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Economics of Climate Change:

Three Essays on Policy and Technology

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Abbreviations and Symbols

Abbreviations

°C	Degree Celsius
ASIC	Application-specific integrated circuit
BTC	Bitcoin
CCGT	Combined cycle gas turbines
CCS	Carbon capture and storage
CDM	Clean development mechanism
CER	Certified emission reduction
CF	Capacity factor
CFC	Chlorofluorocarbon
CH_4	Methane
CO_2	Carbon dioxide
COP	Conference of the parties
CSCC	Country-level social cost of carbon
CPU	Central processing units
EEG	Renewable Energy Act
ERU	Emission reduction unit
ETS	Emissions trading system
EV	Electric vehicles
FPGA	Field-programmable gate array
g	Gram
GH	Gigahash
GHG	Greenhouse gas
$GtCO_2$	Gigaton carbon dioxide
GWP	Global warming potential
h	Hour
IAM	Integrated assessment model
IPCC	Intergovernmental Panel on Climate Change
J	Joule
JI	Joint implementation
LED	Light-emitting diode
LDC	Load duration curve

MACC	Marginal abatement cost curve
$MtCO_2$	Megaton carbon dioxide
Mtoe	Million tonnes of oil equivalent
N_2O	Nitrous oxide
NDC	Nationally determined contribution
OCGT	Open cycle gas turbines
ppm	Parts per million
PH	Petahash
PUE	Power usage effectiveness
PV	Photovoltaics
R&D	Research and development
RES	Renewable energy sources
s	Second
SCC	Social cost of carbon
t	Metric ton
TWh	Terawatt hour
UNFCCC	United Nations Framework Convention on Climate Change
USD	US dollar
VPN	Virtual private network

Symbols

Essay II:

B_a	Annual carbon emissions budget in year *a*
$C_{i\,a}$	Emission factor of technology *i* in year *a*
$D_{i\,a}$	Loading point of technology *i* in year *a*
$e_{i\,j\,a}$	Produced energy by technology *i*, in hour *j* in year *a*
FC_a	Annualized investment cost in year *a*
$k_{i\,a}$	Resource capacity of technology *i* in year *a*
L_a	Load duration curve in year *a*
L_a^m	Peak load during the year *a*
TC_a	Total system cost in year *a*
VC_a	Variable generation cost in year *a*

Essay III:

C	Carbon emissions
E	Energy consumption
e_{APi}	Energy efficiency of ASIC producer *i*
e_N	Realistic energy efficiency of hardware
e_P	Energy efficiency for zero profit
e_{ef}	Energy efficiency of most efficient hardware
H	Hash rate
I_N	Carbon intensity of power production
i	Mining hardware producer
j	Facility type
k	Region
l	Pool type
M	Market price
P	Power consumption
p_N	Electricity price
P_{BG}	Power consumption (best-guess)
P_{LL}	Power consumption (lower limit)
PUE_N	Losses from cooling and IT equipment
PUE_j	Losses from cooling and IT equipment of facility type *j*
R_B	Block reward
R_T	Transaction fee
R_l	Ratio of pool type within the entire network
P_{UL}	Power consumption (upper limit)
S_{APi}	Share of ASIC producer *i*
S_j	Share of facility type *j*
$S_{k,l}$	Share of pool type *l* in region *k*
S_k	Share of region *k*
t	Time period

1 Introduction

1.1 Background

Section 1.1 provides background information on climate change, climate policy, and clean technology, which are essential in order to locate the three essays of this thesis within the broader debate.

1.1.1 Climate Context: Causes and Impacts of Climate Change

The Earth's climate has always been changing. Our planet has been receiving small variations in the irradiance from the sun, which has caused seven cycles of glacial advancement and retreat since 650,000 BC.[1] Nonetheless, the variation in solar irradiation may explain not more than ten percent of global warming since the beginning of industrialization.[2] Today, there is a consensus among scientists – more than 97% of publishing climate scientists agree – that anthropogenic greenhouse gas (GHG) emissions are causing climate change by trapping heat in the lower atmosphere.[3]

However, greenhouse gases are not inherently bad. Without the greenhouse effect, the Earth would not be able to support such a variety and quantity of life, and the average temperature of the Earth would be at -18 degree Celsius (°C) instead of the actual +15 °C.[4] Besides carbon dioxide (CO_2), which accounts for three-quarters of the anthropogenic GHG effect,[5] gases like methane (CH_4), nitrous oxide (N_2O), and Chlorofluorocarbons (CFCs) trap solar irradiation. Some GHGs like water vapor, which is the largest contributor to the natural greenhouse effect, react to changes in temperature physically or chemically.[6]

[1] See (NASA, 2019a).
[2] See (Lean, 2010).
[3] See (Cook et al., 2016).
[4] See (Ma, 1998).
[5] See (Stern, 2008), p. 1.
[6] Note: The recognition of heat-trapping in the atmosphere goes back to (Fourier, 1827) and (Tyndall, 1861) who measured the heat absorption and radiation properties of several types of gases.

Anthropogenic greenhouse gases are stock pollutants, which remain in the atmosphere for long periods of time and continuously accumulate with reoccurring emissions. At the same time, the warming potential accumulates with rising GHG concentration in the atmosphere.[7] Researchers conclude from ice cores that the CO_2 concentration in the atmosphere was below 300 parts per million (ppm) from approximately 800,000 BC until 1950.[8] Figure 1 displays the cumulative CO_2 concentration in the atmosphere over time. At the time of writing in spring 2019, the atmospheric CO_2 level has reached 410 ppm.[9] Simulations going back to a previous period show that we have already reached unprecedented CO_2 levels in the atmosphere, which the planet has never experienced during the Quaternary.[10]

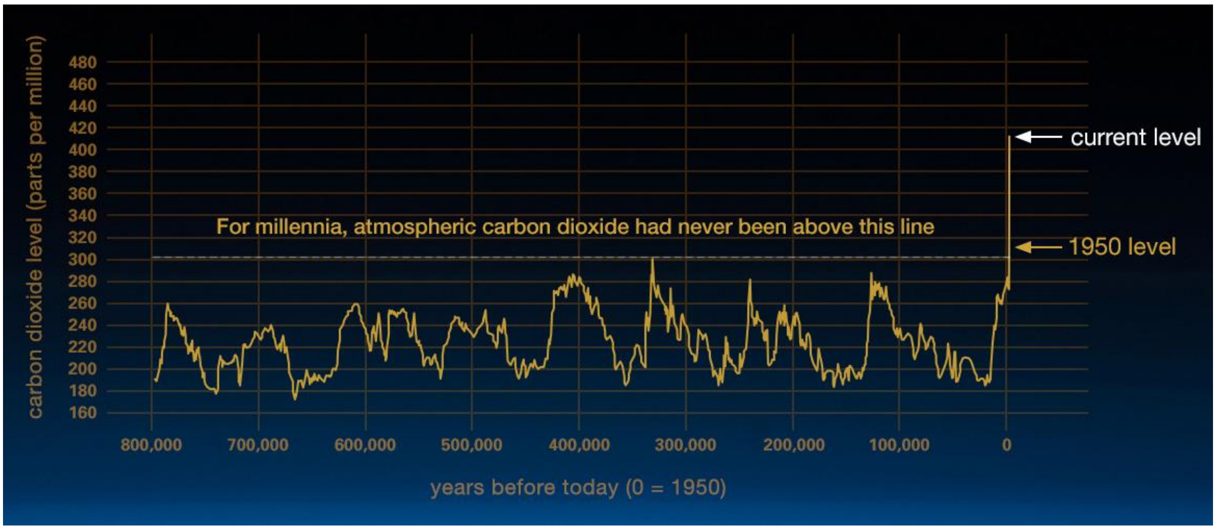

Figure 1: Atmospheric carbon dioxide concentration.[11]

In 2018, the anthropogenic GHG emissions have led the global mean surface temperature to increase by +0.9 °C, when compared to the base period between 1951 and 1980. It is also noteworthy that the land area heats up faster than the sea area. Therefore, the mean surface temperature increase of +0.9 °C signifies a +1.5 °C temperature increase over land and a +0.7 °C temperature increase over sea as depicted in Figure 2.[12] Moreover, anomalies of the mean temperature vary across geographic locations. As depicted in Figure 3, the temperature

[7] Note: The Global Warming Potential (GWP) of different GHGs – usually over 20, 100, and 500 years – is used to compare the warming impact. For instance, CO_2 has a GWP_{100} of 1, and Methane of 17-32; see (Houghton, Bruce, Lee, Callander, & Haites, 1995), p. 226.
[8] See (NASA, 2019a).
[9] See (NOAA, 2019a).
[10] See (Willeit, Ganopolski, Calov, & Brovkin, 2019).
[11] Source: (NASA, 2019a).
[12] See (Hansen, Ruedy, Sato, & Lo, 2010; NASA, 2019b).

anomalies in pole proximity and Eurasia that can be attributed to anthropogenic greenhouse gas emissions frequently reached +2 °C to +4 °C in 2018.

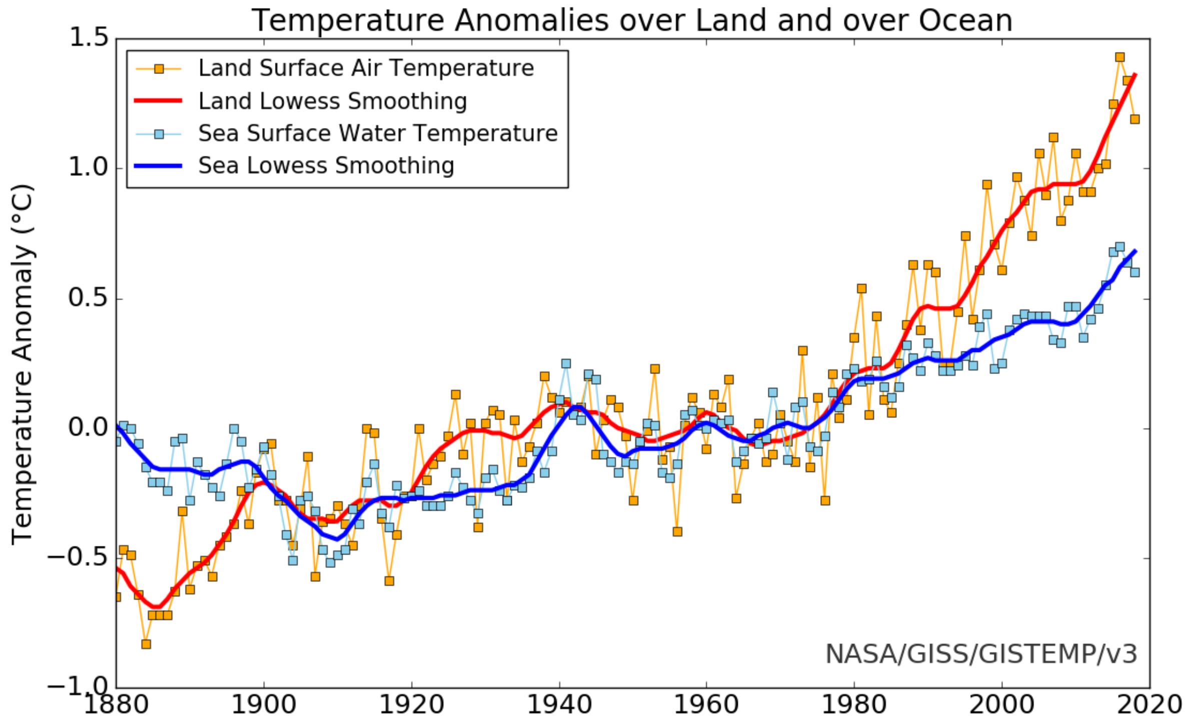

Figure 2: Temperature anomalies on land surface and over ocean – 1880-2018.[13]

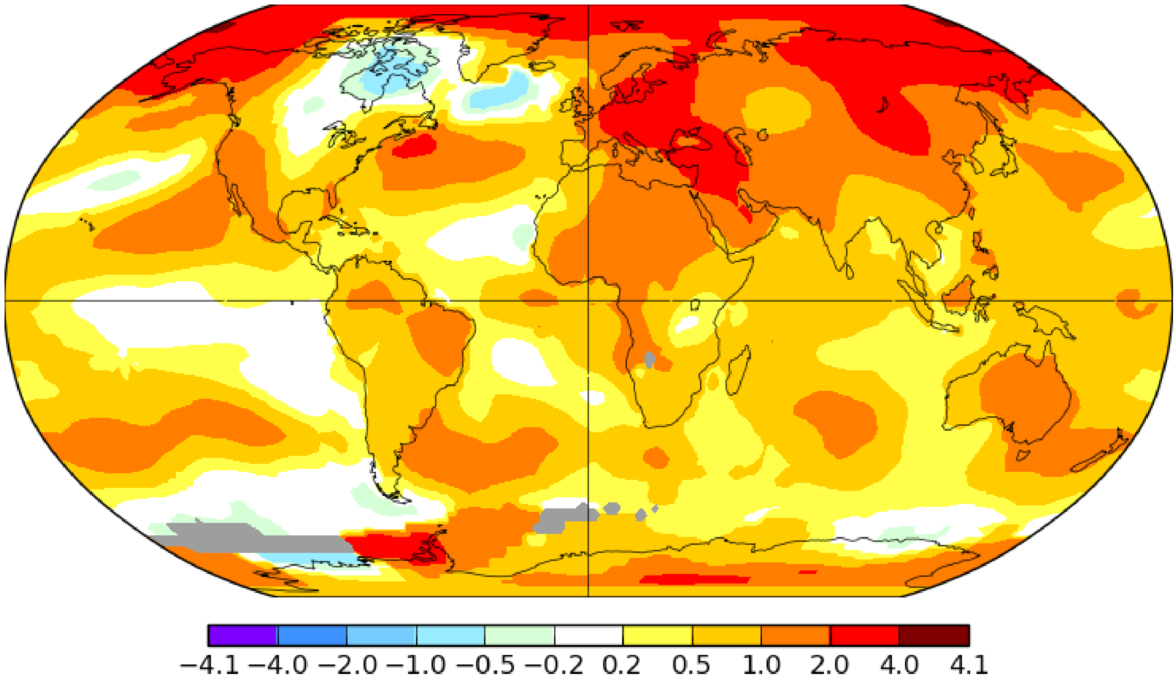

Figure 3: Temperature anomalies vs 1951-80 during meteorological season 2018.[14]

[13] Source: (NASA, 2019b).
[14] Source: (NASA, 2019c).

The increase in temperature impacts our planet in several ways and – from an economic perspective – imposes high costs. This includes unusual and costly weather events, such as hurricanes, which will most likely occur more frequently as temperatures continue to rise.[15] Over the last three decades, the number of significant natural disasters has more than doubled.[16] A further costly consequence of global warming is the rising sea-level due to melting glaciers, as illustrated by the meltdown of the Arctic polar ice cap from 1984 to 2016 in Figure 4.[17] As of October 2018, the melting of polar ice caps increases the sea-level by 3.2 millimeters per year.[18] Although our planet has experienced sea-level amplitudes in a range between -200 meters and +600 meters compared to the current sea-level during the past several hundred million years,[19] already small increases of the sea-level result in high costs as the rising sea-level necessitates relocations and catastrophic events such as floods occur more frequently. Researchers estimate that a sea-level increase of 0.86 meters results in additional annual costs of about $14 trillion.[20]

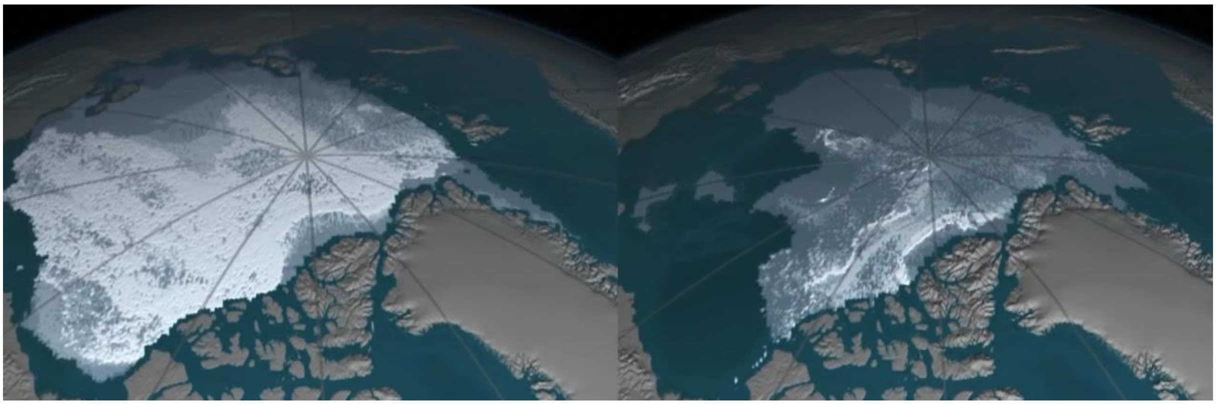

Figure 4: Arctic polar ice cap 1984 (left picture) vs. 2016 (right picture).[21]

2 °C warming is commonly used as the upper limit of temperature increase in order to avoid the worst consequences of climate change. The 2 °C limit was first mentioned by the Nobel economist William Nordhaus,[22] and the reference point of the 2 °C target is the temperature in pre-industrial time, which is commonly defined as the average temperature between 1850 and 1900.[23] More than 2 °C warming increases the probability of events like the disruption

[15] See e.g. U.S. Climate Extremes Index (NOAA, 2019b).
[16] See (Munich RE, 2019).
[17] See (Zemp et al., 2019) for an analysis of glacier mass changes and the impact on the sea-level 1961-2016.
[18] See (NASA, 2019d).
[19] See (Lambeck & Chappell, 2001).
[20] See (Jevrejeva, Jackson, Grinsted, Lincke, & Marzeion, 2018).
[21] Source: (NASA, 2016).
[22] See (William D Nordhaus, 1977).
[23] See (IPCC, 2018), p. 6.

of the Atlantic thermohaline circulation, or it may increase the amplitude of the El Niño/Southern Oscillation.[24] The Atlantic thermohaline circulation is part of the global oceanic circulation, and a disruption could weaken other circulations, such as the Gulf Stream. Similar, the El Niño/Southern Oscillation refers to a circulation system between the ocean and the atmosphere in the tropical Pacific region. The amplitude of the phenomenon fluctuates on a yearly basis and causes either cold (La Niña) or warm (El Niño) climate conditions in the wider region. Depending on the amplitude, the phenomenon can cause extreme weather events such as catastrophic floods and droughts.[25]

To maintain a 50% chance to stay below 2 °C global warming, the CO_2 concentration in the atmosphere must not exceed 450 ppm.[26] If emissions stay at the current level, we will reach this threshold within 17 years,[27] and the timeframe might even be shorter as air pollution currently offsets the greenhouse effect by reflecting sunlight. The pollution umbrella, which consists of aerosol particles, blocks 0.5 °C of surface warming today, but aerosol particles likely diminish once decarbonization attempts gain momentum and combustion processes recede.[28]

In order to stay on the politically agreed pathway of ideally below 1.5 °C warming,[29] carbon neutrality by 2050 and negative emissions afterwards are essential.[30] Figure 5 charts pathways of future carbon emissions that comply with the 1.5 °C target. Thereby, emissions have to peak and start declining within this decade to avoid scenarios with temperature overshoot, which requires more carbon removal from the atmosphere at a later point in time.[31] Figure 5 further charts the rise in annual global CO_2 emissions from 1960 to 2018 to illustrate the historical development. Global emissions are projected to reach 37.1 billion metric tons of carbon dioxide ($GtCO_2$) in 2018 up from below 10 $GtCO_2$ sixty years ago.[32]

[24] See (Lenton et al., 2008).
[25] See (Cai et al., 2015).
[26] See (Stern, 2007).
[27] Note: Threshold of 450 ppm and probability according to (Stern, 2007); calculation based on a concentration of 410 ppm (as of May 2019) and annual emissions of 2.48 ppm in 2018, see (NOAA, 2019a).
[28] See (Samset, 2018; Wigley, 1991); for co-benefits of cleaner air see (Rao et al., 2016).
[29] See (UNFCCC, 2015a).
[30] See (IPCC, 2018).
[31] Note: The potential CO_2 removal through natural/biomass processes appears insufficient to remove accumulated CO_2 from the atmosphere at scale. Therefore, technology to directly capture carbon from the air may be an alternative/additional option; see (National Academies of Sciences & Medicine, 2018); for geoengineering approaches, see Chapter 5.
[32] See (Global Carbon Project, 2018).

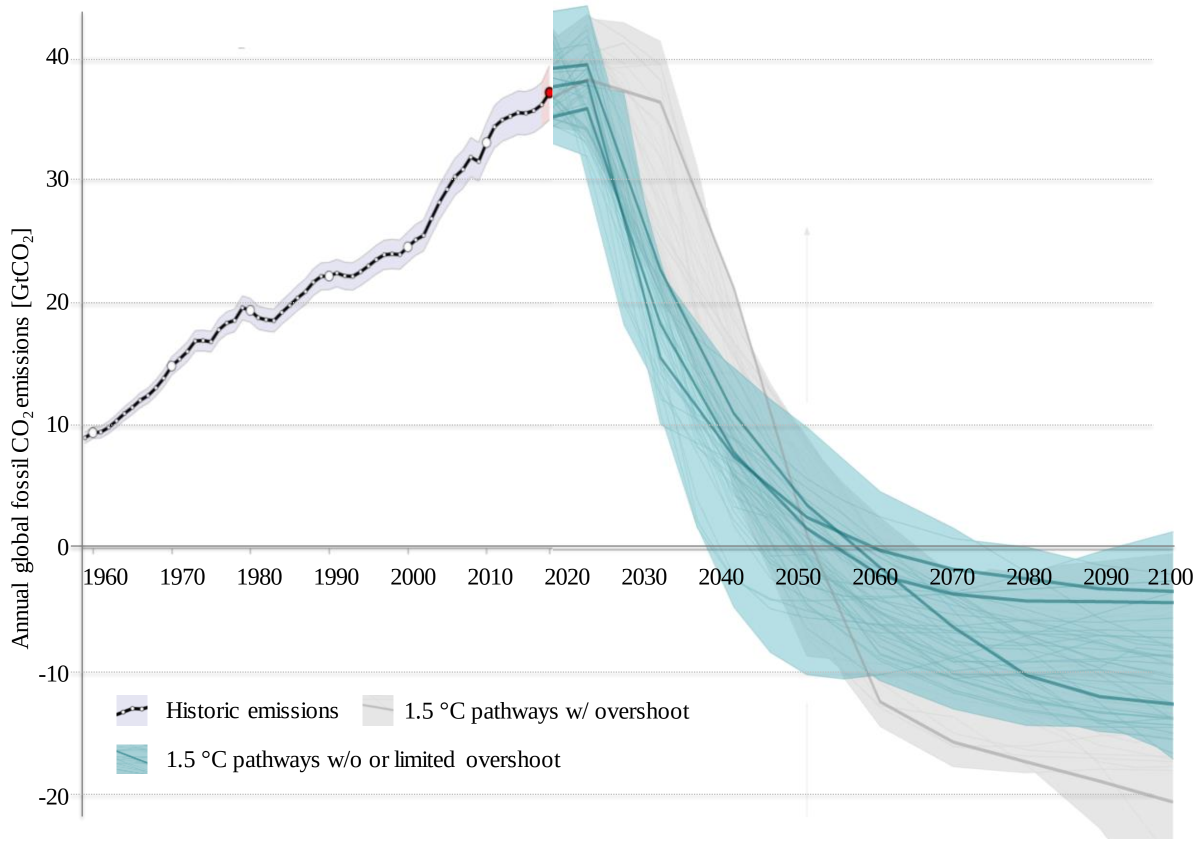

Figure 5: Historic CO_2 emissions and required emissions under 1.5 °C warming scenarios.[33]

1.1.2 Policy Context: Climate Protection on the International Level

Substantial policy interventions are widely considered crucial in order to limit global warming. In 1988, NASA scientist James E. Hansen brought global warming to the political world.[34] By claiming in front of the U.S.-Senate that the atmosphere was heating up with 99% certainty due to anthropogenic carbon emissions, Hansen made the 'greenhouse effect' a common term.[35] Three decades later, the political challenge remains as emissions continue to rise.

In 1992, in response to climate change, negotiations started on an international level with the adoption of the United Nations Framework Convention on Climate Change (UNFCCC).[36]

[33] Source: Own illustration. Historic emission chart from (Global Carbon Project, 2018); 1.5 °C warming scenarios from (IPCC, 2018).
[34] See (Hansen et al., 1988).
[35] See (The New York Times, 1988).
[36] See (UNFCCC, 1992).

Since 1995, the Conference of the Parties (COP) has been established as an annual negotiation and decision-making forum. In 1997, at the third Conference of the Parties (COP3), the first major agreement was adopted with the Kyoto Protocol, which committed participating countries to emission reduction targets.[37] The Kyoto Protocol offered market-based mechanisms complementary to national measures, in order to achieve the targets in a cost-effective way. These market-based mechanisms included international emission trading[38], the Clean Development Mechanism (CDM)[39], and Joint Implementation (JI)[40].

One of the more recent milestones in international climate negotiations was the adoption of the Paris Agreement in 2015. At COP21, the parties agreed to take actions to limit global warming well below 2 °C; ideally below 1.5 °C. Unlike the top-down targets under the Kyoto Protocol, all parties to the Paris Agreement have to announce Nationally Determined Contributions (NDCs) in five-year intervals.[41]

As mentioned in the previous section, most scenarios to stay on the 1.5 °C warming pathway require not only emissions to peak within the next decade but also carbon neutrality by 2050. Figure 6 illustrates the compatibility of current NDCs with the 1.5 °C warming target globally. The displayed tracking method uses the national fair share efforts, which are required in order to achieve the 1.5 °C temperature goal on the international level as agreed in the Paris Agreement, and compares it to the current ambitions on the country level. As of April 2019, only Morocco and Gambia pledged contributions compatible with the 1.5 °C Paris target, while the ambitions of countries like the U.S. and Russia fell short.[42] Although the ambitions of several countries such as India and the Philippines were in line with a 2 °C warming pathway, the ambitions of most countries were either insufficient or highly insufficient in order to limit global warming below the politically agreed threshold.

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[37] See (UNFCCC, 1998).

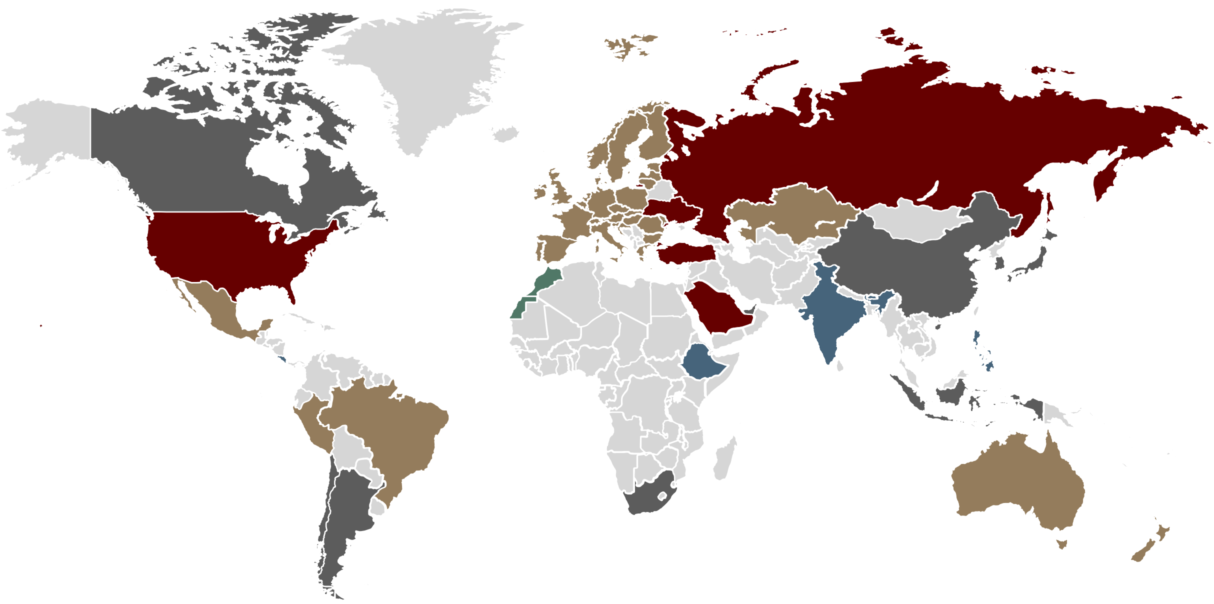
[38] Countries with emission-reduction/-limitation targets (Annex B Parties), which overachieve their emission reduction target can sell the excess emission capacity to other Annex B Parties; see (UNFCCC, 1998), Article 17.

[39] The CDM allows countries with emission-reduction/-limitation targets (Annex B Parties) to invest in emission-reduction projects in developing countries. These projects earn saleable certified emission reduction (CER) credits, which can be used to meet Kyoto targets in Annex B countries; see (UNFCCC, 1998), Article 12.

[40] The JI allows countries with emission-reduction/-limitation targets (Annex B Parties) to invest in emission-reduction projects in Annex B countries. These projects earn emission reduction units (ERUs), which can be used to meet Kyoto targets in the country of the investor; see (UNFCCC, 1998), Article 6.

[41] See COP21 Paris Agreement (UNFCCC, 2015a), Article 4.

[42] See (Climate Action Tracker, 2019).



Critically Insufficient (pathway with > 4 °C)	Highly Insufficient (pathway with < 4 °C)	Insufficient (pathway with < 3 °C)	2 °C Compatible (pathway with < 2 °C)	1.5 °C Compatible (pathway with < 1.5 °C)
• Russia	• Argentina	• Australia	• Bhutan	• Morocco
• Saudi Arabia	• Canada	• Brazil	• Costa Rica	• Gambia
• Turkey	• Chile	• EU	• Ethiopia	
• USA	• China	• Kazakhstan	• India	
• Ukraine	• Indonesia	• Mexico	• Philippines	
	• Japan	• New Zealand		
	• Singapore	• Norway		
	• South Africa	• Peru		
	• South Korea	• Switzerland		
	• UAE			

Figure 6: Committed NDC and compatibility with the 1.5 °C target as of April 2019.[43]

1.1.3 Technology Context: Cleaner Energy for a Growing Demand

Technology plays a key role in the climate puzzle. To limit climate change through deep decarbonization, all sectors must undergo a transformation of a radical extent. Currently, in order to decarbonize the energy sector, three low-carbon technologies for power generation appear suitable to be deployed at a sufficiently large scale. These are renewable energy

[43] Own illustration; source: (Climate Action Tracker, 2019).

sources (RES) such as wind and solar photovoltaics (PV), nuclear generation resources, and fossil generation resources with carbon capture and storage (CCS).[44]

Although the public discussions tend to use rhetoric that we must reach a 100% renewable energy supply, a cost-effective solution to decarbonize the energy sector would consist of a combination of clean resources, which are not necessarily categorized as renewable.[45] The cost of RES, such as wind or solar, and storage technologies to handle volatile generation due to natural conditions continue to decline.[46] At the same time, reactor designs of nuclear generation resources progress,[47] while the economic feasibility of CCS remains uncertain.[48]

Beyond power generation resources, a common approach to compare the potential of low-carbon technologies can be found in marginal abatement cost curves (MACCs). MACCs chart technologies and their CO_2 abatement potential, sorted by the technologies' abatement cost per tonne of CO_2.[49] Figure 7 displays such a MACC, which shows how much it will cost to abate a tonne of carbon dioxide in the year 2030. On the left side of the MACC, one can find the technologies with the lowest abatement costs, which are negative in many cases. This means that these technologies may not only reduce emissions but also save costs compared to the alternatives in use. The classic example of technology with negative abatement cost is Light-Emitting Diodes (LEDs) due to individual irrationality, which prevents the switch from inefficient light bulbs to LEDs.[50]

[44] See (Jenkins & Thernstrom, 2017).
[45] See (Sepulveda, Jenkins, de Sisternes, & Lester, 2018).
[46] See (Lazard, 2018a, 2018b).
[47] See (MIT Energy Initiative, 2018).
[48] E.g. €424 million EU funding for six CCS projects during the past decade resulted in four project terminations after the grants ended, one further project was terminated uncompleted, and the remaining project was a non-commercial-sized demonstration plant, see (European Court of Auditors, 2018).
[49] See (Kesicki & Strachan, 2011).
[50] See (Allcott & Taubinsky, 2015).

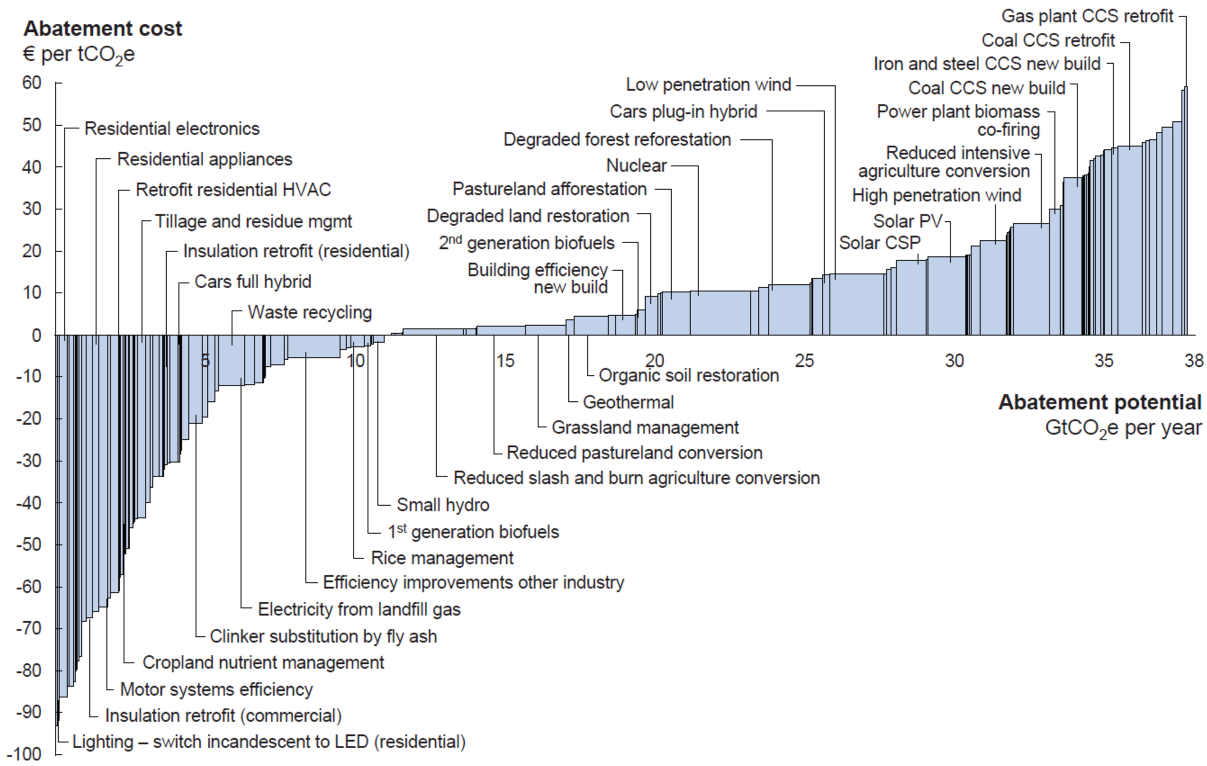


Figure 7: Global GHG abatement cost curve beyond business as usual – 2030.[51]

In order to realize the potential CO_2 abatement, economic theory suggests specific policy tools. These suggestions depend on the characteristics of the low-carbon technology and there are constellations in which single tools outperform in delivering emission reductions. Thereby, three areas within the MACC can be distinguished, and respective theoretical foundations can be found in different fields of economics.[52] First, behavioral economics provides the theoretical foundations of obstacles to energy efficiency, which can be solved with command-and-control policies like standards, bans, or phase-outs (i.e. at the left side of the MACC). Second, neoclassical and welfare economic theory suggests market-based tools, which may realize the potential abatement particularly efficient at the margin (i.e. in the middle of the MACC). For instance, an explicit carbon pricing, through a carbon tax or cap-and-trade mechanism, can trigger fuel-switching in order to decarbonize the power sector. Third, the evolutionary economic toolkit suggests strategic investment to promote technologies, which require large investments and long-term horizons in order to facilitate innovation (i.e. at the right side of the MACC).

[51] Source: (McKinsey, 2013), p. 7.
[52] See (Grubb, Hourcade, & Neuhoff, 2014).

This thesis covers one current topic within each of these three areas within the MACC. In particular, Essay I relates to the topical discussion on climate policy and focuses on market-based policy tools. Essay II addresses the ongoing trend in energy policy of applying non-market-based tools such as phase-out mandates in the power sector. Essay III discusses the externalities of the blockchain technology, which is discussed as a potential enabler to emission reductions, but which also appears particularly energy-intensive.[53]

1.2 Literature Context

Section 1.2 summarizes the relevant literature on climate, energy, and technology policy. An understanding of the theoretical foundations of market-based, non-market-based, and strategic policy tools, which may be applied to abate carbon emissions, facilitates subsuming the subsequent three essays.

1.2.1 Climate Policy and the Role of Market-Based Instruments

Climate change has been coined as the "greatest market failure the world has ever seen".[54] The mainstream economic theory defines market failures as situations in which markets provide inefficient outcomes from a societal point of view, irrespective of the rational agents that pursuit exclusively their individual self-interest with their actions.[55] The externalities resulting from greenhouse gas emissions, which cause global warming by trapping heat in the Earth's atmosphere are not internalized in market prices of goods and services which emit greenhouse gases. Consequently, the results that the market yields are inefficient and call for policy intervention. Thereby, market failure can, for instance, be caused by information problems, market power, externalities and public goods, economies of scale, second-best problems, and free-riding.[56]

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[53] Note: For instance, a blockchain-based infrastructure has been suggested to facilitate international emissions trading, see (Blockchain for Climate Foundation, 2019).
[54] See (Stern, 2007), p. viii.
[55] See (Bator, 1958).
[56] See (Andrew, 2008) for a synthesis in the context of climate policy.

Limiting global warming is widely perceived to require policy intervention of a substantial extent. Today, leading economists suggests the use of 'carbon pricing'[57] as the most cost-efficient policy tool to reduce greenhouse gas emissions.[58] Carbon pricing denotes initiatives that explicitly price greenhouse gas emissions. As of April 2019, on the regional, national, or sub-national level, 44 jurisdictions implemented at least one carbon pricing initiative, covering 8 $GtCO_2$, which equals 14.3% of the global greenhouse gas emissions.[59] Taking the perspective of a welfare-maximizing central planner, carbon pricing, implemented through a carbon tax or a cap-and-trade mechanism, may reduce emissions at the lowest cost. Thus, carbon pricing can reduce emissions in an optimal manner.[60]

Economists try to approximate future damage, which is caused by today's GHG emissions. This future damage then helps to determine the social cost of today's emissions. Implementing a price on carbon emissions at the level of the calculated social cost of carbon (SCC) would result in an optimal level of carbon emissions. This optimal level of carbon emissions would still enable activities with the most beneficial emissions, while at the same time targeting those emitting activities, which are characterized by the lowest abatement cost.[61]

The social cost of carbon varies among countries depending on the current climatic circumstances. At the current temperature level, some countries would benefit from higher temperatures compared to the current level. In these cases, the current level of temperature anomaly is still more than offset by social benefits as illustrated by the current social cost of carbon on country-level (CSCC) in Figure 8. Especially in the northern hemisphere, countries like Canada or Russia would experience welfare gains if temperatures increase further. On the other extreme, some countries already today suffer high social costs from every additional ton of carbon that is emitted. For instance, CSCC of \$86/tCO_2 has been suggested for India.[62]

[57] Definition: "carbon pricing refers to initiatives that put an explicit price on greenhouse gas emissions, i.e. a price expressed as a value per ton of carbon dioxide equivalent", see (Worldbank, 2017).
[58] See (J. Stiglitz, Stern, & Duan, 2017).
[59] See (Worldbank, 2019); note: (Métivier, Postic, Alberola, & Vinnakota, 2017) report that of the covered emissions, 75% were priced below \$10/tCO_2 as of September 2017.
[60] See (Goulder & Schein, 2013).
[61] See (Stern, 2007).
[62] See (Ricke, Drouet, Caldeira, & Tavoni, 2018).

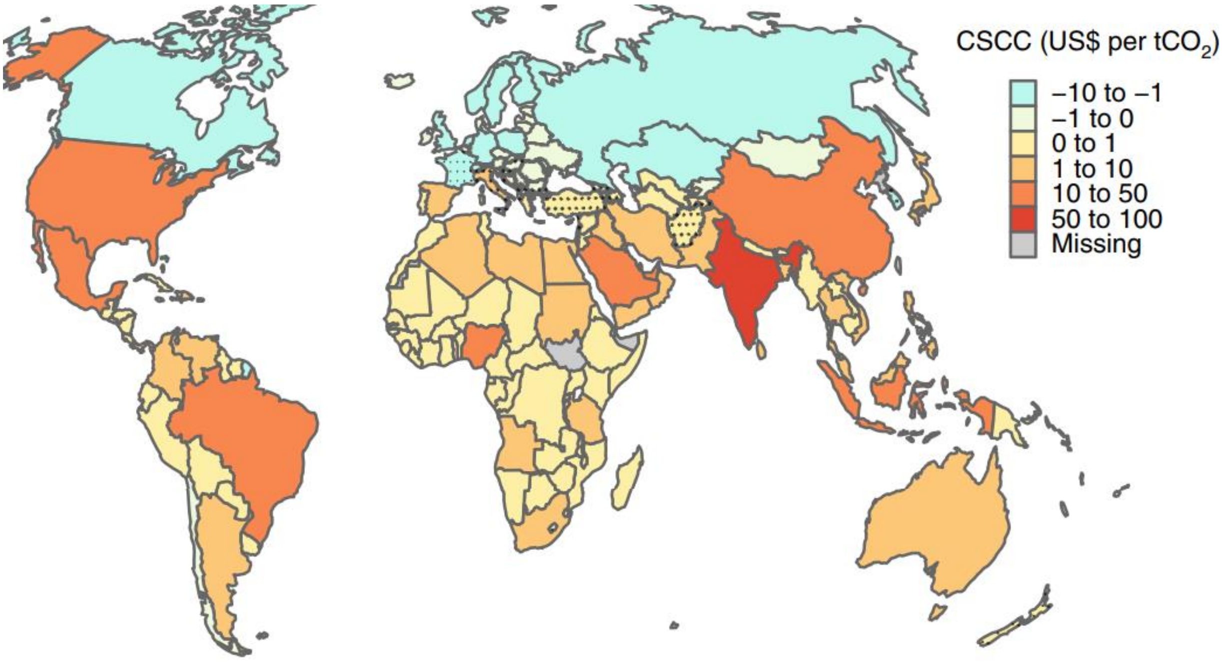

Figure 8: Country-level social cost of carbon.[63]

Besides carbon pricing, which targets the demand-side as a restrictive measure, the climate policy toolkit contains further market-based as well as non-market-based levers. Table 1 clusters climate policy instruments according to their target area and direction: These tools target the energy supply or the energy demand-side, and are either of a restrictive or supportive nature. As already mentioned in the context of the marginal abatement cost curve in the previous section, there are certain constellations in which single policy instruments outperform alternative policy tools in achieving emission reductions. Therefore, a tailored policy mix may be the optimal approach to achieve deep decarbonization.[64]

[63] Source: (Ricke et al., 2018).
[64] See (Mehling & Tvinnereim, 2018).

	Supply-side	Demand-side
Restrictive	• Ban/moratorium/phase-out • Production quotas • Subsidy reduction • Supply tax	• Emissions standards • Cap-and-trade • Carbon tax
Supportive	• Feed-in-tariffs • Government provision of infrastructure • Research and development (R&D) subsidies	• Government procurement policies • Consumer subsidies (e.g. for energy-efficient or low-emitting substitutes)

Table 1: Types of climate policies.[65]

1.2.2 Energy Policy and the Role of Non-Market-Based Instruments

Energy policy is an area where a broad variety of policy instruments are applied. Besides market-based approaches such as carbon pricing[66], economic theory suggests the use of command-and-control policies in order to overcome obstacles of improving energy efficiency, which arise from organizational and behavioral failure. The poster example for such a non-market-based instrument command-and-control policy is the ban of inefficient light bulbs as implemented in many countries to increase the energy efficiency in the residential sector.[67] Likewise, in the transportation sector, bans of cars from inner cities are increasingly under discussion,[68] and the number of announced coal phase-outs in the power sector continues to grow.[69]

Research has suggested that bans or phase-out mandates are more feasible from a political perspective than carbon pricing at a sufficiently high price level to achieve the same results.[70]

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[65] Source: Own illustration based on (Green & Denniss, 2018).
[66] Definition: “carbon pricing refers to initiatives that put an explicit price on greenhouse gas emissions, i.e. a price expressed as a value per ton of carbon dioxide equivalent”, (Worldbank, 2017).
[67] See (Tonzani, 2009).
[68] See (Möhner, 2018).
[69] The number of announced coal phase-outs in the power sector is growing: e.g. France (by 2022), Sweden (by 2022), Italy (by 2025), UK (by 2025), Austria (by 2025), Finland (by 2030), Netherlands (by 2030) and Portugal (by 2030), see (Powering Past Coal Alliance, 2018).
[70] See (Bertram, Luderer, et al., 2015).

Moreover, research has highlighted the ability of phase-out mandates to destroy existing structures while creating space for innovation.[71] Furthermore, phase-out mandates are suggested as a transparent, simple, and powerful tool to create anti-fossil norms.[72] One recent example to support these findings can be found in the German nuclear phase-out. The political decision to phase-out nuclear power in Germany has been identified as the trigger of R&D spending on renewable resources beyond the level of R&D spending that the Germany Renewable Energy Act (EEG) has triggered.[73]

1.2.3 Technology Policy and the Role of Strategic Instruments

In order to facilitate innovation, strategic investments are the option of choice in the evolutionary economic theory. Evolutionary and institutional economics explore the development of economic systems and how they depend on institutional circumstances in the long run. These disciplines combine technological innovation and system development in order to explore the effect of institutional guidance on economic growth. In the context of deep decarbonization, evolutionary and institutional economics may help policy-makers in gaining an understanding of the factors that shape the development of the energy or transportation systems in the long term.[74]

The case of solar photovoltaic illustrates that strategic investment may be an effective tool to promote innovation in the long term. In particular, the German government extensively promoted the expansion of solar PV through feed-in tariffs. On one hand, this approach appears particularly costly if one compares feed-in subsidies to achieved emission reductions: Between 2006 and 2010, the feed-in incentive corresponded to an average abatement cost of €537 per ton of CO_2 abated.[75] On the other hand, without the strategic investments in the context of the German energy transition and similar public investments in other jurisdictions, it appears unlikely that renewable generation technologies would have moved down the

71 See (Geels, Sovacool, Schwanen, & Sorrell, 2017).
72 See (Green, 2018).
73 See (Rogge & Johnstone, 2017).
74 See (Grubb et al., 2014).
75 See (Marcantonini & Ellerman, 2015).

learning curve as quickly,[76] and solar PV might not have become as cost-competitive as it is today.[77]

1.3 Motivation and Research Gaps

As explained in Section 1.1.3, the three essays in this thesis address one current topic within one of the three policy areas along the marginal abatement cost curve. The first essay shall contribute to the current debate on carbon pricing as a lever to realize CO_2 abatement in a particularly efficient and equitable way. The second essay shall contribute to the current political debate on achieving CO_2 reductions in the power sector through a non-market-based instrument; namely phase-out mandates. The third essay shall provide empirical insights into the recent discussion on the externalities of blockchain technology and the potential need for regulation. In the following, Section 1.3 motivates the three essays and discusses how relevant the single aspects are, in the context of the overarching goal to abate CO_2 emissions.

1.3.1 Essay I

The current political discussion and climate activists' demand increasingly focus on carbon pricing as a potential lever to reduce carbon emissions. Two recent examples are the political debate in Germany and the "Fridays For Future" movement. The German political debate deals with carbon pricing as a tool to achieve the emission reduction target as committed for the year 2030.[78] The "Fridays For Future" movement demands a carbon tax in the range of €160/tCO_2 that covers all GHG emissions.[79]

In practice, carbon pricing is typically implemented via an emission tax and tradable emission permits. As of April 2019, 44 jurisdictions have implemented one or more carbon pricing initiatives on regional, national, or sub-national level. Of the 54 implemented carbon pricing initiatives, 27 initiatives are implemented via carbon taxes, and the same number of initiatives

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[76] For the theoretical foundation of the learning curve, see (Arrow, 1962); for an analysis of global learning curves of renewable generation resources in the context of the German Renewable Energy Act (EEG), see (Buchholz, Dippl, & Eichenseer, 2019).
[77] See (Lazard, 2018a).
[78] See (Clean Energy Wire, 2019).
[79] See (Fridays For Future, 2019).

are implemented via emission trading systems (ETSs). Globally, the 54 implemented carbon pricing initiatives in total cover activities with emission in the order of 8.0 $GtCO_2$. Thereof, 2.7 $GtCO_2$ are taxed and 5.3 $GtCO_2$ are subject to ETS. In total, the covered emissions represent a share of 14.3% of global GHG emissions. The price that these initiatives put on every ton of carbon emitted sits in a range between \$0.08/tCO_2 (in case of the Polish carbon tax) and \$126.78/tCO_2 (in case of the Swedish carbon tax), with an average carbon price of \$20.7/tCO_2.[80]

However, in practice, there is limited empirical evidence that carbon pricing delivers emission reductions as anticipated. For instance, Sweden implemented a relatively high carbon tax in 1991, and although Sweden remains the country with the highest carbon tax globally, emissions in the road transportation sector only declined by 4% between 1990 and 2015.[81]

The limited empirical evidence of carbon pricing delivering observable emission reductions results in policy-makers increasingly resorting to alternative policy tools that promise greater transformational potential.[82] For instance, to increase the diffusion of electric vehicles (EV) governments widely grant subsidies.[83] Subsidies are also chosen to promote the deployment of renewable energy sources in many countries.[84]

Oppositely, carbon pricing advocates recommend this policy instrument as the foundation of climate policy. The majority of economists agree and recommend an explicit price on GHG emissions.[85] In theory, carbon pricing reduces GHG emissions in the most cost-effective manner by internalizing the externalities caused by those GHG emissions.[86] Therefore, carbon pricing may reduce emissions at a lower cost from a welfare perspective than direct regulation such as technology mandates or performance standards.[87]

The literature on carbon pricing is fragmented, and many arguments have been made against and in favor of carbon pricing. Given the considerable body of existing literature on the

[80] See (Worldbank, 2019).
[81] See (Tvinnereim & Mehling, 2018).
[82] See (Mehling & Tvinnereim, 2018).
[83] See (Edelenbosch, Hof, Nykvist, Girod, & van Vuuren, 2018; Jin, Searle, & Lutsey, 2014).
[84] IEA's World Energy Outlook 2017 estimates that global subsidies for renewables tripled to \$140 billion from 2007 to 2016, and predicts a further rise to \$200 billion in 2040, see (IEA, 2017), p. 273.
[85] See (Stern, 2007; J. Stiglitz et al., 2017).
[86] See (J. Stiglitz et al., 2017).
[87] See (Goulder & Schein, 2013).

benefits of carbon pricing,[88] and a recent surge in more critical literature analyzing the actual track record of pricing efforts,[89] a review that acknowledges both strands in the literature may add valuable insights by identifying the valid arguments on both sides.

Cases such as the one of the Swedish carbon tax mentioned earlier in this section, contradict the rational agent (*homo economicus*) that the standard economic model uses. Nonetheless, behavioral economics and political science may provide theoretical foundations, which may explain the observed deviation between theory and practice. The conceptual framework that we think is needed to synthesize this fragmented literature is based on the observation that the standard economic model alone may not explain why carbon pricing fails to deliver emission reductions.

First, behavioral failure caused by irrational human behavior may result in undesirable market outcomes, even if measures are implemented, which guide a rational agent to the desired behavior. In order to account for the irrational behavior of over seven billion *homo sapiens* on this planet, behavioral economic theory provides explanations on how humans cause market inefficiency with their individual preferences and cognitive limitations.

Second, government failure caused by (rational or irrational) human behavior of policy-makers (*homo politicus*) may result in bad political decisions and consequently undesirable market outcomes. Due to the human nature of *homo politicus*, findings from the behavioral economic theory apply here as well. In addition, political scientists provide supplementary explanations of how organizational flaws limit governments in regulating in a way that maximizes social welfare.

1.3.2 Essay II

In order to achieve committed emission reductions – instead of relying on market-based instruments like carbon pricing – policy-makers increasingly resort to phase-out mandates. In particular, in the power sector, the number of announced coal phase-outs has increased. Countries such as France, Italy, UK, Finland, the Netherlands, and Portugal announced respective initiatives. Furthermore, in Sweden and Austria, utilities announced final

[88] See e.g. (Baranzini et al., 2017; William D Nordhaus, 1977).
[89] See (Ball, 2018b; Patt & Lilliestam, 2018).

shutdown years for their coal power plants. Figure 9 depicts these coal phase-out announcements, clustered by the year of the final shutdown.[90] The coal exit data of Germany in 2038 is based on a proposal of the German coal exit commission, which was mandated by the government to evaluate the subject.[91]

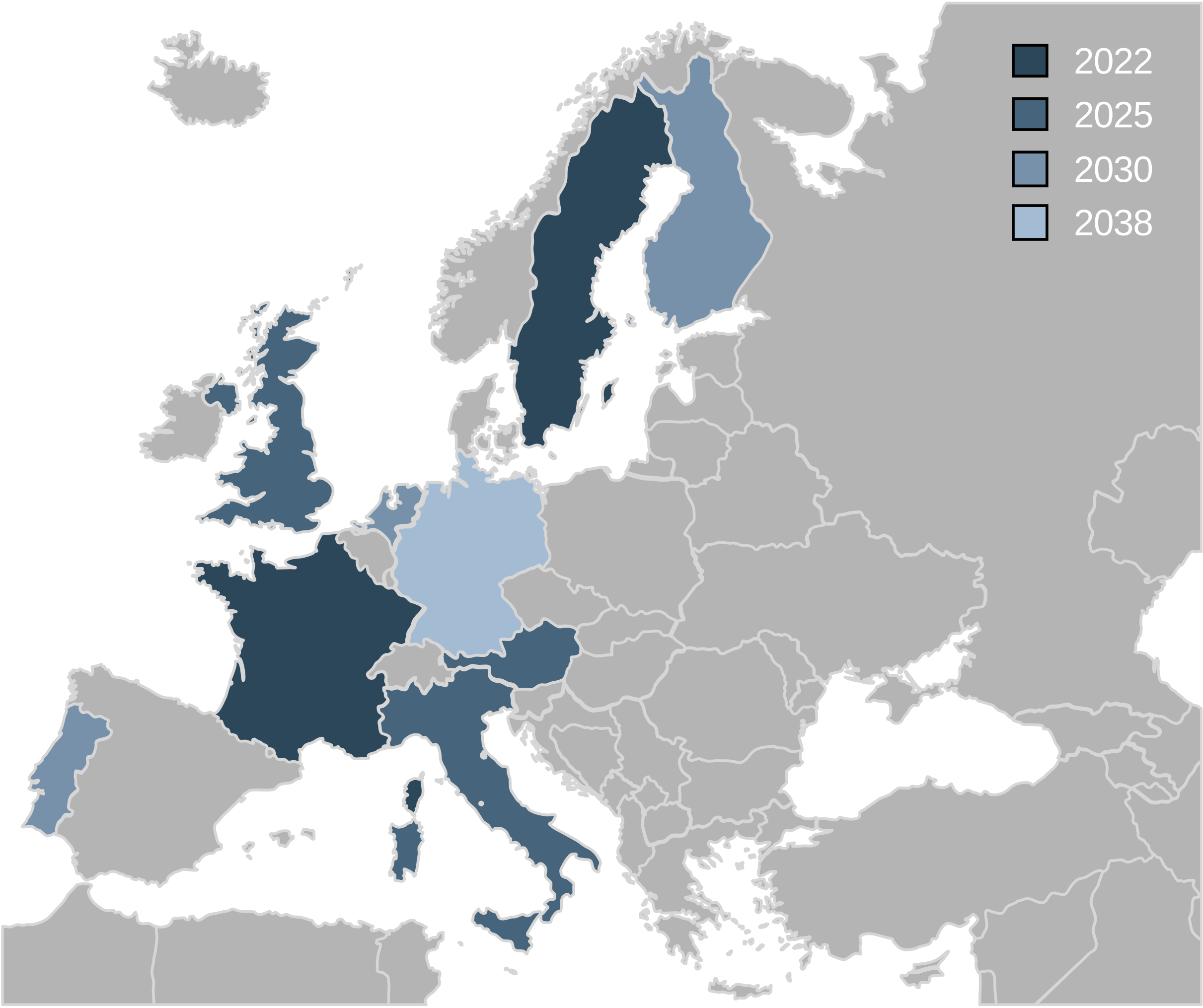

Figure 9: Announced coal phase-outs.[92]

The deviation between the theoretical effectiveness of market-based instruments and the practical trend to announce phase-out mandates underlines the need for more research into such non-market-based climate policy tools. The research on climate policy largely focuses

[90] See (Powering Past Coal Alliance, 2018).
[91] See (Kommission Wachstum, 2019).
[92] Source: Own illustration; announcements retrieved from (Powering Past Coal Alliance, 2018); German coal phase-out date based on the proposal of Germany’s coal exit commission; see (Kommission Wachstum, 2019).

on the effects and design of carbon pricing, while research on non-market-based tools such as phase-out mandates has lagged behind.

In the public debate, there is a strong opinion on the disadvantages of coal-fired power generation compared to gas-fired power generation. Coal-fired power generation is commonly perceived as particularly dirty, and promotors of gas-fired power plants highlight the lower carbon intensity of gas-fueled power generation compared to coal-fueled power generation. Switching from coal-fueled to gas-fueled power generation is therefore expected to contribute to the decarbonization efforts by lowering carbon emissions of every unit of electricity generated.

As the committed climate targets translate into a definite carbon emission budget, a maximum amount of CO_2 that can still be emitted into the atmosphere without causing warming that is incompatible with the definite warming target – switching from coal-fueled to gas-fueled power generation can extend the duration before this carbon budget is depleted. Primarily due to chemical properties, gas-fired power generation emits less than half the amount of CO_2 per unit of electricity compared to coal-fired power generation.[93] Extending the duration until the carbon budget is depleted would give additional time to improve existing or develop new zero-emission technologies that can produce electricity at low cost and are suited for deployment at a sufficiently large scale.[94]

Nevertheless, focusing exclusively on coal-fired and gas-fired power generation ignores the overarching challenge of decarbonizing the power sector. The key question should not be how to reduce the share of coal-fired power generation or how to trigger fuel-switching from coal to gas generation resources. In the context of the politically agreed decarbonization pathway, the key question is which fuel-switching strategy is cost-optimal. Answering this question requires not only including further generation technologies but also includes considering the effects of existing generation capacity. On the one hand, existing fossil-fired power plants and the associated generation infrastructure carries a risk of a lock-in in these high-carbon technologies.[95] Due to economic reasons, power plants continue to operate irrespective of premature write-downs.[96] One the other hand, existing

[93] See (Wilson & Staffell, 2018).
[94] See (Kerr, 2010; Levi, 2013; X. Zhang, Myhrvold, Hausfather, & Caldeira, 2016).
[95] See (Bertram, Johnson, et al., 2015; Seto et al., 2016; Unruh, 2000).
[96] See (Caldecott, Tilbury, & Carey, 2014), p. 2. for a definition of this so-called ‘asset stranding’.

fossil-fired power plants, and the associated generation infrastructure may also be an essential part of the solution to achieve deep decarbonization at least-cost.

1.3.3 Essay III

On the decarbonization pathway, technological innovation will play a key role and the current debate largely focuses on expected efficiency improvements in the future and potential radical innovations in the context of climate change mitigation. Far less attention has been given to the energy demand that some innovative technologies might bring. In the third essay, we use Bitcoin as an example of such an innovative technology with high disruptive potential; the underlying blockchain technology promises significant efficiency gains in various use-cases. Nevertheless, blockchain technology also appears particularly energy-hungry and carbon-intense.

The blockchain technology has its roots in Bitcoin. Bitcoin is a virtual currency and was the first successful attempt to validate transactions via a decentralized data protocol. This validation process requires vast amounts of electricity, which may translate into a significant level of carbon emissions if the used electricity originates from carbon-emitting power generation resources.

In Bitcoin's blockchain, the duration between the additions of two blocks is fixed at about ten minutes. To safeguard this frequency of block additions, the difficulty to solve the next block adjusts regularly in order to account for the connected computing power in the network. That means that if more computing power is added to the network, it becomes more difficult to solve such a Bitcoin puzzle. Between January and November 2018, the connected computing power in the Bitcoin network increased more than fourfold.[97]

According to academic studies, the increase of computing power in the Bitcoin network elevated the required electricity demand accordingly in 2018.[98] However, previous attempts to estimate Bitcoin's electricity consumption largely rely on simplistic estimates and rough assumptions due to missing empirical insights or technical misunderstanding of the blockchain protocol. Furthermore, to translate the estimated power demand into carbon

[97] See (Blockchain.com, 2018).
[98] See (De Vries, 2018).

emissions, previous estimates lack the empirical foundations and technical understandings of the global power market, which are key to produce accurate estimates.[99]

1.4 Contributions and Findings

Each of the three essays in this thesis contributes to one current topic along the marginal abatement cost curve as described in Section 1.1.3. In particular, the first essay identifies valid arguments in favor of and against carbon pricing. Furthermore, Essay I offers a theoretical framework for the rising option in the broader community that carbon pricing is a necessary but insufficient element of any policy portfolio that aims for deep decarbonization. The second essay contributes to the current debate on achieving CO_2 reductions in the power sector that are in line with politically committed targets. A case study for Germany reveals counterintuitive results, which underline the necessity to consider the effect of stranded assets when designing a fuel-switching strategy. The third essay provides empirical insights to the discussion of Bitcoin's power consumption and carbon emissions where previous academic studies rely on simplistic assumptions. The total carbon emissions of Bitcoin – comparable to the emission level of Kansas City – underlines the necessity to consider environmental externalities of the blockchain technology.

1.4.1 Essay I

Essay I provides a meta-analysis, summarizing the imperfections of markets, behavior, and government that hinder carbon pricing's theoretical economic efficiency. Thereby, Essay I highlights the opportunity space where carbon pricing may conduce to deep decarbonization at least cost. Additionally, Essay I assesses the challenge of distributional effects caused by carbon pricing, which would occur if policy-makers take committed emission reductions seriously.

Essay I synthesizes the literature on carbon pricing and suggests a conceptual framework by distinguishing constellations in which the application of carbon pricing may fail to attain the anticipated emission reductions. The conceptual framework is structured along three types of

[99] See e.g. (Krause & Tolaymat, 2018; Mora et al., 2018).

agents: the first type of agents, the *homo economicus*, are characterized by a fully rational pursuit of pure self-interest; the second type of agents, the *homo sapiens*, embody irrational human behavior; and the third type of agents, the *homo politicus*, reflects rational and irrational decision-making in politics.

An understanding of the three types of imperfections as represented by the three agents is crucial to avoid that high expectations of carbon pricing yield deep disappointment. The summarized imperfections can explain inefficient results under carbon pricing policies and help to dissect assessments of carbon pricing.

Additionally, with our review, we bridge discussions of economic efficiency, distributional impacts of climate policies, and how to address such impacts. Unlike subsidy programs and phase-out mandates, carbon pricing generates fiscal revenues. Efficiency is only one side of the coin, and if policy-makers take respective actions to achieve deep decarbonization, the redistribution of wealth within the population will become increasingly important.[100] Carbon pricing offers the opportunity to tackle distributional effects and inequitable market outcomes.[101] The fiscal revenue generated by carbon pricing may be returned in the form of so-called carbon dividends in order to mitigate the distributional effects caused by climate policy.[102]

Essay I contributes to the controversial debate on carbon pricing by offering a conceptual framework for the growing sense that carbon pricing is a necessary, but not sufficient, element of any deep decarbonization policy portfolio. The unique angle of this typology of imperfections may offer a holistic perspective on required policy approaches to synthesize the triad of barriers to efficient carbon pricing operations.

1.4.2 Essay II

Essay II presents a simple model with the objective to find the least-cost power generation resource mix, which is consistent with the committed climate targets at a distinct future point in time. This includes the provision of an accessible explanation of the intuition and logic

[100] See (Büchs, Bardsley, & Duwe, 2011; Fullerton, 2011; Hirth & Ueckerdt, 2013).
[101] See (Boyce, 2018).
[102] Note: Carbon dividends are defined as the redistribution of revenues that were generated by a carbon pricing initiative, see (Climate Leadership Council, 2018).

behind capacity expansion modeling. This further includes establishing a link between capacity planning models and committed climate targets. The model I present can be used to determine the generation resource capacity by technology that covers a given load demand at least-cost while being in line with committed climate targets. Therefore, climate targets are reflected in the model as a carbon constraint.

Using the described model, calibrated with parameters of the German electricity sector and climate commitments, reveals thought-provoking results. The results of the case study of Germany contradict the common opinion that coal power plants should be phased out rather sooner than later. The key assumption that causes this unexpected result can be found in the treatment of existing generation resources. I assume that power plants operate as long as it is economically beneficial to do so from the owners' point of view. That implies that power plants continue to operate even if annualized investment costs are no longer covered; owners will write-down their assets prior to mothballing them.

To consider this economic rationale, and as fixed costs of power plant operations almost exclusively consist of annualized investment costs, I assume zero fixed costs for existing power plants in the model. Under this assumption, a decarbonization pathway includes a gradual decline in coal-fired generation capacity and respective rise in clean generation resources proves to be advantageous in terms of total system cost compared to a forced coal phase-out.

The cost implications of politically forced phase-out policy against a market-driven gradual reduction in coal usage have been studied in many sophisticated integrated models. The significant conceptual advance in scientific understanding that Essay II provides is to highlight the effect of stranded assets. The effects of asset stranding may play a central role in a cost-effective decarbonization pathway but have been largely ignored in previous modeling work.

1.4.3 Essay III

Essay III presents a techno-economic model, which can be used to determine the electricity consumption and associated carbon emissions of the Bitcoin network. This includes methodologies for estimating the geographic locations of network participants. Essay III further provides empirical insights, which enable higher accuracy in estimating Bitcoin's emissions compared to previous work. In particular, Essay III provides empirical insights on the hardware that miners use, the way mining facilities operate, and the locations where miners operate.

Based on recent IPO filings of the three largest hardware manufacturers, we conclude that hardware sold by those three hardware manufacturers provides nearly the entire computing power in the Bitcoin network. The largest market share can be allocated to Bitmain hardware that provides 78% of the network's computing power, followed by Ebang hardware with 13%, Canaan hardware with 8%. Based on the hardware in use and the specific energy efficiency on a model basis, we can calculate the electricity demand of the Bitcoin network. After adding auxiliary losses from mining operations such as cooling and IT-equipment, we conclude that Bitcoin caused a load of 5,232 megawatt in November 2018.

Based on the localization of IP addresses within the Bitcoin network, we estimate the locations where miners are based and where electricity is consumed accordingly. Based on two scenarios, we translate the local power demand into carbon emissions. As of November 2018, we show that the Bitcoin network causes carbon emissions in a range between 22.0 and 22.9 Megatons of carbon dioxide ($MtCO_2$). This ratio sits between the carbon emission levels produced by the nations of Jordan and Sri Lanka,[103] which is comparable the carbon emission level produced by Kansa City.[104]

The amount of carbon emissions caused by the Bitcoin network, in combination with the risk of collusion of network participants, and considerations about the value of sovereign control over the monetary system should not be ignored. In particular, in terms of carbon emissions, our findings point to a need for direct regulation in certain regions as long as the externalities of carbon emissions during power generation are not fully internalized. Regulatory intervention on the regional level may prevent the additional load from cryptocurrency mining that causes vast amounts of carbon emissions (either directly by utilizing dirty power resources, or indirectly by consuming clean energy that has to be replaced by dirty power resources in the surrounding grid area).

What is more important: Blockchain solutions are increasingly discussed for a broad variety of use-cases beyond cryptocurrencies. This debate is largely focusing on anticipated benefits,

[103] See (Global Carbon Project, 2017).
[104] See (Moran et al., 2018).

such as efficiency gains. Although not all blockchain protocols are as energy-intensive as Bitcoin's protocol, environmental aspects, the risk of collusion, and concerns about control must not be ignored in the debate on anticipated benefits. Environmental costs from the energy consumption and required infrastructure (also in case of less energy-intense protocols) have been largely ignored in many cases.

1.5 Structure

This thesis is organized as follows: Section 2 provides Essay I: *Climate Change and Carbon Pricing: Overcoming Three Dimensions of Failure*. Section 3 presents Essay II: *Fuel-switching and Deep Decarbonization*. Essay III: *The Carbon footprint of Bitcoin* can be found in Section 4. Section 5 concludes. As illustrated in Figure 10, each essay contributes to one dedicated policy aspect under the umbrella of climate economics.

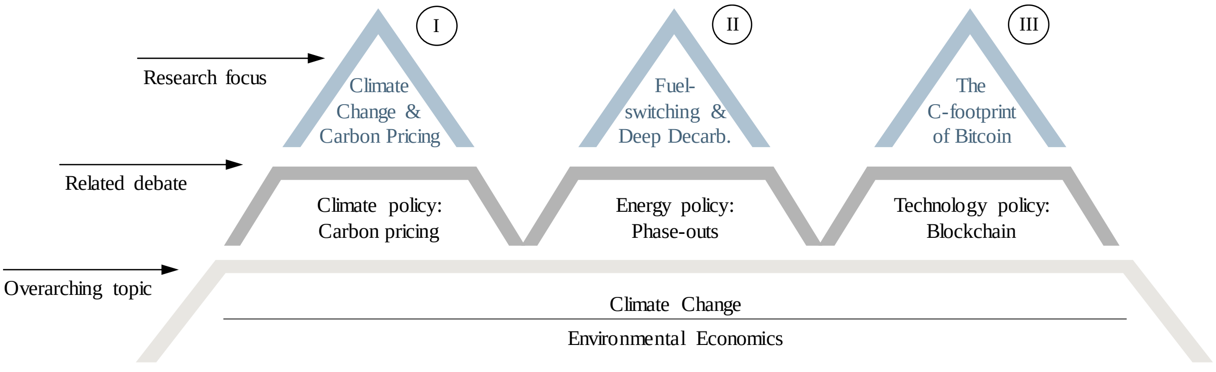

Figure 10: Essay I-III thematic overview.[105]

[105] Source: Own illustration.

2 Essay I – Climate Change and Carbon Pricing: Overcoming Three Dimensions of Failure

by Christian Stoll and Michael A. Mehling*[106]

Abstract

Climate change has been called the "greatest market failure the world has ever seen". Beyond the standard economic model, seven billion individuals cause market inefficiency with their behavioral preferences and limitations. Market failure justifies policy intervention, and many economists recommend carbon pricing as the optimal policy to address climate change. Recent literature has leveled criticism against carbon pricing, however, based on its empirical performance and conceptual limitations. Given the two strands in literature which offer arguments in favor and against carbon pricing, a review that identifies the valid arguments of both strands in the literature can provide valuable conclusions. With our meta-analysis, we dissect such research and suggest a conceptual framework to summarize the failure of markets, human behavior, and governments which interfere with the efficient operation of carbon pricing. We also discuss distributional effects, which are set to become a major challenge once policy-makers take deep decarbonization commitments seriously. Our findings suggest that carbon pricing remains a vital component of an effective policy mix to limit climate change, and, indeed, to prevent it from becoming the greatest government failure the world has ever seen.

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2.1 Introduction

Climate change has been described as the "greatest market failure the world has ever seen".[107] Mainstream economists define market failures as situations in which the rational pursuit of self-interest yields results that are inefficient from a societal point of view.[108] Greenhouse gas (GHG) emissions cause climate change as they trap heat in the Earth's atmosphere. Because the resulting externalities of global warming are not reflected in market prices of goods and services that emit GHGs, market results are inefficient in the absence of policy intervention.[109]

Even if measures are in place to correct market failure of the standard economic model, behavioral failure can still cause undesirable market outcomes, as human behavior deviates from that of a rational *homo economicus*. Behavioral economists aim to account for over seven billion *homo sapiens* causing market inefficiency with their individual preferences and limitations. Such behavioral failure justifies policy intervention to enhance welfare, either by protecting individuals from themselves, or others from externalities that arise from their actions.[110]

Unfortunately, governments can also fail by regulating inadequately, due to cognitive, organizational, and political limitations and shortfalls.[111] Ever since Aristotle's conception of a *zōon politikon*, the notion of a *homo politicus* has existed as a predecessor or counterpart to that of *homo economicus*, with specific social preferences,[112] contingent perceptions of justice,[113] and idiosyncratic self-interests.[114] Many insights from the study of human behavior also apply to politics: Since governments are formed by, recruited from, and serve individuals relying on cognitive heuristics,[115] behavioral economists attempt to understand decision-making in politics, and identify, for instance, individual biases as sources of bad policies.[116]

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[107] See (Stern, 2007), p. viii.
[108] See (Bator, 1958).
[109] Causes of market failure are for instance information problems, market power, externalities and public goods, economies of scale, second best problems and free-riding; see (Andrew, 2008) for an overview in the context of climate policy.
[110] E.g. people who are saving too little for retirement, driving too fast, or emitting GHG.
[111] See (J. E. Stiglitz, 2009), p. 35-37; for general government failure theory including more granular causes comparable to market failure theory, see (Le Grand, 1991; Vining & Weimer, 1990; Wolf Jr, 1979).
[112] See (Nyborg, 2000).
[113] See (Faber, Petersen, & Schiller, 2002).
[114] See (Brown, 2015), p. 86.
[115] See (Max H Bazerman & Watkins, 2004).
[116] See (Sunstein, 2013a, 2013b; Tullock, Seldon, & Brady, 2002).

The failure to address climate change is, in part, also a result of government failure. Economists have therefore routinely recommended carbon pricing as the centerpiece of climate policy.[117] In economic theory, carbon pricing – typically implemented via an emission tax[118] or tradable emission permits[119] – internalizes some or all of the externalities caused by GHG emissions, and reduces GHG emissions in the most cost-efficient manner.[120]

Economists can estimate the future damage caused by today's GHG emissions to determine the social cost of today's emissions. Theoretically, a price on carbon emissions that corresponds to this social cost will result in the optimal level of emissions; that is, a level that still allows the most beneficial emitting activities, while focusing mitigation on activities with the lowest abatement cost.[121]

Such attempts to estimate the social cost of carbon are highly dependent on the chosen input assumptions, however, and relevant calculations tend to therefore deliver a wide range of results.[122] In addition, catastrophic outcomes which defy easy quantification quickly bring this approach to its conceptual limits. Uncertainty about the benefits of climate action,[123] coupled with the Gordian knot of how to quantify risk[124] and factor in space and time,[125] have prompted governments to base their climate policies on politically agreed mitigation targets rather than cost/benefit calculations.

Already implemented at the domestic level in various countries,[126] this approach also found its international application in the Paris Agreement, adopted in 2015. When they concluded that binding treaty, 195 countries agreed to limit global warming below 2 °C.[127] This strict

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[117] Definition: "Carbon pricing refers to initiatives that put an explicit price on greenhouse gas emissions, i.e. a price expressed as a value per ton of carbon dioxide equivalent (tCO_2e)", (Worldbank, 2017).
[118] For the underlying theoretical justification, see (Pigou, 1920).
[119] For the underlying theoretical justification, see (Coase, 1960); first applied to tradable emission permit systems by (Crocker, 1966; Dales, 1968).
[120] See, for instance, 'Economists' Statement on Carbon Dividends', *Wall Street Journal*, Jan. 17, 2019 (https://www.clcouncil.org/media/EconomistsStatement.pdf); (J. Stiglitz et al., 2017).
[121] See (Stern, 2007).
[122] See (William D Nordhaus, 2017; Pizer et al., 2014).
[123] See (Jacoby, 2004).
[124] See (William D. Nordhaus, 2011; Pindyck, 2011; Weitzman, 2009) on how to account for so-called tail events, which are characterized as highly unlikely, yet with infinite expected loss.
[125] See, e.g. (Stern, 2007) on prescriptive vs descriptive discount rates to account for effect with cross-generational consequences; similarly, the social cost of carbon is not uniform across different geographies, see e.g. (Ricke et al., 2018).
[126] See, e.g., for the United Kingdom: (DECC, 2009).
[127] See Paris Agreement (UNFCCC, 2015a); first mentioned by (William D Nordhaus, 1977), the 2 °C bound is commonly used as upper bound to limit cost and risk of climate change and the 2 °C bound is commonly referenced as a threshold to avoid the worst consequences of climate change.

warming limit translates to a maximum GHG concentration in the atmosphere and a remaining (cumulative) carbon budget, respectively. For climate policy, the objective function then no longer is welfare-maximization based on a cost/benefit calculation, but rather cost-minimization in the achievement of a decarbonization pathway that limits warming to 2 °C or less.

In practice, due to limited empirical evidence with carbon pricing delivering the expected emission reductions,[128] policy-makers are increasingly resorting to alternative instruments with greater transformational potential to achieve decarbonization commitments. Subsidies are widely used, for instance, to increase the diffusion of electric vehicles (EV) and the deployment of renewable energy sources (RES).[129] An increasing number of jurisdictions is also resorting to phase-out mandates to reduce emissions from specific sectors or activities.[130] While these policies can correct some of the market failures associated with climate change, they are not a cost-effective tool to address its main cause: the externality of GHG emissions.

Meanwhile, carbon pricing – the policy of choice to internalize this externality – has witnessed a more mixed trajectory. Ambiguous causality of carbon pricing for observed emission reductions, along with a delayed market reaction compared to blunter command-and-control regulation, has recently prompted some criticism in the policy literature.[131] Despite years of steady geographic and sectoral expansion,[132] this contributes to the barriers carbon pricing faces in the political realm. For instance, Australia introduced a carbon tax in 2012 and repealed it two years later in the next legislative period.[133] Although emissions dropped during the carbon pricing period in Australia by about 2%, the causal link to carbon pricing remained uncertain. As depicted in Figure 11, the weak correlation of total emissions and electricity consumption since 2015 exemplify that further variables (such as LNG projects or mining activity) complicate attribution of emission reductions to carbon

[128] See (Mehling & Tvinnereim, 2018).
[129] IEA's World Energy Outlook 2017 estimates that global subsidies for renewables tripled to $140 billion from 2007 to 2016, and predicts a further rise to $200 billion in 2040, see (IEA, 2017), p. 273.
[130] Bans of inefficient light bulbs are a poster example, see (Tonzani, 2009). Banning cars from inner cities is also being discussed in a number of cities, see (Möhner, 2018), and the number of announced coal phase-outs in the power sector is rising, see (Powering Past Coal Alliance, 2018).
[131] See, e.g., (Ball, 2018a, 2018b; Patt & Lilliestam, 2018).
[132] As of 2018, 45 national and 25 subnational jurisdictions were putting a price on carbon, see (Worldbank & Ecofys, 2018), p. 17.
[133] See (Crowley, 2017) for a detailed review of Australian climate policy 2013-2016; (The Guardian, 2013) describes the motivation of Prime Minister Abbott to abolish the carbon tax due to disbelief in need for action and consideration of donors' vested interest.

pricing.[134] Unable to point to a clear mitigation effect, supporters of carbon pricing had to resort to theoretical calculations and forecasts, whereas opponents could cite the present cost facing the Australian economy.

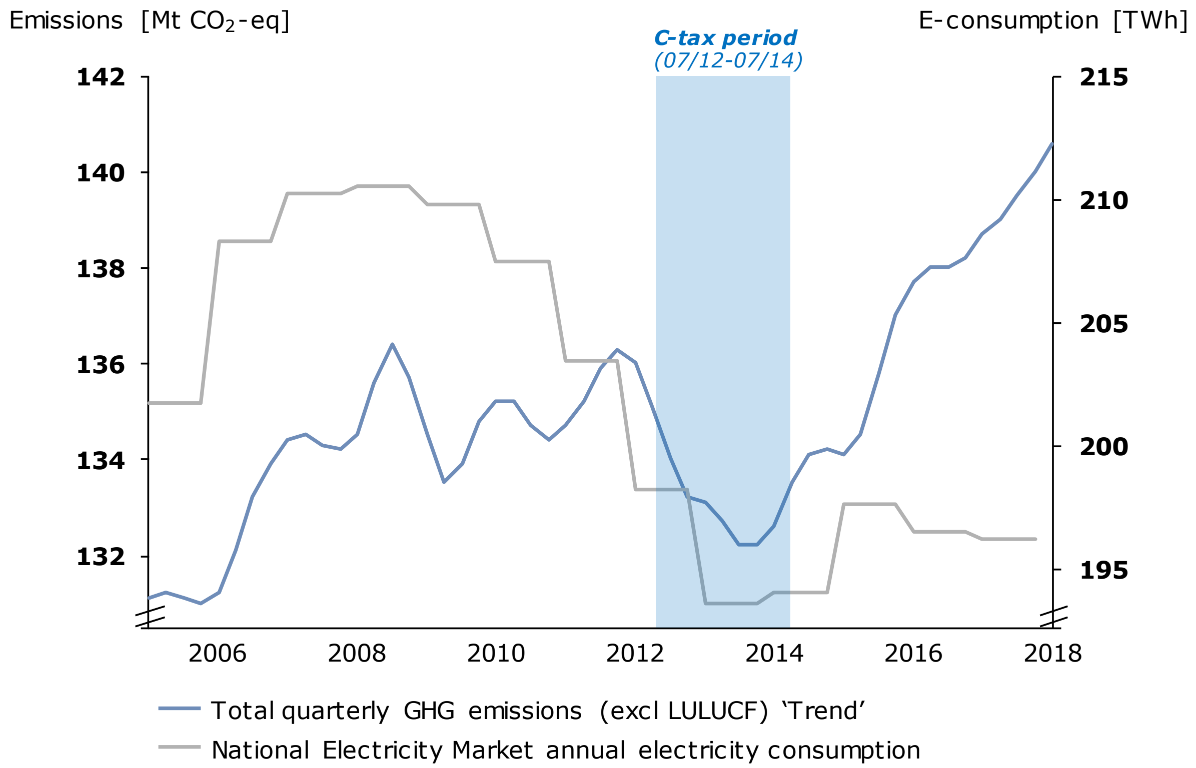

Figure 11: Australian total greenhouse gas emissions 2004-2017.[135]

The objective of this paper is to dissect this rise in critical evaluations of carbon pricing.[136] In some cases, the criticism may be justified; in other cases, the expectations placed on carbon pricing may have been exaggerated, and its role in the climate policy portfolio misunderstood.[137] To ensure that growing disenchantment with carbon pricing does not deter its use even where it is a superior policy option, this paper traces conceptual strengths and weaknesses to identify the appropriate role for carbon pricing on the pathway to decarbonization.

[134] See (O'Gorman & Jotzo, 2014) for difficulties to assess the impact of Australia's carbon tax on emissions.
[135] Own illustration; data sources: (Australian Energy Regulator, 2018; Department of the Environment and Energy, 2018).
[136] See, e.g., the references in footnote 131.
[137] E.g. the European Union Emissions Trading System (EU ETS) has been highlighted as unable to trigger corporate innovation, while its actual core function is to lower the cost of a politically agreed emission reduction, see (Schmidt, Schneider, Rogge, Schuetz, & Hoffmann, 2012).

To that end, we summarize the existing literature in a conceptual framework that captures the imperfections of markets, behavior, and government that interfere with the economic efficiency of carbon pricing. Moreover, we highlight the opportunity space for carbon pricing to contribute to deep decarbonization at least cost. Additionally, we assess the distributional effects of carbon pricing if policy-makers take deep decarbonization seriously.

The efficiency of carbon pricing to achieve emission reductions at the margin has been amply demonstrated.[138] Our review of market, behavioral, and government failures underlines the need for complementary policies to limit global climate change. As we find, however, it is also important to distinguish areas which actually require complementary policies from areas where such policies incur the risk of favoring dead-end technologies while precluding valuable alternatives that are either unknown to policy-makers, or underappreciated in their mitigation potential.[139]

Going forward, the key challenge will be to overcome political constraints in order to approach efficient carbon pricing levels. To solve this challenge, we highlight alliances, stepwise actions, reduced complexity, and the right framing as potential levers. Furthermore, we highlight the opportunity to mitigate distributional effects with carbon dividends, that is, redistribution of revenues generated by carbon pricing.[140]

The paper is organized as follows: Section 2 highlights inefficient market outcomes despite carbon pricing. Section 3 describes inequitable market outcomes caused by carbon pricing, as well as potential solutions. Section 4, finally, summarizes policy recommendations and issues requiring further research.

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[138] See (Grubb et al., 2014) for a detailed summary that carbon pricing should be used at the profitability threshold of the marginal abatement cost curve. Marginal abatement cost curves present options for emission reduction and their respective potential, sorted by abatement cost, see (McKinsey, 2013).
[139] See (Acemoğlu, Akcigit, Hanley, & Kerr, 2016; Fried, 2018) for how pricing can trigger innovation.
[140] See (Climate Leadership Council, 2018).

2.2 Carbon Pricing: Between Market and Government Failure

To identify inefficient market outcomes despite carbon pricing, Section 2 distinguishes constellations in which carbon pricing can fail to deliver expected emission reductions. We differentiate three types of imperfections: first, where the rational pursuit of pure self-interest by an ideal-typical *homo economicus* nonetheless leads to inefficient results; second, situations where an irrationally behaving *homo sapiens* generates results that are inefficient; and third, situations where the rational or irrational decisions of *homo politicus* cause inefficiency.

2.2.1 Market Failure: The Case of *Homo Economicus*

Even if we assume that all economic agents are perfectly rational, as in the standard economic model of *homo economicus*, there are still situations where carbon pricing can fail to reduce emissions. This section focuses on the two main categories of market failure that interfere with the theoretical efficiency of carbon pricing: public goods[141] and principal-agent constellations.[142]

The first-mentioned category of market failure originates from the non-excludability of public goods. Private actors cannot exclude nonpayers from enjoying the benefits of a public good. Consequently, private actors face sub-optimal incentives to provide a public good at Pareto-efficient levels.[143] The following cases illustrate this challenge by drawing on three public goods that are necessary for deep decarbonization. These are innovation, knowledge, and infrastructure.

First, in the case of innovation, private actors might not be able to capture all the benefits of technological advances they achieve.[144] In the absence of perfect initial property protection – that would turn the public into a private good – others co-benefit from innovation through

[141] Definition: Public goods are defined as goods that are non-excludable and non-rival in use; e.g. national security, public health, and clean air, see (Ostrom, 2005), p. 24.
[142] Different objectives and asymmetrical information may cause so-called principle-agent problems, see (Jensen & Meckling, 1976) for agency cost and the issue of separating ownership and control.
[143] See (P. A. Samuelson, 1954).
[144] See (Fischer & Newell, 2008; Fischer, Preonas, & Newell, 2017; Adam B Jaffe, Newell, & Stavins, 2005).

knowledge and adoption spillover. As innovators cannot capture the full benefits, they face sub-optimal incentives to invest in R&D.

Second, in the case of knowledge accumulated through learning-by-doing, experience diffusion and leakage cap the incentives to improve processes and products. For instance, when knowledgeable employees leave a company, they are likely to benefit from earlier trial and error attempts of their employer.[145]

Third, in the case of infrastructure, an investment can help to reduce existing negative externalities, like GHG emissions, and create positive externalities on primary markets from which the demand for infrastructure is derived.[146] Aside from the inability to capture some or all of these benefits, as we also observed with the foregoing innovation and knowledge spillovers, the required upfront investment frequently surpasses the financial capabilities of private actors.[147] Risk aversion, capital market imperfection and regulatory restrictions further amplify the underspending (or even misspending).[148]

The second category of market failure originates from principal-agent constellations. If one party (agent) acts on behalf of another party (principal), problems may arise from divergent objectives and asymmetrical information.[149] Agents may have private information that is ignored by the principal (cases of *hidden knowledge* or *adverse selection*) or, agents may take actions that are unobservable for the principal (cases of *hidden action* or *moral hazard*).[150] Especially *adverse selection* in cases of split incentives and *moral hazard* in cases of divergent time preferences illustrate principal-agent constellations that limit carbon pricing in delivering its full efficiency potential.

First, in the case of split incentives, costs and benefits accrue to different parties, and therefore difficulties can arise from divergent levels of information. In such constellations, investment in measures to improve energy efficiency tends to fall short.[151] The classic example of split incentives due to the separation of ownership and use is the landlord-tenant problem. Landlords have little incentive to enhance energy efficiency if tenants pay for

[145] See (Acs, Audretsch, & Lehmann, 2013; Braunerhjelm, Ding, & Thulin, 2018).
[146] See (Blum, 1998): e.g. labor markets create the demand for transport, which creates the demand for infrastructure.
[147] E.g. annual investment in infrastructure of $6.3 trillion has been suggested for 2016-2030 to facilitate a decarbonization pathway which is compatible with the 2 °C goal, see (OECD, 2017).
[148] See (Lehmann & Söderholm, 2018).
[149] See, e.g. (Jensen & Meckling, 1976; Ross, 1973).
[150] See, e.g. (Laffont & Martimort, 2001), p. 3.
[151] See (IEA, 2007) for quantification of principal-agent problems as obstacles to energy efficiency.

electricity and heat.[152] A similar situation can be found in the relationship of a ship-owner and charterer, where price sensitivity to charter rates prevents the implementation of measures in order to improve fuel efficiency.[153] A third example, where rational behavior on individual level results in collective inefficiency, can be found between a rental car company and the renter. Ex-ante, the rental car company cannot anticipate the renter's driving style and oppositely, the renter has limited knowledge of the car's fuel efficiency.[154]

Second, *moral hazard* can arise from divergent time horizons. The principal's time horizon is typically longer than the agent's. Public and private decision-makers are typically motivated more by short- than by long-term incentives. For instance, employees tend to maximize their personal utility instead of the shareholders' long-term interest.[155] Analogous, business and political cycles do not align well with the time horizon of climate change.[156] Therefore, it is rational for decision-makers to underspend on R&D, which promises potential benefits far in the future. Likewise, self-optimizing agents could misprice long-term risk in order to increase short-term profits. In the case of high carbon assets, the mispricing of risk may result in large-scale asset stranding – with devastating wealth loss and distributional impacts[157] – and potentially destabilize the global financial system.[158]

2.2.2 Behavioral Failure: The Case of *Homo Sapiens*

Assuming agents deviate from the perfectly rational *homo economicus*, there are further situations where the irrational *homo sapiens* creates inefficiencies. In this section, we apply the approach of (Mullainathan & Thaler, 2000) to climate change, identifying where human behavior differs from that of perfectly rational agents due to bounded rationality, bounded willpower, and bounded self-interest.

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[152] See (Davis, 2011; Adam B. Jaffe & Stavins, 1994).

[153] See (Rehmatulla & Smith, 2015). E.g. (Agnolucci, Smith, & Rehmatulla, 2014) find that ship-owners have limited incentive to improve the fuel efficiency of their vessels as they can only capture 40% of the financial savings via higher charter rates.

[154] Note: A related example can be found in the relationship between local governments and international society. Local governments have an incentive to free-ride on (and benefit from) global climate protection, see (W. Nordhaus, 2015). E.g. (Kremen et al., 2000) describe the local benefits of logging vs. global benefits of rain forest conservation.

[155] See (Clarke & Darrough, 1983).

[156] See (Carney, 2015).

[157] See (Mercure et al., 2018).

[158] See (ESRB, 2016).

Bounded rationality describes the cause of irrationality in human decision-making.[159] Due to limited ability, information, or time, humans rely on rules of thumb and heuristics in decision-making. Several leading economists have described mistakes in human decision-making, identifying cognitive biases, predicting failures in choice, and recommending that policy-makers nudge decisions by modifying choice architectures.[160]

The bounded rationality of individuals can lead to strong non-financial preferences. As in the case of alternative fuel vehicles, the individuals' choice depends on the perceived utility derived from factors such as novelty, limited variety, refueling stations, and range. Aside from aspects like location and usage profile, cultural aspects further shape consumer preferences. The price inelasticity of gasoline demand underlines the non-financial preferences of consumers,[161] and SUV sales numbers in recent years have dispelled any remaining doubt.[162]

Given their bounded rationality, individuals can also have preferences regarding the design of financial incentives; it matters if these are designed as subsidies, or as penalties. The example of the transport sector illustrates that subsidies may sometimes be more effective than taxes.[163] Modeling work has shown that a carbon price of \$100/tCO_2 (equal to \$1 per gallon of fuel) would likely increase the global share of electric vehicles (EVs) from 0.3% (in 2017) to 15-34% by 2050;[164] that uptake is far too low to comply with the 2 °C goal, which requires at least 20% alternative-fueled vehicles already by 2030.[165] By contrast, Norway used a subsidy program and achieved its transport emissions target three years early in 2017, with 52% of new car sales being electric, gas, or hybrid vehicles.[166]

How individuals process new information can also be rationally bounded. Investors both overreacting[167] and under-reacting[168] to new information is evident in the stock market. The Volkswagen emissions scandal demonstrates how consumers react to new information and

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159 See (Simon, 1957) arguing that most decisions are fully rational and aligned with individual goals. According to Simon, individuals very rarely take irrational decisions – decisions counterproductive to self-selected goals. However, perceived rational decisions can be irrational from a knowledgeable point of view.
160 See (Kahneman & Tversky, 1979; Thaler & Sunstein, 2008).
161 See (Huse, 2018; Klier & Linn, 2010).
162 See (JATO, 2018) global market share of SUV up from 22.4% in 2014 to 34.0% in 2017.
163 See (Edelenbosch et al., 2018; Jin et al., 2014) in the context of EV sales incentives.
164 See (McCollum et al., 2018).
165 See (UNFCCC, 2015b).
166 See (OFV, 2018); note: The trend continues: sales of electric, gas, or hybrid vehicles accounted for 60% in 2018.
167 See (De Bondt & Thaler, 1985).
168 See (Shleifer, 2000).

change their preferences accordingly: diesel cars have become unpopular across brands.[169] Case studies of this emissions scandal highlight the amplifying effects of media coverage[170] and brand perception spillovers as potential causes.[171]

Bounded willpower, the second category of human deviation from perfectly rational agents, is another behavioral factor affecting how individuals will respond to carbon prices. Even if individuals have the cognitive ability, perfect information, and sufficient time to reach rational decisions, humans tend to be myopic,[172] and self-control issues trigger choices against long-term interest.[173] Humans further favor procrastination[174] and prefer to retain the status quo rather than changing it.[175] In the context of energy efficiency, for instance, people tend to discount future savings with irrationally high rates, and therefore adhere to their current, inefficient energy use patterns. For energy-efficient appliances, implicit discount rates (estimated to be up to 300% for refrigerators[176] and 825% for electric water heaters[177]) underline the challenge.[178]

The third dimension of bounded behavior is selflessness, that is, the willingness to help others at the cost of one's own welfare.[179] Such selfless – or pro-social – behavior can be observed in the intrinsic motivation to make unpaid contributions to society. Once monetary incentives are introduced, individuals tend to lose this intrinsic motivation, crowding out the perceived need for action. This phenomenon of crowding-out has been observed, for instance, in the context of waste recycling and community work.[180]

Crowding-out also occurs when individuals pay for certain types of behavior, such as environmental pollution; such a payment – whether voluntary or mandatory – makes them feel entitled to pollute, diminishing the motivation to change their polluting behavior.[181] The

[169] E.g. car sales in Germany 03/2018 month-to-month: diesel (-25.4%); electric (+73.1%); hybrid (+45.4%); see (Kraftfahrtbundesamt, 2018).
[170] See (Dewenter, Heimeshoff, & Thomas, 2016) for an empirical analysis of how general media coverage influences customer behavior to buy a new car.
[171] See (Trump & Newman, 2017).
[172] See (Loewenstein & Thaler, 1989).
[173] See (Mullainathan & Thaler, 2000).
[174] See (Mullainathan & Thaler, 2000).
[175] See (W. Samuelson & Zeckhauser, 1988).
[176] See (Gately, 1980).
[177] See (Ruderman, Levine, & McMahon, 1987).
[178] See (Frederick, Loewenstein, & O'donoghue, 2002) for a review of studies assessing individual discount rate; results ranging from -6% to infinity.
[179] See (Rabin, 1993).
[180] See (Brekke, Kverndokk, & Nyborg, 2003).
[181] See (Bazin, Ballet, & Touahri, 2004).

example of a daycare center, where the number of delayed pickups increased after the introduction of a late fee, illustrates that effect.[182]

Monetary incentives and disincentives are not the only factors leading to motivational crowding-out. Humans have also been shown to crowd out pro-environmental behavior once the government intervenes. The motivation of households to act in a pro-environmental way, such as energy-saving actions, has been found to decline once the government intervenes.[183]

2.2.3 Government Failure: The Case of *Homo Politicus*

Irrespective of the agents' rationality or irrationality, standard market failure and behavioral failure both call for government intervention. Unfortunately, *homo politicus* can also fail by regulating inadequately due to a variety of factors summarily described by cognitive, organizational, and political constraints.[184] As we show in this section, information is key to all these constraints.

Governments are formed by and act through individuals, whose cognitive limitations can result in flawed policies due to a failure to respond adequately to the available information.[185] This failure to see, seek, use, or share relevant data has been coined 'bounded awareness'.[186] Individuals focused on a specific task have been shown to miss important developments outside their immediate focus.[187] Due to its complexity, climate change incurs a significant risk of policy-makers missing relevant data, ignoring signs, and taking insufficient action.[188]

Firms try to take advantage of this bounded awareness of policy-makers by lobbying for their vested interests, for instance by selectively providing information that supports these interests. From 2000 to 2016, lobbying expenditure on climate-related legislation in the U.S.

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[182] See (Gneezy & Rustichini, 2000).
[183] See (Werfel, 2017).
[184] See (J. E. Stiglitz, 2009), p. 35-37; examples of proposed inability e.g. (Max H Bazerman & Watkins, 2004) arguing that the terrorist attacks of 09/11 could have only happened due to a bounded response of the government to available information.
[185] See (Sunstein, 2013a, 2013b; Tullock et al., 2002).
[186] See (Max H. Bazerman, 2006; Max H Bazerman & Chugh, 2006; Max H Bazerman & Sezer, 2016).
[187] The best-known demonstration of this constraint is an experiment in which an audience is asked to count the number of passes in a basketball game. After the game, most participants are shown to have missed a person with a gorilla costume walking through the scene, as they were so focused on counting passes, see (Simons & Chabris, 1999).
[188] See (Max H. Bazerman, 2006).

added up to over $2 billion, or 3.9% of the total spending on lobbying.[189] It is noteworthy that lobbying on behalf of fossil fuels outpaced renewable lobbying 10:1 in terms of spending.[190]

Lobbying also relates to the second dimension of government failure, termed regulatory capture. This failure has a bearing on the question of why efficient carbon prices are politically unacceptable, while the corresponding mitigation targets are acceptable. As seen during the design phase of the European Union Emissions Trading System (EU ETS), a significant share of emitting installations succeeded in receiving more emission allowances than they needed, undermining the environmental stringency of the entire system.[191] The phenomenon of polluters shaping climate policy is evident across a majority of jurisdictions.[192] That the limited number of large emitters facing major and immediate regulatory costs will rally more effectively than the population at large, which can only expect minor benefits over the long term, might explain this phenomenon.[193]

Besides these cognitive and political constraints, organizational flaws further limit welfare-optimal policy-making.[194] Governments have internal hierarchies that generate contractual hazards between layers. As a result, rational behavior on an individual level does not necessarily eventuate in collective rationality,[195] as pork-barrel politics in the context of climate change shows.[196] And finally, governments may simply lack the human and financial capacity needed to implement first-best policy options.[197] Faced with investments or staffing needs that exceed available budgets, policy-makers may opt for less efficient policy alternatives instead.

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189 See (Brulle, 2018).
190 See also (Delmas, Lim, & Nairn-Birch, 2016) for an analysis of corporate lobbying on climate change between 2006-2009.
191 See (Hepburn, 2010).
192 See (Hughes & Urpelainen, 2015).
193 See (Olson, 1965).
194 See (Williamson, 2000).
195 See (Heckman, 2001; Kirman, 1992).
196 See (Helm, 2010).
197 For a discussion of such capacity constraints in the context of carbon pricing, see (Bell, 2003).

2.3 Carbon Pricing: From Efficiency to Equity

In addition to economic efficiency, distributional effects matter.[198] If policy-makers drive the implementation of climate change mitigation to achieve deep decarbonization, redistribution of wealth will become a major challenge.[199] This section describes inequitable market outcomes, caused by climate policy, and a potential abatement of such outcomes through carbon pricing with carbon dividends.[200]

Subsidies for electric vehicles are an example of how climate policies can be equal and inequitable at the same time. Governments around the globe grant incentives such as tax credits to all buyers of EVs to lower upfront costs. Still, the ability to take advantage of these subsidies is conditional on the financial capacity to purchase an EV in the first place. Considering a base price of $50k+ for a Tesla Model 3 in the U.S., the financial hurdle immediately excludes a significant part of the population, resulting in an inequitable outcome. In other words, tax revenue from lower-income populations is effectively subsidizing the ability of households in a wealthier tax bracket to afford electric vehicles with only a very modest effect – at the margin between both taxpayer groups – of enabling lower-income households to afford EVs.[201]

As with subsidies, carbon pricing may also foster distributional effects and inequity. A sufficiently high price on carbon emissions is essential to act efficiently. Unfortunately, carbon pricing on its own tends to act regressively: Low-income households are hit relatively harder than high-income households, as they spend a relatively larger portion of income on products with a high carbon footprint.[202] However, unlike alternative policy options, pricing carbon has the advantage that it generates government income, through tax payments or auction proceeds of emission certificates. These revenues can be used to reduce fiscal deficits, spent for dedicated purposes like R&D subsidies, or used to mitigate distributional effects on affected households.[203]

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[198] Under certain conditions, the problem of efficiency and distribution can be separated in welfare economics, see (Varian, 1987).
[199] See (Büchs et al., 2011; Fullerton, 2011; Hirth & Ueckerdt, 2013).
[200] Definition: Carbon dividends are the redistribution of revenues generated by the carbon pricing, see (Climate Leadership Council, 2018).
[201] See (Borenstein & Davis, 2016).
[202] See (Kosonen, 2012).
[203] See (Jenkins & Karplus, 2017; Klenert et al., 2018).

The option to mitigate distributional effects by redistributing carbon pricing revenues has been finding increasing support in the current debate. An equally distributed carbon dividend might reduce the regressive effect of carbon pricing and even act as a progressive policy in the short run, as rich people face higher payments than poor people.[204]

Estimates for the U.S. show that a carbon price of \$50/tCO_2 could yield a carbon dividend of \$413 per capita and year. Subtracting the cost increase from the consumption of carbon-containing goods, this dividend payment increases the expendable income of the average person in the lowest income decile by 1.77%. In the decile with the highest income, expendable income would decline by 0.91%. Overall, 84% of people in the bottom half of the income distribution would be better off.[205]

The ability of carbon pricing with dividends to reduce social inequity would grow with higher carbon prices. Using the same model, and assuming a uniform price response of all households, a carbon price of \$230/tCO_2 would yield dividends worth \$2,237 per capita and year. In the bottom income decile, the dividend would offset the cost rise in consumption of \$866, and increase expendable income by 14%. The average person in the top income decile would face a cost increase of \$4,738 and lose 9% of expendable income. Overall, for the bottom six deciles, the dividend would offset the burden of the carbon price with an increase in welfare.[206]

[204] See (Climate Leadership Council, 2018).
[205] See (Fremstad & Paul, 2017b).
[206] See (Fremstad & Paul, 2017a).

2.4 Policy Recommendations

The ability of carbon pricing to achieve sufficient emission reductions at the margin has been sufficiently established.[207] Our review of three failures – conventional market failure, failure of human behavior, and government failure – underlines the need for complementary policies to limit global climate change. These complementary policies include supportive policies with greater transformational effectiveness, as well as restrictive policies with a greater target effectiveness.

However, as the current debate moves in the direction of focusing on such complementary policies, carbon pricing is at risk of being prematurely relegated to a very limited role in the policy mix. Therefore, it is important to distinguish areas that actually require complementary policies from areas where complementary policies incur serious risk of static or dynamic inefficiencies, including, in particular, the promotion of dead-end technologies. In addition to picking wrong winners, such a focus on directed policies would also sacrifice the availability of those technology options which are not favored by support policies, whereas carbon pricing would create a technology-neutral incentive for all mitigation options.[208]

Going forward, the key challenge will be to overcome political and other constraints that currently prevent the introduction of efficient carbon pricing levels. Therefore, future research should support a shift to carbon pricing at the required level through (1) collaboration, (2) stepwise actions, (3) reduced complexity, and (4) the right framing.

1) *Collaborative.* The consequences of climate change create a powerful incentive for sectors such as finance, insurances, and agriculture to engage in mitigation.[209] Recent coal divestments of insurance companies and pension funds underline that potential.[210]
2) *Incremental.* Although researchers highlight the necessity to tackle the challenge rather sooner than later to avoid high costs in the long run,[211] humans stick to habits

[207] See (Grubb et al., 2014) for a detailed summary that carbon pricing should be used at the profitability threshold of the marginal abatement cost curve. Marginal abatement cost curves present options for emission reduction and their respective potential, sorted by abatement cost.
[208] See (Acemoğlu et al., 2016; Fried, 2018) for how pricing can trigger innovation.
[209] See (Newell & Paterson, 1998).
[210] See (Carrington, 2018).
[211] See (Bertram, Luderer, et al., 2015; Johnson et al., 2015).

and dislike rapid change.[212] Therefore, realistic long-term strategies with stepwise action to decarbonize our society are needed, instead of aspirations for radical change.[213] Important, however, such incremental action has to be started quickly; otherwise, we lock ourselves into a future need for radical or risky strategies, such as climate engineering.[214]

3) *Simple*. Policy-makers are no climate scientists. A timeline to reach net-zero emissions is much easier to understand than arguments based on remaining cumulative emission budgets, along scenarios such as the four representative concentration pathways of the Intergovernmental Panel on Climate Change (IPCC).[215]
4) *Attractive*. Policies will not stop people from certain types of conduct.[216] Nonetheless, the boundedness of human rationality is not only a challenge but also an opportunity for crowding in people. Since most people care about the climate,[217] a different framing could lower efficient price levels. Economists have demonstrated the power of nudging.[218] In practice, efforts to lever this tool have just begun.[219]

Besides these four principles to overcome political constraints and approach efficient carbon pricing levels, policy-makers should recognize the opportunity to mitigate distributional effects through carbon pricing plus carbon dividends as highlighted in Section 3. Yet, it appears questionable whether the progressive effect will persist in the long run. Low-income households have far fewer options to reduce their carbon footprint compared to high-income households. Low-income households are more likely tenants, and the upfront cost of energy-efficient devices or vehicles can be a major obstacle for them to reduce their carbon footprint. In addition, only high-income households are able to benefit from some incentives to reduce their carbon footprint, for instance, support for installing rooftop PV, improving thermal

[212] E.g. resistance to the introduction of a speed limit of 100km/h on country roads in Germany (Spiegel, 1971).
[213] See (Jordan & Matt, 2014; Meckling, Kelsey, Biber, & Zysman, 2015; Pahle et al., 2018).
[214] Note: In past extreme situations, societies were able to undergo very radical transformation processes – indeed even demanded them. However, revolutions are typically accompanied by massive risk and sacrifice, see e.g. China during the 20th century, (Rummel, 1991).
[215] See (Sunstein, 2013a) on the importance of simplicity in policy-making.
[216] E.g. people continued to consume alcohol at scale during Prohibition, see (Miron & Zwiebel, 1991).
[217] See (Steg, 2018; Van der Linden, Maibach, & Leiserowitz, 2015).
[218] See (Dean, 2018), (Houde & Aldy, 2017) assess the effect of energy efficiency labels, (Sunstein & Reisch, 2014) assess the effectiveness of green default rules.
[219] See (Lanz, Wurlod, Panzone, & Swanson, 2018) information about product embodied carbon emissions to trigger voluntary substitution; see (Times, 2018) for the proposed initiative in Denmark.

insulation, or acquiring an EV. Therefore, more research is needed to understand the long-term implications of carbon pricing on the carbon footprint by income level.

Throughout history, taxation has been the cause of popular rebellions (e.g. the Protestant Reformation, and the Boston Tea Party).[220] And yet, the protests of the “Yellow Vests” in France in late 2018 and early 2019, which were directed, *inter alia*, against rate hikes for fuel taxes, underline that policy-makers still struggle to understand (and prevent) unintended reactions due to perceived social injustices.[221] As argued in this paper, a well-understood mix of policies is needed, rather sooner than later, to prevent climate change – the greatest market failure ever – from also becoming the greatest human and government failure.

[220] See (Burg, 2004) for a chronology of tax caused riots through history.
[221] See (J. E. Stiglitz, 2019).

3 Essay II – Fuel-switching and Deep Decarbonization

by Christian Stoll

Abstract

Fuel-switching is inevitable to achieve deep decarbonization. Humanity has used approximately two-thirds of the carbon budget compatible with the goal to limit global warming to 2 °C. This has, *inter alia*, contributed to growing opposition against the use of coal, prompting an increasing number of countries to announce coal phase-out mandates in the power sector. Advocates of coal phase-outs highlight the expected climate benefits of fuel-switching from coal to gas. However, a narrow focus on coal and gas generation resources ignores advancements in low-carbon technologies. I present a simple model to find the least-cost approach to achieve committed climate targets, through fuel-switching in the power sector. A case-study, drawing on the example of Germany, reveals counter-intuitive results that go against conventional assumptions about the role of coal. The findings suggest that, when accounting for stranded assets, a decarbonization pathway that is based on a gradual transition to renewable energy and initially retains coal generating assets turns out to be less expensive than a strict coal phase-out.

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3.1 Introduction

Humanity has used up two-thirds of the carbon emission budget compatible with the goal of limiting global warming to 2 °C.[222] The global mean temperature has increased by 0.9 °C, and out of the last twenty years, eighteen were among the warmest since 1880.[223] As emissions continue to rise, limiting global warming below 2 °C is widely considered to require substantial policy intervention. As a result, 195 countries agreed to take respective actions in 2015 in Paris.[224]

To reduce carbon emissions, economic theory suggests the use of carbon pricing[225] as the most cost-efficient policy instrument.[226] From a welfare perspective, carbon pricing, in the form of a carbon tax or cap-and-trade mechanism, reduces emissions at the lowest cost.[227] However, in practice, policy-makers increasingly resort to phase-out mandates to accomplish committed emission reductions.[228] As climate policy research focuses on carbon pricing as the first-best option, research into the effects and design of phase-out mandates has lagged behind.

To decarbonize the power sector, the public debate has increasingly focused on phasing out coal power plants. Promoters of coal phase-outs highlight the expected climate benefits of fuel-switching from coal to gas. For every year of coal displacement, fuel-switching to gas adds 1.4 to 2.4 years until depletion to the carbon budget, as gas combustion emits less than half the CO_2 of coal.[229] Therefore, gas may act as a bridge-fuel until zero-emission technologies are available at scale.[230]

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[222] We have used up 1,890 $GtCO_2$-eq of 2,900 $GtCO_2$-eq that preserve a 66% probability to limit global warming to 2 °C above pre-industrial time, which refers to the average temperature between 1850 and 1900, see (IPCC, 2013), p. 27; see (William D Nordhaus, 1977) on the 2 °C bound, which is commonly used as the upper limit in order to avoid the worst consequences of climate change.
[223] See (GISTEMP, 2018; Hansen et al., 2010).
[224] See COP21 Paris Agreement (UNFCCC, 2015a).
[225] Definition: "carbon pricing refers to initiatives that put an explicit price on greenhouse gas emissions, i.e. a price expressed as a value per ton of carbon dioxide equivalent (tCO2e)", see (Worldbank, 2017).
[226] See (J. Stiglitz et al., 2017).
[227] See (Goulder & Schein, 2013).
[228] The poster example is the ban of inefficient light bulbs in the residential sector, see (Tonzani, 2009). In the transport sector, banning cars from inner cities has been under discussion, see (Möhner, 2018), and there is a growing number of coal phase-out announcements in the power sector: e.g. France (by 2022), Sweden (by 2022), Italy (by 2025), UK (by 2025), Austria (by 2025), Finland (by 2030), Netherlands (by 2030) and Portugal (by 2030), see (Powering Past Coal Alliance, 2018).
[229] See (Wilson & Staffell, 2018).
[230] See (Kerr, 2010; Levi, 2013; X. Zhang et al., 2016).

Research has suggested that phase-outs are politically more feasible than carbon pricing at sufficiently high levels,[231] and highlighted their ability to destroy existing structures while creating space for innovation.[232] Phase-out policies are touted as transparent, simple, and influential in creating anti-fossil norms.[233] An example is the nuclear phase-out in Germany, which has been credited with triggering more R&D spending on renewable resources than the Renewable Energy Act (EEG).[234]

And yet, a view that focuses on coal and gas appears too narrow-minded, as it ignores central factors required for answering the question of which fuel-switching strategy is cost-optimal in order to remain on a politically agreed decarbonization pathway. In particular, zero-carbon resources inevitably become necessary at a certain point to remain on the decarbonization pathway, yet existing infrastructure carries the risk of long-term lock-in of high-carbon technologies.[235] This potential lock-in has its roots in power plants that continue operations as they become stranded.[236]

Previous academic studies highlight the importance to consider a portfolio of low-carbon generation technologies to decarbonize the energy sector in a cost-effective manner,[237] and many sophisticated modeling studies have simulated future power system compositions. However, these simulations typically target single aspects instead of capturing the wider context of deep decarbonization,[238] and to my knowledge, none of the previous studies that capture the overarching decarbonization challenge has highlighted the effects of asset stranding.[239]

I present a simple model to find the least-cost resource mix, which is consistent with the committed climate targets. Firstly, I explain the intuition and logic of the model. This includes an explanation of how a capacity planner can determine the resource mix in order

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[231] See (Bertram, Luderer, et al., 2015).
[232] See (Geels et al., 2017).
[233] See (Green, 2018).
[234] See (Rogge & Johnstone, 2017).
[235] See (Bertram, Johnson, et al., 2015; Seto et al., 2016; Unruh, 2000).
[236] This 'asset stranding' would be accompanied by devastating wealth loss, distributional impacts, see (Mercure et al., 2018), and potential destabilized the financial system, see (ESRB, 2016). 'Stranded assets' are defined as "assets that have suffered from unanticipated or premature write-downs, devaluations or conversion to liabilities", see (Caldecott et al., 2014), p. 2.
[237] See (Sepulveda et al., 2018).
[238] E.g. assessments of the future development of coal-fired power generation, see (Aurora Energy Research, 2018).
[239] See (Samadi, Fischedick, & Lechtenböhmer, 2018) for a comparison of recent studies on decarbonization scenarios in Germany.

to cover load demand at least-cost, how climate targets constrain the task, and how carbon constraints switch the roles of fuel types. Secondly, I mathematically formulate the problem so as to numerically determine the least-cost resource mixes which satisfy distinct targets along the decarbonization pathway. Lastly, I solve the model, drawing on the example of Germany.

The model I present has numerous limitations in comparison to complex integrated modeling work, which is typically used to analyze such scenarios. Nevertheless, the results that my model provides can offer thought-provoking impulse on the impact of stranded assets and how those can be part of a cost-effective decarbonization pathway. These impulses may nudge policy-makers to consider alternative options and may help them to see the challenges in the broader context. Such an expanded mental horizon can be particularly valuable in jurisdictions, which still debate publicly the narrow question of how to reduce power generation from coal generation resources instead of targeting the overarching challenge.

Still, phasing out coal will more than likely trigger the deployment of additional gas resources. In practice, a gas power plant commissioned today would not be in operation prior to 2025, and by 2050, the last emitting resource already has to leave the market if the carbon budget is to be met. Given their useful economic life of 35 years, additional gas resources would therefore inevitably become stranded.

What is more, there is considerable uncertainty about the life-cycle emission factors of gas. Combustion is only the tip of the iceberg, and GHG emissions along the supply chain vary, depending on fuel type, origin, and destination.[240] Novel insights on pipeline leakage[241] and flaring at shale production sites[242] suggest much higher carbon emissions from gas than commonly assumed; climate benefits of gas over coal diminish, or may even reverse in some cases. This aspect has to be clarified prior to assessing the technical feasibility of coal phase-outs,[243] and prior to building new LNG infrastructure.[244]

[240] For instance, the carbon intensity of gas depends on extraction (conventional vs fracking), processing (LNG vs w/o liquefaction), storage, transmission (pipeline vs ship vs distance) and distribution; similar of coal (e.g. underground vs surface extraction), and oil as shown by (Masnadi et al., 2018).
[241] E.g. (Alvarez et al., 2018) find for the U.S. that CH_4 leakage along the gas supply chain causes comparable warming as the emissions from combustion.
[242] See (Elvidge et al., 2018).
[243] See, e.g., (Aurora Energy Research, 2018).
[244] E.g. Subsidized construction of LNG terminals in Europe, see (Bloomberg, 2018).

The case-study, based on the example of Germany, reveals counter-intuitive results that go against conventional opinions on the role of coal. The findings suggest that, when considering stranded assets, a decarbonization pathway that involves the expansion of renewables and includes a continued, but gradually declining role for coal, turns out to be less expensive than a strict coal phase-out. Committed decarbonization targets can still be achieved by adding only minimal new gas capacity. It is more cost-effective to initially keep existing coal resources in the market, and expand zero-carbon technologies. The costs in a scenario with a politically forced coal phase-out are significantly higher, as additional gas resources have to fill the supply gap.

The paper is organized as follows: Section 3.2 provides the intuition and logic of the model. Section 3.3 presents the model. Section 3.4 quantifies the effects, drawing on the example of Germany. Section 3.5 concludes.

3.2 Intuition and Logic of the Model

Fuel-switching in the power sector is inevitable to achieve deep decarbonization. Section 3.2 introduces the impact of decarbonization on capacity expansion modeling. In the first sub-section, I explain the objective of capacity expansion modeling. In the second sub-section, I explain the implications of climate targets for capacity expansion modeling. In the last part, I explain the effects of decarbonization on the roles of fuel types.

3.2.1 Capacity Expansion Modeling

The classic objective of capacity expansion modeling in the power sector is to minimize the total cost of power generation. The total costs of power generation can be divided into fixed costs and variable costs. Fixed costs are largely determined by the initial investment cost, while variable costs are largely determined by the fuel costs of the respective generation technology. The initial investment costs, which are the sum of all costs to build a power plant can be annualized based on the plant life-time and a respective interest rate. By adding the annual variable costs of power generation, one derives the total annual cost of power generation.[245]

For comparability reasons, the annualized fixed costs can be divided by the generation capacity to determine an amount per unit of generation capacity (e.g., in U.S. dollar per megawatt ($/MW)). The annual variable costs of power generation depend on the degree of capacity utilization. The capacity utilization is measured by a so-called capacity factor (CF), which ranges from zero to one. Zero represents no operation, while one denotes full-load operations over 8,760 hours throughout the year. By multiplying the duration of operations (in hours (h)) with the variable costs per unit of generated electricity (e.g. in U.S. dollar per megawatt-hour ($/MWh)), one derives the total variable costs per unit at a certain capacity utilization. Adding the annualized fixed costs per unit reveals the total cost per unit of generated electricity at the respective capacity utilization (e.g. in $/MW).

Based on the technology-specific cost functions, a central planner seeks to find the least-cost resource mix to meet given load demand. The load demand to be covered can be displayed as a load duration curve (LDC), that is, the annual demand sorted by size, starting with the hour of the highest load.

If the planner knows the LDC and the CF-dependent costs by technology, he or she can find the least-cost capacity by resource technology that is required to cover the load demand. The least-cost capacity mix typically consists of resource technologies with different cost functions. For instance, resource technologies with low fixed but high variable cost may be best suited to cover load peaks, while resource technologies with high fixed and low variable are superior to cover based load at high capacity utilization. The capacity planner can find the least-cost resource mix by mapping the cheapest resource technology for each CF to the LDC.

To illustrate the solution process, for now, assume there are only two resource technologies available. The first one is characterized by high fixed and low variable costs of power generation, while the second technology is characterized by low fixed and high variable cost of power generation. An example of two generation technologies with such a relative cost relationship can be found in coal and gas generation resources. Typically, the fixed costs of coal power plants surpass the fixed costs of gas power plants on a per-unit basis. Furthermore,

[245] See (Stoft, 2002).

the variable costs of gas-fired power generation typically surpass the variable costs of coal-fired power generation. Consequently, gas-fired power plants may provide cheaper electricity at low capacity utilization. Yet, at a certain CF, the lower variable costs of coal may offset the fixed costs. A respective constellation is charted in the upper chart of Figure 12. The interception point reveals the capacity utilization, where the annualized total cost per unit of generated electricity of both technologies are equal.

The lower chart in Figure 12 illustrates a load duration curve. The load duration curve represents the hourly load demand during one year, starting with the hour of the highest load and sorted in descending order. If one transfers the interception point of the cost functions in the upper chart down to the load duration curve, one finds the cost-optimal total capacity level of both technologies. Deploying coal resources over this capacity and gas resources over maximum load minus optimal coal capacity results in the least-cost resource mix to cover the respective load. As illustrated in the lower chart of Figure 12 by the dashed horizontal line, the least-cost resource capacity by technology can be read off the y-axis of the LDC.[246]

[246] Note: In the case of more than two technologies only the intersection points of the cost curves at the upper limit of the trapezoid among x-axis, y-axis and cost curves are relevant.

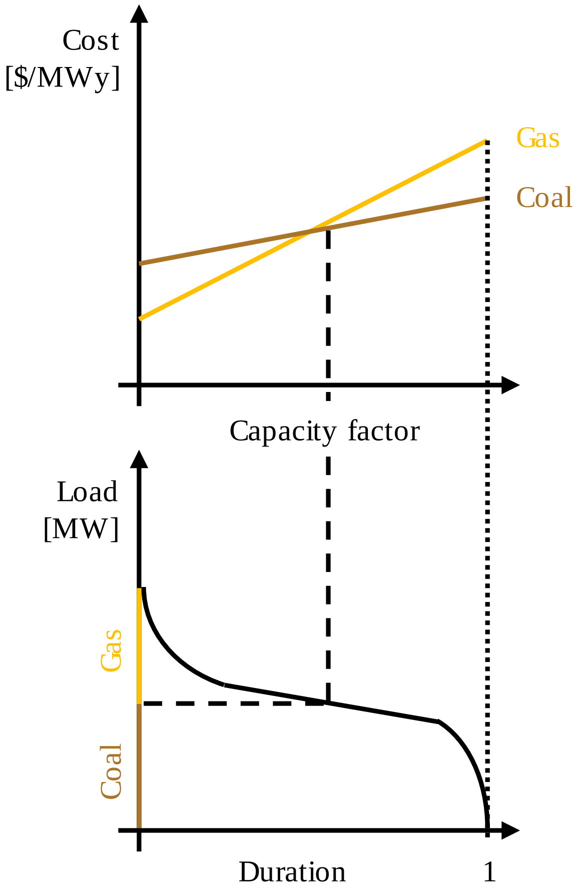


Figure 12: Stylized power system with two technologies.[247]

The illustrated capacity planning model is known as the 'Screening curve method' in energy economics research.[248] The Screening curve method is used to find first-order estimates of the least-cost resource mix to service a given load, as it ignores factors like operational constraints[249] and existing capacity.[250]

3.2.2 Capacity Expansion Modeling with Carbon Constraints

Keeping global warming below 2 °C requires reducing emissions in the power sector. The required emission reductions define an annual carbon budget, which represents the upper

[247] Own illustration.
[248] The method was originally proposed by (Phillips, Jenkin, Pritchard, & Rybicki, 1969).
[249] See (Batlle & Rodilla, 2013; De Sisternes, 2013).
[250] See (Güner, 2018; T. Zhang & Baldick, 2017).

limit of cumulative emissions over a defined time period. This sub-section explains how a carbon budget constrains the central planner when determining the least-cost resource mix.

Economic theory suggests carbon pricing[251] as the most cost-effective policy instrument to reduce carbon emissions.[252] Putting a price on carbon emissions, for instance through a carbon tax or cap-and-trade mechanism, is found to reduce emissions at a lower cost to society, that is, from an aggregate welfare perspective, than direct regulation such as performance standards or technology mandates.[253] In theory, taxes[254] and tradable permits[255] can achieve equal results, and the preference for one or the other policy instrument ultimately depends on the curving of the functions of the marginal damage and benefit of emissions around the optimal quantity level.[256]

In the optimization model, a shrinking carbon budget becomes binding at one point in time and restricts the potential combinations of resource technologies. When solving the model, a binding constraint correlates with a positive shadow price, that is, the marginal cost per unit of carbon in the optimal solution. This shadow price has the exact same effect as a carbon tax at a price level to meet exactly the carbon budget constraint. Consequently, the carbon constraint alters the cost of power generation, in line with the carbon intensity of each resource technology.[257] As a result, low-carbon technologies become increasingly competitive.

3.2.3 Fuel-switching Under Carbon Constraints

The challenge to limit global warming appears to be more than a capacity expansion problem. The challenge also includes capacity dispatch and replacement, as limiting global warming below 2 °C requires achieving carbon neutrality during the second half of the century.[258] Thereby, a rising carbon price can switch the cost-sequence among resource technologies

[251] Definition: "carbon pricing refers to initiatives that put an explicit price on greenhouse gas emissions, i.e. a price expressed as a value per ton of carbon dioxide equivalent (tCO2e)" (Worldbank, 2017).
[252] See (J. Stiglitz et al., 2017).
[253] See (Goulder & Schein, 2013).
[254] See (Pigou, 1920).
[255] See (Coase, 1960).
[256] Based on (Weitzman, 1974), a large body of literature discusses criteria to rank taxes over cap and trade, see e.g. (Karp & Traeger, 2018).
[257] An analysis of regional differences (USA, China, and Germany) can be found in Appendix 1.
[258] See (UNFCCC, 2015a).

with dissimilar carbon intensity. This fuel-switching can refer to a complete switch of the cost sequence (i.e. across the entire LDC) or a partial switch for certain CFs.

Firstly, assume a greenfield decision, as is the case in a capacity expansion problem. In this case, which involves a long-term perspective, investment cost matters. The introduction of a price on carbon alters the variable cost of generation, and a rising carbon price will make low-carbon technologies increasingly competitive. For instance, coal power plants require an increasing number of full-load hours to offset the lower fixed cost of gas resources. At a certain carbon price, gas resources become cheaper than coal at any capacity utilization. The upper left chart of Figure 13 depicts the constellation when gas resources become cheaper at any CF.

Secondly, assume a brownfield decision with existing capacity, as is the case in a short-run dispatch decision. In this case, only the marginal cost of power generation matters. The sorted marginal cost of resource technologies – called merit order – determines which resources are utilized to cover load demand. The upper right chart of Figure 13 depicts the constellation where coal and gas resources break-even for any capacity utilization. In this case, the fuel-switching potential is limited by the idle capacity of low carbon resources and the current amount of power generated by high carbon resources.[259]

Thirdly, assume a combination of the two previous cases, as is the case in a capacity replacement decision. As existing units fully depreciate prior to leaving the market, investment cost only matters for candidate units.[260] Still, new gas resources become competitive to existing coal resources at a certain carbon price, once the lower carbon intensity of gas (and the relative advantage under a carbon price) offsets higher investment costs. The lower left chart of Figure 13 depicts a constellation where new gas resources break even with existing coal at full capacity utilization. With further rise in the carbon price, it becomes increasingly attractive to replace existing high-carbon coal resources with low-carbon gas resources. The lower right chart of Figure 13 depicts an intersection point at 10% capacity utilization.

[259] In many countries, the current power generation from coal surpasses the idle gas capacity. Therefore, the idle gas capacity can be seen as an upper limit of coal-to-gas switching in the short run, as it assumes ideal storage and transmission capacity. See Appendix 2 for an estimate of regional differences (USA, China, and Germany).

[260] As fixed O&M costs are minor (~1% of the capital cost), I assume zero fixed cost for existing resources that are fully written-off, see (Güner, 2018; T. Zhang & Baldick, 2017); The term “candidate units” refers to potential new plants.

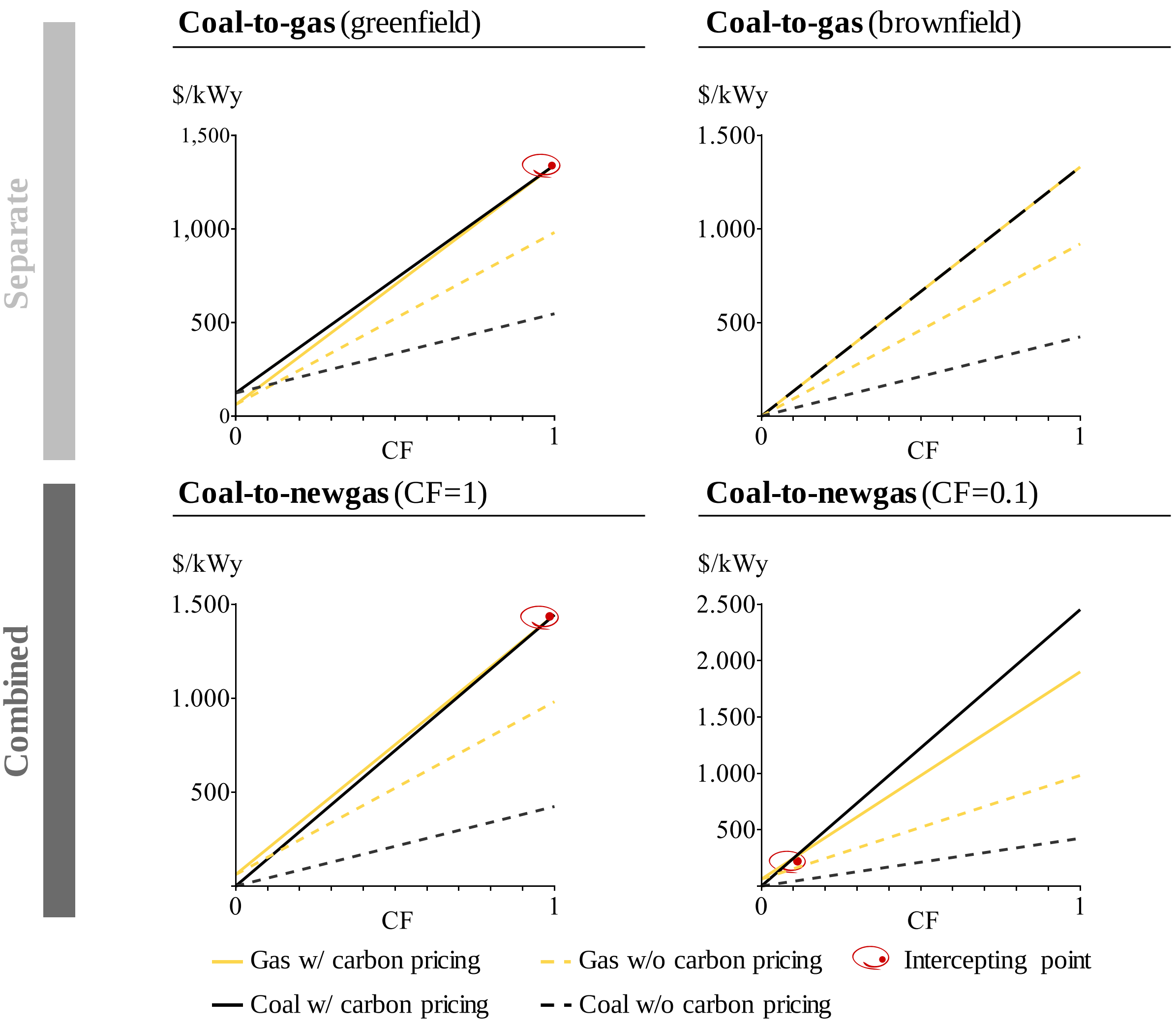


Figure 13: Coal-to-gas fuel-switching under carbon constraints.[261]

[261] Own illustration; The cost functions and carbon intensities are based on German parameters in order to illustrate the relative scale; data sources: carbon emission factors from (UBA, 2017b); cost data from (IEA & NEA, 2015); calculation of annualized fixed cost based on overnight cost assuming 7% interest rate and a plant life-time of 30 years for gas and 40 years for coal-fired power plants in line with (IEA & NEA, 2015); equal split of natural gas in CCGT (Combined Cycle Gas Turbines) and OCGT (Open Cycle Gas Turbines) for Germany as argued in (Schill, Pahle, & Gambardella, 2017).

3.3 Model: Least-cost Power Generation with Carbon Constraints

Section 3.3 provides the mathematical formulation of the model explained in Section 3.2.[262] The aim is to quantify the cost, timing, and scope of fuel-switching under carbon constraints. As explained in Section 2, the objective is to minimize the average cost of electricity, which is equal to minimizing total system cost (*TC*) for a given load demand. Thereby, *TC* consists of annualized investment cost (*FC*) and variable generation cost (*VC*). In mathematical formulation, the objective function can be expressed as:

$$min\ TC_a = \sum_{i=1}^{n} FC_{i\,a} * k_{i\,a} + \sum_{i=1}^{n} \sum_{j=1}^{m} VC_{i\,a} * e_{i\,j\,a}, \tag{1}$$

where the two decision variables $k_{i\,a}$ denotes resource capacity and $e_{i\,j\,a}$ produced energy by technology i, in the hour j of the year a:

$$i = 1, \ldots, n \tag{2}$$

$$a = \{2020; 2030; 2040; 2050\} \tag{3}$$

$$j = 1, \ldots, 8760. \tag{4}$$

To incorporate the effect of existing infrastructure, I assume zero fixed cost for existing resources ($i \in$ old).[263] The cost sequence of resource technologies can be summarized as:

$$VC_{i\,a} < VC_{(i+1)\,a} \qquad \forall\ i, a \tag{5}$$

$$FC_{i\,a} > FC_{(i+1)\,a} \qquad \forall\ i \notin \text{old}, a \tag{6}$$

$$FC_{i\,a} > 0 \qquad \forall\ i \notin \text{old}, a \tag{7}$$

$$FC_{i\,a} = 0 \qquad \forall\ i \in \text{old}, a. \tag{8}$$

The total annual energy produced by technology i is determined by:

[262] The mathematical formulation of the static cost optimization, considering existing units, is derived from formulations in previous studies, see (Levin & Zahavi, 1984; Murphy & Weiss, 1990).
[263] Fixed operation and maintenance costs are minor (~1% of capital costs), see (Güner, 2018; T. Zhang & Baldick, 2017).

$$\sum_j e_{i\,j\,a} = \int_{D_{i\,a}}^{D_{(i+1)\,a}} L_a{}^{-1}\,(z)\,dz \qquad \forall\, i, \text{a} \qquad (9)$$

with $L_a{}^{-1}\,(z)$ being the inverse of the load duration curve in the year a , and $D_{i\,a}$ being the loading point. The loading point of a resource technology is determined by the sum of utilized capacities that come prior in the merit order:

$$D_{1\,\text{a}} = 0 \qquad \forall\, i = 1, \text{a} \qquad (10)$$

$$D_{i\,a} = \sum_{l=1}^{i-1} k_{l\,a} \qquad \forall\, i = 1, \ldots, n + 1, \text{a} \qquad (11)$$

$$D_{n+1\,a} = L_a^m, \qquad \forall\, \text{a} \qquad (12)$$

where L_a^m represents peak load during the year a.
The first constraint of the model is full coverage of price-inelastic demand at all times, which implies a respective capacity:

$$\sum_i k_{i\,a} \geq L_a^m \qquad \forall\, \text{a}. \qquad (13)$$

To illustrate graphically how the first constraint limits the solution space, I again draw on the example of coal and gas resources. As illustrated in Figure 14, all combinations of coal and gas generation equal to or greater than demand fulfill the constraint. As the objective is to minimize cost, the optimal combination can be found on the demand constraint line.

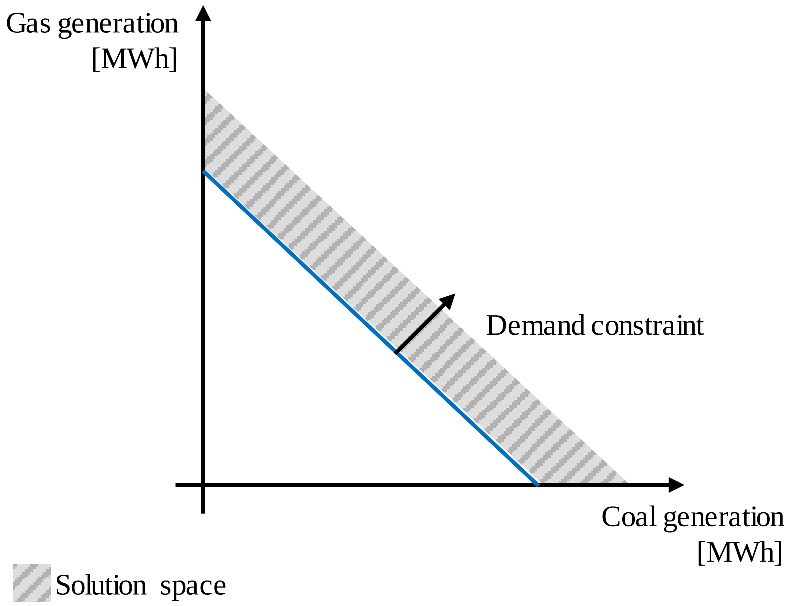


Figure 14: Impact of the demand constraint on the solution space.[264]

I expand the basic formulation of the model by adding a constraint that reflects an annual carbon emissions budget (B_a):

$$\sum_i \sum_j e_{i\,j\,a} * C_{i\,a} \leq B_a \qquad \forall \text{ a} \qquad (14)$$

where the total emissions are the product of generated energy e_{ij} multiplied by the technology-specific emission factor $C_{i\,a}$.

Figure 15 illustrates the effect of a binding carbon constraint in two distinct cases: firstly, a carbon budget below the current emissions level, but achievable with a combination of coal and gas resources (Case I). Second, a carbon budget below the current emissions level that cannot be satisfied with any gas-coal-mix (Case II).

[264] Source: Own illustration.

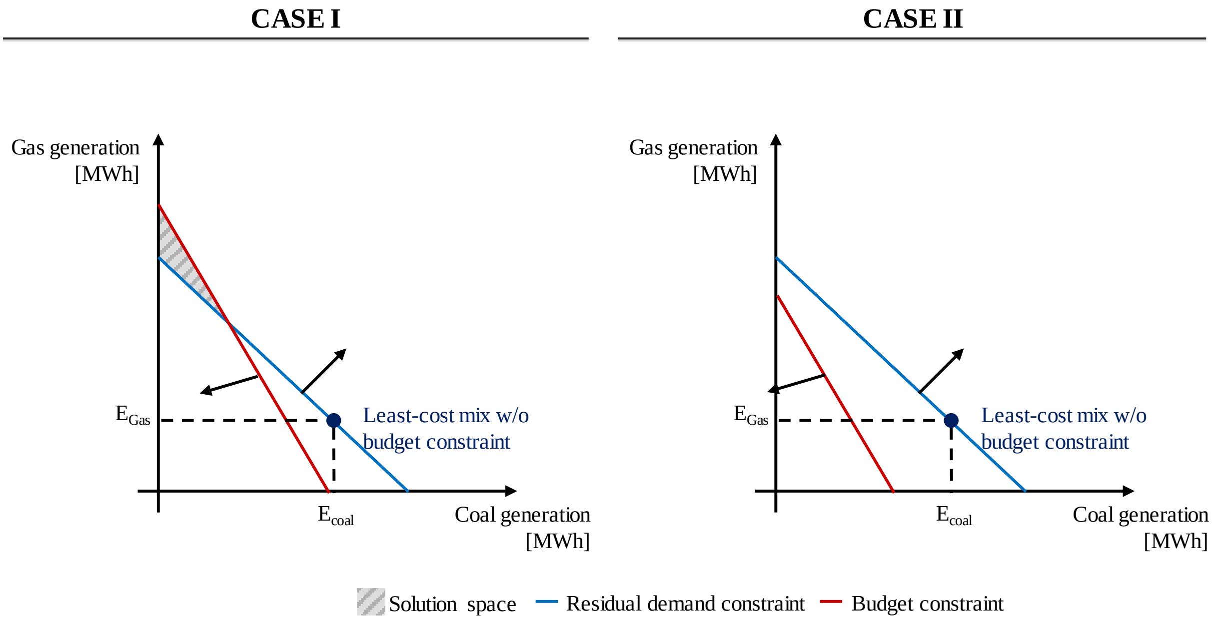


Figure 15: Impact of a tightening budget constraint on the solution space.[265]

To obtain a permissible solution in Case II, a less carbon-intense technology is required. Hence, I introduce 'clean power' as a carbon-neutral technology. Examples for carbon-neutral[266] resources are nuclear, renewables like wind and solar, and fossils plus carbon capture and storage (CCS). By deploying such clean power resources, the residual load to be covered by coal and gas diminishes, as illustrated in Figure 16 by shifting the demand constraint down.

[265] Source: Own illustration; note: The slope of the carbon budget constraint illustrates the carbon intensity of both fuel types.
[266] Note: "Carbon neutral" refers here to the emissions from power generation. This does not include life cycle emissions, which would include for instance emissions during construction or along the fuel supply chain.

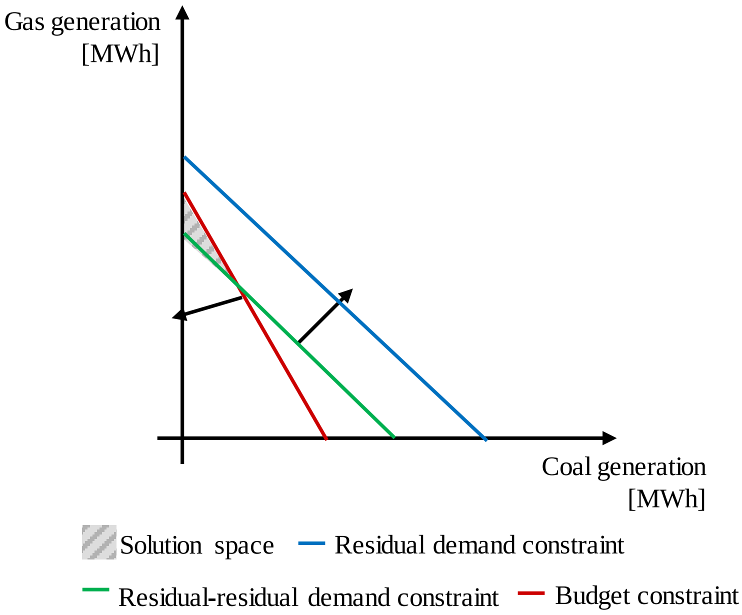


Figure 16: Impact of clean power deployment on the demand constraint and solution space.[267]

The third constraint captures that the installed capacity limits the maximum hourly load:

$$e_{i\,j\,a} \leq k_{i\,a} * 1\text{ h}, \qquad \forall\ \text{i, j, a} \qquad (15)$$

and a non-negativity constraint complements the model:

$$e_{i\,j\,a} \geq 0 \qquad \forall\ \text{i, j, a.} \qquad (16)$$

[267] Source: Own illustration.

3.4 Case-study: Fuel-switching and Deep Decarbonization in Germany

To solve the model introduced in Section 3.3, I draw on the example of Germany. Germany is an example of a country with comparatively ambitious climate targets, as it is committed to a 40% reduction of GHG emissions by 2020, 55 % by 2030, 70 % by 2040, and 80-95 % by 2050, all compared to 1990 levels. Figure 17 charts this decarbonization pathway.

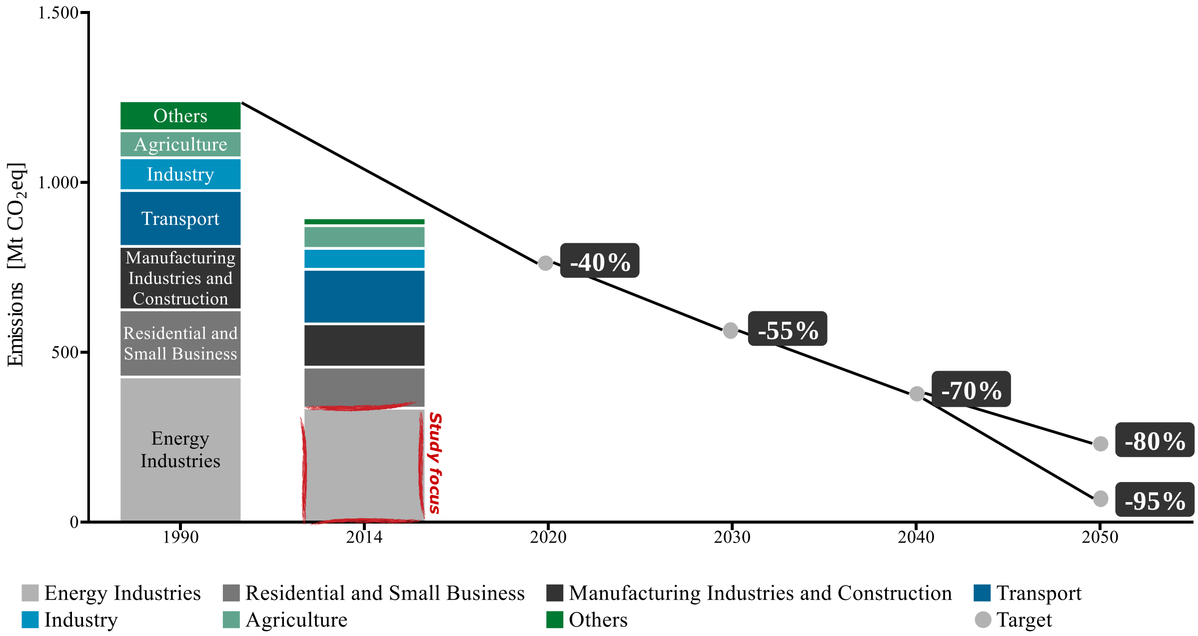


Figure 17: Emissions by sector and German decarbonization targets.[268]

3.4.1 Model Calibration

This sub-section describes the data used to calibrate the model. This includes cost, load, and carbon emission data.

Table 2 depicts annualized fixed and variable costs of lignite, hard coal and gas, based on official statistical data obtained from (IEA & NEA, 2015). Annualized fixed costs are based on overnight costs, which are the sum of all costs to build a respective power plant. These

[268] Own illustration; data source: (BUMB, 2017; UBA, 2017b).

costs can be annualized based on the plant life-time and the respective interest rate. Table 2 further depicts the actual capacity of existing resources.

Technology	Overnight cost [USD/kW]	Annualized fixed costs [USD/kWa]	Variable costs [USD/MWh]	Actual capacity [GW]
Lignite	2,054	154	43	21.2
Hard coal	1,643	123	48	25.0
CCGT	974	78	84	14.8
OCGT	548	44	126	14.8

Table 2: Cost data for generation resources in Germany.[269]

To configure the representative zero-carbon technology clean power, three low-carbon technologies appear suitable for deployment at scale: nuclear, renewables plus storage,[270] fossil resources with CCS, or any combination of those.[271] Due to high uncertainty about the future costs and technological feasibility of each resource technology, combined with the unpredictability of innovation, I use four cost scenarios: First, I assess the effects of coal-to-gas fuel-switching, assuming no competitive clean power alternative is available. Second, clean power generation is not competitive with existing coal and gas resources in the near-term, but available. Third, clean power generation is close to becoming competitive in the near-term.[272] Finally, I consider a politically forced coal phase-out in 2030.

The cost of clean power in Scenario 2-3 are charted in Figure 18. Figure 18 also charts screening curves of wind and solar to underline the appropriateness of the two levels of cost of clean power. Candidate wind and solar resources are already competitive with existing fossil technologies today. However, their generation patterns follow intermittent natural conditions and provide power within a limited capacity factor range.[273] Previous modeling work shows a cost-optimal ratio of the storage capacity to generation capacity of 2.61 in a

[269] Own illustration; data sources: (IEA & NEA, 2015); cost of natural gas as weighted cost of CCGT (Combined Cycle Gas Turbines) and OCGT (Open Cycle Gas Turbines) assuming equal capacity shares in line with (Schill et al., 2017) due to missing data granularity in (UBA, 2017c); calculation of annualized fixed cost based on overnight cost assuming 7% interest rate for fossils and a plant life-time of 30 years for gas and 40 years for coal respectively, in line with (IEA & NEA, 2015).
[270] The increasing number of PPAs for renewables-plus-storage in several U.S. States manifest the assumption to consider these complements as one technology; see (Miller & Carriveau, 2018) for solar-plus-storage PPAs.
[271] See (Jenkins & Thernstrom, 2017).
[272] Note: Lower costs are not considered, as the model targets the residual fossil load share and competitive clean power resources would have been deployed already.
[273] CF of solar PV: minimum 0.13 (residential), maximum 0.34 (utility scale); CF of wind: minimum 0.38 onshore, maximum 0.55 offshore; see (Lazard, 2018a).

system with 100% renewable power supply from intermitting resources.[274] In 2018, adding the respective cost of storage to the cost functions of wind and solar results in clean dispatchable resources, with costs in between the high and low-cost scenarios of clean power.[275]

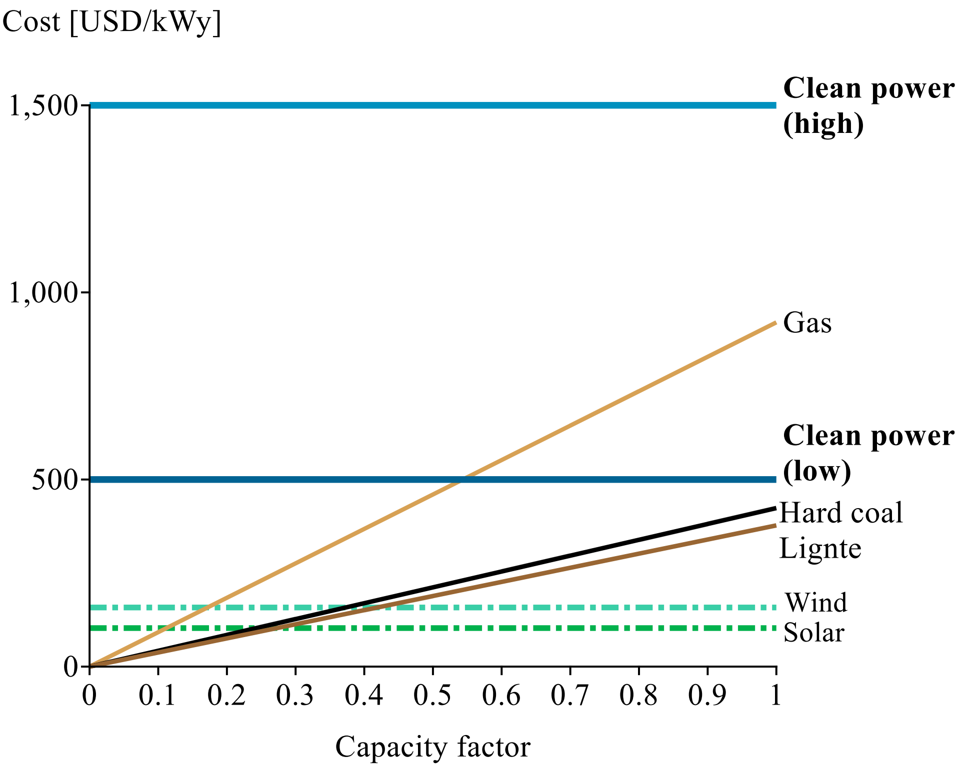


Figure 18: Screening curves of existing fossil and candidate low-carbon technologies.[276]

The hourly load data originate from (ENTSO-E, 2017). As scenario forecasts of electricity consumption in 2050 vary in a narrow range and show no clear direction compared to current consumption, I assume the load duration curve to remain constant.[277] Assuming that existing zero-carbon resources stay in the market, I focus on the residual load demand, which has to

[274] See (Jacobson, Delucchi, Cameron, & Frew, 2015).
[275] Utility-scale lithium batteries start at $251/kWy, see (Lazard, 2018b).
[276] Own illustration; data source: (IEA & NEA, 2015); cost of natural gas as weighted cost of CCGT (Combined Cycle Gas Turbines) and OCGT (Open Cycle Gas Turbines) assuming equal capacity shares in line with (Schill et al., 2017) due to missing data granularity in (UBA, 2017c); calculation of annualized fixed cost based on overnight cost assuming 7% interest rate for fossils and 5% for renewables, as well as a plant life-time of 30 years for gas and 40 years for coal, and 25 years for renewables, in line with (IEA & NEA, 2015).
[277] See (BMWi, 2014; Frauenhofer ISE, 2013; ÖkoInstitut, 2014).

be covered by fossil resources, as it is the part that needs to be decarbonized.[278] To determine the residual load, I deduct all non-fossil generation from the load data. This includes the share of net power generation from renewable resources of 38.3 % in 2017.[279] The resulting residual load duration curve is depicted in Figure 19.

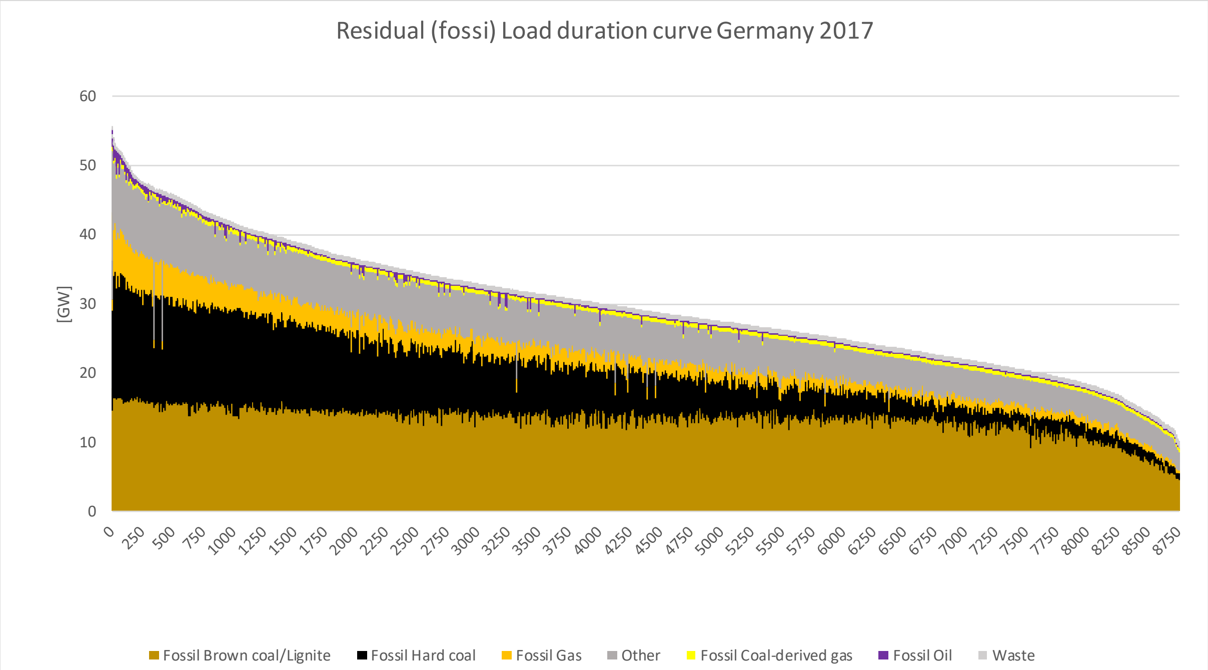


Figure 19: German residual fossil load duration curve.[280]

In the power sector, climate targets require a 61-62% reduction of CO_2 emissions by 2030. By 2050, the German Climate Protection Plan aims for almost complete decarbonization of the power system.[281] Figure 20 illustrates the specific decarbonization pathway of the power sector.

[278] Note: I further assume that existing fossil resources remain available over the period under review, due to parts of the existing fossil generation resources, which have been commissioned recently, German fossil power plant fleet installations by capacity and commissioning year in Appendix 6.
[279] See (ENTSO-E, 2017).
[280] Source: Own illustration; data source: (ENTSO-E, 2017); the load duration curve can be found in Appendix 3.
[281] See (BUMB, 2017); I use the lower limit of 95% in the case study.

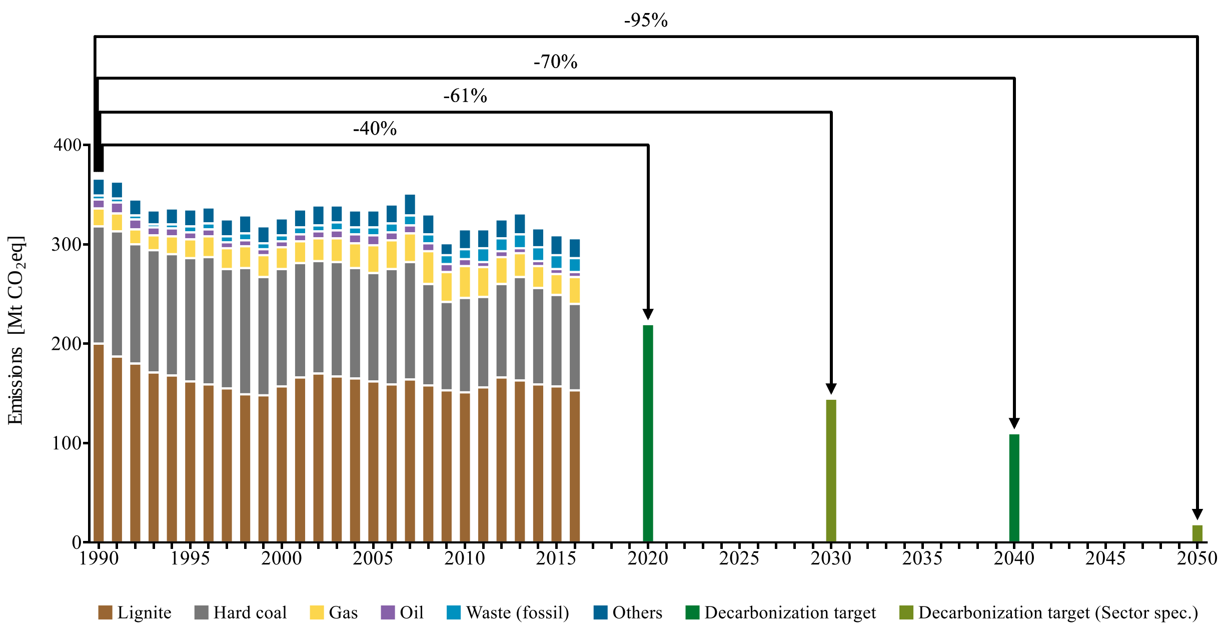


Figure 20: German decarbonization targets in the power sector.[282]

To calculate the carbon emissions of each resource technology, I use the emission factors of lignite, coal, and gas as stated by the German Federal Environmental Agency. The respective carbon emission factors are 1,151 g/kWh for lignite, 863 g/kWh for coal, and 391 g/kWh for gas.[283]

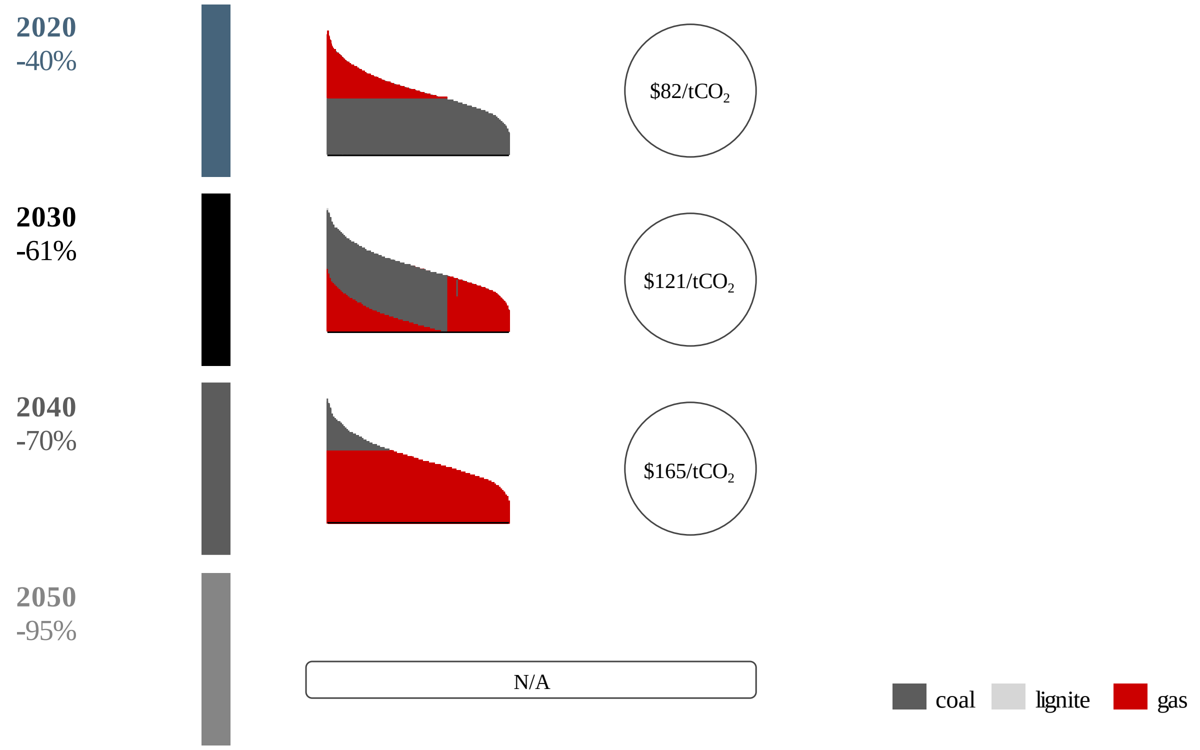
3.4.2 Model Results

Section 3.4.2 provides the numerical results of the model introduced in Section 3.3, using German parameters as described in the previous section.[284] Section 3.4.2 is structured along the four scenarios introduced in Section 3.4.1.

In the scenario without a clean power alternative, to achieve the 2020 target of 40% CO_2 emission reduction, a carbon price of \$82/tCO_2 is needed. Lignite-to-coal fuel-switching occurs at a carbon price of \$18/tCO_2 and \$82/tCO_2 is the threshold, where the cost sequence of existing lignite and gas generation resources switches. At \$121/tCO_2 the cost sequence of existing coal and gas switches, which is required to meet the 2030 target. For the 2040 target,

[282] Own illustration; data sources: (BUMB, 2017; UBA, 2017a); note: The resulting carbon budgets to achieve the targets are 220 MtCO2 (2020), 143 MtCO2 (2030), 110 MtCO2 (2040) and 18 MtCO2 (2050).
[283] See (UBA, 2017b).
[284] The model is written in GAMS, using a Cplex solver; the model characteristics are summarized in Appendix 4; the source code is depicted in Appendix 5.

additional gas resources have to replace existing coal. At a carbon price of $165/tCO_2$, new gas replaces coal in a CF range of 0.33 to 1.00. However, the 2050 target cannot be achieved with 100% gas power generation. Figure 21 illustrates which resource technology serves residual fossil load between 2020 and 2050 at least cost.



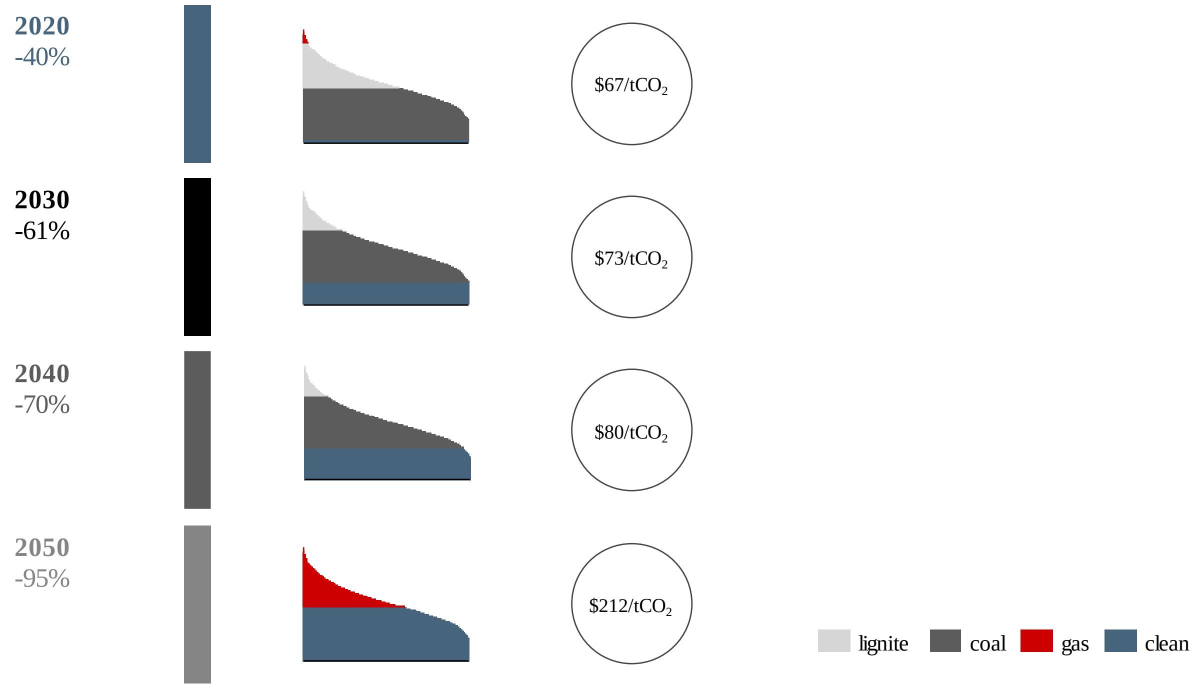
	Capacity [GW]				Generation [TWh]				Cost [USD]	
	Clean	*Gas*	*Coal*	*Lignite*	*Clean*	*Gas*	*Coal*	*Lignite*	*Total [bn]*	*Total [per kWh]*
2020	x	29.2	25.0	21.3	x	21.8	203.8	30.6	13.4	0.05
2030	x	29.5	25.0	0.8	x	166.0	90.2	0.0	21.8	0.08
2040	x	32.5	22.8	-	x	235.8	20.4	-	25.9	0.10
2050	x	N/A								

Figure 21: Least-cost decarbonization pathway (w/o a clean power alternative).[285]

In a scenario with a low cost of clean power, a carbon price of $67/tCO_2$ is needed to achieve the 2020 target of 40% CO_2 emission reduction. Lignite-to-coal fuel-switching occurs again at a carbon price of $18/tCO_2$, and at $67/tCO_2$, 1.8 GW of clean power resources become cost-effective. Achieving the 2030 target requires a carbon price of $73/tCO_2$ to expand clean power to 10.8 GW in order to push the remaining gas and parts of the lignite power generation out of the market. To meet the 2040 target, further lignite capacity has to exit. Expansion of clean power at a carbon price of $212/tCO_2$, after a lignite-to-gas switch at $82/tCO_2$ and a

285 Source: Own illustration.

coal-to-gas at \$121/tCO_2, ensures achievement of the 2050 target. Figure 22 illustrates which resource technology serves residual fossil load between 2020 and 2050 at least cost. It is noteworthy that no additional gas capacity is required to meet the targets.

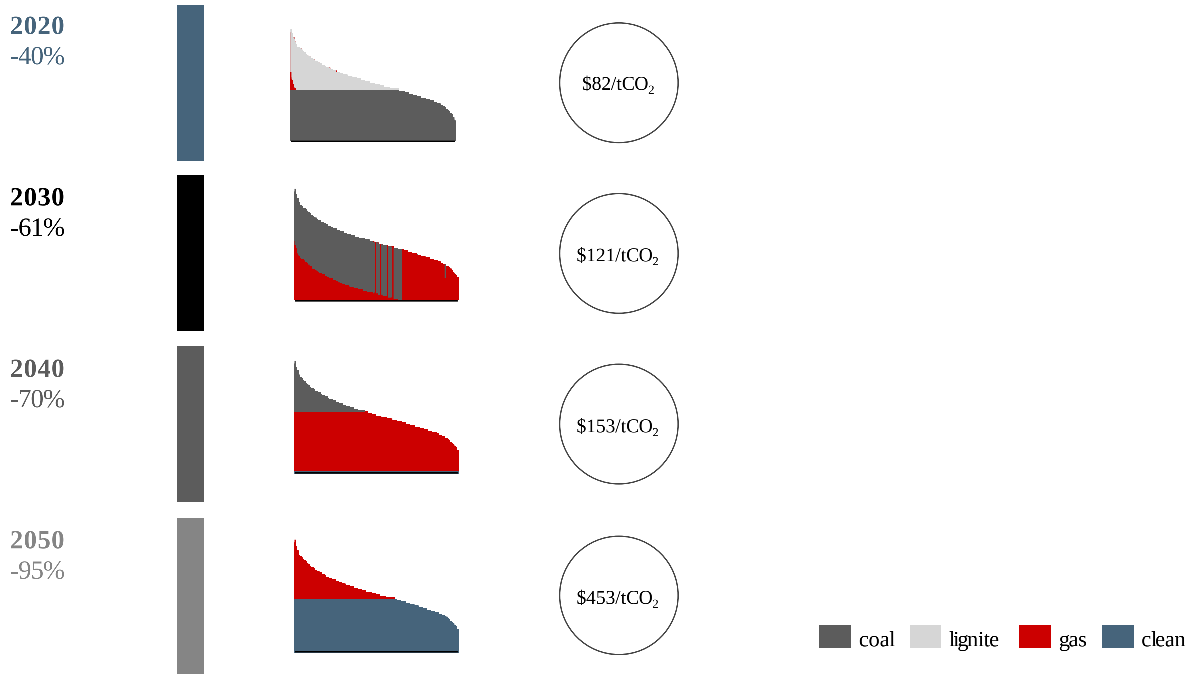


	Capacity [GW]				Generation [TWh]				Cost [USD]	
	Clean (l)	*Gas*	*Coal*	*Lignite*	*Clean (l)*	*Gas*	*Coal*	*Lignite*	*Total*	*Total [per kWh]*
2020	1.8	7.2	25.0	21.3	15.6	0.5	197.8	42.3	13.1	0.05
2030	10.8	-	25.0	19.4	94.8	-	149.2	12.2	18.5	0.07
2040	15.0	-	25.0	15.2	130.8	-	119.8	5.6	21.0	0.08
2050	26.0	29.3	-	-	209.4	46.8	-	-	31.0	0.12

Figure 22: Least-cost decarbonization pathway (low cost of clean power).[286]

In the scenario with a high cost of clean power, lignite-to-coal and lignite-to-gas at \$82/tCO_2 are needed. An emissions reduction of 61% occurs at 121/tCO_2 through coal-to-gas fuel-switching, and a carbon price of \$153/tCO_2 triggers an expansion of new gas by 0.3 GW. 95% emission reduction can be achieved at a carbon price of \$453/tCO_2, with gas resources covering CF = [0.04-0.58] and clean power resources covering CF = [0.58-1.00]. Figure 23 illustrates which resource technology serves residual fossil load between 2020 and 2050. Again, it is noteworthy that only minor additional gas capacity is required to meet the targets.

[286] Source: Own illustration.



	Capacity [GW]				Generation [TWh]				Cost [USD]	
	Clean (h)	*Gas*	*Coal*	*Lignite*	*Clean (h)*	*Gas*	*Coal*	*Lignite*	*Total*	*Total [per kWh]*
2020	-	29.2	25.0	21.3	-	21.8	203.8	30.6	13.4	0.05
2030	-	29.5	25.0	0.8	-	166.0	90.2	0.0	21.8	0.08
2040	0.9	29.5	24.9	-	8.2	220.7	27.2	-	25.9	0.10
2050	26.0	29.3	-	-	209.4	46.8	-	-	44.0	0.17

Figure 23: Least-cost decarbonization pathway (high cost of clean power).[287]

In the scenario with a politically forced coal phase-out in 2030, the results for 2020 and 2050 do not change as depicted in Figure 24. However, in the interim, additional gas capacity is needed to fill the supply gap. Compared to a phase-out strategy, in a scenario with the availability of low-cost clean power resources, the phase-out increases annual system cost by $10 billion in 2040; by 2050, the annual additional costs total $7.5 billion. In a scenario with a high cost of clean power, the additional costs of a coal phase-out are $6.7 billion (by 2040) and $2.6 billion (by 2050).

[287] Source: Own illustration.

	Capacity [GW]				Generation [TWh]				Cost [USDbn]	
	Clean (l)	*Gas*	*Coal*	*Lignite*	*Clean (l)*	*Gas*	*Coal*	*Lignite*	*Total*	
2020	1.8	7.2	25.0	21.3	15.6	0.5	197.8	42.3	13.1	0.05
2030	-	55.3	x	x	-	256.2	x	x	28.5	0.11
2040	-	55.3	x	x	-	256.2	x	x	28.5	0.11
2050	26.0	29.3	x	x	209.4	46.8	x	x	31.0	0.12

	Capacity [GW]				Generation [TWh]				Cost [USDbn]	
	Clean (h)	*Gas*	*Coal*	*Lignite*	*Clean (h)*	*Gas*	*Coal*	*Lignite*	*Total*	
2020	-	29.2	25.0	21.3	-	21.8	203.8	30.6	13.4	0.05
2030	-	55.3	x	x	-	256.2	x	x	28.5	0.11
2040	-	55.3	x	x	-	256.2	x	x	28.5	0.11
2050	26.0	29.3	x	x	209.4	46.8	x	x	44.0	0.17

Figure 24: Least-cost decarbonization pathway (coal phase-out in 2030).[288]

3.5 Conclusions

This paper highlights the need for a broader focus on available technology options when decarbonizing the power sector, as opposed to narrow reliance on a coal phase-out mandate. The case study of Germany illustrates that a gradually declining operation of existing fossil resources can play an important role in achieving deep decarbonization at least-cost because it avoids new investment in lower-carbon, but still emitting gas generation.

The model I present in order to find the least-cost fuel-switching sequence has numerous limitations compared to sophisticated integrated models, which are typically used to study such scenarios. My method ignores fixed unit expansion size, economies of scale in supply, the market power of generators, imports and exports, sector coupling, and cycling constraints. The method further omits transmission constraints and specific factors on a single power plant level.

Nonetheless, the model results may provide thought-provoking impulse on the impact of stranded assets and how those can be part of a cost-effective decarbonization pathway. These impulses – supported by a coherent and comprehensible model – may nudge policy-makers to think in the broader context. Such broader thinking can be particularly valuable in Germany and other countries, which currently debate the narrow question of how to reduce power generation from coal resources instead of grasping the wider context.

[288] Source: Own illustration.

Still, phasing out coal will very likely trigger the deployment of additional gas-fired generation resources. In practice, a gas power plant, which is commissioned today will not be operational prior to 2025, and by the year 2050, the last emitting generation resource definitely has to stop operations and leave the market if the carbon budget is to be met. Given their useful economic life of 35 years, additional gas resources would therefore inevitably become stranded assets.

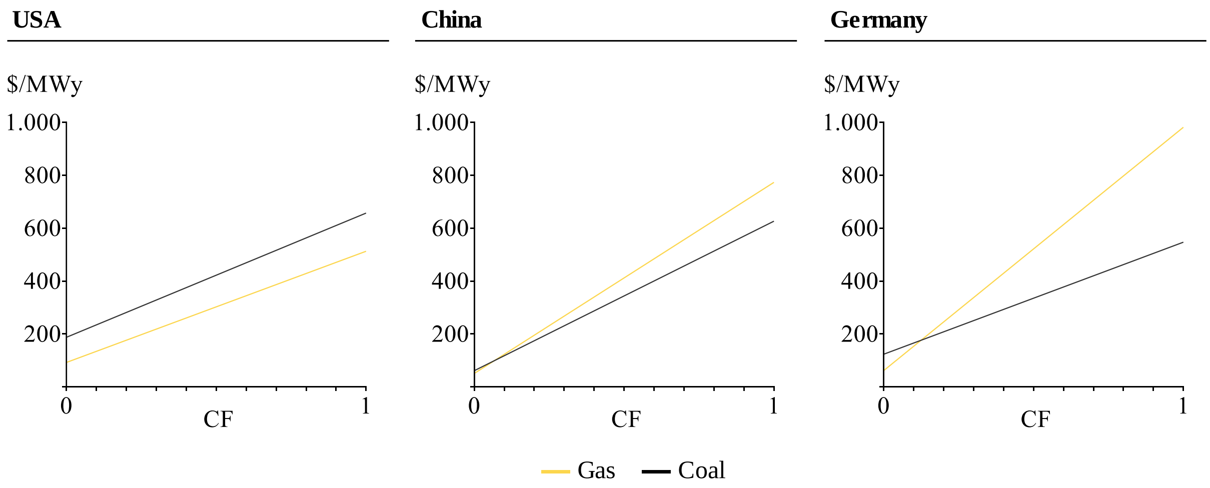
What is more, there is considerable uncertainty about the life-cycle emission factors of gas. Fuel combustion is only the tip of the iceberg, and GHG emissions along the supply chain vary, depending on fuel type, origin, and destination.[289] Novel insights on pipeline leakage[290] and flaring at shale production sites[291] suggest much higher carbon emissions from gas than commonly assumed. In consequence, climate benefits of gas over coal diminish or may even reverse in some cases. This aspect has to be clarified prior to assessing the technical feasibility of coal phase-outs,[292] and prior to building new LNG infrastructure.[293]

Not following the coal phase-out trend may generate welfare savings, which could be reallocated, for instance, to subsidize clean power resources. The estimated incremental cost of a strict coal phase-out of up to $10 billion annually is considerable and rivals the annual financial support for renewable energy sources under German feed-in tariff legislation.[294]

[289] For instance, the carbon intensity of gas depends on extraction (conventional vs fracking), processing (LNG vs w/o liquefaction), storage, transmission (pipeline vs ship vs distance) and distribution; similar of coal (e.g. underground vs surface extraction), and oil as shown by (Masnadi et al., 2018).
[290] E.g. (Alvarez et al., 2018) find for the U.S. that CH_4 leakage along the gas supply chain causes comparable warming as the emissions from combustion.
[291] See (Elvidge et al., 2018).
[292] See, e.g., (Aurora Energy Research, 2018).
[293] E.g. Subsidized construction of LNG terminals in Europe, see (Bloomberg, 2018).
[294] Note: EEG subsidies, which have triggered a large scale expansion of renewables, totalled €30.4 billion in 2017, see (BMWi, 2018).

3.6 Appendix

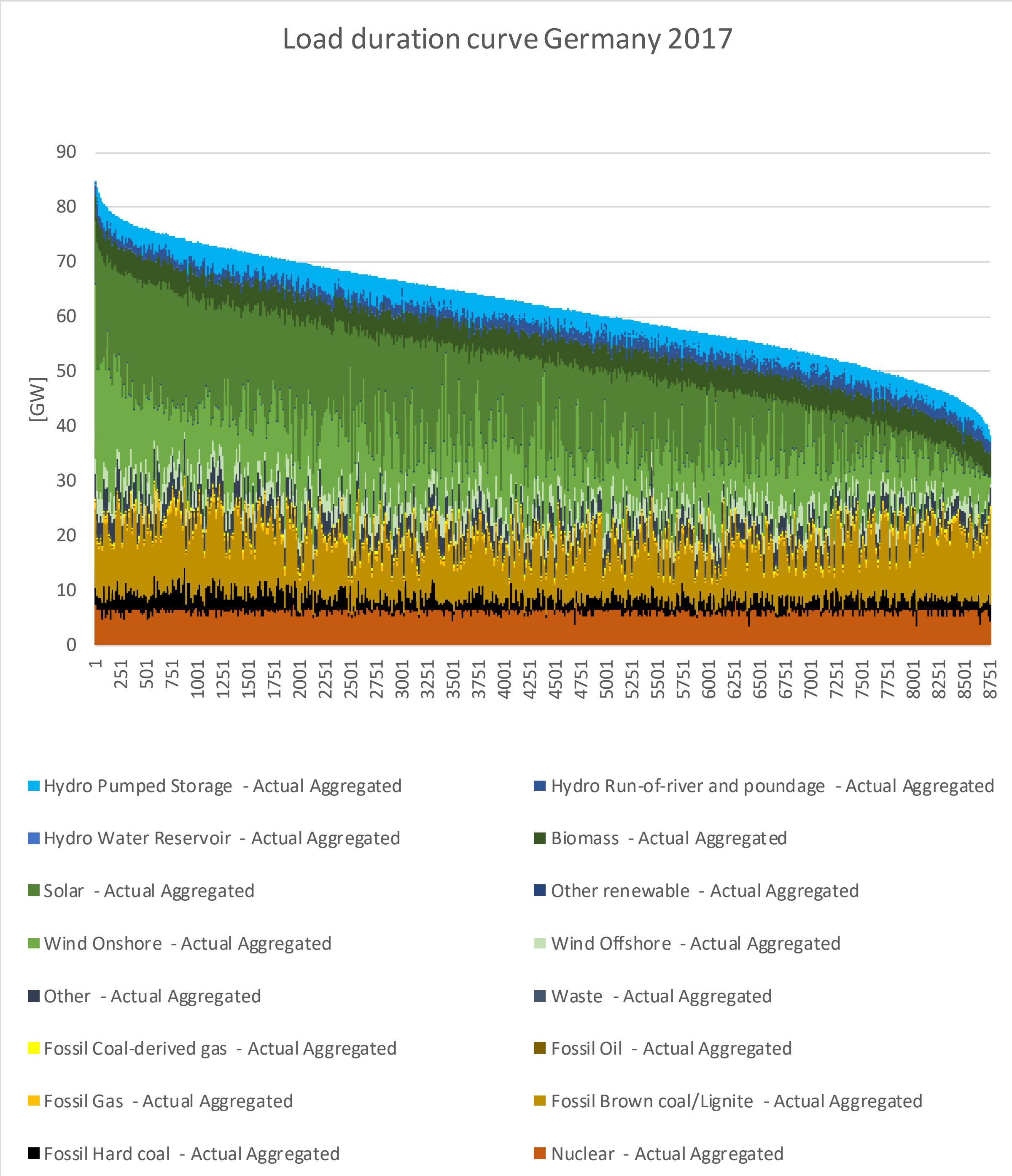
Appendix 1: Regional differences - Screening curves for coal and gas in the USA, China, and Germany. Own illustration; data sources: cost data from (IEA & NEA, 2015); calculation of annualized fixed cost based on overnight cost assuming 7% interest rate and a plant life-time of 30 years for gas and 40 years for coal-fired power plants in line with (IEA & NEA, 2015); equal split of natural gas in CCGT (Combined Cycle Gas Turbines) and OCGT (Open Cycle Gas Turbines) for Germany in line with (Schill et al., 2017); note: Global carbon emission factors lie in a narrow ranges for both coal and gas-fired electricity generation [in gCO2/kWh] (gas in brackets): USA: 0.928 (0.401), China: 0.919 (0.432), and Germany: 0.900 (0.332), see (IEA, 2017).



Appendix 2: Resource capacity and actual generation by fuel type. Assuming a theoretical maximum of 8,760 hours of operation without interruption; data from (Global Energy Observatory, Google, KTH Royal Institute of Technology in Stockholm, Enipedia, & Institute, 2018); note: The idle gas capacity varies from 78 % in China, to 54 % in the USA, and 71 % in Germany, as depicted in the right column of the table.

	Capacity [GW]	Generation [TWh]	CF = 1 [TWh]	Current CF
USA				
Coal	327	1,713	2,864	0.60
Gas	291	1,166	2,546	0.46
China				
Coal	829	4,115	7,259	0.57
Gas	60	115	528	0.22
Germany				
Coal	47	285	412	0.69
Gas	24	62	214	0.29

Appendix 3: Actual production by resource type Germany 2017. Data from (ENTSO-E, 2017).



Appendix 4: Model characteristics

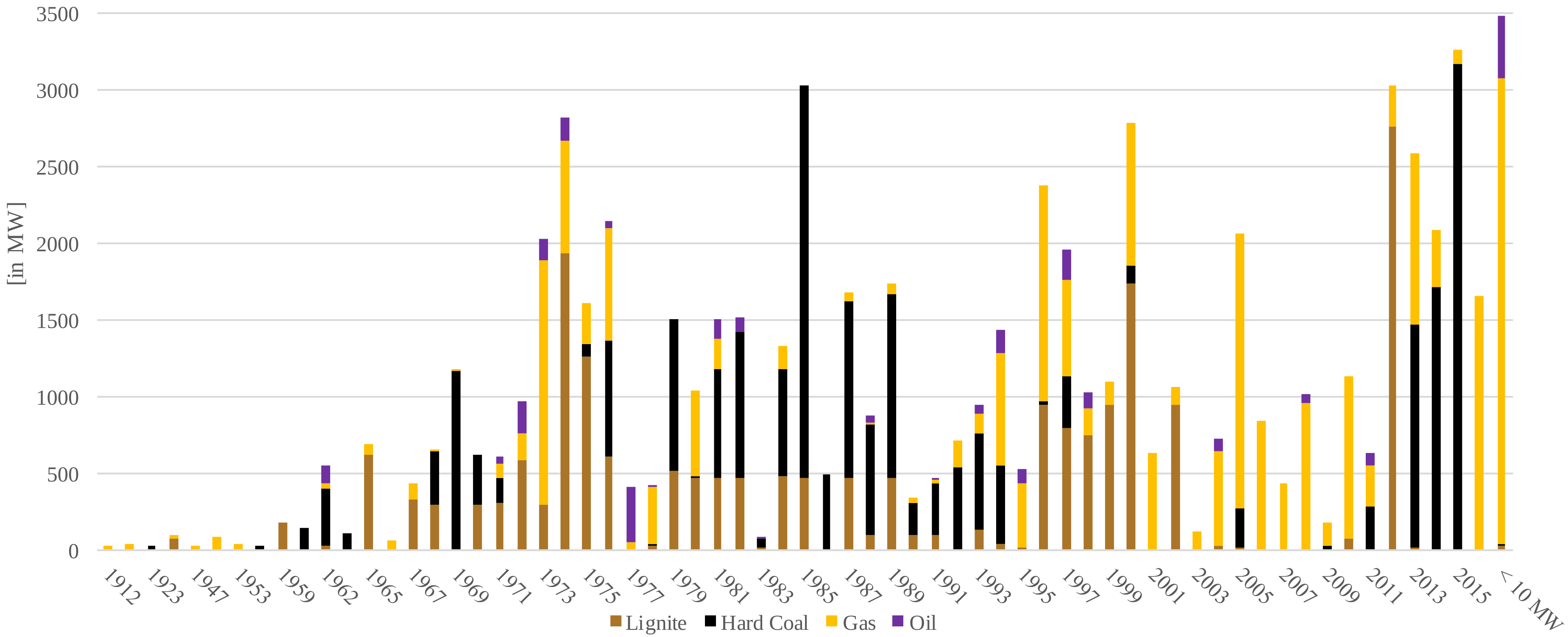
Item	Detailing
Objective function	• Minimize total system costs
Variables	• Capacity investment • Hourly dispatch
Constraints	• Demand coverage • Capacity limit • Carbon budget • Non-negativity
Resolution	• Hourly granularity • Four resource technologies
Input data	• Hourly demand (ENTSO-E, 2017) • Existing capacity (UBA, 2017c) • Technology specific cost (IEA & NEA, 2010, 2015) • Technology specific emissions (UBA, 2017b) • Decarbonization targets (BUMB, 2017)
Assumptions	• Price-inelastic demand • Existing capacity available until 2050 • Resource capacity can be adjusted annually
Equilibrium	• Short-term (hourly/production) • Mid-term (yearly/investment) • Long-term (2020-2050/decarbonization)
Limitations	• No fixed unit expansion size • No economies of scale in supply • No market power of generators • No detailed power plant fleet • No imports/exports • No sector coupling • No transmission cost/constraints • No system service provisions • No cycling cost/ramping constraints • No location-based assessment
Implementation	• Program type: Linear program • Model language: GAMS • Solver: Cplex

Appendix 5: GAMS source code

```
Sets
         i technology /hardcoal, lignite, gas, clean/
         r hour of the year

Parameters
         f(i) fixed cost of technology i [USD per MWy]
         /        hardcoal 123240
                  lignite 154069
                  gas 61362
                  clean 1500000  /
         v(i) variable cost of technology i [USD per MWh]
         /        hardcoal 48
                  lignite 43
                  gas  105
                  clean 0  /
         c(i) existing capacity of technology i [MW]
         /        hardcoal 25048
                  lignite 21288
                  gas  29498
                  clean 0  /
         d(r)   demand (load) in hour r [MW]
         ce(i)  emissions of technology i [t CO2 per MWh]
         /        hardcoal 0.863
                  lignite 1.151
                  gas  0.391
                  clean 0           /
         b carbon emission budget [t CO2]
         /        219600000   / ;

$onecho> tasks1.txt
dset=r rng=a1:a8761    rdim=1
par=d  rng=a1          rdim=1
$offecho
$call GDXXRW resdemand.xlsx trace=3 @tasks1.txt
$GDXIN resdemand.gdx
$Load r
$Load d
$GDXIN

Positive Variables
         k(i)   additional capacity of technology i [MW]
         e(i,r) load of technology i in hour r [MW];

Free variables
         z     total cost;

Equations
         cost          total system cost
         carbon        satisfy carbon budget
         supply(r)     satisfy demand in every hour r
         capa(i,r)     capacity limit of technology i in hour r ;
```

```
        cost..             z =e= sum(i, f(i)*k(i)) + sum((i,r), v(i)*e(i,r));
        carbon..           b =g= sum((i,r), ce(i)*e(i,r));
        supply(r)..        sum(i, e(i,r)) =e= d(r);
        capa(i,r)..        k(i)+c(i) =g= e(i,r);


Model m2 /all/;
Solve m2 using LP minimizing z;

execute_UNLOAD 'capacity.gdx', k;
execute 'GDXXRW.EXE capacity.gdx var=k.l';
execute_UNLOAD 'energy.gdx', e;
execute 'GDXXRW.EXE energy.gdx var=e.l';
```

Appendix 6: German fossil power plant fleet installations by capacity and commissioning year. Data from (UBA, 2017c); note: In case of modification or expansion, the chart shows the date of the latest change as commissioning-year.



4 Essay III – The Carbon Footprint of Bitcoin

by Christian Stoll,[*] Lena Klaaßen,[295] Ulrich Gallersdörfer[296]

Abstract

Participation in the Bitcoin blockchain validation process requires specialized hardware and vast amounts of electricity, which translates into a significant carbon footprint. Here we demonstrate a methodology for estimating the power consumption associated with Bitcoin's blockchain based on IPO filings of major hardware manufacturers, insights on mining facility operations, and mining pool compositions. We then translate our power consumption estimate into carbon emissions, using the localization of IP-addresses. We determine the annual electricity consumption of Bitcoin, as of November 2018, to be 45.8 TWh, and estimate that annual carbon emissions range from 22.0 to 22.9 $MtCO_2$. This means that the emissions produced by Bitcoin sit between the levels produced by the nations of Jordan and Sri Lanka, which is comparable to the level of Kansas City. With this article, we aim to gauge the external costs of Bitcoin, and inform the broader debate on the costs and benefits of cryptocurrencies.

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Data availability: All data used in this analysis are included in the Supplementary Notes File (https://www.cell.com/cms/10.1016/j.joule.2019.05.012/attachment/771dc380-a6ef-4de2-9dd9-723be0b14a5c/mmc1.zip), or publicly available online under the noted sources.

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Author contributions: C.S. conceived of the study. All authors contributed to the design of the study and data acquisition. L.K. and C.S. aggregated and analyzed the data. C.S. drafted the manuscript. L.K. and U.G. reviewed several drafts, made substantial revisions, and provided additions.

4.1 Introduction

In 2008, Satoshi, the pseudonymous founder of Bitcoin, published a vision of a digital currency which,[297] only a decade later, reached a peak market capitalization of over $800 billion.[298] The revolutionary element of Bitcoin was not the idea of a digital currency in itself, but the underlying blockchain technology. Instead of a trusted third party, incentivized network participants validate transactions and ensure the integrity of the network via the decentralized administration of a data protocol. The distributed ledger protocol created by Satoshi has since been referred to as the 'first blockchain'.[299]

Bitcoin's blockchain uses a Proof-of-Work consensus mechanism to avoid double-spending and manipulation. The validation of ownership and transactions is based on search puzzles of hash-functions. These search puzzles have to be solved by network participants in order to add valid blocks to the chain. The difficulty of these puzzles adjusts regularly in order to account for changes in connected computing power and to maintain approximately ten minutes between the addition of each block.[300]

During 2018, the computing power required to solve a Bitcoin puzzle increased until October more than fourfold,[301] and heightened electricity consumption accordingly.[302] Speculations about the Bitcoin network's source of fuel have suggested, among other things, Chinese coal, Icelandic geothermal power, and Venezuelan subsidies.[303] In order to keep global warming below 2 °C – as internationally agreed in Paris COP21 – net-zero carbon emissions during the second half of the century are crucial.[304] To take the right measures, policy-makers need to understand the carbon footprint of cryptocurrencies.

We present a techno-economic model for determining the electricity consumption of the Bitcoin network in order to provide an accurate estimate of its carbon footprint. Firstly, we narrow down the power consumption, based on mining hardware, facilities, and pools. Secondly, we develop three scenarios representing the geographic footprint of Bitcoin

[297] See (Nakamoto, 2008).
[298] See (CoinMarketCap, 2018).
[299] See (Yaga, Mell, Roby, & Scarfone, 2018).
[300] See (Narayanan, Bonneau, Felten, Miller, & Goldfeder, 2016).
[301] See (Blockchain.com, 2018).
[302] See (De Vries, 2018).
[303] See (The Economist, 2018b).
[304] See (UNFCCC, 2015a).

mining, based on pool server IP, node IP, and device IP-addresses. Thirdly, we calculate the carbon footprint, based on the regional carbon intensity of power generation.

In comparison to previous work, our analysis is based on empirical insights. We use hardware data derived from recent IPO filings, which are key to a reliable estimate of power consumption as the efficiency of the hardware in use is an essential parameter in this calculation. Furthermore, we include assumptions about auxiliary factors which determine the power usage effectiveness (PUE). Losses from cooling and IT-equipment have a significant impact, but have been largely neglected in prior studies. Besides estimating the total power consumption, we determine the geographical footprint of mining activity based on IP-addresses. This geographical footprint allows for more accurate estimation of carbon emissions compared to earlier work.

Previous academic studies, such as predictions of future carbon emissions,[305] or comparisons of cryptocurrency and metal mining,[306] are based on simplistic estimates of power consumption, and lack empirical foundations. Consequently, the estimates produced vary significantly among studies, as depicted in Figure 25. For instance, De Vries published in Joule an estimate of 2.55 to 7.67 gigawatts as of 03/2018 while his Digiconomist site suggested a number at the very upper end of this range at that time.[307]

[305] See (Mora et al., 2018).
[306] See (Krause & Tolaymat, 2018).
[307] See (De Vries, 2018; Digiconomist, 2018a).

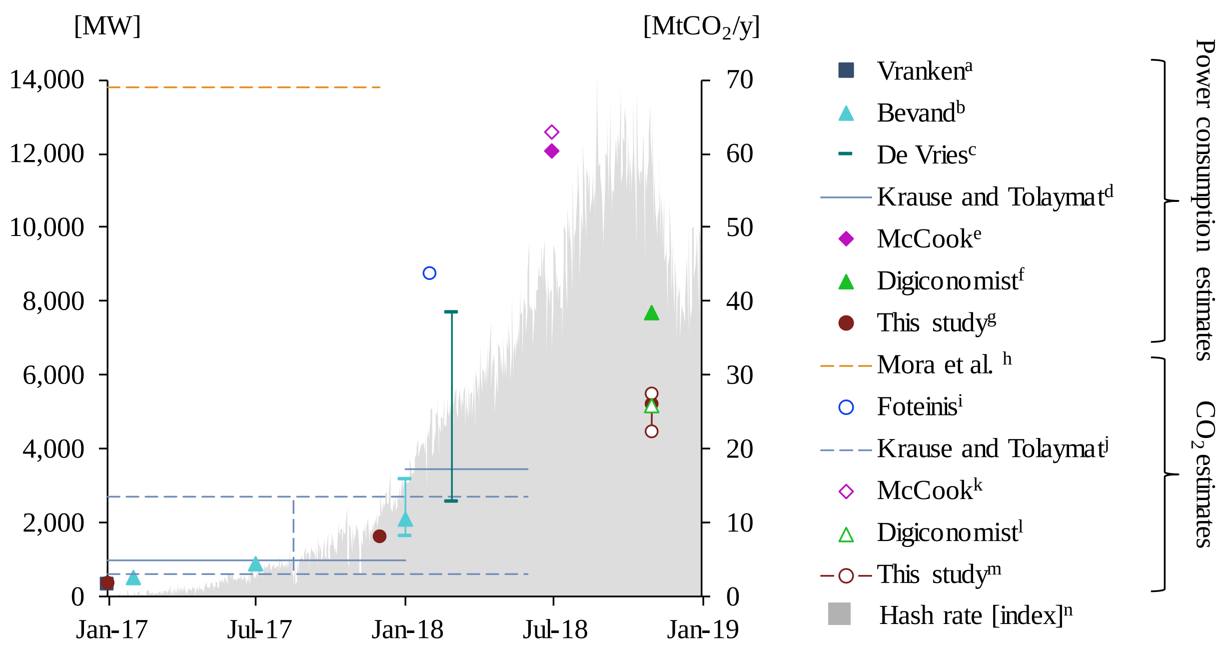

Figure 25: Power consumption and carbon emission estimates in previous studies.[308]

We show that, as of November 2018, the annual electricity consumption of Bitcoin had a magnitude of 45.8 TWh. We further calculate that the resulting annual carbon emissions range between 22.0 and 22.9 $MtCO_2$; a ratio which sits between the levels produced by Jordan and Sri Lanka,[309] which is comparable to the level of Kansas City.[310] The magnitude of these

---

[308] Note: The data reflect the power consumption at a specific date. Thus, the data are presented in power (W) rather than energy (J). a. 100-500 MW power consumption as of 1/1/2017, see (Vranken, 2017); b. 470-540 MW as of 2/2017; 816-944 MW as of 7/2017; 1,620-3,136 MW with a best guess of 2,100 MW as of 11/1/2018, see (Bevand, 2018); c. 2,550-7,670 MW as of 3/2018; calculated by assuming miners spent 40% of all revenues on hardware and 60% on electricity, see (De Vries, 2018); d. 948 MW as 2017 average; 3,441 MW as first six months 2018 average, see (Krause & Tolaymat, 2018); e. 12,080 MW as of 7/2018; only figure that includes the power spent on manufacturing of the mining hardware, which represents 57% of this total power (and emissions) estimate; PUE of 1.25 considered, see (McCook, 2018); f. 7,687 MW average of daily estimates in 11/2018; daily estimates range from 5,983 MW to 8,347 MW in 11/2018; estimates calculated by assuming 60% of revenues are spent on operational costs incl. electricity, hardware, and cooling costs, see (Digiconomist, 2018a); g. 345 MW as of 12/2016; 1,637 MW as of 12/2017; 5,232 MW as of 11/2018; PUE of 1.05 considered, h. 69 $MtCO_2$ emissions as of 2017 calculation based on the flawed assumption that the number of transactions drives power consumption, see (Mora et al., 2018); i. 43.9 $MtCO_2$ emissions as of 02/2018; including Ethereum, see (Foteinis, 2018); j. 2.9-13.5 $MtCO_2$ emissions range calculated using the median daily power consumption from 01/2016 to 06/2018 multiplied by CO_2 emission factors of seven countries, assuming all miners would be based in one of these countries, see (Krause & Tolaymat, 2018); k. 61 $MtCO_2$ emissions as of 07/2018; using a global average CO_2 emission factor, see (McCook, 2018); l. 25.8 $MtCO_2$ emissions as of 11/2018; using an emission factor of 0.7 kg CO2 per kWh for 70% of the power consumption (based on China's average emission factor), and assuming clean energy for the remaining 30%, see (Digiconomist, 2018a); m. 22.4-27.4 $MtCO_2$ emissions as of 11/2018; range reflects three footprint scenarios with respective local carbon intensity of power generation, n. Indexed hash rate (required computing power) since 1/1/2017; data retrieved from Blockchain.com (https://www.blockchain.com/charts), see (Blockchain.com, 2018); see also Figure 26 for absolute values.

[309] See (Global Carbon Project, 2017).

[310] See (Moran et al., 2018).

carbon emissions, combined with the risk of collusion and concerns about control over the monetary system, might justify regulatory intervention to protect individuals from themselves and others from their actions.

4.2 Mining Hardware

Bitcoin prices for 2017 chart a curve shaped like an upturned hockey stick, and boosted the investment made by network participants in mining hardware. First-generation miners used central processing units (CPU) in conventional personal computers with computing power of less than 0.01 gigahashes per second (GH/s) and an efficiency of 9,000 joule per gigahash (J/GH). Over time, miners switched to graphic processing units (GPU), with 0.2-2 GH/s and 1,500-400 J/GH in 2010 and, starting in 2011, moved to field-programmable gate arrays (FPGA) with 0.1-25 GH/s and 100-45 J/GH.[311] Since 2013, application-specific integrated circuit (ASIC) based mining systems, with up to 44,000 GH/s and less than 0.05 J/GH have prevailed.[312] Figure 26 charts the market price (in US dollar per Bitcoin (USD/BTC)), network hash rate (in petahashes per second (PH/s)), and resulting profitability threshold (in J/GH), where miners' income equals cost. Comparing this profitability threshold to the efficiencies of mining hardware shows that only ASIC-based mining systems operate profitably nowadays.

[311] See (Bhaskar & Chuen, 2015).
[312] See (Taylor, 2017).

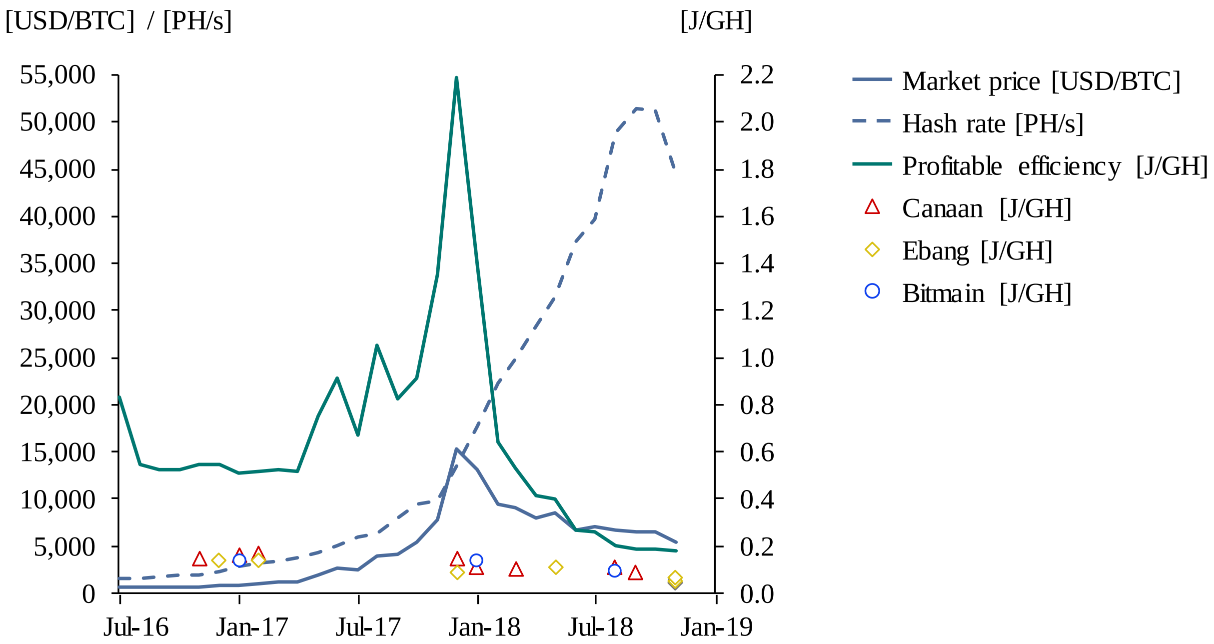

Figure 26: Bitcoin market price, network hash rate, profitable efficiency, and hardware efficiencies of ASIC-based mining systems released by major mining hardware producers.[313]

From IPO filings disclosed in 2018, we determine the distribution of market share held by the three major mining hardware producers; Bitmain, Canaan, and Ebang. The hardware in use and its efficiency are key to a reliable estimate of power consumption. Based on the IPO filings, we conclude that, as of November 2018, Bitmain's hardware provides 78% of the network's computing power, while the hardware of Ebang provides 13% and of Canaan 8% (see Supplementary Notes Sheet 3.2; the IPO filings and the calculation of the distribution are embedded in Sheet 3.4).

[313] Note: Values in Figure 26 are charted at monthly intervals; hash rate and market price were retrieved from Blockchain.com (www.blockchain.com/charts), see (Blockchain.com, 2018); calculations of the profitable hardware efficiency are reported in Supplementary Notes Sheet 3.6; we assume an average electricity price of USD 0.05/kWh as argued in previous estimates, see (Bevand, 2017; Digiconomist, 2018a); a detailed overview of ASIC-based mining systems releases can be found in Supplementary Notes Sheet 4.1.

4.3 Mining Facilities

There is no typical size of cryptocurrency mining operations, but a wide scale ranging from students who do not pay for their electricity (some of whom applied to support this research),[314] to gamers who leverage their graphics cards whenever they are not playing (as reflected in Nvidia's volatile sales allocated to crypto),[315] all the way up to dedicated, large-scale crypto-mining farms (for instance, in abandoned olivine mines in Norway).[316]

Depending on the scale of mining operation, auxiliary efficiency losses may occur in addition to losses caused by mining hardware. The two main categories of auxiliary losses are cooling and IT-equipment. We classify miners into three groups according to the scale of their operation: small (S) miners consume less than 0.1 MW of electricity (comparable to providing less than 0.9 PH/s or twenty of the most efficient ASIC-based mining systems), medium (M) miners consume 1 MW or less (and provide less than 9 PH/s), and large (L) miners consume more than 1 MW. This classification is based on personal communications with medium and large-scale miners.

For large-scale miners, we use the power usage effectiveness (PUE) of 1.05. For medium-scale miners, we use a PUE of 1.10 due to less optimized cooling systems. For small-scale miners, we assume a PUE of 1.00, as there is no need for cooling systems, AC/DC converters, load transformers, and adapters (see Supplementary Notes Sheet 2 for a sensitivity analysis of these assumptions and Sheet 3.7 for interview notes with a mining company).

We determine the distribution among these three categories using Slushpool data, displayed in Figure 27. Slushpool is a public mining pool, which provides live statistics on the computing power of connected users. By assuming that distribution is the same for all public pools in the rest of the network, we determine that 15% are small, 19% are medium, and 65% are large-scale miners for these pools. Regarding private pools, we classify them as 100% large-scale miners since they are usually run by big institutions. This results in an overall PUE of 1.05.

[314] See, e.g. (Schlesinger & Day, 2018).
[315] See (Huang, 2018).
[316] See (Harper, 2018).

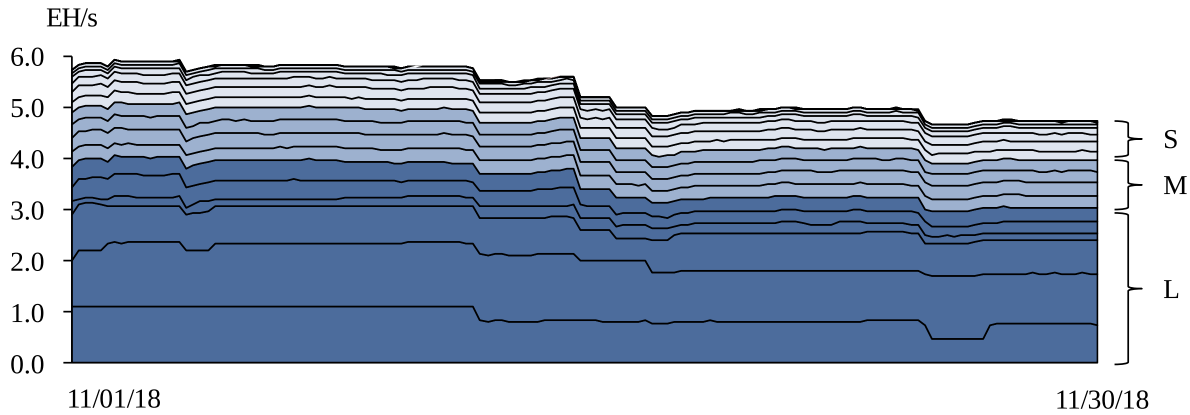

Figure 27: Hash rate distribution of Slushpool grouped by individual miners' hash rate.[317]

4.4 Mining Pools

Miners combine their computing power and share the block rewards and transaction fees in order to reduce the time and variance of finding a new block. Back in January 2011, a miner with an up-to-date GPU (2 GH/s) could expect to find more than two blocks a day. In November 2018, due to the increasing difficulty of the search puzzle, the same miner could expect to find a block every 472,339 years. Even today's most powerful ASIC-based mining system (44,000 GH/s) yields an expected discovery rate of one block every 21 years (the calculations can be found in Supplementary Notes Sheet 4.3).

The average time it takes to find a new block depends on the network's current level of difficulty and computing power of the hardware in use. The average number of hashes to be computed in order to solve a block, is given by the difficulty multiplied by the number of hashes per block (each block has $2^{48}/65,535$ hashes). The difficulty adjusts every 2016 blocks to account for changes in connected computing power in order to maintain approximately ten minutes between the addition of each block.[318]

Solving a block is rewarded with new Bitcoins and the fees of all newly-included transactions. The reward per block in new Bitcoins started at 50 for the first blocks and halves every 210,000 blocks. At the current number of blocks in November 2018 (552,100), the block reward equals 12.5 Bitcoins per block and as a result, 1,800 (=12.5 x 24h x 6/h) new

[317] Note: Data generated in web scrawling of Slushpool pool statistics (https://slushpool.com/stats/?c=btc), see (Slushpool, 2018), which differentiates 27 size groups that we group in S, M, and L; data reported in Supplementary Notes Sheet 3.7; source code available under https://github.com/UliGall/cfootprint_bitcoin.
[318] See (Narayanan et al., 2016).

Bitcoins are currently mined every day. As the time to solve one block remains constant and the reward continues to halve, the last of about 21 million Bitcoins will be mined in 121 years from now.

Nowadays, nearly all network participants are organized in public pools or self-organized private pools. Thereby, more than two-thirds of the current computing power is grouped by Chinese pools, followed by the 11% of pools registered in the EU, as depicted in the chart in Figure 28. We consider "Unknown pools" (with unknown origin of the hash rate) as private, as it only makes sense to mine without joining a pool if one has enough hash power to expect finding a block within a reasonable period of time in order to prefer income variance over pool fees.

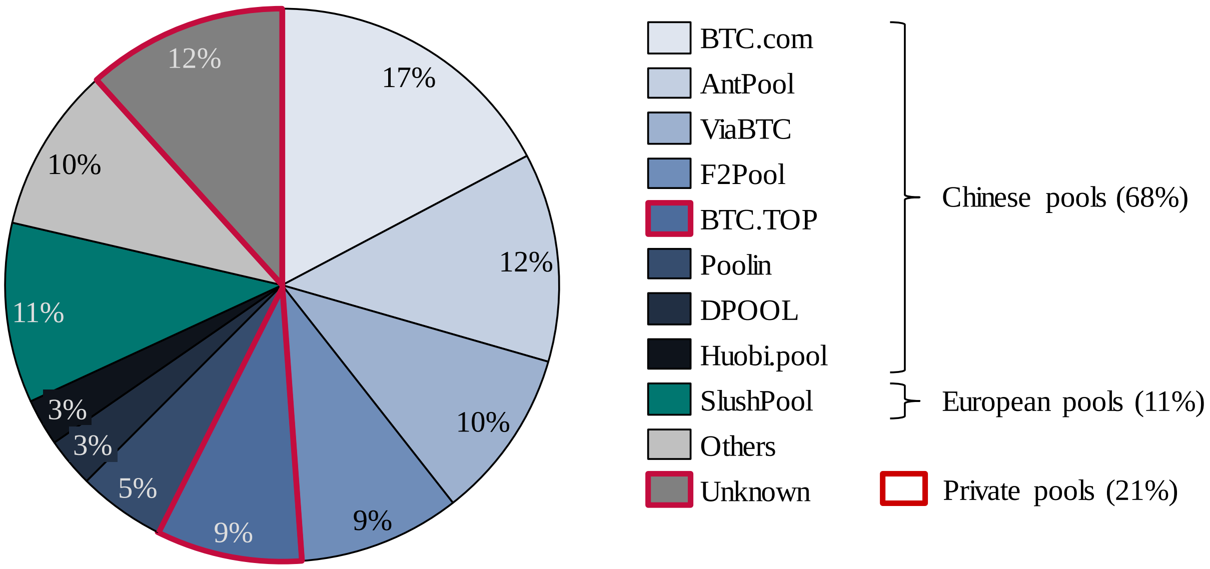

Figure 28: Hash rate distribution among mining pools as of November 2018.[319]

[319] Note: Data pulled from btc.com (https://btc.com/stats/pool?percent_mode=latest#pool-history), see (BTC.com, 2018a), and reported in Supplementary Notes Sheet 4.2.

4.5 Power Consumption

Prior to estimating a realistic level of electricity consumption by Bitcoin, we narrow down the solution range by calculating a lower and an upper limit. The lower limit is defined by a scenario in which all miners use the most efficient hardware. The upper limit is defined as the break-even point of mining revenues and electricity costs. Figure 29 charts the range including our best-guess estimate, which follows the approach of the lower limit, but includes the anticipated energy efficiency of the network, based on hardware sales and auxiliary losses (see 4.11 Methods for details).

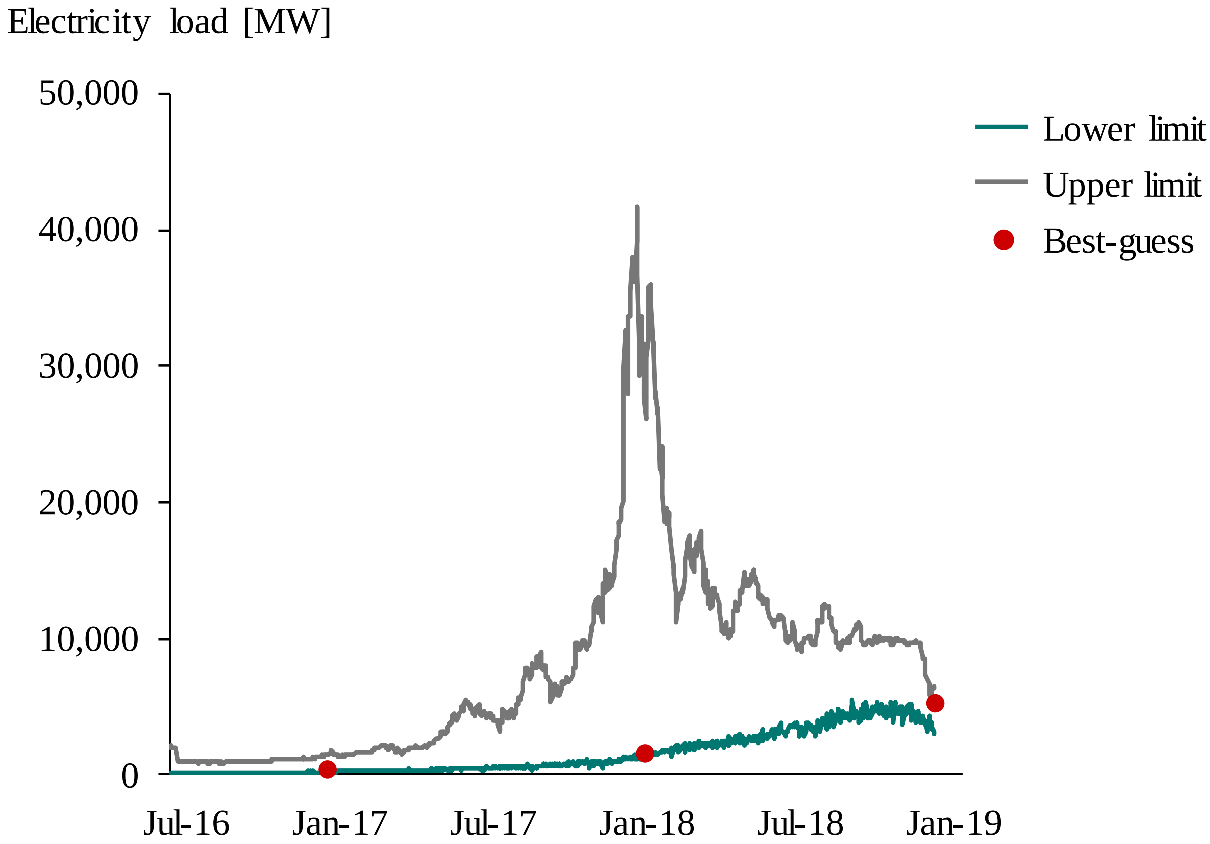

Figure 29: Power consumption corridor.[320]

Figure 29 shows that the upper limit of power consumption is more volatile as it follows the market price of Bitcoin. The lower limit is more stable as it is defined by hardware efficiency and hash rate. We estimate a power consumption of 345 MW at the end of 2016, 1,637 MW at the end of 2017, and 5,232 MW in November 2018, based on auxiliary losses and ASIC-

[320] Note: Values are charted at daily intervals. Data are reported in Supplementary Notes Sheet 3.2-3.3. Sensitivities are shown in Supplementary Notes Sheet 2.

based mining system sales. By multiplying the power consumption as of November 2018 with 8,760 hours, we get an annual power consumption of 45.8 TWh.

4.6 Mining Locations

Below, we develop three scenarios examining the regional footprint of Bitcoin, which are based on the localization of pool server IP, device IP, and node IP-addresses. First, the pool server IP method localizes IP address of pool servers where participants connect to the pool. Second, the device IP method localizes ASIC-based mining systems via an IoT-search engine. Third, the node IP method resorts to peer-to-peer nodes first seen relaying a block. Some miners may use services like TOR or Virtual Private Networks (VPN) to disguise their locations, for instance, for legal reasons. However, as a good overall network connection increases the probability of having a new block accepted in the network, it is generally advantageous to propagate blocks through the fastest connection.

Based on pool regional statistics on BTC.com and Slushpool that localize IP-addresses of pool servers, we find evidence that miners tend to allocate their computing power to local pools. BTC.com and Slushpool are the largest mining pools administrated in China and Europe, and in both pools, regional miners comprise the vast majority of participants. U.S-based miners tend to join the European pool. Combining these insights from pool server IP-addresses with pool shares and assuming that those pools are representative for other pools within the region, we determine that there is 68% Asian, 17% European, and 15% North American computing power in the network. This approximation includes the assumption that the weighted distribution in terms of their regional origin within Chinese and European pools is representative for the remaining 21% of computing power that cannot be localized (see Supplementary Notes Sheet 3.1, 4.2 and 4.5). The downside of this first scenario is that it might overestimate the share of Chinese miners. The location of some participants might be misreported as Chinese due to default settings of the recommended mining software.

Based on device IPs, we find a stronger U.S. concentration compared to the pool server IP method. We identify the location of ASIC-based mining systems via the IoT-search engine Shodan. By searching for connected mining hardware, we can view the distribution on a national level. We are able to localize 2,260 devices of Bitmain, and the query results show a significant concentration in the U.S. (19%). Venezuela (16%), Russia (11%), Korea (7%), Ukraine (5%), and China (4%) appear next on the list, and Figure 30 charts all the locations of internet nodes with connected Antminers. The methodology reveals locations that we could not detect with the pool server IP methodology that resorts to a higher aggregation level within the Bitcoin network.

Figure 30: Local footprint of device IP-addresses.[321]

With the third method, we derive IP-addresses from peer-to-peer nodes first seen relaying a block. The full nodes and miners in the network communicate via a peer-to-peer network. Information (such as new transactions or blocks) are sent to connected peers via a gossip-protocol, in order to reach all nodes in a timely manner. Therefore, we monitor the IP-addresses relaying new blocks recorded by Blockcypher.[322] We record that 93% of all blocks are relayed on U.S. soil. Hence, we conclude from the data that Blockcypher has too few connections within the network as it receives blocks from better-connected relayers' nodes, and not only from miners' nodes. Obtaining valid IP-addresses in future research would require a large set of well-connected nodes throughout the network. (The source code is

[321] Note: Map and data from IoT-search engine Shodan (https://www.shodan.io), see (Shodan, 2018), as reported in Supplementary Notes Sheet 4.7.
[322] See (Blockcypher, 2018).

available under https://github.com/UliGall/cfootprint_bitcoin; node IP-addresses are localized with ipinfo.io and reported in Supplementary Notes Sheet 4.6.)

4.7 Carbon Footprint

We calculate Bitcoin's carbon footprint based on its total power consumption and geographic footprint. To determine the amount of carbon emitted in each country, we multiply the power consumption of Bitcoin mining by average and marginal emission factors of power generation. Our best guess is based on average emission factors, which represent the carbon intensity of the power generation resource mix, while marginal emission factors account for the carbon intensity of incremental load change.

We find that the annual global carbon emissions of Bitcoin range between 22.0 and 22.9 $MtCO_2$; a ratio which sits between the levels produced by Jordan and Sri Lanka,[323] and which is comparable to the level of Kansas City.[324] 22.0 $MtCO_2$ is based on the footprint of the device IP method, and 22.9 $MtCO_2$ assumes the footprint of the pool server IP method. (We apply emission factors from the IEA;[325] the calculation can be found in Supplementary Notes Sheet 3.1.) Compared to the global annual energy demand of approximately 13,760 Mtoe (~160 PWh), or the global energy-related CO_2 emissions of more than 30 $GtCO_2$ in 2016,[326] this might seem small. Still, Bitcoin's CO_2 equivalent ranks between number 82 and 83 on the list of biggest emitting countries.[327]

Many have argued that clean surplus energy fuels Bitcoin to a significant degree. In the short run, which is relevant for our snapshot, curtailment rates of clean resources may be large in certain areas with Bitcoin mining activity. Especially in southwestern China, hydropower accounts for around 80% of the generated electricity in the provinces of Yunnan and Sichuan.[328] Yunnan curtailed 31.2 TWh of hydropower in 2016, which equaled 11.6% of the total electricity generation in the province.[329] However, mining activities can also be found

[323] See (Global Carbon Project, 2017).
[324] See (Moran et al., 2018).
[325] See (IEA, 2017).
[326] See (IEA, 2017).
[327] See (Global Carbon Project, 2017).
[328] See (Li, Chalvatzis, & Pappas, 2018).
[329] See (Liu, Liao, Cheng, Chen, & Li, 2018).

in regions with coal-heavy power generation, like in the province of Inner Mongolia.[330] Pool regional statistics of BTC.com suggest a 58% versus 42% split between hydro-rich and coal-heavy regions in China. The ratio represents the computing power reported from Shenzhen (server location closer to hydro-rich regions) versus Beijing (server location closer to coal-heavy regions).[331] If we weight the emission factors of Sichuan (265 g/kWh) and Inner Mongolia (947 g/kWh) accordingly,[332] we obtain an adjusted emission factor of 550 g/kWh, which we use in our calculations to account for the special case of China.

If we assume fossil fuels cover the additional load entirely, we find that annual emissions caused by Bitcoin mining could be as high as 51.0 $MtCO_2$ (in a footprint scenario of device IP-addresses and marginal emission factors of coal; all remaining combinations of footprint scenarios and marginal emission factors of gas and coal are depicted in Supplementary Notes Sheet 1). On the contrary, assuming a higher share of clean power consumption decreases CO_2 emissions.

Some have argued that miners do not operate continuously. We assume that miners run their hardware continuously throughout the year. A comparison of break-even electricity prices for ASIC-based mining systems shows that this assumption is valid for most fixed-rate retail tariffs, and especially for regions with high mining activity (see Supplementary Notes Sheet 3.5). The steadiness of the hash rate distribution in Figure 27 supports this assumption. That is also the reason for ignoring potential additional sources of revenue from price volatility in the wholesale market or from the provision of load-balancing services as these would not change the duration of mining operations.

In the long run, we can envision Bitcoin miners to increasingly establish their operations nearby large sources of renewable energy, which also triggers further development of renewable generation resources at the respective sites.[333] Therefore, long run emissions factors of the Bitcoin network might be lower than the current grid average.

[330] See (Hileman & Rauchs, 2017).
[331] See (BTC.com, 2018b).
[332] See (Qu, Liang, & Xu, 2017).
[333] See (Fridgen, Keller, Thimmel, & Wederhake, 2017).

4.8 Social Cost and Benefit

Our approximation of Bitcoin's carbon footprint underlines the need to tackle the environmental externalities that result from cryptocurrencies,[334] and highlights the necessity of cost/benefit trade-offs for blockchain applications in general. We do not question the efficiency gains that blockchain technology could, in certain cases, provide. However, the current debate is focused on anticipated benefits, and more attention needs to be given to costs. Policy-makers should not ignore the following aspects:

Carbon. As global electricity prices do not reflect the future damage caused by today's emissions, economic theory calls for government intervention to correct this market failure in order to enhance social welfare. The issue of the social cost of carbon is of course not specific to cryptocurrency and as mentioned in the previous section, cryptocurrencies cause a relatively small fraction of global emissions. Still, regulating this largely gambling-driven source of carbon emissions appears to be a simple means to contribute to decarbonizing the economy.[335]

Concentration. The case of Bitcoin shows that the risk of concentration must not be ignored. Irrespective of the decentralized nature of Bitcoin's blockchain, the four largest Chinese pools now provide almost 50% of the total hash rate, and Bitmain operates three of these four pools. If one player controls the majority of computing power, it could start reversing new transactions, double-spend coins, and systematically destroy trust in the cryptocurrency. In case of Bitcoin pool operators, continuous fee income has so far discouraged from colluding to attack, and it appears unlikely to happen in the future as miners would instantaneously reallocate their hash rate. Nonetheless, the risk of concentrations must not be ignored in other blockchain use-cases.

Control. With their idea, Satoshi intended for Bitcoin to increase privacy and reduce dependency on trusted third parties.[336] However, protecting individuals from themselves and others from their actions might justify the downsides of central control, as the potential benefit of anonymity spurs illegal conduct such as buying drugs, weapons, or child pornography. Therefore, a use-case specific degree of central governance is essential. Today,

[334] See (Foteinis, 2018).
[335] See (The Economist, 2018a).
[336] See (Nakamoto, 2008).

most intermediate parties serve useful functions, and a decentralized socio-economic construct like blockchain should only replace them if it can ensure the same functionality, or if efficiency gains outweigh their value. Therefore, cryptocurrency systems are unlikely to replace fully the existing financial systems. Nonetheless, they may be superior for specific applications.[337]

4.9 Beyond Bitcoin

Bitcoin's power consumption may only be the tip of the iceberg. Including estimates for three other cryptocurrencies adds 30 TWh to our annual estimate for Bitcoin alone.[338] If we assume correlation to market capitalization, and only consider mineable currencies (unlike second layer tokens or coins with other consensus mechanisms), the remaining 618 currencies could potentially add a power demand over 40 TWh.[339] This then more than doubles the power consumption we estimate for Bitcoin.

While other blockchain platforms (e.g., the second largest cryptocurrency, Ethereum) develop on switching protocols from Proof-of-Work to other, less energy-consuming consensus mechanisms, such as Proof-of-Stake, it is likely that Bitcoin will continue to use the established algorithm. Miners, who have a large influence on the development of Bitcoin, are not interested in removing the algorithm, which is central to their own business. Therefore, it is likely that Bitcoin will remain the largest energy consumer among public blockchain systems, and will continue to consume a considerable amount of energy.

Besides cryptocurrencies, there are other uses for blockchain. Bitcoin has managed to establish a global, decentralized monetary system, but fails as a general-purpose blockchain platform. For instance, Smart Contracts are seen to disrupt traditional business models in finance, trade, and logistics. Like many earlier disruptive technologies, blockchain is merely the foundation and enabler of novel applications.[340] Alternative protocols will help to reduce the power requirements of future blockchain applications, and many blockchain-based systems will certainly be private, permissioned blockchains, which do not need a Proof-of-

337 See (Giungato, Rana, Tarabella, & Tricase, 2017).
338 See (Digiconomist, 2018b; Swanson, 2018).
339 See (CoinMarketCap, 2018).
340 See (Iansiti & Lakhani, 2017).

Work like Bitcoin. Notwithstanding, our findings for the first stage of blockchain diffusion underline the need for further research on externalities, in order to support policy-makers in setting the right rules for the adoption of these technologies.

4.10 Validity of Results

As of November 2018, Bitcoin's annual power consumption sits between 35.0 and 72.7 TWh as argued in the Section "Power consumption". Estimating a more precise number requires assumptions on mining hardware and operations. Our results show that the efficiency of the hardware in use is an essential parameter in this calculation. Our estimated hardware efficiency of 0.11 J/GH is based on IPO filings of major hardware manufacturers, which we consider to be the most reliable reference point at present. Nonetheless, the IPO filings we used have a cutoff date, and sales per model are not always explicitly stated. At the extremes, if we assume that only the least or most efficient systems are sold in all cases where the numbers are not explicitly stated, we obtain a power consumption of 37.0 and 56.2 TWh. Regarding operations, we determine a power usage effectiveness of 1.05, based on pool statistics and industry insights. If we vary this assumption and use ideal operations (PUE of 1.0) or least-efficient mining operations that appear realistic (PUE of 1.1), the estimated power consumption of 45.8 TWh differs by plus/minus 5%. Varying the size distribution of miners changes the resulting PUE within these two extremes: If we assume that all public pools beside Slushpool consist of only small, medium, or large miners, we obtain PUEs of 1.015, 1.083, and 1.049.

Our best guess power consumption of 45.8 TWh may result in carbon emissions between zero and 51.0 $MtCO_2$ (100% clean surplus electricity vs. 100% coal-fired power generation). The extreme cases illustrate that the assumed carbon intensity of power consumption has a major effect on results. Estimating a more precise number requires assumptions on locations of mining activities and regional carbon intensities of electricity. Our best guess is based on average emission factors to account for the carbon intensity of incremental load change as well as for clean energy in the power generation resource mix. Assuming a less balanced share between fossil-fueled and clean Bitcoin mining, or a different power consumption in the first place, may change the results accordingly. Here we demonstrate three methods to develop scenarios representing the geographic footprint of Bitcoin mining. Although these methods are associated with high uncertainty, the results of the carbon footprint of Bitcoin vary within a relatively narrow range from 22.0 to 22.9 $MtCO_2$.

4.11 Methods

This section provides the methodology for calculating the range of power consumption, and the approach to derive a best-guess estimate:

(1) Lower limit

The lower limit is defined by a scenario in which all miners use the most efficient hardware. We calculate the lower limit of the range by multiplying the required computing power – indicated by the hash rate – by the energy efficiency of the most efficient hardware:

$$P_{LL} = H * e_{ef}, \tag{1}$$

with:

- $P_{LL} = power\ consumption\ (lower\ limit)\ [W]$
- $H = hash\ rate\ [H/s]$
- $e_{ef} = energy\ efficiency\ of\ most\ efficient\ hardware\ [J/H].$

(2) Upper limit

The upper limit is defined by the break-even point of revenues and electricity cost. Rational behavior would lead miners to disconnect their hardware from the network as soon as their costs exceed their revenues from mining and validation:

$$P_{UL} = \frac{(R_B + R_T) * M}{p_N} * \frac{1}{t}, \tag{2}$$

with:

- $P_{UL} = power\ consumption\ (upper\ limit)\ [W]$
- $R_B = block\ reward\ [BTC]$
- $R_T = transaction\ fees\ [BTC]$
- $M = market\ price\ [USD/BTC]$
- $p_N = electricity\ price\ [USD/kWh]$
- $t = time\ period\ [h].$

(3) Best-guess

The best-guess estimate follows the approach of the lower limit, but includes the anticipated energy efficiency of the network, as well as further losses from cooling and IT components:

$$P_{BG} = H * e_N * PUE_N, \tag{3}$$

with

- $P_{BG} = power\ consumption\ (best\ guess)\ [W]$
- $e_N = realistic\ energy\ efficiency\ of\ hardware\ [J/H]$
- $PUE_N = losses\ from\ cooling\ and\ IT\ equipment$ [%].

The realistic energy efficiency of the network can be determined using the market shares of mining hardware producers and the energy efficiency of the hardware in operation:

$$e_N = \left[\sum_{i=1}^{n} S_{APi} * e_{APi}\right] + \left[1 - \left(\sum_{i=1}^{n} S_{APi}\right)\right] * e_P, \tag{4}$$

with

- $i = mining\ hardware\ producer\ (1, \ldots, n)$
- $e_N = realistic\ energy\ efficiency\ of\ hardware\ [J/H]$
- $S_{APi} = share\ of\ ASIC\ producer\ i$ [%]
- $e_{APi} = energy\ efficiency\ of\ ASIC\ producer\ i\ [J/H]$
- $e_P = energy\ efficiency\ for\ zero\ profit\ [J/H]$.

If some of the computing power cannot be assigned to one of the major mining hardware producers, we assume this computing power originates from hardware, which generates zero profit. By equalizing P_{LL} and $P_{BG,}$ we derive:

$$e_P = \frac{(R_B + R_T) * M}{p_N * H * PUE_N} * \frac{1}{t}\,. \tag{5}$$

In terms of the average losses from cooling and equipment, we differentiate between three types of mining facilities according to size, and weight them by their share in terms of computing power:

$$PUE_N = S_S * PUE_S + S_M * PUE_M + S_L * PUE_L, \tag{6}$$

with

- $j = facility\ type\ (Small,\ Medium,\ Large)$
- $S_j\ = share\ of\ facility\ type\ j$ [%]
- $PUE_j\ = losses\ from\ cooling\ and\ IT\ equipment\ of\ facility\ type\ j$ [%].

We derive the energy consumption by multiplying the power consumption by a respective time period:

$$E = P * t, \tag{7}$$

with

- $E = energy\ consumption\ [Wh]$
- $P = power\ consumption\ [W]$.

The resulting carbon footprint of the Bitcoin network depends on the carbon intensity I_N of the power mix:

$$C = E * I_N, \tag{8}$$

with

- $C = carbon\ emissions\ [g\ CO_2]$
- $I_N\ = carbon\ intensity\ of\ power\ production\ [g\ CO_2/Wh]$.

In order to incorporate local differences in the carbon intensity of the power mix, we differentiate among regions and weight them by computing power share:

$$I_N = \sum_{k=Reg\ 1}^{n} S_{Reg\ 1} * I_{Reg\ 1} + \cdots + S_{Reg\ n} * I_{Reg\ n}, \tag{9}$$

with

- $k = region\ (1, \ldots, n)$
- $S_k = share\ of\ region\ k$ [%].

In the scenario with pool IP-addresses, we determine the share of each region based on the geographical distribution of BTC.com (representing the Chinese pools), and of Slushpool (representing the European pools). For the hash rate of the remaining network with unknown origin, we assume the distribution to be in line with the weighted average of BTC.com and Slushpool:

$$S_k = \frac{S_{Reg\ k,\ \ BTC.com} * R_{Chinese\ Pools} + S_{Reg\ k,\ \ Slushpool} * R_{European\ Pools}}{R_{Chinese\ Pools} + R_{European\ Pools}}\,, \tag{10}$$

with

- $l\ =$ pool type ($Chinese\ pool, European\ pool, Other\ pool$)
- $S_{k,l} = share\ of\ pool\ type\ l\ in\ region\ k$ [%]
- $R_l = ratio\ of\ pool\ type\ within\ the\ entire\ network$ [%].

5 Conclusion

"All political lives, unless they are cut off in midstream at a happy juncture, end in failure, because that is the nature of politics and of human affairs."[341] To refute the quote, this thesis may help policy-makers to better understand the reasons for failure in order to make the right regulatory decisions. Section 5 concludes this thesis by first summarizing the key findings and highlighting the associated contributions, second, disclosing the caveats of the performed work and pointing to future research needs, and last providing an outlook on the overarching topic.

5.1 Contributions and Findings

This thesis addresses the current discussion on climate policy, which is concerned with market-based tools and highlights opportunity spaces for carbon pricing to contribute to deep decarbonization. Furthermore, this thesis addresses the current trend in energy policy of applying non-market-based tools such as phase-out mandates and demonstrates that phase-out policies in the energy sector may be sub-optimal. Last but not least, this thesis discusses the externalities of the blockchain technology and emphasizes that more attention must be paid to the carbon footprint of digital innovations. Section 5.1 summarizes the key findings and major contributions of the three Essays and demonstrates the connections between the three essays.

The first essay contributes to the public debate, which increasingly focuses on carbon pricing to reduce emissions across sectors.[342] The findings recommend that carbon pricing should remain a central element of an effective climate policy portfolio mix, and indeed, to prevent climate change from becoming the greatest government failure the world has ever seen. The conceptual framework that we suggest may help policy-makers in understanding the limitations of carbon pricing and thereby support the implementation of more effective policy designs.

[341] See (Powell, 1977), p. 151.
[342] Note: The recent public debate in Germany on carbon pricing to achieve committed 2030 emission reduction targets of -55% compared to the 1990 level underlines the trend, see (Clean Energy Wire, 2019).

The insights that Essay I provides can be applied to the challenges that are addressed in Essay II and Essay III. Thereby, carbon pricing represents one potential option to solve the challenge covered in Essay II and Essay III. In particular, in the context of Essay II, an understanding of carbon pricing's strengths and weaknesses may help to design a cost-efficient decarbonization strategy in the power sector. Personal communication with a member of Germany's coal exit commission revealed the challenges in the political decision process. The challenge to find a compromise among vested interests of policy-makers, industry organizations, and environmental organizations bears the risk of deprioritizing cost-effectiveness and taking decisions, which result in sub-optimal solutions from a social welfare perspective. The conceptual framework of Essay I can explain such challenges and consequently help to improve such decision processes.

The second essay emphasizes that an increasing number of jurisdictions are resorting to phase-out mandates in order to reduce emissions from specific sectors or activities. In Essay II, I present a simple model to demonstrate that phase-out policies may not be as cost-effective as market-based instruments in achieving emission reductions. Furthermore, the case-study drawing on the example of Germany reveals counter-intuitive results that go against conventional assumptions about the role of coal. The results show that a gradual transition from coal to clean generation resources may be cheaper than a strict coal phase-out from a societal point of view. The results of Essay II contribute to the current political debate through transparent and simple explanations of fuel-switching effects in the energy sector. Especially pointing out the effects of stranded assets and how they can be part of a cost-effective decarbonization strategy may help policy-makers in their decision process.

As discussed in Essay I, the implementation of a global carbon pricing initiative, which covers all emitting activities and imposes a price at the optimal level represents a mammoth task. Such an optimal price on carbon emissions would also solve the challenge of Bitcoins carbon emissions in the welfare optimal way. In the absence of such an ideal-theoretic carbon pricing initiative, alternative regulatory options might be required. To assess the necessity of regulatory intervention, the first step is an understanding of the respective challenge. Therefore, the third essay in this thesis underlines the need to tackle the environmental externalities that result from innovative technologies or digital concepts by quantifying emissions associated with cryptocurrencies.

We find that the annual electricity consumption of the Bitcoin network, as of November 2018, summed up to 45.8 TWh. We further estimate that annual carbon emissions range from 22.0 to 22.9 $MtCO_2$. Therefore, the carbon emissions caused by the Bitcoin network sit between the emission levels produced by the nations of Jordan and Sri Lanka. This level of emissions emphasizes the necessity of cost/benefit trade-offs for blockchain applications beyond cryptocurrencies and for innovative technologies in general.[343]

These findings for the first phase of blockchain diffusion, and the externalities we discuss may help policy-makers in setting the right rules as the adoption journey of blockchain technology has just started. The challenge of carbon emissions is of course not cryptocurrency specific, and from an economic perspective – as highlighted in Essay I – the most-efficient solution would be a regulatory intervention in form of a carbon pricing initiative. Such a welfare-maximizing solution would induce a price on every ton of carbon emitted, and the price would reflect the future climate damage caused by today's emissions.

All three essays demonstrate that there are options to tackle the challenges of climate change within the three areas of policy by establishing an appropriate framework. Going forward, the key question will be whether societies can agree to take strong action on the national and international level, which will affect our society's habits today but also brings benefits far in the future. This thesis shall provide thought-provoking impulses on three current topics from policy and technology, and in the wake of this contribute to the larger climate puzzle. "There is still time to avoid the worst impacts of climate change, if we take strong action now."[344]

5.2 Caveats and Further Research

The three essays in this thesis cover one specific aspect of the extensive climate puzzle. To provide answers to the respective questions, several assumptions have to be made and thematic boundaries have to the set. Section 5.2 summarizes the caveats of the three essays and points to areas for future research.

[343] Note: For instance, negative-emission technologies may play an important role in the decarbonization pathway, and as the potential from biomass appears insufficient to remove CO_2 from the atmosphere at scale, direct carbon capture from the air may be the option of choice; see (National Academies of Sciences & Medicine, 2018). However, carbon capture from the air requires vast amounts of energy; see (Creutzig et al., 2019).

[344] See (Stern, 2007), p. vi.

Essay I highlights the importance to understand the implications of climate policy tools. A recent example that illustrates the relevance of such an understanding can be found in France. Policy-makers in France dropped the idea of a fuel-tax rise after the plan triggered violent protests.[345] The so-called 'yellow vest' protests highlight the importance of public support in policy-making.[346] More importantly, the protests underline the importance to understand the strengths, weaknesses, and implications of climate policy instruments prior to implementation. This applies in particular to the distributional effects and the potential mitigations, which we mention from a theoretical perspective but whose public acceptance and practicality remain to be seen.

The model I present in Essay II has numerous limitations compared to detailed power system models. The model I present ignores factors such as fixed unit expansion size, economies of scale in supply, market power of generators, imports and exports, sector coupling, and cycling constraints. Furthermore, the chosen method omits transmission constraints and specific factors on a single power plant level. However, the simple model provides transparent and comprehensible first-order estimates that reveal valuable insights into basic economic effects. These highlighted effects of stranded assets must not be ignored on the decarbonization pathway and should be included in sophisticated modeling work.

Essay III formalizes several novel methodologies in the comparably young research field on cryptocurrencies and blockchain applications in general. Nevertheless, the absolute results of Essay III only provide a snapshot in time. Due to the interplay of connected computing power, the difficulty of the Bitcoin puzzles, monetary incentives to mine, hardware efficiency, protocol configurations, and many other factors, our results may provide a reference point but may not be used to forecast future developments. Some have predicted future emissions based on market penetration rates,[347] which appears technically flawed,[348] but the attempt addresses an important issue. Blockchain applications are envisioned for all types of use-cases beyond cryptocurrencies. In many of these use-cases, a less decentralized validation process can be used, for instance, if a lower degree of anonymity or decentralized control is

[345] See (The New York Times, 2018).
[346] See (Carattini, Kallbekken, & Orlov, 2019).
[347] See (Mora et al., 2018) for a calculation of Bitcoin's future emissions and how these emissions cause warming incompatible with the 2° C warming target.
[348] Note: The power requirements do not automatically scale with the number of transactions; the difficulty to solve a Bitcoin puzzle does not change with the number of transactions that are included in the block.

acceptable or desired.[349] Such alternative blockchain protocols may be far less energy-intensive than Bitcoin's protocol but raise other questions about the regulatory oversight and implications on monetary policy. Beyond cryptocurrencies, the debate on potential use-cases is strongly driven by anticipated benefits. Even if efficient protocols are in place, or if clean energy supply can be guaranteed, the required infrastructure components have to be produced and recycled. There have been first attempts to quantify the environmental impact of electronic waste in the case of Bitcoin mining hardware.[350] A better understanding of lifecycle emissions of such infrastructure components could provide valuable insights into the debate.

5.3 Outlook

"Intelligence is the ability to adapt to change."[351] The example of the dodo bird who lived for centuries on Mauritius illustrates the challenge the introducing quote refers to. The first recorded mentioning of the dodo was by Dutch sailors in 1598. The last sighting was 64 years later in 1662.[352] Due to no natural enemy, he was completely fearless. When humans arrived on Mauritius and introduced other animals to the ecosystem, the fearless dodo fell victim to the other species within a few years. Charles Darwin found the explanation for the phenomenon two hundred years later: The dodo was perfectly adjusted to its surrounding, but unable to adapt to quickly changing conditions.[353] This thesis covers one current topic within each of the three areas of climate policy along the marginal abatement cost curve as described in Section 1.1.3. The results may help policy-makers to adapt to one of the biggest challenges of time.

The current willingness to adapt by limiting greenhouse gas emissions is still low on the global level. The current level of temperature anomaly is still more than offset by economic benefit in certain regions.[354] The global climate protection efforts are accordingly low.[355]

[349] See e.g. (Libra Association Members, 2019) for the design of Facebook's Libra coin. In the LibraBFT consensus protocol, all parties that validate transactions know each other.
[350] See (De Vries, 2019).
[351] This quote has been attributed to Stephen Hawking.
[352] See (Parish, 2013).
[353] See (Darwin, 1859).
[354] See (Ricke et al., 2018) and Section 1.1.1.
[355] E.g. the sum of national pledges is insufficiently low to achieve the targets of the Paris Agreement, see (Climate Action Tracker, 2019).

However, in the absence of strong and timely actions, the temperature may rise by more than 4 °C until the end of the century. Even if we achieve net zero emissions by mid-century, temperature may still rise by 2-3 °C until the end of the century.[356] Remembering the local variance of the global rise in surface temperature as depicted in Section 1, local as well as global climate change adaption strategies will become increasingly important.

In 2050, I will be 59 years old. Carbon pricing will likely be a central element of climate politics, with carbon prices much higher than today and closer to the true social cost of carbon. Our power supply will be much cleaner than today (coal-fired power generation will have been phased-out or become uneconomical in most places), and blockchain solutions might have achieved efficiency gains and enabled a broad variety of use-cases. Likely, coastlines will look different than today, billions of people will have migrated, and temperatures will still be rising.

Unlike the dodo bird, humans have demonstrated adaption skills in the past. *Homo sapiens* have survived two ice ages during the past 200,000 years,[357] with average temperatures more than 8 °C below the current level.[358] In a future scenario with high and comparably fast increasing temperatures, adaption strategies will become more and more important. Research on climate adoption strategies has lagged behind as the current research debate focuses on climate change mitigation.

At a certain level of warming, in order to avoid catastrophic climate change, removing CO_2 from the atmosphere, or blocking solar irradiation through injecting dust in the stratosphere (or an innovation unknown to us today), will increasingly move into focus. These approaches are at the moment either too expensive or associated with high uncertainty and risk.[359] Nonetheless, more research is needed to gain an understanding of such options of last resort. The famous example of a turkey that lives a happy life, fully unaware that Thanksgiving is approaching, illustrates the challenge of inductive reasoning and heuristic decision-making in cases of high uncertainty but a huge impact.[360] Action towards a cleaner future is urgently needed today, and it should include more research on options of last resort.

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356 See (Sokolov et al., 2017), p. 10.
357 See, (Bräuer et al., 2003); note: A more recent example of adjustment skills can be found in progressing technology, e.g. the reserves-to-consumption ratio of crude oil remained very stable at around 50 years since 1980, see (Covert, Greenstone, & Knittel, 2016).
358 See (Petit et al., 1999).
359 See (Vaughan & Lenton, 2011).
360 See (Taleb, 2007) for so-called ‘Black swan’ events.

6 References

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