to further development. As such, assumptions on the learning rate within a field of technology become critical information with large effects on the outcomes of a model (Sue Wing, 2006). A common result of this approach is that the carbon tax required to attain a target tends to be lower than in other models without LBD. Another result is that short-term abatement tends to be higher than future abatement as large short-term investments would develop the technology the quickest (Popp, Newell, & Jaffe, 2010; Sue Wing, 2006).

Another important shortcoming for this approach is the possible issue of endogeneity caused by the presence of both R&D and learning-by-doing as both are expressed as a function of the other.

Accounting for this issue results in learning-by-doing rates that are far lower than those in the literature. Instead of 15-20% learning rates, a 5% learning rate might be more realistic (Popp et al., 2010).

Aside from other theoretical inaccuracies and issues, modelling this approach becomes problematic in the presence of multiple technologies and sectors that all have their own learning rates and can influence the progress in other sectors due to spill-overs. Finding realistic values for the learning and spill-over parameters requires a large amount of empirical data and a proper application of this approach requires transparency (Sue Wing, 2006).

A commonly used specification models decreasing cost C for a technology as:

$$C = \alpha K^{-\beta} \tag{18}$$

where α is a normalization parameter, K the installed capacity and β a learning elasticity (Löschel, 2002). This form is used in the WITCH model by Bosetti, Carraro, Massetti and Tavoni (2008) to represent learning effects in a model that also deals with knowledge spill-overs. Some models like MERGE-ETL, model multiple technologies and therefore use a total cumulative cost curve instead of a technology specific cost curve (Kypreos & Bahn, 2003).

Another specification of this approach is discussed by Sue Wing (2006):

$$\psi = {V_m}^{\varsigma m} \tag{19}$$

where ψ is experience, V_m an index of cumulative production at time t and the learning exponent ςm, which is defined as:

$$\varsigma_m = \log(1 + \lambda_m) / log2 \tag{20}$$

where λ_m presents the learning rate (Sue Wing, 2006).

5.2.3 R&D induced innovation

Innovation is the product of explicit investment in R&D. It is an economic activity that is the result of profit-maximizing agents that act on profit incentives (Löschel & Schymura, 2013). In the models that use this approach, knowledge is treated as a non-rival and not fully appropriable good indicating the presence of spill-overs (Castelnuovo, Galeotti, Gambarelli, & Vergalli, 2005; Clarke et al., 2008; Romer, 1990). It often introduces a knowledge stock that increases over time as R&D investments increase. Additional parameters are added to indicate the diminishing returns of R&D over time.

In turn, the knowledge stock can usually do two things. The first is that it reduces the costs of production or energy use meaning producers become more efficient at producing their products or need less energy for its production (Popp, 2004). The second is that it can improve the quality of the product (Smulders & de Nooij, 2003).

One example of the former is the modification of DICE by Popp (2004). His modelling of the knowledge stock is aimed at energy efficiency, so knowledge here reduces the amount of emissions as a result of higher energy efficiency or more effective emissions control (Popp, 2004).

$$H_{E,t} = h(R_{E,t}) + (1 - \delta_H) * H_{E,t-1} \tag{21}$$

where $H_{E,t}$ is the stock of energy-based human capital, $h(R_{E,t})$, the innovation possibility frontier and $\delta_H$the rate of knowledge depreciation. The innovation possibility frontier is modelled as:

$$h(R_{E,t}) = a{R_{E,t}}^b {H_{E,t}}^\theta \tag{22}$$

where $R_{E,t}$ is energy R&D. The parameters are chosen so that energy research shows diminishing returns over time which is done by choosing a value between 0 and 1 for both θ and b. In a later model that adds the effects of R&D on the progress of a backstop technology, Popp also adds a separate knowledge stock for this technology (Popp, 2006).

An example where the quality of a good increases as a result of technological change is presented by Smulders and De Nooij (2003), which they model as follows:

$$q_{ik} = [\varepsilon_i Q_i {D_i}^{1-w_i}] {D_{ik}}^{w_i} \tag{23}$$

where ε_i is a normalization parameter or more specific, an indicator of research productivity. Q_i is the representation of the knowledge stock which is an approximation of the current aggregate quality level, D_i the R&D investments of the whole sector and D_{ik} the R&D investments of a specific firm. w_i represents the appropriability of the returns from an innovation. It thus incorporates two types of R&D spill-overs, being the innovations efforts of previous firms that increase the knowledge pool and quality level, and the level of spill-overs coming from other firms at that point in time which are represented by the parameters w_i and $1 - w_i$.

One important aspect of this approach is the nature and source of R&D investments which can be divided into two general ideas. The first is the "standing-on-shoulders" concept where extensive R&D efforts in the previous period lead to more innovation in the next period because innovation builds on the knowledge acquired in previous periods (Nordhaus, 2002; Sequeira & Neves, 2020). Jones (2009) suggests that this actually has adverse effects as it becomes increasingly more difficult to reach the level of knowledge left by predecessors. The second concept is the "stepping-on-toes" concept where extensive R&D efforts in the previous period lead to reduced innovation in the next period (Jones, 2009; Kijek & Kijek, 2020; Sequeira & Neves, 2020). The underlying thought here can be that innovation in the previous period removes the opportunity for innovation in the next (Nordhaus, 2002).

5.2.4 Spill-over effects

Spill-overs provide one of the sources of long-term economic growth. Spill-overs mean that the actions of one party produce knowledge that can be used by other parties to produce or improve their products. These spill-overs in the form of new knowledge and technology have the potential to influence other companies and technologies thus promoting further development (Aghion & Jaravel, 2015; Jaffe, Trajtenberg, & Fogarty, 2000). The result is that the social rate of return on R&D can be far higher than the private rate of return (Clarke et al., 2008; Löschel, 2002). The implementation of spill-overs is far from simple though as there are several aspects one must consider like the difference between sectors and low and high-income countries.

An issue with this approach is the distinction between spill-over types. The diffusion of knowledge has mainly positive effects on technological progress overall, but product market rivalry effects can have negative influences. At the firm-level, the knowledge that not all returns to R&D are appropriable influences investment decisions (Aghion & Jaravel, 2015). The knowledge that one's innovation or knowledge will be used by others might make a company more averse to making big investments which could lead to sub-optimal innovation efforts. This is why some advise to look only at macro-level effects (Löschel, 2002). The scale of the model is an important factor as spill-overs can manifest themselves on multiple economic levels. Lucking, Bloom and Van Reenen (2018) find that spill-overs have remained largely stable during the last decades but do state that the difference between the marginal social returns and marginal private returns might have been bigger than previously estimated.

Goulder and Schneider (1999) model spill-overs as a simple function over time where the benefits from spill-overs consist of the knowledge in the previous period in addition to the industry-wide R&D investments multiplied by the magnitude of potential spill-overs:

$$H_{t+1} = H_t + \beta * R_t \tag{24}$$

where H_t is the initial stock of knowledge, R_t the amount of industry wide R&D expenditures and β the rate of potential spill-overs. H_t is then inserted in the production function.

$$X = \gamma(H_t) * \ N^{\rho} * G^{(\rho*1/\rho)} \tag{25}$$

where γ is a scale factor, N the appropriable knowledge and G the aggregate of all other production inputs. ρ is the substitution parameter (Goulder & Schneider, 1999; Löschel, 2002).

The WITCH model by Bosetti et al. (2008) implements spill-overs as the multiplication of the world knowledge pool with the absorption capacity of each region which is then incorporated in a separate innovation function.

$$SPILL_{n,t} = \gamma_{n,t} * KP_{n,t} \tag{26}$$

where $\gamma_{n,t}$ represents a country's ability to absorb knowledge and $KP_{n,t}$ the available knowledge pool from which technology can be adopted.

The production of new ideas in a country n at time t is then presented as:

$$Z_{n,t} = \alpha {I_{n,t}}^{\beta} * {HE_{n,t}}^{c} * {SPILL_{n,t}}^{d} \tag{27}$$

where I presents the R&D investments and HE the stock of knowledge. β and c together must be lower than 1 to account for diminishing returns and d is the elasticity of the production of new ideas to international R&D spill-overs.

Buonanno et al. (2003) adopt a similar approach in their adaption of the ETC-RICE model where knowledge is introduced in both the production function and the emission-output ratio. This model does still allow for exogenous technological change alongside R&D and spill-over driven technological change.

One problem the multi-region models have to deal with is the knowledge gap between low and high-income countries. The further a country lies away from the technological frontier, the harder it becomes to reach it. Potential spill-overs are thus wasted as low-income countries lack the absorption capacity to benefit from the knowledge creation of more advanced countries (Bosetti, Carraro, Massetti, & Tavoni, 2008).

5.3 Concluding remarks

Overall, climate-economy models have mostly changed to endogenous specifications of technological change. As technological progress is a complicated issue, models choose to combine different approaches to simulate real-life innovation processes. They combine R&D induced innovation with spill-overs for example to replicate the diffusion and non-appropriability of new ideas. While the use of Solow production functions with Hicks neutral technical change has decreased, other exogenous specifications like AEEI parameters or backstop technologies are often combined with endogenous approaches like R&D induced innovation. All of these models recognize the increasing difficulty with which technology can be developed as the amount of knowledge or R&D investments increase. This is often represented by parameters indicating decreasing returns.

As far as I am aware, none of these models discussed the conceptual limits of technological progress or rapid decreases in research productivity. It could also be that this information, in the form of model values for example, was simply omitted due to article constraints.

In addition, there was an unexpected lack of attention for the exogenous development of technology which is surprising given that it is still part of a number of models. Most models merely state its presence and do not go into its development. Assigned values are rarely discussed which is odd given that small changes in technological growth assumptions can have noticeable impacts on the model outcomes.

6 Alternative modelling in DICE

In this chapter I will further elaborate on the original DICE model and introduce three different scenarios. These scenarios each tackle the issue of declining technological progress in a different way. The first will only adjust the values responsible for TFP growth. The second will introduce an economic limit by changing the equations and the third will alter the values for the decline of TFP growth. All of these will be compared to the unchanged model which will act as the baseline scenario. Table 6.1 gives an overview of the different scenarios and a short description of the change.

Table 6-1
Overview of the different scenarios.

Scenario	Concept
Original	Baseline model. No changes.
Potential	Lower technological progress. Changes value for G_t from 0.076 to 0.051 per model period
Limit	Sets a limit to the size of TFP by introducing a new function for TFP level A_t.
Decline	Declining rate of TC. Changes value for θ from 0.005 to 0.01 per model period

Note: Each scenario has a non-optimized version and an optimized version.

6.1 Baseline

In chapter 4, it was discussed how the DICE model incorporates technological change into its model. Here, the impacts of this approach will be visualized by giving an overview of the development and values of the most important variables. The model can be run in both a non-optimized (business-as-usual) and an optimized mode. The underlying thoughts are the following.

The unoptimized baseline model maximizes utility without the presence of environmental policies. It thus presents the case where the population cares only about consumption and is not affected by costly environmental policies. Emissions go mostly unchecked, resulting very high damages.

The optimized case presents a scenario where utility is maximized under the influence of environmental policy. Emissions abatement as a result of carbon taxes is far higher and leads to lower damages to society.

The full model runs from 2015 to 2510. The results however, will only focus on the period 2015-2100. Covering the full model is not desirable for two reasons. The first is that predictions for such a distant future are bound to be unrealistic and full of uncertainty. Some parameter values like the population size or availability of fossil fuels can be estimated with some certainty while estimates for the size of the economy are a shot in the dark. The second reason relates to why the original model runs for so long. This is done to eliminate or at least postpone the appearance of doomsday scenarios. Some models or solvers see drastic increases in emissions when the model approaches its final periods. The reason being that there is no reason to account for negative effects after the model has reached its final period. A solution is to let the model run for a longer period of time than the timeframe one is interested in.

6.2 Lower potential for technological change

This scenario simulates slowing technological progress by adjusting the starting value in the model. In model terms, this means that G_t is adjusted. As previously explained, Nordhaus assumes the growth of TFP to be synonymous to technological progress. A lower value for G_t means that the potential for technological progress has decreased. When comparing the value for G_t in the original model (7.6% per 5 years), we see that it is too optimistic compared to recent growth statistics. Therefore, a lower and more realistic value is chosen. Assuming that recent growth statistics are correct, the global average should be somewhere between -0.5 and 1% per year (Adler, Duval, Furceri, Koloskova, & Poplawski-Ribeiro, 2017; Crafts, 2018; The Conference Board, 2019). The most modern economies are showing low or even negative growth (The Conference Board, 2019).

My choice for this scenario was a growth rate of 1% per annum which comes down to 5.1% in the model. This growth rate is rather optimistic but leaves some room for the benefits of a new technological breakthrough and possible mismeasurement.

6.3 A limit to the economy

For this scenario I implement a limit to the economy by changing the function for TFP. While there are not many researchers who dare to predict a value for the maximum size of the economy, this conceptual limit is discussed and heavily debated, with Meadows et al. (1972) being one of the first and most influential. Their original model predicted a decline in economic growth as well as a possible global economic collapse in 2 of their scenarios. Over the years, various updates have come out that compare original and updated model predictions with empirical data. These updates found that empirical data still closely matches the business-as-usual scenarios (Herrington, 2020; Turner, 2008).

Since the model used by Meadows et al. (1972) was not meant to predict point values, it cannot be used to update the numerical limit in DICE. It can however be used to add an assumption to the model, stating that economic growth ceases to exist in the year 2100, with a steady decline in growth in the years prior. More accurately, it limits the potential of technology-driven economic growth by not allowing TFP to exceed a certain level. Gross output continues to slightly increase as a result of higher labour and capital use but to a far smaller degree compared to the original model.

The numerical limit is based on the value for 2100 produced by the basic DICE model. The choice to take 2100 as the limit is also reasonable as this is the model period where population growth is approaching 0%. I changed the TFP equation to:

$$A_t = A_0 + (\mathrm{Z} - A_0) * (1 - e^{-G_0 * t}) \tag{28}$$

Where A_0 is the starting value for TFP, Z the assumed limit on TFP, G_0 the growth rate of TFP and t the value for the current period. This function is similar to growth functions like the Verhulst Logistic Growth Model and has similar properties. Initial growth is high and decreases over time as it approaches an asymptotic limit.

6.4 Faster decline of technological progress

In the fourth scenario I change the decline rate of technological progress. This is done in the model by changing the value for the parameter θ. The value for θ is 0.005 (0.5%) in the original model. This exogenous parameter is straightforward in its meaning but the processes behind it can differ a lot and are not well understood. For example, a decrease in TFP growth can be caused by a decrease in research productivity or any other factor that can negatively influence TFP. If we assume that the first is the case, it might not be too farfetched to make this parameter time dependent following the findings by Bloom et al. (2020) that research productivity seems to decline with around 6% every year in a number of important industries. If we assume the latter, meaning that the decline parameter captures every factor (including technology) that negatively affects TFP it becomes difficult to make a substantiated guess as to what a proper value would be. The safest approach here is to take a few slightly higher values as growth statistics show that TFP growth has been declining more rapidly. The high difference between the value suggested by Bloom et al. (2020) and the original parameter value in the model indicates that there are other factors in play that dampen the impact of the rapid decrease in research productivity.

The current value for the decline of TFP growth is 0.5% per period which comes down to approximately 0.1% per year. Most growth statistics show similar trends with a few differences severity and the occasional discrepancies coming from different data sets (Adler et al., 2017). Growth statistics show that TFP growth has been lower than -0.1% at a number of occasions (International Finance Corporation, 2016; The Conference Board, 2019). The decline in growth is even harder to specify. It seems that de most matured economies have reached a low but relatively stable growth while the developing countries show declining growth rates of around 1% per 5 years (The Conference Board, 2019). This scenario will therefore look at a decrease of 0.2% decline annually or a 1% decline per period.

7 Results

This chapter discusses the model outcomes of the scenarios introduced in chapter 6. The chapter will follow the same order as chapter 6 and scenarios will follow the format described in table 6.1.

7.1 Baseline

Chapter 4 discussed the specification of technology in the basic model and showed the development of the technological parameters. This chapter shows the impact of technology on the most important indicators for environmental policy. The indicators to be discussed are TFP, abatement, carbon price, emissions control rate, emissions and temperature. The baseline scenario consists of the unoptimized and the optimized model which will from hereon be referred to as Original Non-opt and Original Opt respectively.

To maximize utility, the model choses to control emissions at different rates. Original Non-opt barely controls any emissions while Original Opt reached 84% control in 2100 (Figure 7.1).

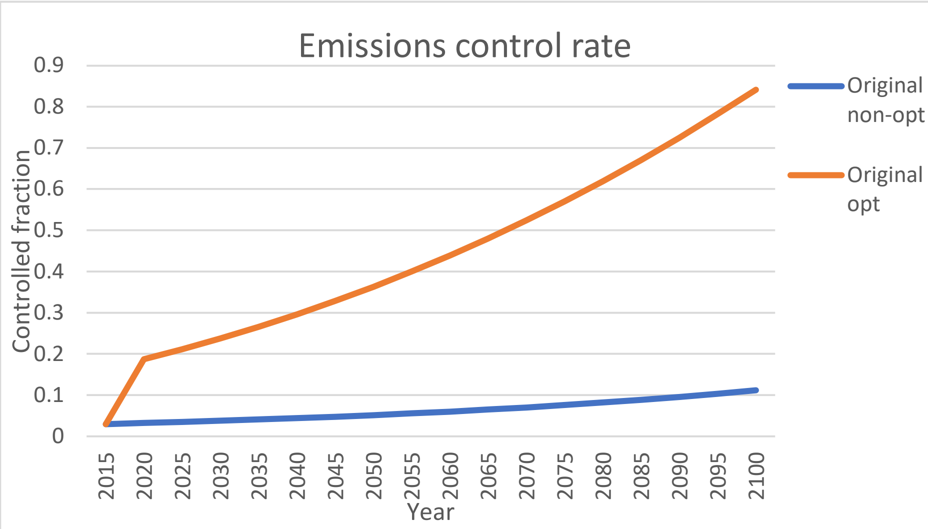

Figure 7.1 The controlled fraction of emissions for the optimized and non-optimized original model.
Note: A control rate of 0.6 means that 60% of emissions are controlled as a result of some form of policy.

The emissions control is related to abatement, carbon price and emissions. Abatement in Original Non-opt remains close to 0 for the chosen time period while it gradually increases in Original Opt (Figure 7.2). Abatement in Original Opt is more than 200 times larger than in the Non-opt scenario which greatly decreases the amount of emissions and ultimately allows for more production (Table 7.1)

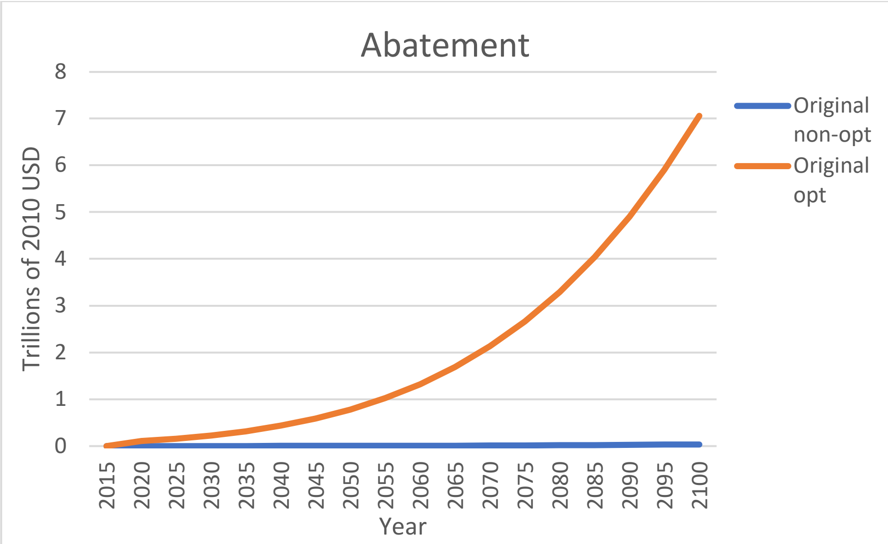

Figure 7.2 The costs of abatement efforts in trillions of 2010 USD

Table 7-1
Results from scenario 'Original'

Variable	Sum 2015-2100		2050		2100	
	Non-opt	Opt	Non-opt	Opt	Non-opt	Opt
Industrial emissions (GT CO2)	1052.5	579.3	58.2	39.1	70.9	12.7
Output net of damages and abatement (trillions of 2010 USD)	6815.4	6841.3	292.5	292.6	757.0	764.5
Abatement (trillions of 2010 USD)	0.2	36.6	0.004	0.8	0.03	7.1

DICE clearly postpones abatement to a later point in time, waiting for the backstop technology to develop and decrease the cost of abatement per ton CO2. This also indicates that the damage function in DICE might be too optimistic.

To provide an incentive for abatement, carbon prices should increase as they affect the profitability of polluting production practices. Carbon prices in Original Opt quickly increase and reach a value of \$271.33 per ton CO2 in 2100 (Table 12.1). The development of carbon prices (Figure 7.3) shows a similarity to the development of the emission control rate in Figure 7.1. This can be explained by the way these variables are determined. Nordhaus (1993) states that “the model determines the optimal control rate along with its dual variable, the derivative of the objective function with respect to emissions, which is the carbon tax.” (Nordhaus, 1993, p.314).

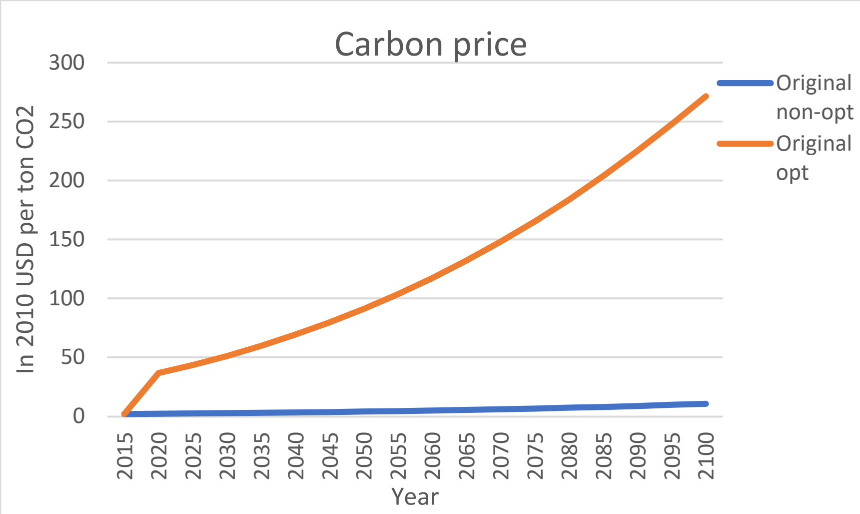

Figure 7.3 Carbon prices in 2010 USD per ton CO2

Finally, the change in temperature which is the most important variable next to the objective. Due to the delay between emissions and their impact on the atmospheric temperature, the increase in temperature is roughly the same for the first 30 years or so (Figure 7.4). After 2045, the impact of emissions abatement shows itself. In the end, the unoptimized model reaches an increase of 4.10℃ compared to an increase of 3.48℃ in the optimized model, a difference of 15.13% (Table 12.2).

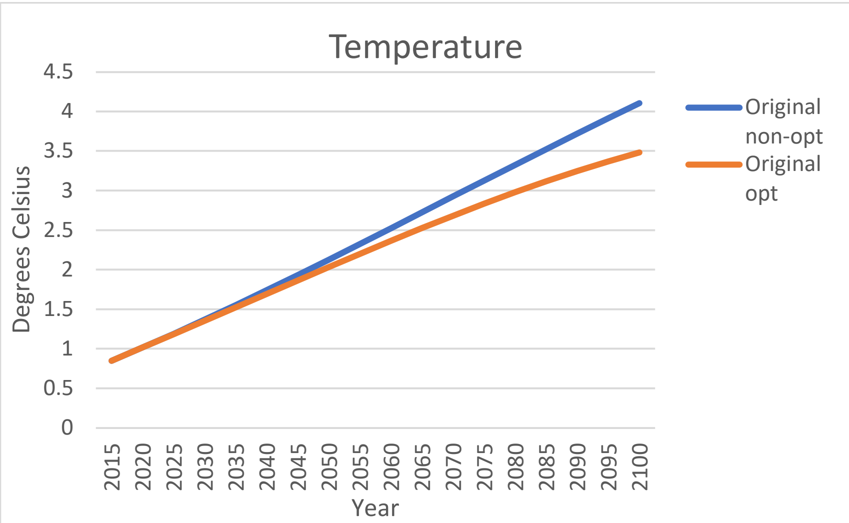

Figure 7.4 Temperature increase in degrees Celsius

7.2 Lower potential for technological change

The change in TFP growth has a straightforward result. Lowering the rate of technological potential lowers the level of TFP and in turn also lowers the growth rate of gross output. TFP in year 2100 is almost 5 trillion lower than in the original model (Table 12.3).

Abatement in this scenario is slightly higher in the first periods for the optimized version. It also grows far slower compared to Original Opt (Figure 7.4). The main reason for this temporary increase in abatement efforts seems to be the lower economic output (Table 7.3). Whether this effect is more pronounced under even lower economic output will be discussed in chapter 8.

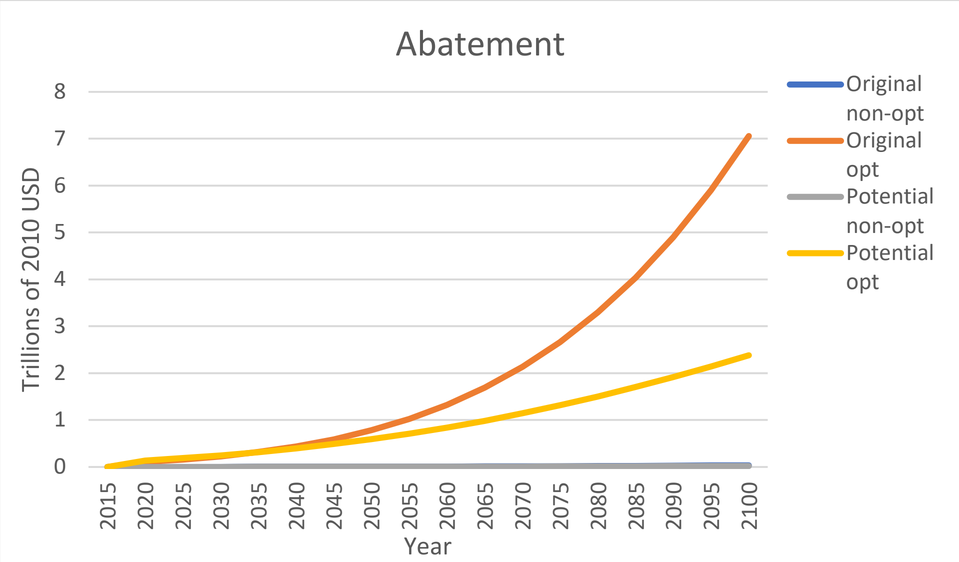

Figure 7.5 Annual costs of emission abatement resulting from a decrease in G_t

Total emissions in this case are lower than in Original Non-opt but emissions in Potential Opt in 2100 are actually higher than in Original Opt (Table 7.2). This means that lower technological progress leads to lower economic output and slower control of emissions overall (Table 7.2).

Table 7-2

Results for scenario 'Potential', where the value for G_t was lowered to 0.051 for period 1.

Variable	Sum 2015-2100		2050		2100	
	Non-opt	Opt	Non-opt	Opt	Non-opt	Opt
Industrial emissions (GT CO2)	805.7	509.1	47.3	32.3	43.3	16.1
Output net of damages and abatement (trillions of 2010 USD)	4954.3	4967.6	237.7	237.7	465	468.8
Abatement (trillions of 2010 USD)	0.1	17.0	0.003	0.6	0.02	2.4

Given that abatement is lower one would also expect carbon prices to be lower. This is indeed true but only after a certain year. In the short-term, carbon prices are actually higher in the case with lower growth potential. This is only true for the optimized runs as the non-optimized runs show identical carbon prices (Figure 7.5). To maximize utility, the model chooses higher carbon prices in early periods if technological progress is low.

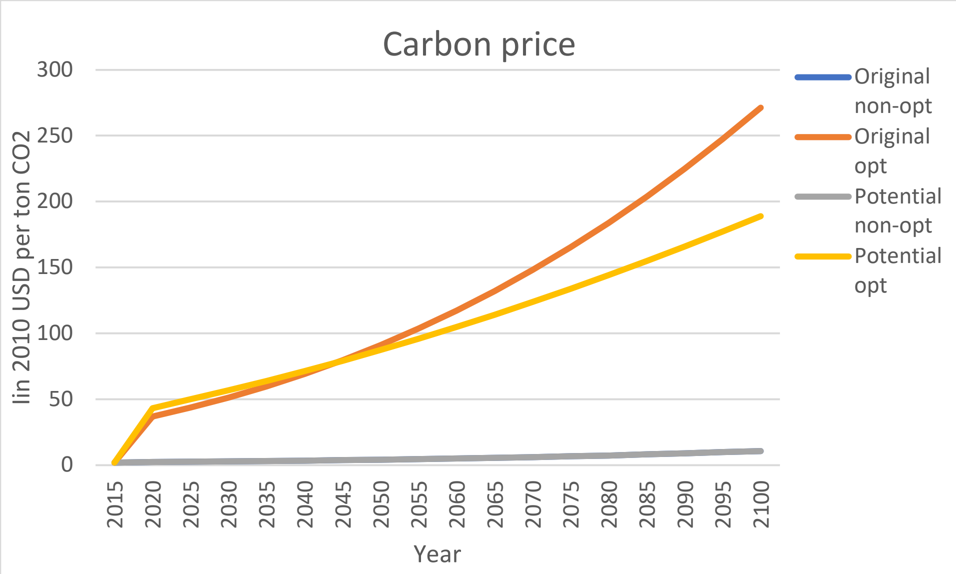

Figure 7.6 Carbon prices in 2010 USD per ton CO2 resulting from a decrease G_t

The development of the emissions control rate follows the same trend as in Figure 7.5. Emission control rates in the scenario with lower growth potential were higher in the first 15 years or so. Afterwards the original model overtakes it and reaches a higher controlled fraction in 2100. In 2100, Original Opt controls 84% of emissions while Potential Opt only controls 67% (Table 12.4).

Finally, the increase in temperature. It is good to realize once more that the model optimizes utility and is not aimed at keeping the temperature increase below 2 degrees Celsius. The effects of abatement and lower production become clear after a few decades (Figure 7.7). In 2100, Potential Non-opt sees a temperature increase of 3.79°C which is 7.55% lower than Original Non-opt. Temperature increase in Potential Opt 3.32°C which is 19.07% lower than Original Non-opt. The increase in Potential Opt is 3.94 percentage point lower than Original Opt (Table 12.2).

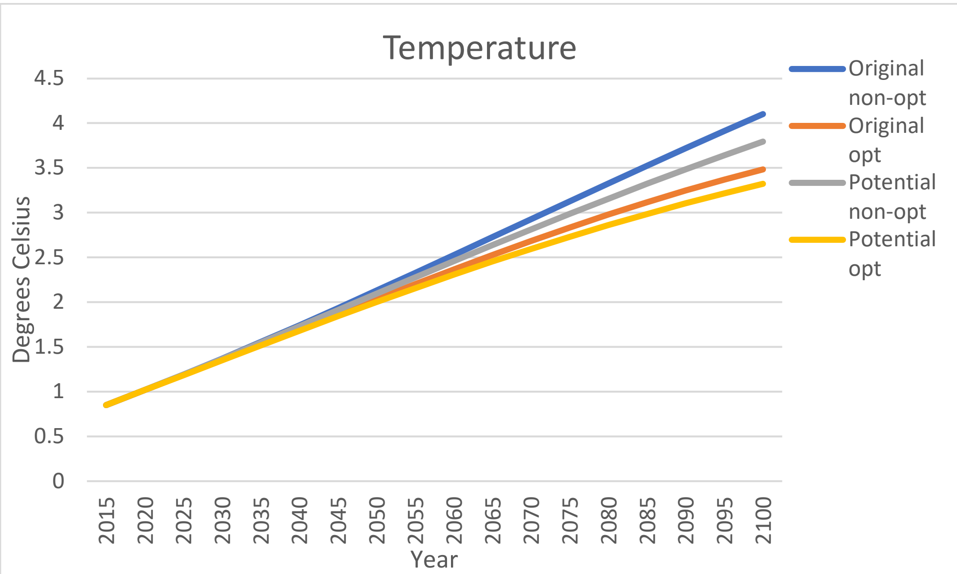

Figure 7.7 The temperature increase in degrees Celsius resulting from a decrease in G_t

7.3 A limit to the economy

Following the same structure as before, TFP is discussed first. Compared to the original scenario, the introduction of a limit results in relatively high 2050 values and lower TFP in the year 2100 compared to Original (Table 12.3). This indicates faster growth in the first periods of the model and a more rapid decline towards the end. In 2100, the model with an economic limit is close to reaching the maximum TFP size.

While TFP differences might not be too big, abatement is strongly affected by these differences and the future growth prospects in both scenarios. Total abatement was around 14 trillion higher in Limit Opt (Table 7.3), with the biggest differences in abatement efforts in the period 2050-2075 (Figure 7.8). The figure also shows that that abatement efforts catch up with a lag. TFP in the original model exceeds TFP in the model with a limit around the year 2070 while the same happens for abatement in the year 2095.

Table 7-3

Results for scenario 'Limit', where a maximum size to the level of TFP was introduced.

Variable	Sum 2015-2100		2050		2100	
	Non-opt	Opt	Non-opt	Opt	Non-opt	Opt
Industrial emissions (GT CO2)	1073.3	510.6	66.9	37.2	56.2	7.4
Output net of damages and abatement (trillions of 2010 USD)	6680.9	6710.5	336.18	336.2	599.1	607.2
Abatement (trillions of 2010 USD)	0.2	50.5	0.005	1.8	0.02	6.7

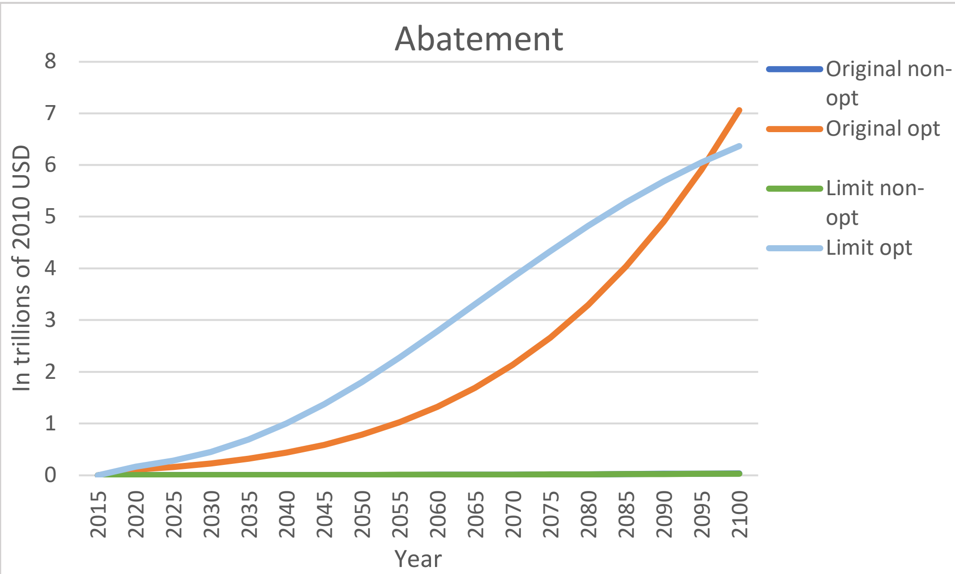

Figure 7.8 The costs of abatement efforts in trillions of 2010 USD after the implementation of a limit

Carbon prices are far higher in the model with a limit until after 2100. Contrary to the previous scenario, the increase in carbon prices cannot be caused by lower TFP or economic output as the model with a limit actually has higher TFP in the first decades. The different trajectory of TFP has a clear impact on carbon prices. The gap in carbon prices is more than $60 in 2075. Carbon prices converge but only after 2100 will the optimized original model catch up to the model with an economic limit (Figure 7.9).

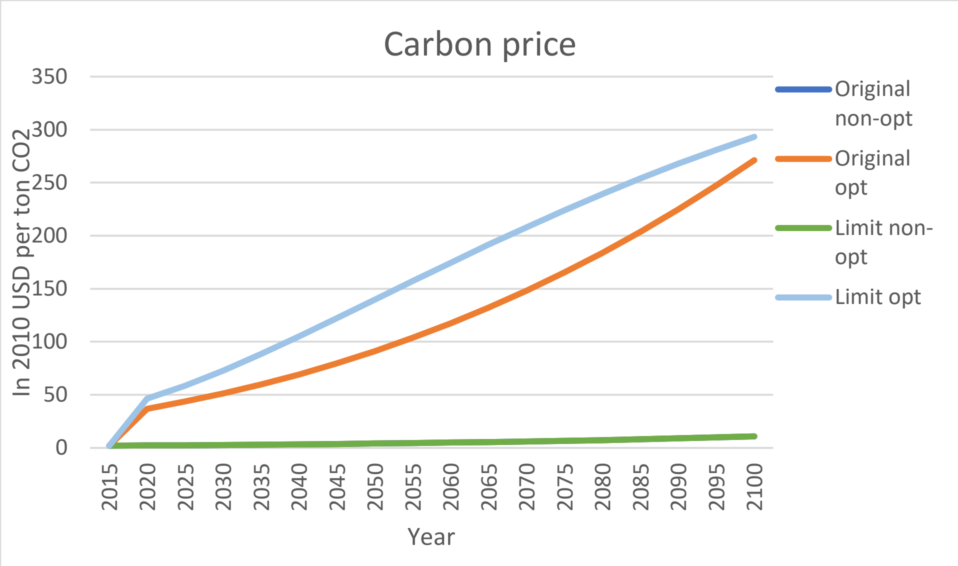

Figure 7.9 Carbon prices in 2010 USD per ton CO2 after implementing a limit

The Limit scenario differs from Original in its emissions control rate trajectory. The optimized original model shows a gradually increasing development reaching control rates of 84.14% in 2100. Compared to this, the model with a limit shows an almost linear increase, reaching 88.38% control in 2100. While this scenario has higher control rates throughout the time period, it actually reaches a control rate of 100% one period later than the optimized original model (Table 12.4).

The overall impact of these changes on temperature is small but nevertheless important as it shows how the model deals with relatively big changes in the economy. The rapid short-term growth of TFP provides an incentive for strong abatement efforts at higher prices and more control. Even when TFP growth slows down rapidly, strong emission control continues for a few more years. It eventually results in lower emissions than Original Opt and slightly higher consumption per capita (Table 12.5).

Temperature increase in Limit Non-opt is 4.21°C, which is 2.65% higher than Original Opt. The increase in Limit Opt is 3.38°C, which is a decrease of 17.42% compared to Original Non-opt and 2.29 percentage point lower than Original Opt (Table 12.2).

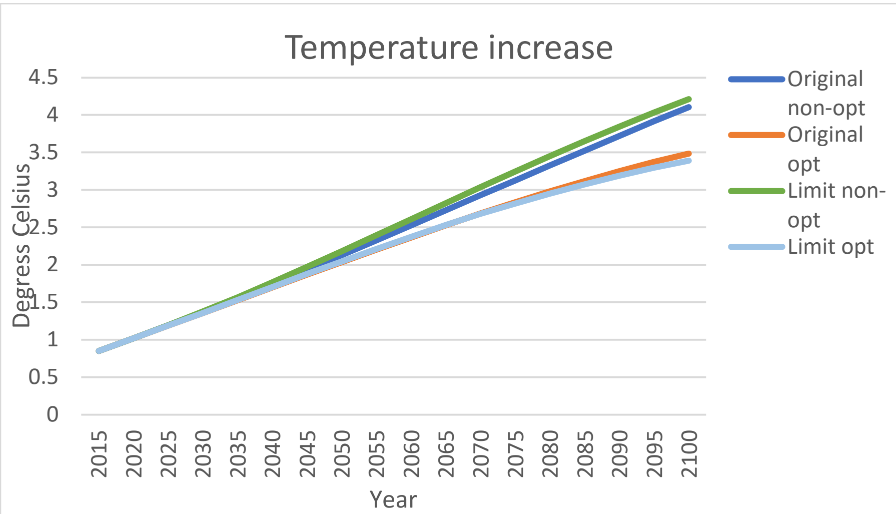

Figure 7.10 Temperature increase in degrees Celsius after the implementation of a limit

7.4 Faster decline of technological progress.

We now approach the issue of a technological slowdown from another angle. This time the value for θ, the decline rate of productivity growth is adjusted. This simulates the idea that technological progress is decreasing at a faster pace.

The main effect this has on TFP is that it increases at a slower rate. The decline in TFP does not have a big enough effect to completely negate TFP growth. It will continue to grow throughout the entire period of time. As seen in Table 12.3, the value for TFP in 2050 is close to that of the original while the value for 2100 differs a lot. This indicates that TFP increasingly diverges after 2050.

Output net of damages and abatement is almost the same as in Limit Opt (Table 7.4). Discounted consumption per capita however, was almost $125,000 lower in the Decline scenario (Table 12.5). Compared to Original Opt, discounted consumption per capita in Decline Opt was only $103,000 lower (Table 12.5) while the difference in output was far larger.

Table 7-4

Results for scenario 'Decline' where the decline rate of technological growth θ was increased

Variable	Sum 2015-2100		2050		2100	
	Non-opt	Opt	Non-opt	Opt	Non-opt	Opt
Industrial emissions (GT CO2)	960.1	529.2	57.4	36.0	56.0	11.8
Output net of damages and abatement (trillions of 2010 USD)	6052.4	6073.8	281.2	281.2	599.5	605.4
Abatement (trillions of 2010 USD)	0.2	32.5	0.004	0.9	0.02	5.1

Abatement efforts show that Decline Opt closely follows the trajectory of Original Opt for 50 years after which they diverge. The difference in 2050 was around 0.1 trillion while it was 2 trillion in 2100 (Figure 7.12). Doubling the decline rate of technological growth seems to have a minor influence on abatement efforts for the first 6 decades.

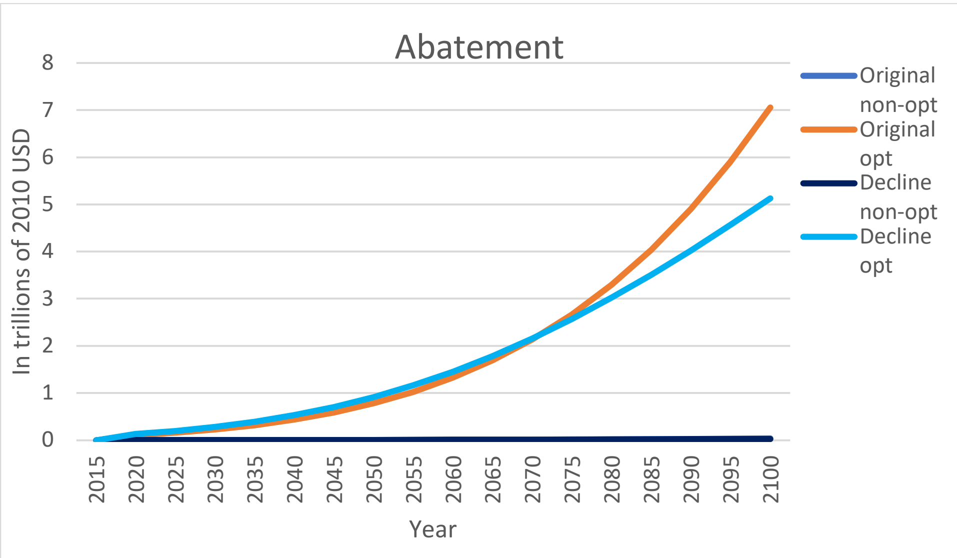

Figure 7.11 Annual costs of emission abatement under a higher value of θ

Following up on this, the carbon price for this scenario is slightly higher than in Original for most of the time given that its mean value is around $6 higher. The 2100 value for Decline Opt is around $14 lower indicating that carbon prices in Original Opt overtake those of Decline Opt toward the end of the period (Figure 7.12, Table 12.1).

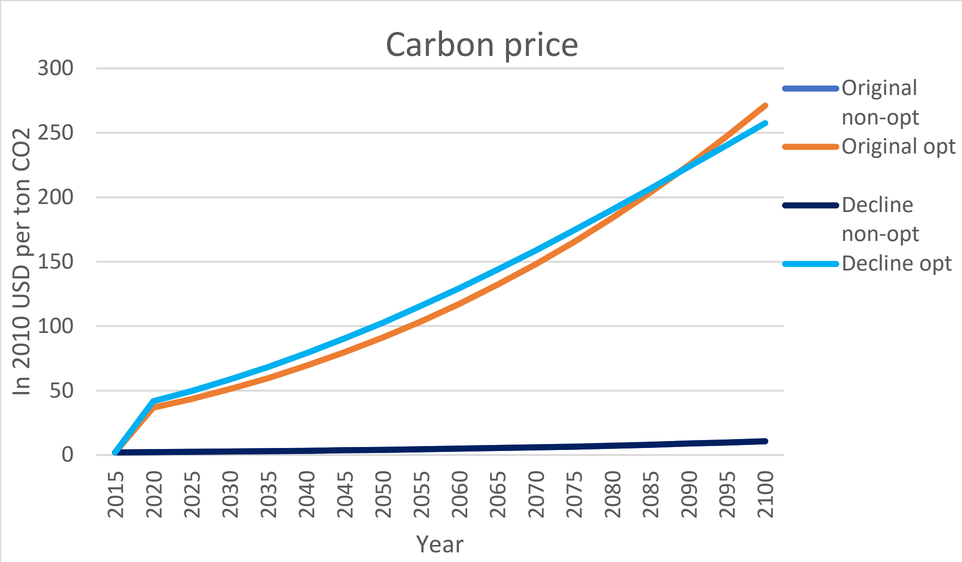

Figure 7.12 Carbon prices in 2010 USD per ton CO2 under a higher value of θ

The fraction of controlled emissions in these scenarios follows roughly the same development as the carbon prices. The emission control rate is higher in the first years but the base model eventually catches up. The emissions control rate follows the Original Opt scenario closely as it takes Decline Opt only 5 more years to reach 100% control (Table 12.4).

Finally, the temperature increase was lower than the baseline but not by much. The temperature increase in 2100 in Decline Opt was 3.39℃, which is 17.39% lower compared to Original Non-opt and 2.26 percentage points lower than Original Opt. Decline Non-opt was 2.24% lower than Original Non-opt (Table 12.2).

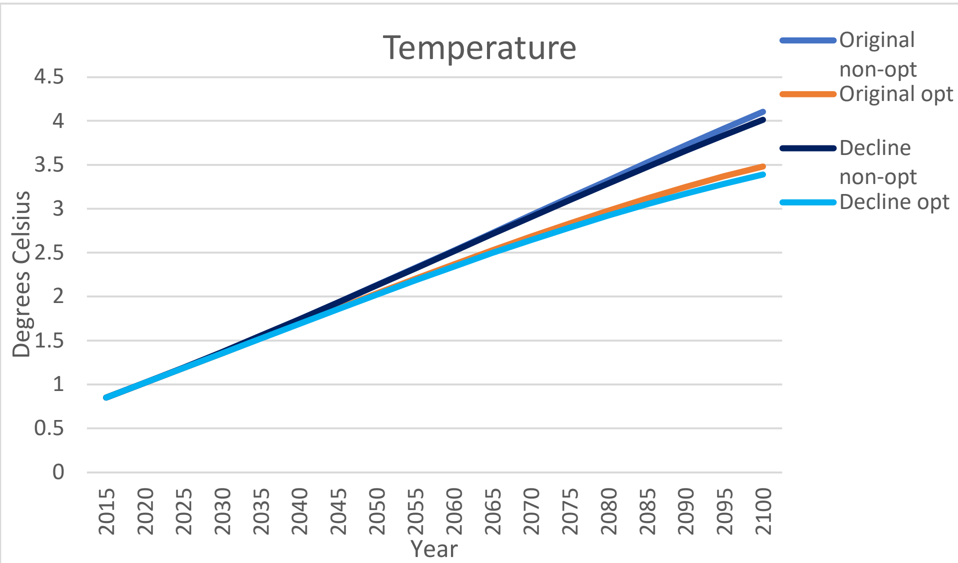

Figure 7.13 Temperature increase in degrees Celsius under a higher value of θ

8 Sensitivity analysis

The scenarios in chapter 6 each introduced a change to the model. Value adjustments were based on the most recent growth statistics. This chapter takes a closer look at the effects of alternative values for these scenarios. Section 8.1 introduces the alternatives for each scenario and 8.2 will discuss their impact on the scenario outcomes.

8.1 Scenario changes

Apart from scenario 1 which was the original model, each scenario will be discussed again with different values for the parameter in question.

8.1.1 Lower potential for technological change

The original scenario assumed a starting growth G_t of 1% per year which came down to 5.1% per model period. Recent growth statistics show that this 1% is a rather positive estimate given that we have seen almost 2 decades of TFP growth fluctuating between -0.5% and 1% (The Conference Board, 2019). I now change the value for G_t to 1% per period, which comes down to approximately 0.2% growth per year and -0.5% per period, which is approximately -0.1% per year.

8.1.2 A limit to the economy

The previous choice for the limit to the economy was based on the year suggested by Meadows et al. (1972), which was used to extract an upper limit from the original model. This time, I set the limit to the economy as the starting value multiplied by a certain factor. The factors to be tried are two, five and ten resulting in a maximum TFP level of 10.23, 25.575 and 51.15, respectively. These will be indicated as X2, X5 and X10 in following sections.

8.1.3 Faster decline of technological progress

The original decline of TFP growth θ, had a value of 0.5% per model period which is approximately 0.1% per year. As TFP growth shows large fluctuations in real-world statistics, it is difficult to estimate a value for a model like DICE, where it decreases at a constant rate throughout time. Chapter 7 covered an annual decrease of 0.2% and here I will look at an annual decline rate of 0.4%.

8.2 Results

8.2.1 Lower potential for technological change

Section 7.2 introduced the assumption that the variable differences in the short- and long-term increase when technological growth decreases. The results from the sensitivity analysis confirm that this is indeed true when technological growth changes as a result of different values for G_t.

At the end of the period, society controls more than 30% less emissions than in the Potential Opt scenario. Abatement efforts suffer an even larger decrease in both the optimized and non-optimized runs. With the exception of the emissions control rate and carbon price in the Non-opt model, each variable in the -0.005 scenario shows lower values than the 0.01004 variation (Table 8.1).

Table 8-1

Results for 'Potential' variations with 0.01004 and -0.005 growth potential.

Variable	Growth potential G_t	2100 value		% difference to original Potential scenario	
		Non-opt	Opt	Non-opt	Opt
Emissions control rate (fraction controlled)	0.01004	0.11	0.46	/	-31.34%
	-0.005	0.11	0.44	/	-34.32%
Abatement (trillions of 2010 USD)	0.01004	0.01	0.42	-54.54%	-82.35%
	-0.005	0.007	0.23	-68.18%	-90.33%
Industrial emissions (GT CO2)	0.01004	19.75	11.82	-54.34%	-26.58%
	-0.005	14.92	9.86	-65.51%	-38.75%
Carbon price (2010 USD)	0.01004	10.76	106.74	/	-43.48%
	-0.005	10.76	87.20	/	-53.83%
Temperature (℃)	0.01004	3.41	3.07	-10.12%	-7.55%
	-0.005	3.30	3.00	-13.02%	-9.66%
Consumption per capita	0.01004	14.44	14.50	-54.51%	-54.53%
	-0.005	10.88	10.93	-65.73%	-65.72%
Discounted sum consumption per capita (2015-2100) in thousands of 2010 USD	0.01004	614.75	614.18	-30.84%	-30.85%
	-0.005	545.52	544.91	-38.63%	-38.64%

Note: The percentage difference shows the difference of Non-opt compared to Non-opt and Opt compared to Opt. The variations are compared with the Potential scenario from chapter 7, not with the Original scenario.

In chapter 7, the results showed that after several years, Original Opt will overtake Potential Opt when it comes to abatement, carbon taxes and emission control rates. Lowering the value for G_t exacerbates the short- and long-term differences but it does nothing about the moment where one model overtakes the other. It appears to be the case that no matter the value for G_t, the point in time where they intersect with each other and Original Opt is the same (Figure 8.1). This seems to happen for carbon price and the emissions control rate in the same year/period (2045/7). It happens earlier for abatement.

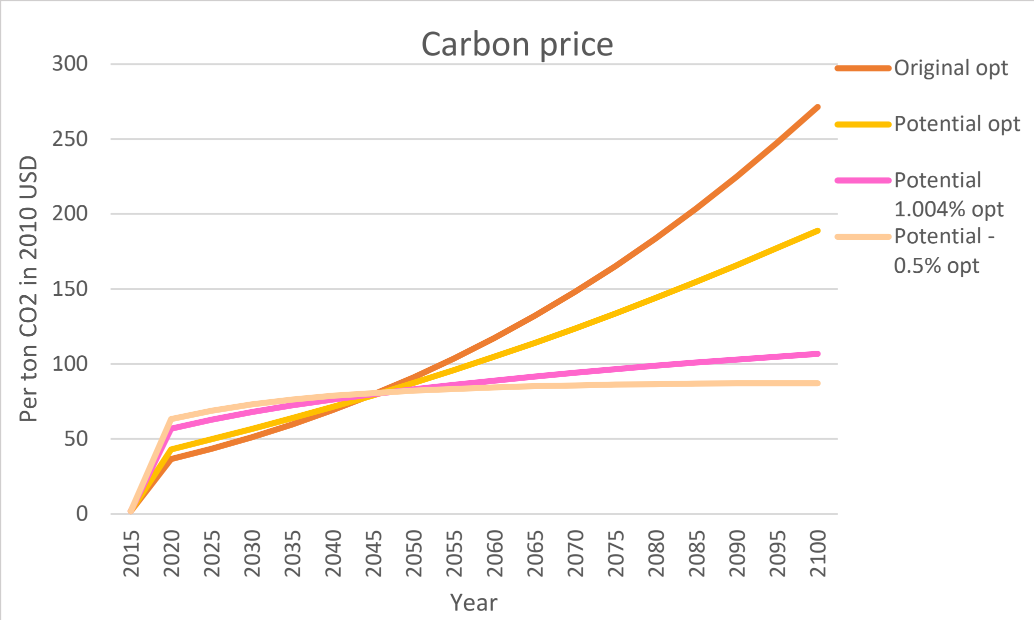

Figure 8.1 Carbon price in 2010 USD per ton CO2 over time in the model variations with lower technological potential

Adjusting these carbon prices for inflation would results in optimal carbon prices of $52.0, $68.6 and $76.2 in 2020 for the Potential variations 5.1%, 1.004% and -0.5% respectively. Converting these values to euros results in carbon prices of €43.7, €57.6 and €64.1 respectively.

Changing the value for growth potential had immediate effects on every part of the model. Emissions are far lower resulting in lower damages and lower temperature increases. The massive long-term decreases in abatement and the slower long-term increase of emissions control are also caused by this.

In the optimized runs, the difference between 1.004% and -0.5% growth in temperature is only 0.07°C but the -0.5% variation suffers a loss in discounted consumption per capita of roughly $70,000 (Table 8.1).

8.2.2 A limit to the economy

8.1.2 suggested three different TFP sizes for the sensitivity analysis. Only two are presented in Table 8.2. The X10 variant with a limit of 51.15 was omitted since it resulted in short-term TFP increases that far exceeded even the most positive estimates. This is good to know because it indicates that this specification does not work for high maximum sizes. This variation is not useful for further analysis as the results lie outside the realm of possibilities. The others are still in line with positive estimates of cases with a new breakthrough.

The times five variant is the highest value that is still somewhat justifiable in terms of TFP growth. The resulting growth rate of around 5% per year in the first period has not been seen on a global level but has been seen on industrial levels (Shackleton, 2013).

Table 8-2
Results of 'Limit' variations with X2 and X5 economic limits

Variable	Maximum size of TFP	2100 value		% difference to original Limit scenario	
		Non-opt	Opt	Non-opt	Opt
Emissions control rate (fraction controlled)	X2 (10.230)	0.11	0.59	/	-32.95%
	X5 (25.575)	0.11	1	/	13.25%
Abatement (trillions of 2010 USD)	X2 (10.230)	0.015	1.20	-48.27%	-81.13%
	X5 (25.575)	0.05	16.77	72.41%	163.67%
Industrial emissions (GT CO2)	X2 (10.230)	29.99	13.73	-46.62%	85.29%
	X5 (25.575)	106.46	0	89.46%	-100%
Carbon price (2010 USD)	X2 (10.230)	10.76	155.77	/	-46.92%
	X5 (25.575)	10.76	357.63	/	21.84%
Temperature (℃)	X2 (10.230)	3.62	3.19	-14.07%	-5.87%
	X5 (25.575)	5.01	3.41	18.91%	0.61%
Consumption per capita	X2 (10.230)	21.92	22.02	-46.12%	-46.26%
	X5 (25.575)	76.11	78.02	87.04%	90.38%
Discounted sum consumption per capita (2015-2100) in thousands of 2010 USD	X2 (10.230)	755.53	754.74	-35.96%	-35.85%
	X5 (25.575)	1905.94	1896.70	61.53%	61.20%

Note: The percentage difference shows the difference of Non-opt compared to Non-opt and Opt compared to Opt.

Even though the specification for TFP was different in this scenario, the results are similar to the previous scenario. A lower limit results in lower total abatement and emission control while showing higher values in the first years and a higher limit results in the opposite.

The optimized X2 limit variation sees low economic growth and lower industrial emissions. This variation had less need of rapid abatement which results in emissions in 2100 that are higher than in the Limit Opt case. Implementing a lower limit in this model would lead to a lenient environmental policy with emission levels in 2100 that are still relatively high. In fact, the emissions in the optimized X2 variant are even higher than in Original Opt (Table 7.1, Table 8.2).

The differences in abatement and carbon prices are far less pronounced than they were in chapter 8.2.1. Looking at the carbon price in Figure 8.2 for example, one can barely distinguish the short-term differences between scenario variations. It seems that the impact of different maximum economy sizes truly shows itself in the long term. Adjusting for inflation results in optimal carbon prices in

2020 of \$55.9 for Limit, \$61.0 for the X2 variation and \$50.8 for the X5 variation. Converted to euros, those become €46.9, €51.2 and €42.6.

What is also remarkable is that the intersection between all scenario variations happens very early on. This happens in period 2 somewhere in the years 2020-2025, at least two decades earlier than seen in the Potential variations. Unlike the Potential scenario where all variations intersected Original Opt and each other at the same time, in the Limit scenario all variations intersect with each other at the same time but not with Original Opt.

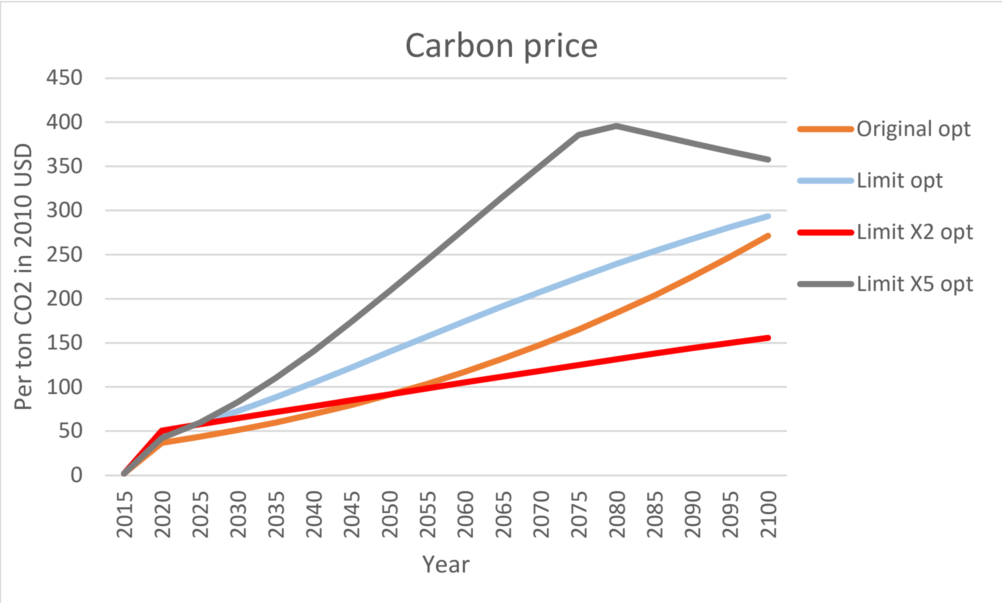

Figure 8.2 Carbon price in 2010 USD per ton CO2 for the X2 and X5 economic limits

Finally, the temperature increase in the optimized X2 variation is 5.87% lower than Limit Opt. Intensive abatement could have further decreased temperatures, but this would be at the expense of the already low utility indicated by consumption per capita. The difference in temperature change in Limit X5 Opt is remarkably low though. This was made possible by far stricter emission control and higher carbon prices (Table 8.2). In 2100, this variation had already completely reached an emissions control rate of 100% for several years.

Assumptions about technological potential are therefore vital for environmental policies in this model. A low limit appears to result in lax environmental policies that allow for emissions throughout the whole period, which leads me to believe that the model possibly understates the impact of sustained CO2 emissions.

8.2.3 Faster decline of technological progress

The scenario Decline in chapter 7 discussed the results from changing the decline of technological progress to 1% per model period. This variation looks at a value of 2.01% per model period.

Aside from the abatement trajectory, each of the previously discussed variables behaved in a similar way under a higher decline rate. TFP declined faster resulting in lower emissions and higher short-term abatement. The percentage of controlled emissions is larger for most of the time but quickly diverges after 2075, eventually ending up almost 10 percentage points lower than in Decline Opt (Table 8.3).

Table 8-3

An overview of important variables for the 2.01% decline scenario variation.

Variable	2100 value		% difference to original scenario Decline	
	Non-opt	Opt	Non-opt	Opt
Emissions control rate (fraction controlled)	0.11	0.73	/	-9.88%
Abatement (trillions of 2010 USD)	0.021	2.82	-27.58%	-44.92%
Industrial emissions (GT CO2)	40.76	12.36	-27.21%	+5.10%
Carbon price (2010 USD)	10.76	217.18	/	-15.71%
Temperature (℃)	3.88	3.08	-3.24%	-9.14%
Consumption per capita	29.63	29.80	-27.60%	-27.47%
Discounted sum of consumption per capita 2015-2100 in thousands of 2010 USD	935.04	933.38	-11.37%	-11.38%

Note: The percentage difference shows the difference of Non-opt compared to Non-opt and Opt compared to Opt.

The results from 8.2.1 and 8.2.2 showed how the development of variables like carbon price, abatement efforts and the emissions control rate under different scenario variations all intersected each other at the same point in time. In the Potential scenario they even intersected with the Original scenario while in the Limit scenario, the different variations intersected with Original at different points. Take carbon prices as an example, it can be seen that Decline Opt and the optimized 2.01% variation intersect with Original Opt at different points in time (Figure 8.3). When adjusting the decline rate of technological growth, higher values result in more intense but shorter-lived abatement efforts. Adjusted for inflation, the optimal carbon price in 2020 would be $50.27 for Decline and $58.6 for the 2.01% variation. Converted to euros, these prices are €42.2 and €49.2.

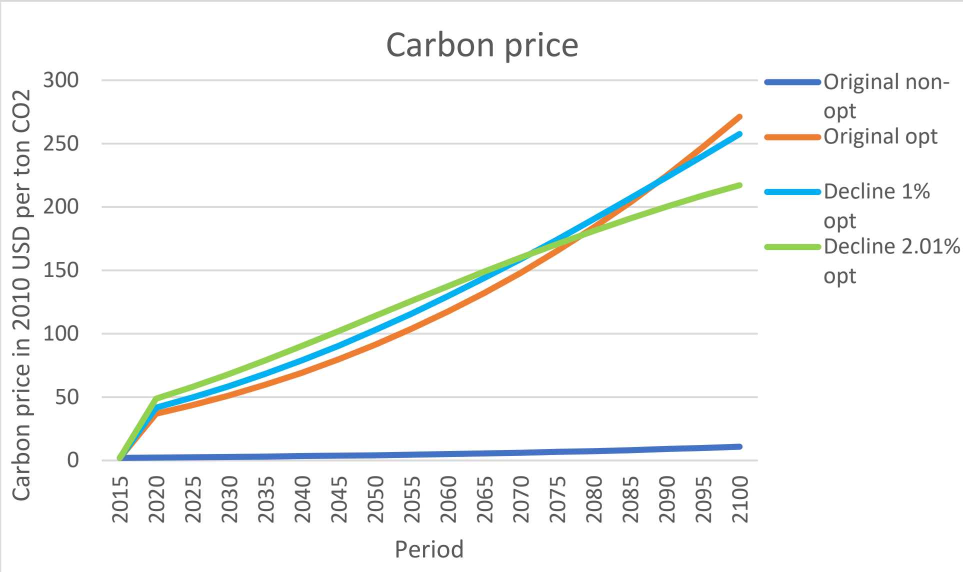

Figure 8.3 Carbon price in 2010 USD per ton CO2 for the Decline variations with 1.01% and 2.01% decline

The rate at which emissions must be controlled also follows a more gradual increase, taking almost four decades longer to reach 100% control and another four decades to reach the limits of carbon capture possibilities. The result of this leniency is that compared to Decline Opt, the industrial emissions in this variation are slightly higher in 2100 (Table 8.3). In fact, comparing it to the Original Opt value of 12.74, industrial emissions are only slightly lower.

The temperature increase in this variation is roughly 9% lower than in Decline Opt. The accompanying decrease in consumption per capita was about 12% (Table 8.3).

Depending on the assumptions on the pace of technological decline, we could experience fast increases in carbon prices, abatement efforts and emission control rates only to end up with a level of emissions that is almost the same as in the case of sustained technological progress in the Original scenario.

9 Discussion

Environmental policy is as much a scientific issue as a political issue. Models that form the backbone of such policies differ fundamentally from each other and at times, so do their results. Well-known climate-economy models seem to overstate the effects of technological progress as a result of outdated parameter values and model specifications. A less optimistic specification of technological progress in climate-economy models will emphasize the need to take quicker and stronger action to tackle climate issues.

In this thesis, I looked into the determinants of a technological slowdown, modelling approaches in other relevant models and investigated several scenarios in the well-known DICE model. Due to the vast number of influences and the complexity of measuring technological progress, it is still inconclusive whether technological progress or the benefits of technology are declining. Numerous models attempt to model technology 'correctly' with differing degrees of success although there is a clear consensus on the need for endogenous specifications. The different scenarios are in line with each other, and all indicate that compared to the baseline, the optimal environmental policy under lower technological progress should be more intense in the coming years. This means higher abatement costs, higher carbon prices and a higher rate of control for the coming decades. When the decline of technological progress or the limit of the economy surpassed an unknown lower boundary, the model proposed to keep emissions at a higher level than the original model indicating that the damage function might understate the impact of sustained emissions. An interesting finding is that the suggested carbon prices are all higher than the current EU carbon price of roughly €40 but that the complete control of emissions occurs after 2100 as opposed to the EU goal of net-zero emissions by 2050.

As many models receive frequent updates, the research on earlier models does not necessarily lead to the same results when applied to the most recent model versions. Some conclusions seem to be valid even now. Rezai (2010) finds that DICE has fundamental flaws that lead to the postponement of abatement efforts. The results from his adapted model suggest that immediate changes in policy are necessary to intensify abatement efforts. His conclusion is in line with the results of this thesis as they state that short-term abatement efforts should be more intense. There is a difference in intensity as his model recommends carbon prices of almost $200 in the first years. This difference is likely caused by his alternative damage function where emissions directly contribute to damages, requiring higher carbon prices to offset the larger impacts of emissions.

Jensen and Traeger (2014) look at the impacts of growth uncertainty and risk uncertainty. They find that growth uncertainty results in higher optimal carbon taxes than in the base deterministic DICE model. Higher risk aversion in their adjusted model could lead to an increase in the optimal carbon tax of 20-45%. While introducing uncertainty to the model is not the same as lowering technological growth, the results of this thesis can still be considered to be in line with the results of Jensen and Traeger, as both indicate higher carbon prices under uncertain economic growth.

Aside from the uncertainties around the proper implementation of technology in models, there is also substantial uncertainty when it comes to technological and economic growth. Furceri, Celik, Jalles and Koloskova (2021) find that deep recessions like the current COVID-19 crisis can result in permanent TFP decreases of 3-5% as a result of structural misallocation. This would mean that the values tested in this thesis should be even lower and that optimal short-term abatement should be even more intense.

The results of this research could be of value to existing literature by increasing the number of scenarios. Existing model scenarios in DICE that retain the exogenous specification focus primarily on temperature limits, interest changes and elasticity changes. Only limited attention has been paid to the impact and development of technology under different parameter values and as far as I know, a conceptual limit on technological progress has not been implemented yet. The results of this study therefore add to the literature by showing the impact of both parameter and formula changes. In addition, the results also emphasize the need to take strong and immediate action. Simple value adjustments that coincide with the latest statistics show noticeable increases in carbon price and abatement.

The adjusted formula for the development of TFP is one of the shortcomings of this study as it likely overstates short-term technological growth. The limits set on the size of the economy are based on assumptions and have little real-world evidence supporting them. The formula used will always show higher growth in the first periods which only makes sense in the case of an expected technological breakthrough. Some undocumented model runs included economy sizes far larger than in the discussed scenarios which resulted in unrealistic scenarios with unprecedented economic growth rates. This would suggest that the formula used to introduce a limit can only be used when we assume that the maximum size of the economy is already in sight and far lower than the maximum size predicted in the original DICE model. Even the relatively low limit used in the first Limit scenario results in growth rates that are very optimistic for the first decades. The impact on abatement is therefore likely to be overestimated. The literature was not able to give a conclusive answer on whether technological progress is reaching its final days, making it difficult to give a substantiated estimate for this limit. If we keep R&D investments at an appropriate level, it might be possible to continue pushing the technological frontier and with it, the size of the economy. On the other hand, it might be a better idea to stop expanding the economy and use technological progress as a way of increasing welfare in other ways.

A second point concerns the use of TFP as an indicator for technological progress. The concept itself is highly debated and recently, new indicators for technology have been developed with different results. These could improve the ability to measure productivity or welfare gains from new technologies like the internet. The modelling efforts took neither the TFP debate nor the new indicators into account which is problematic as these issues are highly related to the validity of the sources that discuss TFP and the calculation of TFP itself. The different approaches and datasets used by researchers often point in the same direction but can have clear differences in the magnitude of TFP growth and decline rates. The assumptions I made to determine the values used might be exaggerated. From what we have seen from the literature, the actual TFP growth might be larger than reported in which case the results might be overstated. On the other hand, I did not account for possible permanent TFP decreases as a result of the COVID-19 crisis, meaning that the results might also be understated. As there is no conclusive evidence on whether TFP statistics should be higher or lower, the results of this thesis could both be understatements and overstatements of the true technological progress.

10 Conclusion

In this thesis I investigated the impact of a technological slowdown on the optimal abatement trajectory. I did so by researching the literature to find the determinants of technological change and the different approaches to implementing technology in models. Afterwards, I adjusted the well-known climate-economy model DICE in three different ways to see how lower technology would influence environmental policy.

The ever-shifting knowledge frontier seems to be one of the most important determinants of the current technological slowdown. New innovations require more specialized knowledge and reaching this level of knowledge takes increasingly more time. The shift in innovation efforts to traditionally slow-changing sectors like the energy sector could also play an important role. TFP-based indicators of technological change indicate a decline in research productivity despite increasing R&D. Measuring the true progress of technology is challenging however and results differ between indicators. Indicators based on book sales for example, show a rebound in productivity growth. The known measurement issues surrounding TFP, alternative indicators and high expectations of ICT might be reasons for optimism.

The climate-economy models have mostly switched to completely endogenous or partly endogenous specifications when it comes to technology. Here too, a lot of discussion is present and there is no perfect approach. These endogenous approaches are often based on concepts like R&D investments, learning-by-doing and knowledge spill-overs. They are often combined with other, sometimes exogenous, approaches that have a specific focus on environmental aspects like AEEI parameters and backstop technologies. The focus on environmental technology in the literature means that general technological progress is often neglected. This is problematic as exogenous technological change still exists alongside endogenous technological change in some models. Decreasing technological progress is often represented as decreasing returns to investment or knowledge. Conceptual limits on technological growth are rarely discussed in model specifications.

In each of the three additional scenarios, lower technological growth resulted in increased abatement costs, higher carbon prices and accelerated emission control in the first periods of the model. These effects were most pronounced when an economic limit was implemented and when the decline rate for technological growth was increased. The combination of higher abatement and lower economic growth resulted in temperature increases for the optimized scenarios that were lower than the original model. Of the three scenarios in chapter 7, Potential Opt was the only one that ended up with a higher level of emissions in 2100 compared to Original.

The way in which technological progress was lowered had a noticeable impact on the intensity and duration of abatement efforts. The higher carbon prices and abatement seen in the sensitivity analysis for the scenario Potential only lasted a few decades and ended at the same time for each variation. The Decline scenario showed longer periods of high intensity but here, a stronger decline also meant a shorter period with higher abatement efforts. The Limit scenario showed even stronger long-term variations in abatement intensity. The sensitivity analysis also showed that emission levels could end up being higher than in the original model under a low economic limit. The Decline variation ended up with emissions only just below the original model. These results stress the need for intense short-term abatement in the event that technological progress is reaching a limit and its effects on economic growth are decreasing.

Future research could investigate existing models with endogenous technological change and see how these react to a technological slowdown or the implementation of an upper limit on technological progress. This could be done by performing sensitivity analyses where the returns to research or learning rates are lowered. It would also be interesting to see how recent changes affect the dynamics of concepts like the learning-by-doing approach. Does the increasing complexity of new technology decrease the learning rate or is this obstacle negated by the lower number of new technologies, more intense use of new technologies, better education or our improving ability to make good user interfaces? Finally, it would be interesting to compare the existing variations of DICE and see how they react to similar changes in technological growth assumptions.

Based on the results of this research, postponing abatement to wait for expected advances in carbon capture technologies is ill-advised. Lower technological progress leads to more intense abatement efforts and the intensity depends on our assumptions about the severity of the technological slowdown. Abatement will depend on financial incentives for some time to come, meaning that carbon prices will play a vital role. Based on the current EU carbon price of roughly €40.0 per ton, an immediate increase in carbon prices of at least €10 and preferably €20 per ton should be the priority.

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12 Appendix

Appendix A

An overview of technology use in climate-economy models

Abbreviations: CGE, computational general equilibrium; ES, energy system model; IAM, integrated assessment model; ME, macro econometric model; CF, cost-function model; AEEI, autonomous energy efficiency improvement; LBD, learning-by-doing; PIEEI, price induced energy efficiency improvement; TS, technology snapshot model; EX, exogenous technology; PR, price-induced; DTC, directed technological change;

Model	Type	Representation of TC	Reference
DEMETER	IAM	LBD	(Gerlagh, 2008)
DGEM	CGE	EX, Factor price bias	(Jorgenson & Wilcoxen, 1993)
DICE/RICE	IAM	AEEI, EX, Backstop	(Nordhaus, 2020; Nordhaus, 1992)
E3ME	ME	R&D	(Barker & Köhler, 1998)
ENTICE	IAM	R&D	(Popp, 2004)
ENTICE-BR	IAM	R&D, Spill-overs, Backstop, EX	(Popp, 2006)
ETC-RICE	CGE	R&D, Spill-overs	(Buonanno, Carraro, & Galeotti, 2003)
FUND	IAM	AEEI, TS	(Tol, 1999)
G-CUBED	CGE	EX	(McKibbin & Wilcoxen, 1993)
GEM-E3	CGE	AEEI, EX	(Capros et al., 1997)
GOULDER	CGE	R&D, Spill-overs	(Goulder & Schneider, 1999)
GOULDER2	ME	LBD, R&D, Spill-overs	(Goulder & Mathai, 2000)
GREEN	CGE	AEEI, EX, vintages	(Burniaux, Martin, Nicoletti, & Martins, 1991)
GTEM	CGE	PR	(Jakeman, Hanslow, Hinchy, Fisher, & Woffenden, 2004)
HEGGERDAL	CGE	R&D, DTC	(Heggedal & Jacobsen, 2011)
ICAM3	IAM	LBD, PR	(Dowlatabadi, 1998)
IMAGE	IAM	R&D, PIEEI	(Alcamo, Leemans, & Kreileman, 1998)
MACRO	CGE/IAM	EX	(Manne & Richels, 1992)
MARKAL	ES	LBD, TS	(Barreto & Kypreos, 1999)
MARKAL-(MACRO)	ES	LBD	(Loulou, Goldstein, & Noble, 2004)
MERGE2004	CGE/IAM	AEEI, LDB, Backstop	(Manne & Richels, 2004)
MERGE2008	IAM	AEEI, PIEEI	(Richels & Blanford, 2008)
MESSAGE	ES	LBD, TS	(Grübler & Messner, 1998)
MESSAGE-MACRO	LBD	LBD	(Messner & Schrattenholzer, 2000)
MIND	IAM		(Edenhofer, Bauer, & Kriegler, 2005)
MIT-EPPA	CGE	AEEI, Backstop	(Jacoby, Reilly, McFarland, & Paltsev, 2006)
NEMS	ES	EX, PR, LBD	(Energy Information Administration, 2003)
OTTO2008	CGE	DTC	(Otto, Löschel, & Reilly, 2008)
PACE	CGE	AEEI, Backstop	(Böhringer, 1998)
PAGE2002	IAM	AEEI, LBD	(Alberth & Hope, 2007)
PIZER	CGE/IAM	EX	(Pizer, 1999)
POLES	ES	LBD	(Kouvaritakis, Soria, & Isoard, 2000)
PRIMES	ES	LBD	(Capros & Mantzos, 2000)
R&DICE	IAM	R&D, Spill-overs	(Nordhaus, 2002)
SGM	CGE	EX	(MacCracken, Edmonds, Kim, & Sands, 1999)
SMULDERS	CGE	R&D	(Smulders & de Nooij, 2003)
Sue Wing-EPPA	CGE	R&D	(Sue Wing, 2001)
TIMES	ES	LBD	(Loulou, Remme, Kanudia, Lehtila, & Goldstein, 2005)
WARM	ME	R&D, Capital stock	(Carraro & Galeotti, 1997)

WITCH2009	CGE/IAM	R&D, Backstop	(Bosetti, Carraro, Massetti, Sgobbi, & Tavoni, 2009)
WITCH2011	CGE/IAM	R&D, Backstop	(Bosetti, Carraro, Duval, & Tavoni, 2011)

Note: Adapted from '*Modeling endogenous technological change for climate policy analysis' by Gillingham, K., Newell, R. G., & Pizer, W. A. (2008).* Energy Economics, 30*(6), 2734-2753.; 'Technological change in economic models of environmental policy: a survey.' by Löschel, A. (2002).* Ecological Economics, 43*(2), 105-126.; 'Modeling Technological Change in Economic Models of Climate Change: A Survey.' by Löschel, A., & Schymura, M. (2013).* Encyclopedia of Energy, Natural Resource, and Environmental Economics*.*

Appendix B

Overview tables of important variables for chapter 7

Table 12-1

Carbon prices per ton CO2 in 2010 USD

Scenario	Mean 2015-2100		2100	
	Non-opt	Opt	Non-opt	Opt
Original	5.3	123.9	10.8	271.3
Potential	5.3	103.1	10.8	188.9
Limit	5.3	162.5	10.8	293.5
Decline	5.3	129.5	10.8	257.7

Table 12-2

The temperature increase in degrees Celsius since 1990 and the percentage difference to the baseline

Scenario	2100		% difference to baseline	
	Non-opt	Opt	Non-opt	Opt
Original	4.10	3.48	/	-15.13%
Potential	3.79	3.32	-7.55%	-19.07%
Limit	4.21	3.38	+2.65%	-17.42%
Decline	4.01	3.39	-2.24%	-17.39%

Table 12-3

Total Factor Productivity in trillions of 2010 USD

Variable	Sum 205-2100	2050	2100
Original	175.16	8.53	15.38
Potential	139.38	7.18	10.62
Limit	172.28	9.35	12.55
Decline	160.74	8.22	12.76

Note: No distinction is made between optimized and non-optimized as the values are the same for both

Table 12-4

Emission control rate

Scenario	2100		Year in which 100% is reached	
	Non-opt	Opt	Non-opt	Opt
Original	0.1	0.8	2240	2115
Potential	0.1	0.7	2240	2140
Limit	0.1	0.9	2240	2120
Decline	0.1	0.8	2240	2120

Table 12-5
Consumption per capita in thousands of 2010 USD

Scenario	2100		% difference to baseline		Discounted sum	
	Non-opt	Opt	Non-opt	Opt	Non-opt	Opt
Original	52.1	52.2	/	0.3%	1152.2	1150.6
Potential	31.8	31.9	-39.0%	-38.7%	889.0	888.2
Limit	40.7	41.0	-21.8%	-21.3%	1179.9	1176.6
Decline	40.9	41.1	-21.4%	-21.1%	1055.1	1053.3