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Global growth and stagnation of nuclear power

A case of diffusion of a new energy technology in a heterogenous system

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Abstract

Reaching the targets of the Paris Agreement requires acceleration of low-carbon energy transitions. At the same time, it is not fully understood why some technologies spread more rapidly and widely than others. This thesis advances our understanding of the diffusion of large-scale low-carbon technologies by bridging technology diffusion studies and political economy of transitions. Through combining modelling of the S-curve of technology diffusion with statistical analysis, the thesis explores how socio-economic characteristics in a heterogenous world, influence the growth and saturation phases of the technology life cycle, as well as the speed and ceiling of diffusion. This study estimates maximum growth rates for nuclear power to a median of 2.6% of national electricity supplies, which is substantially higher than the same metric for wind and solar power. This indicates that nuclear power can replace carbon-intensive energy technologies faster than granular renewables. Moreover, this study demonstrates that western countries tend to reach higher growth rates and higher saturation levels than other countries. However, the results also show that diffusion of nuclear power has stagnated globally, and increasing growth rates are found outside of OECD, most notably in China and India. The results also indicate that diffusion can be successful independent of GDP per capita, electricity demand growth, and the time of adoption. Further research should advance the analysis by employing more sophisticated statistical methods as well as further explore how diffusion of nuclear power diverges in different parts of the world.

Keywords: technology diffusion, energy transitions, growth modelling, nuclear power, low-carbon technologies.

Executive Summary

Limiting climate change to 2°C requires a rapid transformation of the energy sector that currently is the largest contributor to greenhouse gases (IPCC, 2018). While extensive research and investments into renewables are being made, these improvements are currently being outweighed by increased energy demand which often is met by fossil-based energy technologies (IEA, 2019).

How technologies spread is the centre of the research field technology diffusion. This body of literature has found that there are distinct patterns in how technology spreads throughout the world. Most notable are the characteristic logistic S-shaped curve and the diffusion phases (formative, growth, and saturation) (Grubler et al., 2016; Wilson & Grubler, 2011). Scholars have also developed growth models where future diffusion of technologies can be estimated (Wilson et al., 2013). However, this scholarship has historically been focused on western countries meaning that socio-economic characteristics in a heterogenous world have not been accounted for. In a time of rapid environmental degradation where energy demand is predicted to primarily take place in emerging and developing economies (IEA, 2020), it is imperative to understand how diffusion of low carbon technologies could be fostered outside the west.

Another body of literature is addressing the question of why the use of modern technologies varies across countries by examining how different socio-economic and institutional characteristics shape the diffusion of new technologies (Neumann et al., 2020; Sovacool & Valentine, 2012). Thereby this research is complementing technology diffusion studies by seeking to account for the contextual differences in a heterogenous world. However, this literature often fails to incorporate insights from the technology diffusion scholarship, e.g., the diffusion phases and the S-shaped growth curves mentioned above.

This thesis bridges the gap between these two fields and applies them to the case of nuclear power. Nuclear power was first introduced in the 1950s and soon became one of the dominating energy technologies in the world, but is now declining on a global level (Markard et al., 2020). Nuclear power, therefore, offers data that covers the whole life cycle of the technology, which is not the case for other low-carbon technologies that still are in their respective formative or growth phase.

By studying nuclear power, as a case of a new low-carbon technology, this thesis aims to advance knowledge on how large-scale energy transitions can be facilitated efficiently and sustained over time. The following research questions are addressed:

> RQ1: What are the maximum growth rates and saturation levels of nuclear power and how do they vary across countries?
>
> RQ2: What factors explain variability in the diffusion growth rate of nuclear power?
>
> RQ3: What factors explain the ceiling/saturation of nuclear power use?
>
> RQ4: What happens to the speed and depth of nuclear power diffusion in late adopter markets?

The results show that the diffusion of nuclear power has stagnated globally but that there are distinct regional differences. Most countries with stalling growth rates are in Europe and none of the countries with accelerating growth rates is a member of the OECD. Moreover, this study finds that growth rates of nuclear power are substantially higher than those of wind and

solar power, see Figure 0-1. This study estimates the maximum growth rates for nuclear power to a median of 2.6% of national electricity supplies, compared with less than 1% for wind and solar power (Cherp et al., In Press). This can be seen as nuclear power potentially can offset carbon-intensive energy technologies faster than renewables, contrasting some of the previous comparisons made (Sovacool et al., 2020; Wilson et al., 2020).

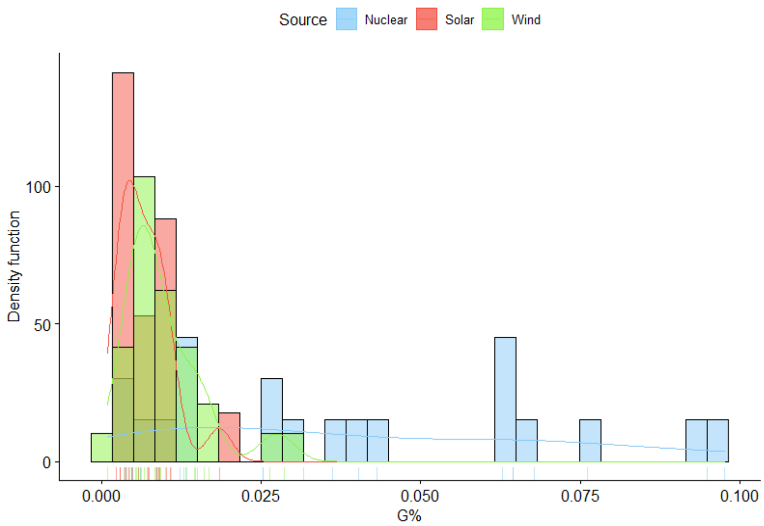

Figure 0-1. Density plot of the distribution of maximum growth rates (G%) for nuclear (blue), solar (red) and wind (green) power. Data on wind and solar power is retrieved from Cherp et al., (In Press).

Policymakers should be aware that nuclear power appears to be able to grow faster, and thereby replacing more carbon, than granular renewables. The current dismantling of reactors and decline in investments in nuclear power (Markard et al., 2020) might inhibit the ability of the international community to reach climate targets.

Moreover, the result of this study indicates that few variables are explaining variance in growth rates of nuclear power. Electricity supply is the only variable with a statistically significant effect when using growth parameters from different growth models. Increasing electricity supply is indicated to be negatively related to growth rates, meaning that growth is slower in larger systems which is consistent with similar studies on wind and solar power (Cherp et al., In Press). Additionally, no variables have a statistically significant effect on saturation levels when using growth parameters from different growth models, indicating that mechanisms determining growth and saturation are different. Whether a country adopted nuclear power earlier or later, is indicated to influence neither growth rates nor saturation levels.

Lastly, this study finds that both growth rates and saturation levels are generally higher in Western countries. As the diffusion of new low-carbon technologies needs to be global, these differences pose a challenge for the international community.

Future research should further explore how socio-economic characteristics affect diffusion with more sophisticated statistical methods and include relevant control variables. Moreover, while the division of the sample into a Western and non-Western group provides interesting insights, there is a lot of heterogeneity in both groups, that future studies can disaggregate and explore. Lastly, it is important to keep in mind that even if nuclear power might have been observed to grow faster than renewables, there are more parameters, such as cost per TWh, that determines the feasibility of a technology that could be explored in future research.

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Abbreviations

IEA – International Energy Agency

OECD – Organisation for Economic Co-operation and Development

USSR – Union of Soviet Socialist Republics (Soviet Union)

GDP – Gross Domestic Product

CCS – Carbon Capture and Storage

SLM – Simple Logistic Model

LSM – Logistic Substitution Model

GWh – Gigawatt hours

TWh – Terawatt hours

1 Introduction

1.1 Background and significance

Reaching the targets of the Paris Agreement requires increased speed of energy transitions in favour of low-carbon technologies. The energy sector is the largest contributor to global greenhouse gas emissions (IPCC, 2018) and the emissions continue to rise. Even though there is extensive growth of solar and wind power, the emissions reductions from the increased use of renewables, are still outpaced by the growing energy demand which requires continuous expansion of fossil-based power generation (IEA, 2019).

To foster and accelerate low-carbon energy transitions, we need to improve our understanding of why some technologies are adopted and diffused rapidly and widely while others are not (Grubler et al., 2016).

> "Only when we can explain why transitions happen fast or slow, can we also start to address the question of how to address failed transitions (lack of diffusion), or carefully craft strategies of accelerated transitions, in case these are judged highly desirable from a social or environmental perspective." (Grubler et al., 2016, p. 7)

This thesis answers this call by exploring how fast new energy technologies can grow and what factors constrain or enable this growth, using the case of nuclear power. The thesis uses a mix of qualitative and quantitative methods and national nuclear energy production data from the International Energy Association (IEA). To map the diffusion of nuclear power, the thesis uses a new method to model technology diffusion and a new metric to track the maximum technology growth rate (G) developed by Cherp et al., (In Press). Subsequently, the thesis examines the social factors which affect this parameter. The intention is that the lessons learned from nuclear power diffusion could be transferred to other low-carbon technologies similar in characteristics. Hopefully, this will provide insights into the feasibility and preconditions for rapid low-carbon energy transitions.

Nuclear power is an appropriate case of a new low-carbon energy technology to study for several reasons: *first,* it diffused swiftly in countries like France (Araújo, 2017) and Sweden (Hultman et al., 2012) which is what needs to happen with low carbon technologies if we are going to reach the climate targets. *Second,* it did not diffuse evenly across the globe and is today in global decline, at least in member states of the Organisation for Economic Co-operation and Development (OECD) (Markard et al., 2020). We want to avoid diverging and declining diffusion for other low-carbon technologies, and we can therefore learn from the varying diffusion of nuclear power. *Third*, nuclear power has been used for decades and is well documented which means that reliable time-series data is available (Markard et al., 2020). While a similar study could be done on renewables, nuclear power provides data from a longer time period and across a wider range of countries. Nuclear power furthermore provides empirical data on the entire technology lifecycle, including the saturation and decline phases, which is not the case for many renewables that are still growing. It is generally hard to predict the saturation level for younger technologies (Martino, 2003) (see limitations and methods sections) meaning that nuclear power could provide insights that renewables cannot. *Four*, nuclear power represents a policy-driven technology (not necessarily self-sustaining from a market economy perspective) (Sovacool & Valentine, 2012) and low-carbon technologies and energy transitions are expected to be increasingly policy-driven in the future (Cherp et al., 2018; Fouquet & Pearson, 2012). *Five*, even though Markard et al., (2020) found that nuclear power is currently declining, there is a debate in the scientific community whether the technology could, and (due to climate reasons) should be upscaled again (Cao, Cohen, Hansen, Lester, Peterson, Qvist, et al., 2016; Cao, Cohen, Hansen, Lester, Peterson, & Xu, 2016; Lovins et al., 2018). This thesis, therefore, forwards this debate, contributing with knowledge on how fast nuclear power has grown compared to other low-carbon technologies.

1.2 Problem definition

1.2.1 Technology diffusion in a heterogenous world

Studies of technology diffusion have their roots in studies of new corn varieties in the USA (Griliches, 1957) and agricultural innovations in Sweden (Hägerstrand, 1967). Scholars have found that several characteristics and patterns are consistent across technologies, allowing modelling and prediction of spatial and temporal diffusion. Some of the more prominent theories that have emerged from this literature are the diffusion phases (formative, growth and saturation) and representing technology growth as an S-shaped curve (Griliches, 1957; Grubler et al., 2016; Grübler, 1996; Markard, 2018), see Figure 2-1 and section 2.1. In light of climate change, technology diffusion scholars have increasingly become interested in studying the diffusion of low-carbon technologies and renewables (Brutschin et al., In review; Cherp et al., In Press; Markard, 2018; Wilson & Grubler, 2011). This literature, even though when looking at diffusion globally (Wilson & Grubler, 2011), often studies technologies more diffused in Europe and the USA. Therefore, there is a risk that crucial elements, deciding the faith of technologies in other geographical and cultural contexts in a heterogenous world, are overlooked. This is especially important in the case of nuclear power as its diffusion often is argued to be strongly conditioned by socio-economic and political factors (Fuhrmann, 2012; Gourley & Stulberg, 2011; Jewell, 2011). In a time of rapid environmental degradation where energy demand is predicted to be increasingly intensive in emerging and developing economies, i.e. not in Europe and the USA (IEA, 2020), it is imperative to understand how diffusion of low carbon technologies could be fostered globally, and especially in late adopting markets.

1.2.2 Political economy of transitions

Another body of literature is addressing precisely the question of why the use of modern technologies varies across countries by examining how different characteristics of countries and international cooperation shape the diffusion of new technologies (Geels et al., 2016; Neumann et al., 2020; Skiti, 2020; Sovacool & Valentine, 2012). Thereby this research is complementing technology diffusion studies by seeking to account for the contextual differences in a heterogenous world. However, this literature often fails to incorporate insights from the technology diffusion scholarship, for example, the technology lifecycle and the S-shaped growth curves mentioned above.

1.2.3 Integrating different perspectives for a comprehensive understanding of energy transitions

According to Cherp et al., (2018), understanding energy transitions requires an integration of several disciplinary perspectives. In this case, we integrate technology diffusion theories and political economy of energy transitions to advance the understanding of how rapid and large-scale energy transitions can be fostered in different socio, political and economic contexts. Moreover, this thesis is particularly inspired by two recent studies of nuclear power built on these perspectives: Brutschin et al., (In Press) that *quantitatively* examines how nuclear power has spread to different countries (the formative phase of diffusion) and Markard et al., (2020) that *qualitatively* explores how nuclear power diffusion has matured and declined (saturation phase of diffusion). Therefore, there is a knowledge gap that could be bridged by quantitative as well as qualitative studies examining the growth phase (not explored using the perspective discussed above) and the mature/decline phase (not studied quantitatively).

1.3 Aim and research questions

By studying nuclear power, as a case of a new low-carbon technology, this thesis aims to advance knowledge on how large-scale energy transitions can be facilitated efficiently and sustained over time. It is the intention of the thesis, that lessons learned from nuclear power will be possible to transfer to other low-carbon technologies.

To produce this knowledge national data on nuclear power will be analysed for identifying the key parameters of its growth as a function of societal and institutional characteristics making it possible to investigate how societies can foster new low-carbon technologies. The following research questions are addressed:

RQ1: What are the maximum growth rates and saturation levels of nuclear power and how do they vary across countries?

RQ2: What factors explain variability in the diffusion growth rate of nuclear power?

RQ3: What factors explain the ceiling/saturation of nuclear power use?

RQ4: What happens to the speed and depth of nuclear power diffusion in late adopter markets?

1.4 Ethical considerations

The research design has been reviewed against the criteria for research requiring an ethics board review at Lund University and has been found to not require a statement from the ethics committee.

The project is not done in collaboration with any external partners and the author does not have any conflict of interest. No personal information has been used in this study. The study uses, with explicit acknowledgement, externally provided programming code for fitting growth models to empirical data, see 3.3.

1.5 Scope and limitations

The units of analysis within the scope of the thesis are countries with commercial nuclear reactors being in operation between 1960 and 2019. The temporal scope is chosen as electricity generation data for this period are available in the Extended Energy Statistics and Balances dataset provided by the IEA (IEA, 2021a) and encompass most of the timespan for nuclear power diffusion (except three small reactors deployed in the US, UK and the USSR in the 1950s). The analysis does however not cover all countries with commercial nuclear reactors being in operation during this period. This is due to data requirements for growth modelling such as extended time-series data, and lack of disaggregated data from the USSR. Therefore, an important nuclear country such as Russia is excluded. USSR is included in the analysis and treated as one country. Even though not all countries are included in the analysis, the sample covers all continents hopefully capturing the diversity of energy transitions in a heterogenous world.

The intention of this thesis is not to estimate the future trajectory of the global nuclear power diffusion cycle, but rather to learn from the diffusion in the past and transfer those lessons to low-carbon technologies of the future. However, as the result of the thesis builds upon and could be used for modelling purposes, it is important to discuss some of the limitations of estimating and modelling future diffusion scenarios.

The thesis relies on mathematical functions that fit empirical production data to growth curves. Subsequently, these functions produce growth parameters that could be used for descriptive and inferential statistics. While the use of these functions and growth models opens up a plethora of possibilities in terms of how to analyse technology diffusion, there are inherent limitations and data requirements.

No mathematical growth model represents reality to a 100% and even if the output of a model is a precise numerical value, the results should often be interpreted as indications rather than exact answers (Jaakkola, 1996). This is especially true for those countries that have only recently started their journey that is technology diffusion (Gosens et al., 2017; Martino, 2003). This could be due to that they either recently deployed nuclear power or for some reason are diffusing it slowly. In essence for the growth modelling to yield a reliable estimate, they need consistent time-series data that could be fitted to the curves.

One illustrative example is Italy that connected its first reactor to the grid in 1963 (IEA, 2021a). The following year Italy expanded their capacity. Between 1981 and 1982 they increased their nuclear-powered electricity generation by almost a factor three, and between 1981 and 1986 it was further expanded. However, after 1986 (the year of the Chernobyl accident) generation was highly reduced and a few years later Italy shut down their last reactor. As Italy experienced rapid growth in the last years before shutting down, the models estimate that Italy is still increasing its nuclear-powered electricity generation, despite that, not a single Wh has been generated from an Italian nuclear power plant for 30 years. Instead, the model shows a scenario where Italy continued on its trajectory prior to 1986.

The models used in this thesis are growth models and they are not constructed to estimate decline and phase out. Therefore, this thesis only addresses variances in growth trajectories and saturation levels. With similar models that address decline, it would also be possible to study variance in the decline of nuclear power. What the growth models entail and how their inherent limitations are handled is further discussed in section 3.

Another limitation is in generalising the findings of this thesis from nuclear power to other low-carbon technologies. Many low-carbon energy technologies, for example, wind and solar power, are vastly different from nuclear power in several ways such as investment cost, construction time, and level of complexity (Markard, 2020; Wilson et al., 2020), therefore making generalisation of parts of the results questionable. Even though the results on how to catalyse large-scale energy transition from this thesis might not be adequate for low-carbon technologies across the board, it will provide insights on how to deploy energy transitions through *lumpy* technologies such as off-shore wind parks. Moreover, it is often assumed when modelling different climate scenarios that technologies such as Carbon Capture and Storage (CCS), a technology similar to nuclear power in terms of cost, are in operation (Bazilian & Coddington, 2020; IPCC, 2015). More knowledge on the diffusion of *lumpy* technologies is therefore needed.

By being aware of and accounting for the constraints with growth modelling and how the results could be transferred to other technologies it is believed that the limitations could be mitigated and thereby produce reliable results.

1.6 Audience

The primary audience for this thesis is scholars within the technology diffusion and energy transition fields. As this thesis combines insights from the fields of technology diffusion and political economy of transitions, the results could inform similar studies on other technologies. Moreover, the results could be used to assess the feasibility of energy transitions and assess whether current diffusion trajectories are in line with climate targets as called for by Jewell & Cherp, (2020)

The hope is furthermore that the result also could be used by policymakers and advocacy organisations who wants a more thorough understanding of how to design policies, that enhances the speed and depth of the diffusion of low-carbon technologies. Furthermore, the results could be used to compare the growth rates of nuclear power with other new low-carbon technologies to see which can replace carbon most efficiently.

1.7 Disposition

The following parts of the thesis are structured in the following outline. Section 2 contains a literature review presenting the current knowledge on technology diffusion in general, how it applies to nuclear power specifically and the theoretical underpinnings of the topic. Section 3 presents the research design. Section 4 covers the empirical results and analysis. In section 5 the results are discussed considering previous research. Finally, section 6 contains conclusions along with advice to policymakers and avenues for further research.

2 Literature review

Understanding the interplay between society and energy technologies requires more than technological insights. Theories, perspectives, and methods from the social sciences have often been neglected in energy studies (Sovacool, 2014) which is an important element of this thesis.

The value of an interdisciplinary perspective when studying energy transition is conceptualised by Cherp et al., (2018). The authors present a framework including three overarching perspectives in energy transition studies. One focused on the technical and financial elements of transitions and neoclassic economic theory, one focused on the social aspects exploring socio-technical systems and lastly a perspective incorporating political science. The message is that a single field or body of literature cannot solely explain energy transitions in a modern and complex society. Several disciplines and theories are needed to understand energy transitions. This thesis is highly influenced by Cherp et al., (2018) in that it utilises the multi-dimensional concept in the research design and merges the technology diffusion literature, political economy of transitions, and political science in the analysis.

To mirror the multidisciplinary perspective of the thesis, the literature review has two parts. The first part reviews technology diffusion literature along with methodological considerations. It points out the main insights of historical technology diffusion studies including S-curves and diffusion from core to the periphery. It also identifies a gap in that technology diffusion literature pays insufficient attention to the socio-economic and institutional differences in a heterogenous world. Thereby their findings might not apply to low-income and emerging economies where the biggest energy demand growth is expected to be found (IEA, 2020).

The second part of the literature review is specifically focused on the diffusion of nuclear power and how it can be analysed. It identifies important insights concerning the role of the state and the importance of the economic and institutional capacity for successful development of nuclear power. Furthermore, it is found that it is not fully understood how institutional and societal elements can affect nuclear power diffusion in the different (especially the latter) phases of the diffusion cycle.

2.1 The evolution of technology diffusion studies; theories and concepts

The discussion and research around how technology is diffused and adopted in society date back a long time and has been applied to various cases ranging from the extended use of new varieties of corn in the USA (Griliches, 1957) to the diffusion of agricultural equipment in Sweden (Hägerstrand, 1967). In a seminal paper by Griliches, (1957) it is illustrated that one can describe the diffusion process as a logistic S-curve, see Figure 2-1. This makes it possible to construct econometric models along with dependent variables allowing for quantitative analysis of diffusion and growth modelling. Furthermore, Griliches, (1957) argues that variability of diffusion to a great extent can be explained by two factors: whether the new technology is more profitable than its successor and whether a switch could be done efficiently. That one or two variables explained most of the variance provides an important takeaway since it implies that fostering diffusion might not be overly complex.

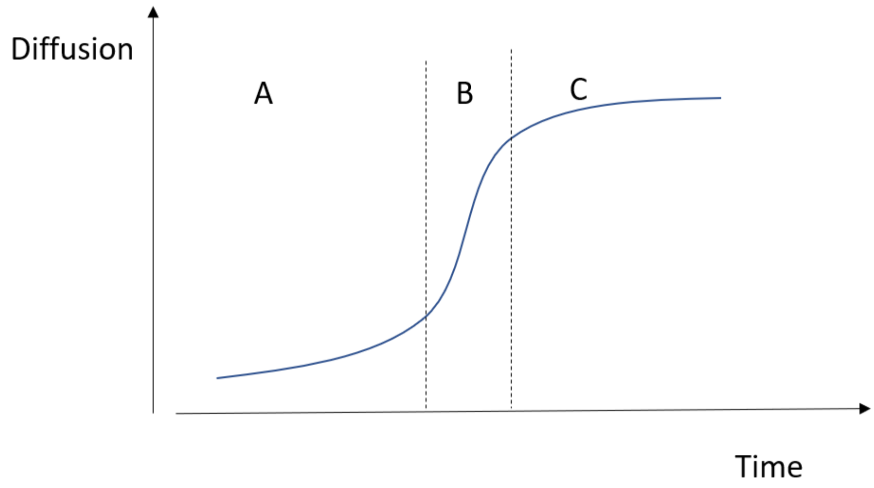

Figure 2-1. A stylised S-shaped logistic growth curve. The Y-axis represents the level of diffusion whereas the X-axis represents time. The diffusion cycle is traditionally understood as different phases. A: formative phase, B: growth phase and C: saturation phase. This thesis mostly concerns phase B and C.

Given the possibility to model and curve-fitting technology diffusion, research has also shown how temporal and spatial patterns of technology diffusion has remained quite constant. Beyond that recent research has confirmed the previously mentioned S-curve, it has also been found that even though technology is changing, the problems that technology is intended to solve remain rather persistent e.g., transport and communication (Grübler, 1996).

It is also usually understood that technology diffusion tends to start at a core of early adopters followed by late adopters and a periphery, and that diffusion could be different in the three diffusion phases seen in Figure 2-1 (Grübler, 1996; Markard, 2018). The first phase is characterised by novel technologies that cannot compete with other technologies on an open market without financial support (Grübler, 1996; Markard, 2018). Many technologies end their lifecycle in this phase since they are found not being able to sustain their selves. In this phase, early adopters, which tend to be richer countries (Gosens et al., 2017; Grübler et al., 1999b; Wilson, 2012) are investing resources as they see future potential in the technology. In the following growth phase, the technology is becoming more financially viable, more actors are adopting the technology and its use is growing. At some point, the marginal benefit of diffusing the technology shrinks and the curve flattens and thus the technology enters the saturation phase. After this point, a technology can remain in the saturation phase, enter a new growth phase (due to developments of the technology) or experience a decline (Grübler, 1996).

Furthermore, technology scholars pointed to the importance of social and spatial networks. It is not enough that there is a technology available. It must also align with networks and strong centres that have the capacity to diffuse the technology. The example given by Grübler, (1996) is the diffusion of cars in the US that was made possible by new production methods and demand from the public, which was lacking in many other countries. Advocators of energy transitions should therefore keep in mind that one must create strong and functioning networks that allow for efficient diffusion, not only focus on the technology in itself.

Thus already early technology diffusion and innovation scholars have argued that the rate of diffusion is dependent on contextual factors beyond the characteristics of the technology itself (Rogers, 2003). Most notably the pace and depth of diffusion vary between early and late adopting markets. Usually, it is low-income countries and emerging economies that comprise the late adopters (Gosens et al., 2017; Grübler et al., 1999b; Charlie Wilson, 2012), and research has found that Gross Domestic Product (GDP) is positively associated with diffusion speed (Sadorsky, 2009). With that in mind, one would expect that the speed and depth of diffusion would level off at late adopters given this group's lower financial capacity. This is also one of the findings by Griliches, (1957) whose results indicated that diffusion tends to slow down in late adopting markets, later supported by Dixon, (1980) who remade Griliches analysis. Cherp et al., (In Press) also find that countries with later "*takeoff years*" (the year when the examined technology exceeds 1% of total electricity generation) experience statistically significantly lower growth rates in the case of solar power. The authors also examine how the take-off year affects the growth of wind power and do not find a statistically significant effect, indicating that the hypothesis that early adopters diffuse faster is not a universal rule.

The picture becomes increasingly nuanced as Dekimpe et al., (1998) in the case of cell phones do not find any effect on diffusion speed from the time of technology adoption. More complexity is added as others have found that late adopting markets are associated with faster diffusion speed for a wide range of technologies (Gosens et al., 2017; Grübler, 1996; Wilson, 2012). This is however a logical effect given that early stages of diffusion often are characterised by less refinement and higher cost per unit compared to the latter stages (Rosenberg, 1994). An increased pace of diffusion is usually explained by increased technology learning and knowledge spill-over from early adopters (Grübler, 1996; Marchetti, 1983) that can outweigh the dampening effect from e.g. lower GDP in the late adopter countries (Gosens et al., 2017). Comin & Mestieri, (2018) contribute to the debate as they find that the diffusion time for late adopters has been shortened over time. Essentially, they argue that the newer the technology, the smaller is the observed difference between early and late adopters in diffusion speed. For new low-carbon energy technologies used to tackle climate change, it is imperative to understand the dynamics of diffusion speed in late adopting markets if diffusion is to be global.

Furthermore is that even if diffusion may be faster in later adopter markets, studies have found that it is less deep, i.e., lower saturation levels (Grubler, 2012; Grubler et al., 2016; Hägerstrand, 1967). Additionally, Comin & Mestieri, (2018) have argued that the gap in saturation levels between high and low-income countries is increasing. A finding which is alarming from a climate perspective as we need rapid, deep and global energy transitions.

The two findings from Comin & Mestieri, (2018) thereby points to that, if unattended, diffusion of low-carbon technologies poses the risk of while being fast, not reaching the saturation levels required globally. Therefore, it is important to learn how diffusion can be faster, not only in terms of time but also in terms of increased levels of low-carbon Wh being generated.

Comin & Mestieri, (2018) findings also point to a fundamental aspect of technology diffusion; that a swift diffusion process does not necessarily equal high saturation levels. To successfully diffuse low carbon technologies globally and reach climate targets, it is fundamental to understand the net effect of two counteracting mechanisms in late adopting markets; on the one hand, knowledge spill-over and technology learning can accelerate diffusion in late adopting markets. On the other hand, the less favourable socio-economic conditions in these markets may dampen diffusion speed and saturation levels. Which of these two mechanisms that prevail is of big scientific and societal interest since low-carbon energy technologies need to be diffused globally, including late adopting (usually poorer) countries.

Despite scholars such as Comin & Mestieri, (2018) points to that diffusion might be suffering due to tough economic conditions, little attention has been put on energy transitions in low-income countries and emerging economies. A common element of the technology diffusion literature is that it either specifically focus on Western countries (Western Europe, USA, and Canada) which tend to be the early adopters, or use global samples without disaggregating the analysis to different regions of the world (Grubler, 2012; Grübler, 1996; Wilson et al., 2013). This is despite that it is often recognised in the technology diffusion literature that the regional and/or local context likely is highly influential (Jacobsson & Lauber, 2006). Therefore, for many technologies, it is not well understood how diffusion differ between regions and cultural contexts.

Lastly, technology diffusion research has found that it is not always the optimal technology that diffuses most. Diffusion is often the accumulated effect of small and random events, interacting with existing technologies that together with positive feedback loops eventually leads to lock-in (Grübler, 1996; Wilson & Grubler, 2011). This is a fundamental point since it highlights why it is important to advance our understanding of how diffusion can be steered, as random diffusion likely would be too slow to reach the goals of the Paris Agreement.

2.1.1 Modelling growth through curve fitting and methodological considerations

The literature on technology diffusion and growth modelling has evolved substantially since Griliches, (1957). While the merits of modelling growth through curve-fitting have been shown by several scholars (Bento et al., 2018; Cherp et al., In Press; Wilson et al., 2013; Wilson et al., 2020) the topic has been a subject of methodological discussions. Before continuing into how technology diffusion could be studied via nuclear power, it is relevant to understand how growth models are used and important methodological considerations.

In a seminal piece by Wilson et al., (2013) the authors show that by looking at historic data on technology diffusion, one can distinguish a relationship between how much (extent) a technology diffuses and the time (duration) it takes for the technology to diffuse, i.e., an “extent-duration relationship” (Wilson et al., 2013, p. 388). Bento et al., (2018) further explores the duration of the formative phase of different technologies and thereby find that certain variables are related to shorter formative phases and vice versa. The findings of these studies allow scholars to fit empirical observations to a curve, and thereby model future diffusion trajectories of low-carbon technologies to see whether they are consistent with climate targets. Their work is later forwarded as modelling is used to compare the diffusion pathways of granular and lumpy energy technologies (Wilson et al., 2020) and in this thesis.

The insights from Wilson et al., (2013) are also utilized by Napp et al., (2017) who not only test whether a certain energy transition is consistent with climate targets but also explores their feasibility and in essence whether they are plausible or not. This is done as the authors inserts growth-constraining factors in the model (e.g., unabated use of existing coal plants) similar to a diagnostics test which limits the global energy systems ability to align with 2°C targets.

While this thesis does not aim at modelling future trajectories of nuclear diffusion. It does however builds on knowledge from growth modelling studies (Bento et al., 2018; Napp et al., 2017; Wilson et al., 2013; Wilson et al., 2020) in the sense that there are complex dynamics in growth models (extent-duration). Moreover, it is recognized in the thesis that factors constraining growth needs to be controlled for to better represent reality. Another important aspect is provided by Napp et al., (2017) that point out that there is always the possibility of unexpected growth patterns that do not follow the past historical trend. Therefore, the interpretation of growth models needs to be done parsimoniously.

One of the most important aspects to consider in growth modelling is what is being measured, i.e., what is being fitted to a curve. This is particularly important when comparing the growth curves of different technologies to ensure that they are comparable. This discussion is exemplified by Grubler et al., (2016) who discusses the results from Sovacool, (2016) concerning the feasibility of fast energy transitions in light of the method of measurement. Sovacool, (2016) uses *flow* variables to study the introduction of flexi-fuel cars in Brazil, measuring diffusion rates based on the share of flexi-fuel cars of the total number of new cars sold. By only looking at new cars, where the new technology was diffused quickly, one does not capture the diffusion in the total car fleet. To indicate the diffusion rate Grubler et al., (2016) argues that using *stock* variables are more appropriate which in this case would be to measure the share of flexi-fuel cars of the total number of cars *registered*. The importance of being careful when choosing your metrics is also highlighted by Lovins et al., (2018). In their paper, they discuss that the technology diffusion literature often uses relative numbers such as per-capita and absolute numbers differently and sometimes interchangeably. Lovins et al., (2018) argue that using per-capita numbers is appropriate when studying one technology and comparing countries, but not when comparing technologies as those do not meet like-for-like or ceteris paribus requirements. An example is Cao et al., (2016) that compares the diffusion of nuclear power in Sweden with the diffusion of renewables in China using per-capita metrics. The results thereby show that the diffusion of low carbon energy technologies per-capita is vastly faster in Sweden due to its population being only a fraction of China´s. This is at the same time as China is a leader in diffusion of renewable energy in absolute numbers (Lovins et al., 2018).

This becomes important when studying nuclear power as the diffusion measured using metrics in absolute terms could yield vastly different result compared to metrics in relative terms. E.g., Sweden and Belgium are two countries where nuclear power historically has made up a substantial share of the total electricity supply. However compared to bigger countries such as the USA, both Sweden´s and Belgium´s nuclear-powered electricity generation in absolute figures is only fractional (IEA, 2021a).

The issue of comparing like-for-like and ceteris paribus requirements is further highlighted by a recently published article by Sovacool et al., (2020). The authors argue, backed up by regression analysis, that renewable energy technologies can replace more carbon than nuclear power. However, these findings have been criticised for methodological flaws (Fell et al., 2021; Perez, 2021). Some of the issues are the substantial difference in the number of countries in the samples, 30 in the nuclear power sample and about 120 in the renewables sample. Comparing regression outputs from these samples (they e.g., find that renewables have a negative statistically significant on carbon emission while there is no statistically significant effect from nuclear) is problematic. That Sovacool et al., (2020) fails to find a statistically significant result means that they cannot reject the null hypothesis (Cortinhas, 2012), which in this case means that the effect on carbon emissions due to nuclear power is not significantly different from zero. However, the authors seem to interpret the non-significant results as robust finding indicating that nuclear is associated with higher carbon emission.

The methodological issues in Sovacool et al., (2020) pinpoint some potential issues of testing statistical inferences and making causal claims based on the small number of countries employing nuclear power. This has implications for the research design of this thesis as the number of countries having available time-series data on nuclear-powered electricity generation is relatively limited.

Moreover, to separate the diffusion into the three phases (Griliches, 1957; Grubler et al., 2016; Markard, 2018), have methodological implications. The result of a study exploring the entire diffusion cycle is necessarily not representative of e.g., the formative phase and vice versa (Grubler et al., 2016). These insights are important to consider when making comparative studies (both when comparing diffusion of different technologies and comparing diffusion of one technology in different countries) as one should account for the stages. There are several complex dynamics within each phase which makes it hard to compare them. High upfront costs, political support, and limited returns causing a low diffusion pace in the formative phase. Technology learning, economy of scale, and increasing consumer demand in the growth phase. Decreasing marginal benefits of diffusion and increasing competition from alternatives in the saturation phase. As discussed there is empirical evidence saying that nuclear power has reached the saturation phase, or even the subsequent decline phase (Markard, 2020). This makes the case of nuclear power particularly interesting as, if it is indeed in decline, is the first incumbent energy technology to do so (Markard et al., 2020).

Comparing two technologies without controlling for the phases will likely yield skewed results. Especially in the case of nuclear power as not applying the different phases could fail to capture that both capacity and generation numbers are declining overall while still increasing in some countries (Markard, 2020).

2.1.2 Key messages from the technology diffusion literature

Most of the literature agrees that there are distinct diffusion patterns across temporal and spatial aspects as well as different types of technology. *First*, technology tends to follow an S-shaped pattern and tend to start in cores and spread via established networks. *Second*, it is contested whether the rate of diffusion is faster or slower in the later stages of the diffusion cycle. *Third*, technology diffusion is a sequential process with several distinct phases. *Fourth*, technology diffusion and transition studies often fail to disaggregate the analysis to different geographical and socio-economic contexts, with studies of technology diffusion on the periphery especially rare. *Five*, modelling growth is useful to compare whether diffusion trajectories are consistent with climate targets. *Six*, researchers of technology diffusion are faced with several methodological choices: are relative or absolute numbers most relevant and which phase of the diffusion cycle is studied?

2.2 Technology diffusion theories applied to nuclear power diffusion

In a seminal paper Jewell, (2011) identifies several factors important for the historical diffusion of nuclear power. She furthermore benchmarks those factors to 52 newcomer countries that at the time had expressed a will to develop nuclear power. Jewell, (2011) shows that nuclear power historically has been deployed in countries with higher GDP, rising energy demand, stable institutions, and higher government effectiveness. The result present new explanatory factors for variability in nuclear power diffusion and indicate that most countries in the newcomer group either lack the financial and/or institutional capacity, have too unstable political landscapes or simply do not have the energy demand required to deploy nuclear power (Jewell, 2011). Jewell argues that the deployment of nuclear power is almost conditioned by a certain degree of energy demand growth, financial and institutional capacity. This is followed up in a case study of Turkey that despite ticking several boxes for a successful diffusion (energy demand growth, size of the economy and aspirations of energy dependence) have failed with its nuclear deployment, partly due to political unrest and instability (Jewell & Ates, 2015).

The general explanatory value of political stability is however not supported by Brutschin et al., (In review) who do not find any statistically significant effect using a global sample and quantitative methods. That being said, Jewell, (2011) gets support for other factors such as the importance of a favourable financial situation. Csereklyei et al., (2016) find that higher economic growth and per capita income shortens the construction time of reactors. Furthermore, more researchers have found that national motivations such as energy demand growth and energy security drives nuclear power diffusion (Fuhrmann, 2012; Gourley & Stulberg, 2011).

The previously mentioned study by Markard et al., (2020) qualitatively study whether nuclear power is declining on a global level using the construction of new reactors as their indicator. The results suggest that nuclear power is declining globally with Russia and China being exceptions. For a long time, nuclear power was a staple of the world's energy generation. In 1996 nuclear power provided almost 18% of the world's energy but its contribution has declined since then and is currently at about 10% (Markard et al., 2020). The authors also propose some theories (but do not test them) on why that might be the case. Aspects such as accelerating costs, competition from cheaper fossil fuel and/or renewables and fear of accidents are suggested explanatory variables. At the same time, they see that there is an increasing interest in the low-carbon properties of nuclear power, which might contribute to the technology's survival. As the study explores the maturity and subsequent decline phase this is one of the two studies that merge perspectives from the technology diffusion literature with the political economy of transitions.

Cherp et al., (2017) conduct a comparative study where they explore why Germany and Japan, despite having similar energy trajectories prior to the 1990s, had very different energy patterns by 2010 with ambitious nuclear plans in Japan but not in Germany. The higher use of nuclear power in Japan is found to be due to increased demand for electricity (in accordance with Jewell, (2011)), ambitions of increased energy security as well as unfavourable preconditions for onshore wind in Japan. In Germany, the nuclear regime was at the same time weakened by stagnated energy demand growth, increasing competition from renewables, and a domestic coal industry with strong political influence (Cherp et al., 2017). Beyond that the result support theories on e.g., the explanatory value of energy demand growth, the study also highlights the importance of applying an interdisciplinary perspective, as in this thesis, to understand energy transitions. Understanding the differences merely through either a technical or political science perspective might fail to capture the political influence of the coal industry in Germany or the technical preconditions of onshore wind in Japan.

The concept of cores and networks and their importance for technology diffusion (Grübler, 1996) have also been explored within the context of nuclear power. Jewell et al., (2019) utilise network analysis and compile a data set with statements of cooperation for nuclear power between states. The results show that suppliers of nuclear technology are highly concentrated (much more so than for fossil fuels) especially to Russia but also the USA and France. The authors argue that international cooperation is as important as national motivations and capacities when analysing the diffusion of nuclear power (Jewell et al., 2019). This could be seen as there have been (and is) a distinct core that drives diffusion.

The results of Jewell et al., (2019) are developed and supported in a seminal paper by Brutschin et al., (In review) that finds that political affinity to the USA and USSR (two out of three cores) are critical for nuclear power diffusion. The authors use a sample of 79 countries, including countries with sufficient capacity for deploying nuclear power (see discussion on Jewell, (2011) above). The study is focusing on the initial formative phase of the diffusion process (this is the second study accounting for the different phases of the diffusion cycle) and uses the year when the first reactor was connected to the grid as the dependent variable.

Neumann et al., (2020) hypothesise that nuclear power is more likely to be developed in less democratic countries. The idea is that while more democratic countries might have better administrative capacity to deploy complex technologies, they also have a larger amount of veto players (Tsebelis, 1999). Due to the high financial cost and (technological and institutional) complexity of the technology, it is plausible that this effect would be stronger for nuclear power. Neumann et al., (2020) examine nuclear power in general i.e., not accounting for the different phases of diffusion. They are using a sample of 166 countries and the indicator for nuclear power is whether a given country is building or has reactors in operation. Their result supports their hypothesis: less democracy associate with more nuclear power. They also suggest that whether a country has acquired at least one nuclear warhead increases the likelihood of entering nuclear power.

Whether regime type is an important explanatory variable is however contested. In the previously discussed paper by Brutschin et al., (In review), the authors do not find that political regime type is a statistically significant explanatory variable. They explain the difference in relation to previous research as: *first,* Neumann et al., (2020) do not control for affinity to the USSR. As the diffusion of nuclear power in less democratic countries in Eastern Europe is found to be driven by USSR, democracy is negatively correlated with affinity to USSR and nuclear power diffusion. *Second,* Neumann et al., (2020) do no control for the democratisation wave occurring at the same time as the nuclear power diffusion saturated which makes stagnating growth rates correlating with higher levels of democracy. Despite that Brutschin et al., (In review) give reasons why the studies indicate different results, it is no fully understood how regime type affects diffusion in the later stages of the diffusion cycle. Furthermore, there are more nuances to regime type than the level of democracy. Some scholars have argued that countries with centralised governance (such as France) are more inclined to deploy nuclear power than countries with a higher degree of decentralisation (such as the USA) (Jasper, 1992; Sovacool & Valentine, 2012).

Two factors that are unique for nuclear power and its diffusion are accidents (such as Three Mile Island (TMI) 1979, Chernobyl 1986, and more recent Fukushima 2011) and oil crises (such as the oil crisis in the 1970s) a subsequent price increase.

It has been discussed in the literature whether accidents have had a dampening effect on diffusion (Markard et al., 2020). While some studies have found that the TMI and Chernobyl accidents had a negative and statistically significant effect on nuclear power diffusion (Fuhrmann, 2012; Gourley & Stulberg, 2011), others have landed in the opposite conclusion (Brutschin et al., In review; Csereklyei et al., 2016).

Csereklyei et al., (2016) furthermore found that the highly unstable oil market of the 1970s increased the deployment of new nuclear power plants. Fluctuating and especially rising oil prices increases the incentives to deploy nuclear power. This relationship is plausible given that the 1970s was the decade with the largest growth of reactors in absolute terms (Markard et al., 2020). However, Brutschin et al., (In review) does not find statistically significant effects that support this relationship.

Instead of regime type, accidents and oil shocks the results from Brutschin et al., (In review) show that two variables are explaining most of the variance. *First*, ease of diffusion operationalised through political and geographical affinity to USA and USSR (see Jewell et al., (2019) highlighting the importance of networks and innovation centres for the diffusion discussed by Grübler, (1996). *Second*, market attractiveness (size of economy, electricity demand growth, and absence of major oil exports), in line with previous studies (Griliches, 1957; Rogers, 2003). The results from Brutschin et al., (In review) are interesting as it shows that only two variables can make a big difference, giving hope to the deployment of other large-scale energy technologies.

While this body of literature explores national factors´ effect on technology diffusion, with some recent exceptions (Brutschin et al., In review; Markard et al., 2020), it does not account for the different phases of the diffusion cycle (Figure 2-1) often discussed in diffusion and transition literature. A potential effect of not accounting for the different phases comes with the risk of producing results that are harder to put into the context of different countries. Furthermore, it becomes harder to develop reliable metrics and dependent variables that represent the whole cycle. When focusing on one phase at a time, it is easier to develop dependent variables e.g., for the formative as in Brutschin et al., (In review) where the year of grid connection acts as a dependent variable and indicator for diffusion.

2.2.1 Key messages from the nuclear power diffusion literature

While technology diffusion is not a new field, the application of its theories on the case of nuclear power is relatively new. From section 2.2 we learn that nuclear power diffusion to a great extent seems to be influenced or driven by economic factors such as investment cost, energy demand growth and size of the economy etc. as well as political factors such as geopolitical ties. However, there are some ambiguities in the literature in terms of the explanatory value of factors such as regime type and accidents.

Furthermore, there is a lack of understanding in the literature of how different national and international socio-economic factors influence the different stages of diffusion. One phase might not be representative of the whole cycle and vice versa. E.g., one can imagine that a country experiences a rapid diffusion in the formative while losing pace in the subsequent phases. Especially there is a gap to be bridged by studies of both qualitative and quantitative nature that examines the proposed explanatory factors in section 2.2 and apply them to the latter phases of the diffusion cycle (growth and saturation phase).

2.3 Conclusions from the literature review

A lot of research has been done around historical trends of technology diffusion and what regional and cultural factors that constrain and/or enables nuclear power diffusion. However, it is only recently that theories and concepts from these two bodies of literature have been used in the same study.

In essence, it is explained in the literature that there are various patterns of diffusion and that diffusion usually is understood through different phases and a logistic S-curve (Figure 2-1). Moreover, it is empirically documented how various country characteristics such as economic development and energy demand influence diffusion. However, it is not fully understood how these perspectives together, could increase our understanding of how country characteristics could influence diffusion in the different phases.

In order to get a comprehensive understanding of how low-carbon technologies can diffuse, it is necessary to understand the dynamics within the different phases of the diffusion cycle as well as the effect of socio-economic characteristics in a heterogenous world. The gap identified in the literature, that this thesis aims to bridge, is therefore the lack of studies exploring the growth and saturation phases using qualitative and/or quantitative methods as well as exploring the saturation phase with quantitative methods. Moreover, this thesis uses a new growth metric that will compare the maximum observed growth rate of nuclear power to the same metric for wind and solar power.

3 Research design, materials and methods

The thesis employs both qualitative and quantitative methods. The material used to map nuclear power diffusion and construct the dependent variables comes from secondary time-series data retrieved from the Extended Energy Statistics and Balances database provided by the IEA (IEA, 2021a). The analysis is done in two steps. The first part is done by fitting growth curves to nuclear power deployment, assessing the growth rates and qualitative comparison of these rates across countries, and the descriptive statistics. The second part of the analysis qualitatively and quantitatively explores variability in growth rates and saturation levels.

The research design chapter has the following outline: in 3.1 the growth models used in the thesis are explained along with the dependent variables. 3.2 explains how the independent variables have been chosen and their respective expected effect. In 3.3 it is explained how the sample is constructed and what sources are used. Lastly, 3.4 discusses limitations that come with the research design.

3.1 Modelling and measuring the growth of nuclear power

As discussed in the literature review there are a few studies that quantitatively study nuclear power diffusion (Bento et al., 2018; Brutschin et al., In review; Neumann et al., 2020). The authors are using a binary variable, and thereby logistic regression, for describing nuclear power entries i.e., either a country has nuclear power, or it does not. However, the dependent variables in this thesis are not binary and therefore linear regression is employed.

The thesis explores two dependent variables. One is representing the max growth rate of nuclear power while the other represents the saturation of nuclear power in each country included in the analysis. The dependent variables are conceptually quite uncomplicated and can be traced back to Griliches, (1957). All estimated growth parameters are found in Table 3-1 and how they are calculated is described in 3.3.

3.1.1 Max growth rate G

The max growth rate metric (further referred to as G) is a new metric developed by Cherp et al., (In Press) who also used the equations presented below. G builds upon previously used growth metrics such as saturation level (further referred to as L) which illustrates when a technology hits its diffusion ceiling and duration of transition (further referred to as dT) which illustrates the number of years going from 10% to 90% of L.

Table 3-1. The growth parameters estimated by the logistic and Gompertz growth models. Exceptions are Y0 and Lyear that are observed, not estimated by the models.

G	Max growth rate of diffusion located at the inflection point of the S-curve. When comparing different countries G is normalised to total electricity supply the year G occurs. G is expressed in % of the total electricity supply.
L	Saturation level, the upper asymptote of the S-curve. When comparing different countries, L is normalised to total electricity supply the year when the last empirical observation was made, which is the last year electricity generation increased. L is expressed in % of the total electricity supply.
TMax	The year G occurred.
Y0	The year the first commercial reactor was connected to the grid.
ΔY	The number of years going from Y0 to TMax. Also referred to as the acceleration cycle.
Lyear	The year when the last empirical observation was made, which is the last year of increased electricity generation.
K	Growth constant, which is used to estimate the other growth parameters.
dT	Duration of transition, the number of years required for the diffusion to go from 10% to 90% saturation.
Maturity	The percent of achieved saturation in the last observed year.
RSS.Rel (relative Residual Sum of Squares)	A measure of the goodness of fit when using different models in the same dataset (a smaller number indicates a better fit). RSS.Rel is used to compare whether Gompertz or the logistic model is the best representation of growth.

Cherp et al., (In Press) give four reasons why G is an appropriate metrics to use:

1. G has as opposed to other growth metrics such as duration of transition a physical representation. In this thesis, G is used to depict both the maximum growth of generation and capacity. The former is used for the primary analysis and the latter for robustness check. In both cases, G could be normalised to allow for comparison of growth rates across countries, technologies and time. Moreover, G could be compared to energy transition rates used in modelling of climate scenarios (Napp et al., 2017) and compared to historical rates of energy transitions. In this thesis, when G represents the electricity generation, it is normalised to the total electricity supply at TMax. When G represents capacity in the robustness check G is normalised to the total national electricity generation capacity at TMax. When normalised, G is expressed in a percentage of the total electricity supply and capacity. Furthermore, as G

represents something tangible, such as the growth of electricity generation, it can be used to compare different energy sources. Thereby G can illustrate whether it is possible to replace e.g., coal with renewables, or nuclear power, making the metric easier than others[1] to use for policymakers when assessing different energy sources and energy trajectories.

2. G aid to explore the net effect of a faster yet more shallow diffusion in the late adopting markets as discussed in section 2.1, which is harder with other metrics such as dT and L. As G represents dT and L in relation to each other (see section 3.3.3) it is possible to analyse the result of a faster yet shallower diffusion cycle. Moreover, the G metric is based on the accumulative technology diffusion throughout the diffusion lifecycle and therefore mitigate the problem with yearly fluctuations in diffusion.

3. As discussed, there is a complex web of interacting factors that determines the faith of technology. There are factors that enable diffusion (cost efficiency, energy demand, technology learning, etc.) and there are factors that constrain (public acceptance, compatibility with existing systems, etc.). As G represents the accumulated parameters of the diffusion curve it presents the net effect of this complex interplay. Therefore G could be used to explore the so-called "*feasibility space*" (Jewell & Cherp, 2020, p. 7) showing what level of diffusion that is feasible in reality, when controlling for contextual factors and not only the technology in itself.

4. Growth modelling always inhibits a degree of uncertainty. However, G reduces some uncertainties associated with several other accumulated growth metrics. Previously mentioned aggregated metrics such as dT and L could both be reliable estimated in cases where diffusion is far gone and close to L. In cases when assumptions about growth models such as the S-curve are weaker or if diffusion has not come that far, estimating these aggregated parameters require extrapolation for the curve on both sides of the inflection point of the S-curve which is related to uncertainties (Cherp et al., In Press; Gosens et al., 2017; Martino, 2003). However, as G can be estimated before saturation is reached, these issues are pre-empted making the metric more robust. However, estimations become less reliable for countries in the earliest stages of the diffusion cycle which have implications for the construction of the sample (see 3.3.2).

3.1.2 Growth models

The growth parameters are estimated by fitting the empirical observations of nuclear powered-electricity generation to growth curves as described. There are several methods to model, assess, and curve-fit empirical observations to growth curves. Two of the more common ones are Simple Logistic Models (SLM) and Gompertz curves that are the ones used in this thesis. Both models originate from biology and scholars studying population growth given the carrying capacity of an environment.

Logistic function

Logistic functions and their respective curves are widely used in technology diffusion studies (Napp et al., 2017) and have empirically been shown to fit ample diffusion processes (Kucharavy & De Guio, 2011; Lekvall & Wahlbin, 1973; Marchetti & Nakicenovic, 1979).

[1] See compound annual growth rate (Iyer et al., 2015), extent duration relationship (Wilson et al., 2013) and emergence growth rate (Grubb et al., 2020)

The seminal paper of Griliches, (1957) mentioned in the literature review, cited more than 4000 times (February 2021) uses a logistic function to model the diffusion of hybrid corn in the USA. The output is a characteristic S-shaped curve, dividing diffusion into three stages. This method is also known as the Logistic Substitution Method (LSM) (Grubb et al., 2020; Kucharavy & De Guio, 2011).

This function postulate that the curve is symmetric on either side of the inflection point (the steepest part of the curve). With that in mind, if the inflection point is known, it is possible to calculate the ceiling/saturation level or carrying capacity (twice the depth of the left side of the inflection point) of the population (Cherp et al., In Press). The equation for the logistic model is as follows:

$$f(t) = \frac{L}{1 + e^{-k(t-t_0)}}$$

Equation 1. Three-parameter logistic model. A widely used function in technology diffusion growth modelling. The model assumes that the curve is symmetrical.

L depicts the saturation level, or upper asymptote (the line where the growth curve stagnates and the distance between the curve and the line/asymptote approaches zero. E is Eulers Number and K is the growth constant. t_0 is the inflection point of the S-curve, referred to as G in this thesis.

Gompertz function

Another function used to model diffusion is the Gompertz model (Gompertz, 1825; Winsor, 1932), named after the mathematician Benjamin Gompertz. Gompertz function does not assume that diffusion is symmetrical on either side of the inflection point (Cherp et al., In Press; Jaakkola, 1996). Scholars have argued that one should consider asymmetrical models when plotting diffusion (Lund, 2015; Vieira & Hoffmann, 1977). In fact, Dixon, (1980) revisited the corn study (Griliches, 1957) and found that a Gompertz curve provided a better fit than the SLM. Furthermore is Davies & Diaz-Rainey, (2011), that studied the diffusion of wind power, and found evidence of asymmetrical diffusion. The idea they propose is that the asymmetry is due to strong government influence which, as discussed in the literature review, is likely to apply to nuclear power as well.

Countries, where the models converge, are used to construct the sample to increase robustness. In the qualitative assessment, growth parameters from the logistic model are used to simplify the illustrations. However, in the regression analysis growth parameters from both models are used and presented. The equation for the Gompertz model is as follows:

$$f(t) = Le^{-e^{-k(t-t_0)}}$$

Equation 2. Three-parameter Gompertz model. Researchers have argued that the Gompertz curve, which is similar to the logistic function, is more suitable to describe growth. An important difference to the logistic curve is that the Gompertz model does not assume symmetry.

3.2 Dependent and independent variables for regression analysis

3.2.1 Dependent variables

Two dependent variables are used. G is representing the maximum growth rate of nuclear power diffusion in a country. G is measured in terawatt-hours (TWh) and represents the point where the growth of electricity generation is estimated to peak, i.e., the point where the slope of the growth curve is steepest. G is normalised to the total electricity supply at TMax in each country.

The other dependent variable, L, is representing the saturation level of nuclear-powered electricity generation in a country. L is also measured in TWh and represents the upper asymptote of the S-curve. L is normalised to the total electricity supply the year when the last empirical observation was made in each country.

As the dependent variables are country-specific it requires individual dependent variables for each country. How the dependent variables are calculated is described in section 3.3.3.

3.2.2 Independent variables

The independent variables are various country characteristics such as GDP, electricity demand growth, regime type, electricity supply, and nuclear accidents. All are retrieved from theories and hypotheses discussed in the literature review. By utilising regression analysis, it is possible to isolate the effect of the different independent variables and thereby, hopefully, aid in answering what causes variability in diffusion. The independent variables are found in Table 3-2 below. Potential inferences between the different growth parameters in Table 3-1 are also explored.

Table 3-2. Hypotheses and independent variables

Hypothesis	Independent variable and source	Mechanism/reason for inclusion
Adopting later associate with faster growth of technology diffusion.	The year when the first reactor was connected to the grid. Data retrieved from IEA, (2021a).	Late adopters can benefit from e.g. technology learning and thereby diffuse faster than early adopters (Gosens et al., 2017; Grübler, 1996; Wilson, 2012).
Economic development enables the diffusion of nuclear power.	GDP per capita at TMax. GDP per capita in current USD from Gleditsch, (2002) accessed through (Dahlberg et al., 2021).	Due to high upfront costs, it is expected that larger economies can diffuse nuclear power faster. (Brutschin et al., In review; Csereklyei et al., 2016).
Nuclear power diffusion requires electricity demand growth.	The difference in electricity consumption the five years preceding TMax expressed in %. The same method is employed by Vinichenko, (2018). Data retrieved from IEA, (2021c)	Given the lumpiness of the technology, there needs to be a demand for its product. Electricity demand growth was fount to explain nuclear power diffusion (Brutschin et al., In review; Fuhrmann, 2012; Gourley & Stulberg, 2011; Jewell, 2011).

Hypothesis	Independent variable and source	Mechanism/reason for inclusion
Democracy associates negatively with nuclear power.	Electoral democracy index (vdem_polyarchy). Data retrieved from Coppedge et al., (2020) and accessed through Dahlberg et al., (2021).	The complexity of nuclear power constrains diffusion in more democratic countries with a larger number of veto players (Neumann et al., 2020; Tsebelis, 1999).
Nuclear accidents constrain the diffusion of nuclear power	The year when the three major nuclear accidents occurred: 1979, 1986 and 2011	Nuclear accidents decrease public acceptance of the technology. Some researchers have found that accidents have a statistically significant effect (Fuhrmann, 2012; Gourley & Stulberg, 2011). However, others have not found a statistically significant effect (Brutschin et al., In review; Csereklyei et al., 2016)
The relative growth rate and saturation levels are lower in larger systems (countries).	The total electricity supply in TWh at TMax for growth and the total electricity supply at Lyear for saturation. Data retrieved from (IEA, 2021a).	Larger systems are more likely to be more heterogenous in socio-economic and geographical conditions. It is therefore less likely that growth is fast, and saturation is high in all regions of a large country (Cherp et al., In Press).
Late adopters have shorter acceleration cycles.	The year when the first reactor was connected to the grid. Data retrieved from IEA, (2021a).	Late adopters can benefit from e.g. technology learning and thereby diffuse faster than early adopters. (Gosens et al., 2017; Grübler, 1996; Wilson, 2012).
Countries experiencing faster growth rates also reach high saturation levels.	Maximum growth rate (G).	Reaching high saturation levels likely requires higher growth rates.
Early adopters have higher GDP per capita.	The year when the first reactor was connected to the grid. Data retrieved from IEA, (2021a). GDP per capita at TMax. GDP per capita in current USD from Gleditsch, (2002) accessed through (Dahlberg et al., 2021).	Several technology diffusion studies have found that countries in the early adopter group tend to have higher levels of economic development (Grübler et al., 1999b; Charlie Wilson, 2012). This allows the early adopters to take greater financial risks with new technologies.

A system for choosing independent variables has implications for the direction of causality as making causal conclusions from a statistical design can be problematic (Menard, 2010). Using the gold standards when it comes to making causal claims based on quantitative data, randomised control trials (Blaikie & Priest, 2019) is not possible in this case, one needs to be cautious when interpreting the inferences. Even if it is found that there is a strong relationship between one of the dependent variables and one of the independent variables, it is hard to rule out that the direction of causality is not reversed. Moreover, strong correlations between variables could just be correlations, not necessarily cause and effect. In the case of this thesis, one could think that e.g., increased use of nuclear power increases electricity demand, and not the other way around as the model says. In order to affirm causality, one would normally need additional arguments, e.g. the observation that electricity demand starts growing before the expansion of nuclear power (Cherp et al., 2017; Jewell, 2011).

Another reason for being cautious when interpreting the result is the difficulty to exclude the possibility of underlying variables. It might be other variables, strongly correlated with e.g., energy demand, that causes increased use of nuclear power, not the electricity demand per se. This further highlights the importance of justifying the included independent variables with theory and/or empirics as in Table 3-2.

3.3 Data, sample, and software

3.3.1 Data

The data used to calculate the growth parameters come from the Extended Energy Statistics and Balances database which is compiled by the IEA. The information retrieved from the database is nuclear-powered electricity generation data from each country in the sample between 1960 and 2019 IEA, (2021a). The database is based on queries and the ones used for retrieving the data used in this thesis are Product: Nuclear and Flow: Electricity Output (GWh).

The data is showing how much electricity was generated in a particular year. The growth models can however also be used for curve-fitting of capacity data, i.e., how much electricity can be generated. The decision is however to use generation data as *first*, more data of this type is available through IEA. *Second*, Cherp et al., (In Press), which is a big source of inspiration for the research design also uses generation data which also means that the results could be compared.

Data for regime type is retrieved from Coppedge et al., (2020) via Dahlberg et al., (2021). The variable is called Electoral Democracy Index (vdem_polyarchy) and a country is evaluated by a country expert and assigned a score ranging from 0 to 1 where 1 is the ideal electoral democracy[2]. The dataset is a time-series dataset and the score at TMax and Lyear are used as independent variables.

GDP per capita data is retrieved from Gleditsch, (2002) via Dahlberg et al., (2021)[3] and is presented in current USD. The GDP per capita at TMax and Lyear are used as the independent variables.

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[2] (Coppedge et al., 2020) is a part of the Varieties of Democracy Institute. More information about the methodology could be found here: https://www.v-dem.net/en/about/.

[3] Dahlberg et al., (2021) is a part of the Quality of Government Institute and provide datasets on multiple indicators for quality of government such as GDP and regime type.

The data for electricity demand growth is obtained from the IEA, (2021) and coded as the percental increase over the five years preceding TMax. By using the percental increase over several years it is possible to see the effect of relative energy demand growth. E.g., if a small emerging economy experiences rapid growth in energy demand expressed in percent, it might still be a fraction of a big, industrialised countries´ absolute increase. A similar method has been employed by previous diffusion researchers (Gosens et al., 2017; Vinichenko, 2018).

3.3.2 Sample

The sample is comprised of countries having commercial nuclear reactors between 1960 and 2019. Although the number of units of analysis in the whole population, the countries with commercial nuclear reactors, is limited it is not useful to include all of them in the analysis. Instead, countries with reliable estimates and extended time-series are chosen. As such, both Belarus and the United Araba Emirates connected their first reactors to the grid in 2020, i.e., one year after the last available observation. Both countries are therefore omitted. Moreover, data from countries that inherited their nuclear power plants from the Soviet Union such as Armenia, Russia, Ukraine, Slovenia, and Lithuania are excluded from the analysis. All four countries do have or had substantial amounts of nuclear power. Unfortunately, prior to 1990, generation data is not available for the individual countries. USSR is included and treated as one country with data available until 1989.

To successfully meet climate targets, it is imperative to understand how geographic and demographic factors in a heterogenous world might influence the diffusion of low-carbon technologies (Brutschin et al., In review). Therefore the sample is separated into a “Western” and “non-Western” group in parts of the analysis. The Western group is comprised of countries from western Europe, the USA, and Canada, and the rest of the sample comprise the non-Western group. Which group a country belongs to is, of course, a normative statement and it could be argued that e.g Japan belongs to the Western group. The list of the countries and their respective group affiliation is found the Appendix C.

In addition, the idea of using two growth models is to enhance the robustness of the result. Therefore, as mentioned, only countries where the growth curves converge are used in the analysis. There is no clear line when two curves diverge “too much” which is important to note. Therefore, countries, such as China, where the curves are deemed to diverge are included in the descriptive statistics but not in the analysis of variability in G and L. As there are difficulties in estimating growth parameters for countries still at the beginning of their diffusion cycle, countries such as India, where diffusion hardly is expected to peak within this century, are also omitted from the analysis but included in the descriptive statistics.

3.3.3 Software and equations

The construction of the growth curves and regression analysis is done in the R programming language and related RStudio software. The algorithms in these R-functions yield L and K for every country which in turn is used in the equations below to compute G. In addition, a separate code is provided by Vadim Vinichenko to generate visual illustrations of the growth curves[4].

[4] The codes for the growth curves can be retrieved from the following link: https://github.com/poletresearch/RES_article

The equations for estimating max growth rates are as follows:

$$G_{log} = \frac{Lk}{4}$$

Equation 3. G, max growth rate based on the logistic function

$$G_{gmp} = \frac{Lk}{e}$$

Equation 4. G, max growth rate based on Gompertz function

dT, the number of years between 10% and 90% of complete diffusion, is based on L and k and can be calculated as demonstrated below.

$$dT_{log} = \frac{\ln{(81)}}{k}$$

Equation 5. dT based on the logistic function

$$dT_{gmp} = \frac{\ln{(\frac{\ln(0.1)}{\ln(0.9)})}}{k}$$

Equation 6. dT based on Gompertz function

G is related to L and dT similarly in both the logistic and Gompertz function as seen in the equations below.

$$G_{log} = \frac{Lk}{4} = \frac{L}{\Delta t} * \frac{\ln(81)}{4} \approx \frac{1.1L}{\Delta t}$$

Equation 7. G related to L and dT in the logistic function

$$G_{gmp} = \frac{Lk}{e} = \frac{L}{e} * \frac{\ln\left(\frac{\ln(0.1)}{\ln(0.9)}\right)}{\Delta t} \approx \frac{1.1L}{\Delta t}$$

Equation 8. G related to L and dT in Gompertz function

Based on the fits yielded from the equations above, the metrics called maturity and relative sums of squares (RSS.Rel)[5] are computed. Maturity indicates where in the diffusion cycle a country, for the year of the last available empirical observation, is situated in relation to L. Maturity is ranging from zero (no diffusion) to one (complete diffusion). RSS.Rel measures the goodness of fit when using different models in the same dataset (a smaller number indicates a better fit) and can be used to compare whether the logistic or Gompertz model offers the best fit.

The regression analysis uses the lm[6] function. The curve fitting is done with the nls[7] and the nlsLM[8] functions found in the minpack.lm package in the same programming language and software. The scatterplots in section 4 are made in Excel and RStudio.

3.4 Limitations

It is important to be aware of the inherent limitations of quantitative designs in general and how the limitations apply to the thesis. There are some potential issues with some of the independent variables and the small size of the sample.

A good example is regime type which could be (and is) measured differently. E.g. it could be coded as a binary variable (authoritarian/democratic) or a non-binary variable (more or less democratic). If coded as non-binary it can be done in different scales that in turn affect which specific method of analysis that is appropriate (Blaikie & Priest, 2019). The choice of what measurement and scales to use is up to the researcher. Furthermore, one could argue that there is always some level of arbitrariness when measuring social characteristics such as democracy. However, Coppedge et al., (2020) is a widely used and recognised index for measuring regime types.

Another example is the subsamples of Western and non-Western countries. As mentioned, it is to a certain extent a normative judgment of what group a country belongs to. Moreover, it is important to point out that there is a lot of heterogeneity within these two groups that hopefully could be further explored in future research.

The sample is due to data availability relatively small which is important to keep in mind in the interpretation of the quantitative results. The interpretation should be done parsimoniously, and further research will likely be needed to either confirm or reject the quantitative findings.

Even though a similar thesis using only qualitative methods could be done (such as a study examining a typical case), mitigating some of the limitations discussed above, the decision is to use a mix of qualitative and quantitative methods. Generalisation is typically harder in qualitative research (Blaikie & Priest, 2019) and as mentioned there are no quantitative studies on the latter phases of the diffusion process, meaning that there is a need to complement the qualitative studies in the field.

Three primary measures are being taken to alleviate the limitations of the design. *First*, the material is both qualitatively and quantitatively analysed (triangulation). *Second*, two different

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5 See Nash, (2014)

6 A function for linear regression analysis or linear models (*RDocumentation.Lm*, n.d.)

7 A function for estimating the least squares of the parameters in a non-linear model such as the logistic and Gompertz models (*RDocumentation.Nls*, n.d.)

8 A function that returns information from the nls function such as residuals, coefficients, summaries etc (*RDocumentation.NlsLM*, n.d.)

growth models are used (Logistic and Gompertz) to construct the growth parameters. Thereby, one can compare them and exclude countries where estimates of growth rates are diverging. For cases where both models converge and indicate a similar fit, one can expect that the estimations are more robust. *Third*, the growth curves are based on nuclear-powered electricity generation data. However, the curves and growth parameters can also be estimated based on nuclear power capacity data. Thus, the distributions of e.g., G based on generation data can be compared with the same metric based on capacity data. If the shapes of respective distributions are similar and the relative sizes of G are similar when using different data, the results are likely more robust.

4 Results

This chapter is structured in accordance with the Research Questions of the thesis:

RQ1: What are the maximum growth rates and saturation levels of nuclear power and how do they vary across countries?

RQ2: What factors explain variability in the diffusion growth rate of nuclear power?

RQ3: What factors explain the ceiling/saturation of nuclear power use?

RQ4: What happens to the speed and depth of nuclear power diffusion in late adopter markets?

The chapter contains four sections. 4.1 determines the type of nuclear power growth (accelerating, stable, or stalling) in each country in the sample. It further estimates the maximum growth rates of nuclear power (G) and reports descriptive statistics on this newly developed G metric. In 4.2 the dependence of G and TMax on selected independent variables is presented. In 4.3 the dependence of L on selected independent variables is presented. The results are summarised in 4.4. Lastly, the chapter is finalised with reflections on the robustness of the results in 4.5.

4.1 RQ1: Growth curve parameters

4.1.1 Accelerating, stable and stalling growth

To distinguish the different types of growth trajectories the sample is divided into three growth categories: Accelerating, Stable and Stalling. Table 4-1 lists the key growth parameters for all groups, which in total is 29 countries where nuclear power historically has been used.

In four countries, China, India, Pakistan, and Romania, both models estimate that TMax will occur in the future i.e., after 2021. In essence, this could be interpreted as the growth is still **accelerating** in these countries. The growth curves in this group are therefore steep upward sloping, illustrated in the top row of figure Figure 4-1. This group also has the biggest variance between the models as can be expected for the early diffusion phases (Martino, 2003). Therefore, an elaborate analysis of this group is less reliable.

The presence of China and India in this group is important since they are expected to be driving electricity demand growth in the future (IEA, 2020). It is therefore of great importance that a substantial share of their energy mixes is produced by low-carbon technologies. Romania is the only European country in the accelerating group and there are no OECD members.

The **stalling** category consists of five countries with a maturity level of at least 90%, meaning that they approach their upper asymptote, according to both models. The growth curves in this group are similar to the S-shaped curve (Figure 2-1) and are showing distinct stagnation in growth rates on the end of the X-axis, seen in the bottom row of Figure 4-1. This means that they may be at the end of their estimated diffusion cycle. The majority of countries (20) are in this group. The two models' estimations of G, L, TMax, and Maturity are more harmonized in this category, likely due to that the countries have come far in the diffusion cycle and the estimations are not based on extrapolation. The stalling group has as expected the lowest Y0, i.e., connected their first reactor to the grid first, of all three groups (stalling group: early 1970s, stable group: early and mid-1970s, and the accelerating group: early 1980s), see

Appendix B. The **stable** category consists of five countries with a maturity level below 90% according to at least one of the models. The growth curves in this group are upwards sloping but not as steep as in the accelerating group, see the middle row in Figure 4-1. As in the stalling category, both models yield less variance than in the accelerating group. The growth curves for all countries can be found in Appendix A.

Table 4-1. Growth parameters estimated from observations of nuclear-powered electricity generation fitted to growth curves

		Gompertz					Logistic					
Country	**Y0**	**L**	**TMax**	**dT, years**	**G**	**Maturity**	**L**	**Tmax**	**dT, years**	**G**	**Maturity**	**Best fit**
Accelerating growth												
China	1991		2279	299		0		2059	27		0	Log
India	1969		2193	306		0		2027	54		0	Log
Pakistan	1971		2363	397		0		2071	36		0	Gmb
Romania	1996		2356	431		0		2074	49		0	Log
Stable growth												
Iran	2011	3.5%	2014	11	0.4%	0.72	3.1%	2015	9	0.4%	0.82	Gmb
Czech Republic	1985	101.4%	2008	76	1.5%	0.45	64.0%	2004	45	1.6%	0.71	Gmb
Italy	1963	8.9%	1996	129	0.1%	0.29	4.6%	1983	70	0.1%	0.56	Equal
United Kingdom	1956	149.5%	2022	136	1.4%	0.18	51.6%	1997	58	1.0%	0.52	Gmb
USSR (until 1991)	1954	41.7%	1991	42	1.1%	0.32	18.6%	1985	19	1.2%	0.7	Log
Stalling growth												
Argentina	1974	5.3%	1979	18	1.2%	1.00	5.2%	1982	18	1.1%	1.00	Log
Taiwan	1977	15.5%	1982	14	7.6%	1.00	15.2%	1984	13	6.1%	1.00	Gmb
Hungary	1983	31.4%	1985	6	9.8%	1.00	31.2%	1985	6	9.6%	1.00	Log
Japan	1963	30.6%	1983	24	2.5%	0.94	28.6%	1986	21	2.5%	0.98	Log
Korea	1977	32.9%	1994	32	4.0%	0.89	29.4%	1996	25	3.5%	0.97	Log
Mexico	1989	3.1%	1992	10	0.8%	1.00	3.0%	1993	10	0.8%	1.00	Equal
Slovakia	1972	59.0%	1983	23	4.3%	0.95	54.8%	1985	20	3.9%	0.99	Gmb
South Africa	1984	5.3%	1983	20	0.6%	0.99	5.3%	1985	24	0.4%	1.00	Gmb
Brazil	1982	2.4%	1999	11	0.5%	1.00	2.3%	2000	10	0.5%	1.00	Log
Bulgaria	1974	38.0%	1978	17	3.6%	1.00	37.7%	1980	18	3.0%	1.00	Gmb
Belgium	1965	52.4%	1980	16	6.4%	1.00	51.1%	1983	14	7.2%	1.00	Log
The Netherlands	1968	3.2%	1973	2	4.9%	1.00	3.3%	1973	2	4.0%	1.00	Log
Canada	1962	15.1%	1979	20	1.5%	1.00	14.7%	1982	18	1.5%	1.00	Log
Finland	1977	25.0%	1979	9	6.8%	1.00	24.7%	1981	8	7.1%	1.00	Gmb
France	1959	86.2%	1983	18	9.5%	1.00	84.4%	1986	17	7.7%	1.00	Gmb
Germany	1961	27.7%	1980	16	2.5%	0.99	27.0%	1982	15	2.6%	1.00	Log
Spain	1968	25.2%	1984	9	6.4%	1.00	24.9%	1985	10	5.4%	1.00	Log
Sweden	1964	48.3%	1979	14	6.3%	1.00	47.4%	1981	13	6.0%	1.00	Log
Switzerland	1968	42.0%	1977	21	3.2%	1.00	41.1%	1980	20	3.0%	1.00	Gmb
United States	1957	20.2%	1981	31	1.3%	0.97	19.2%	1985	27	1.3%	0.99	Gmb

Note: The estimates are based on empirical observations of nuclear power electricity generation. The estimates are more reliable for the stalling and stable group as those countries have come further in their respective diffusion cycle. L is normalized to the electricity supply at the year of the last empirical observation. G is normalized to the electricity supply at TMax. Note that G is not available for the accelerating group as electricity supply for their respective TMax is not available. In the UK, TMax for Gompertz function is estimated to 2022, and G is therefore normalized to the electricity *supply in 2019. L is moreover not presented for the accelerating group since the electricity supply the year when last observation is made, is centuries or decades before saturation is reached.*

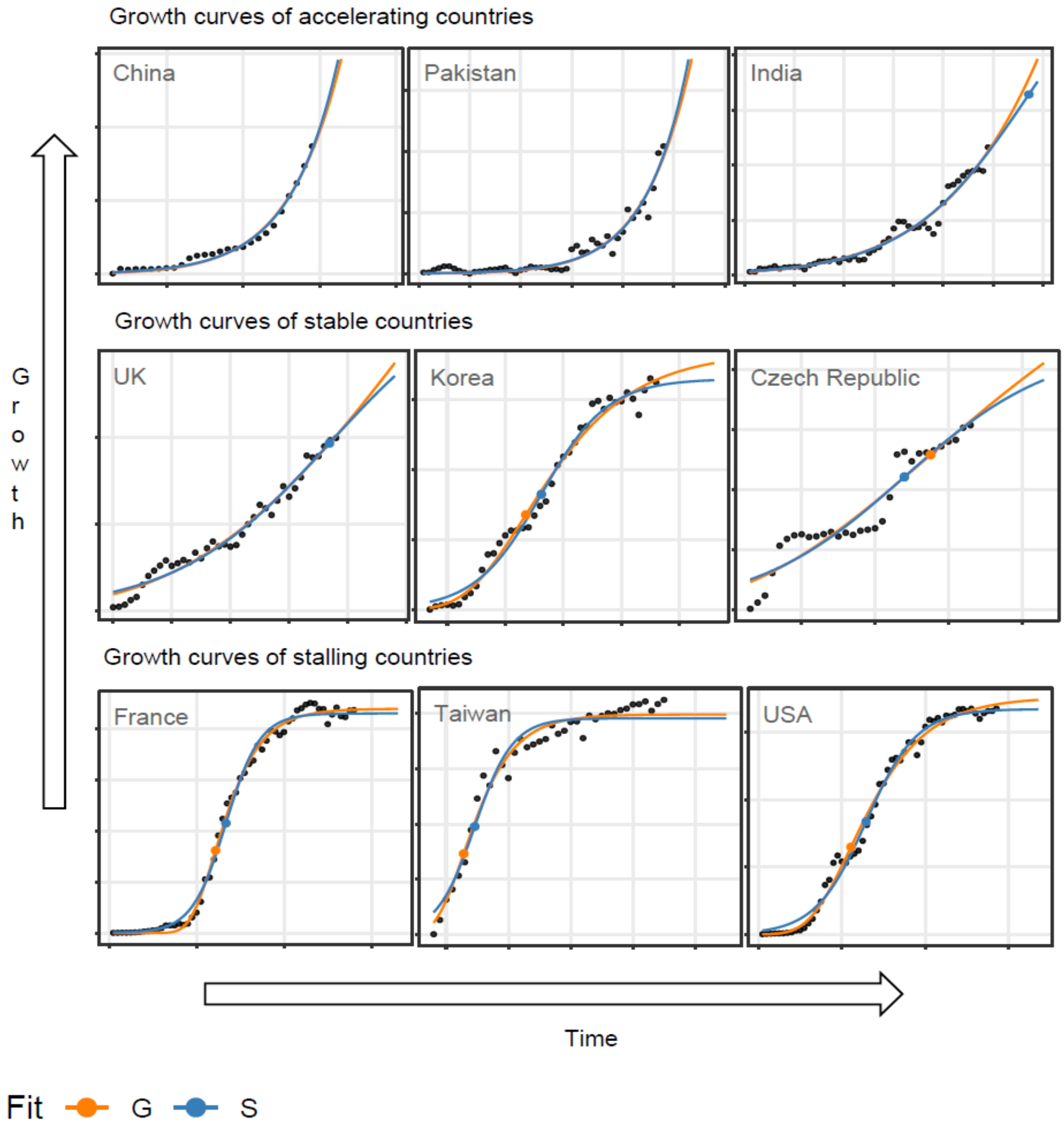


Figure 4-1. Generated electricity fitted to growth curves in a selection of countries. Empirical data from 1960 to 2019. Orange lines/dots depict the curves/max growth rates generated from the Gompertz model and the blue lines/dots show the curves/max growth rates generated from the logistic model. The growth rates in the accelerating group are increasing, the growth rate in the stalling group has stagnated and the stable countries fall in between. Note that G is not visible in the accelerating group (except for the Gompertz G in India) as TMax is estimated to be in the future.

In absolute numbers, France and the United States experienced the highest maximum growth rates of around 30 TWh/year. However, G in absolute numbers depends on the size of the system. To increase comparability and account for the total system size when measuring G, it is normalised to the total electricity supply at TMax for each respective country. G is henceforth denoted G% when normalised to the total electricity supply. France reaches high levels of G% as well and is accompanied by Hungary in the top with respective G% of almost 10%, see Table 4-1. The countries with the highest rates are located in Europe, except for Taiwan in third place. More on regional differences in 4.2.3 The picture is similar for saturation levels as the USA has the highest with about 850 TWh/year. This metric is however normalised (for the same reason as G) with the electricity supply at the year when the last observation was made. L is henceforth called L% when normalised to the total electricity supply. UK peaks with an L% of 149% but other countries such as the Check Republic and France also experience high levels with peaks of 101% and 86% respectively. As for G%, the countries with the highest levels of L% are located in Europe, see section 4.2.3.

When excluding the accelerating group, the median G% is 2.6% (growth parameters from the logistic model) and 2.5% (growth parameters from Gompertz model) whereas the median L% is 26% (growth parameters from the logistic model) and 29.2% (growth parameters from Gompertz model).

4.2 RQ2 & 4: Growth parameters and socio-economic characteristics

Several potential reasons for variance in nuclear power growth are explored below. The independent variables are derived from theories and hypotheses discussed in the literature review. A summary of the independent variables along with the mechanism behind the hypothesised relationship with diffusion is found in Table 3-2. To reiterate the relationships that will be tested addressing growth, see Table 4-2 below.

Table 4-2. Explored relationships addressing variance in maximum growth rate

Independent and dependent variables	**Expected effect**
GDP per capita at TMax and G%	+
Y0 and G%	-
Electricity supply at TMax and G%	-
L and G%	+
dT and G%	-
Δ years and Y0	-
Level of democracy and G%	-
Nuclear accidents and TMax	-
Oil crises and G%	+

For the analysis of G, L, dT, and TMax further data reductions are made. Only countries with at least 50% Maturity when using growth parameters from the logistic function are included as the models are less accurate for countries still at the beginning of their diffusion process (Martino, 2003). Having the limit at 50% Maturity is chosen as Cherp et al., (In Press) find that G converges between the models after this point. Moreover, they find that there are no significant changes in G after 50% Maturity of the logistic model (Cherp et al., In Press). In practice, these are the countries in the stalling and stable groups. The Netherlands is furthermore omitted as their dT is only two years. An intensive leap of growth, as in The Netherlands, followed by stagnation and decline is not a good indicator of sustained growth. Lastly, Iran is omitted due to only having one reactor.

The resulting sample includes 23 countries with data points ranging from 1960 to 2019. The models are yielding similar results. This is further demonstrated by the measurements of central tendencies of RSS.Rel. (a lower value means a better fit) from respective models. The logistic model yields a slightly better fit with a mean of 1.058 and median of 1 compared to the Gompertz model which yields a mean of 1.067 and a mean of 1.010. However, the models overall present similar results indicating that the models are close to each other. Nevertheless, the logistic function is indicated to be slightly more accurate and is therefore used in the qualitative analysis to make the interpretation of the figures easier. Both models are however included in the quantitative analysis and using both models acts as a robustness check. That the models are close to each other is in itself an interesting observation as it means that nuclear power diffusion, understood through the G metric could be both symmetrical as well as asymmetrical at both sides of the inflection point.

Figure 4-2 depicts a histogram of the distribution of G% for nuclear, solar, and wind power. The data for wind and solar power are from Cherp et al., (In Press). As seen in the figure, G% is notably more concentrated in the case of wind and solar power. Moreover, G% for nuclear power is in general substantially larger than for wind and solar power. This is an important finding as it is indicating that nuclear power has grown faster than wind and solar power and that nuclear power potentially can replace more carbon than granular renewables.

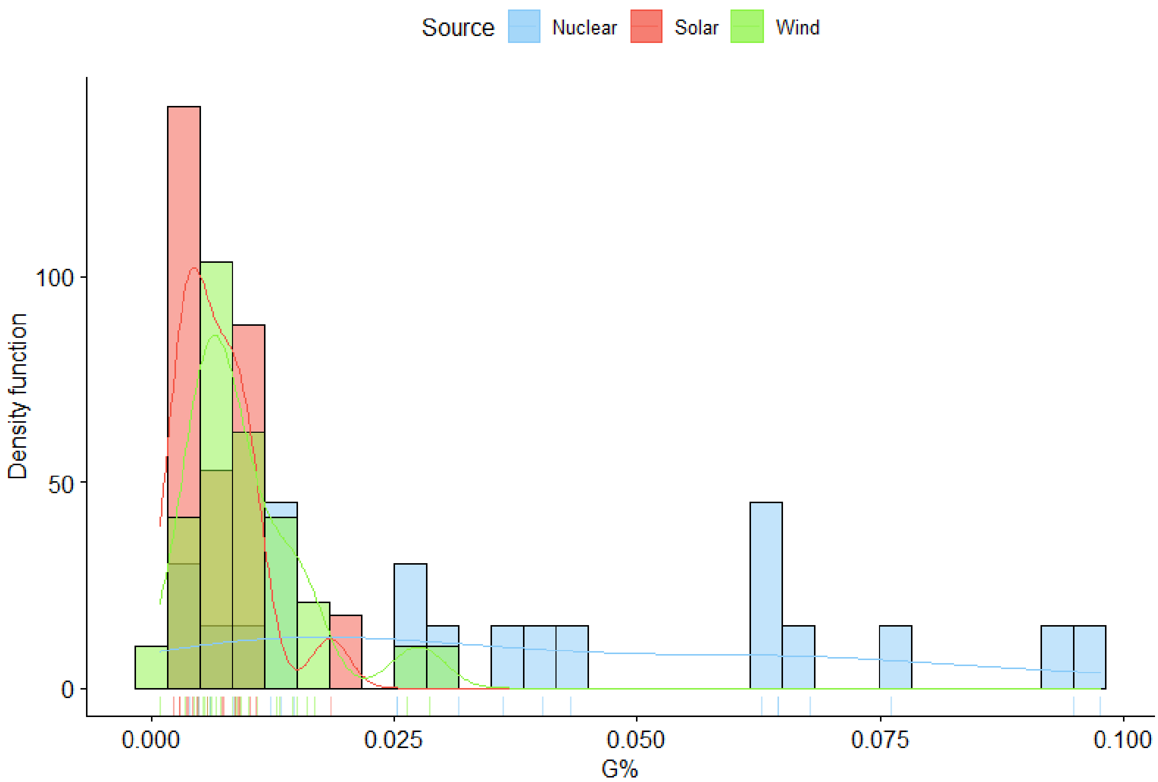


Figure 4-2. Density plot of the distribution of maximum growth rates (G%) for nuclear (blue), solar (red), and wind (green) power. Data on wind and solar power is retrieved from Cherp et al., (In Press). The Y-axis and lines represent the Kernel density function. The distribution for wind and solar power is less dispersed than for nuclear power. Nevertheless, G% is in general higher for nuclear power.

4.2.1 Dependence of G and TMax on other growth parameters

In this section, the dependence of G% on other growth parameters such as Y0 and dT is explored.

Figure 4-3 indicates that countries that connect their first reactor to the grid sooner tend to experience longer dT. Why late adopters diffuse faster is often understood through the positive effects of technology learning and knowledge spill-over (Grübler, 1996; Marchetti, 1983). This is positive in terms of diffusion of low-carbon technologies as it shows that the pace of diffusion could increase over time.

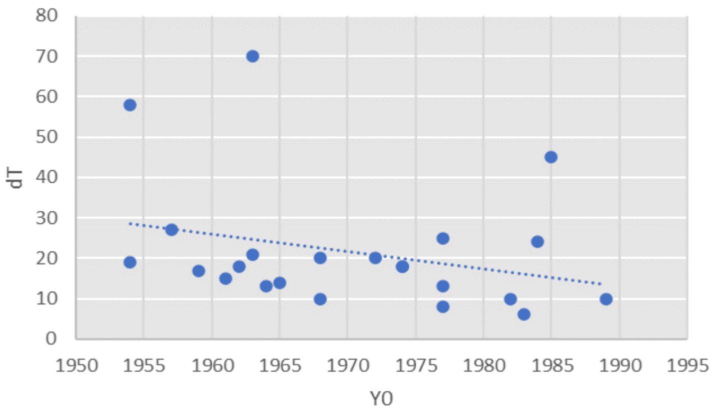


Figure 4-3 dT as a function of Y0

If early adopter tends to have longer dT, one could expect that G% and Y0 should be positively associated, i.e., higher G% for those connecting a reactor to the grid later. Figure 4-4 does however not show any clear signs of G% being affected by Y0. The importance and the effect of the timing of technology adoption are, as discussed in the literature review not completely understood. That G% is not increasing over time could be problematic for the diffusion of other low-carbon technologies since the speed of energy transitions needs to increase. Moreover, that Y0 and G% do not seem to associate is confirmed by regression analysis, see Table 4-3.

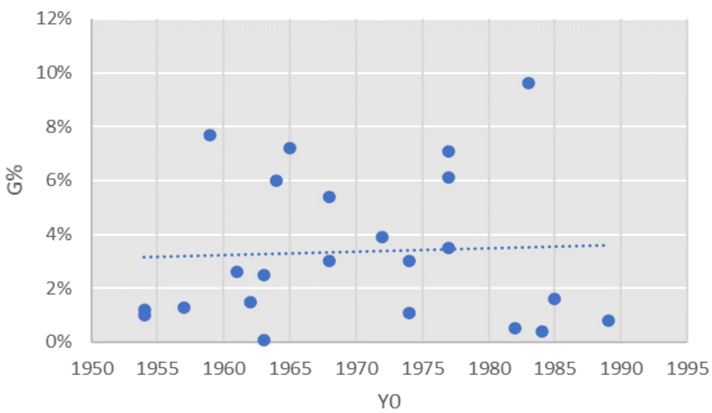


Figure 4-4. G% as a function of Y0

The combined picture of Figure 4-5 and Figure 4-6 is particularly interesting. First, it is indicated that countries that connect their first reactor to the grid later tend to have shorter acceleration cycles (ΔY). In addition, it is indicated that countries with shorter acceleration cycles also experience higher G%. In essence, this implies that late adopters experience shorter acceleration cycles and higher G%, implying an accelerating transition. Given that the speed of energy transitions needs to increase, this is a positive result. While Figure 4-5 is supported through regression analysis Figure 4-6 is not, see Table 4-3.

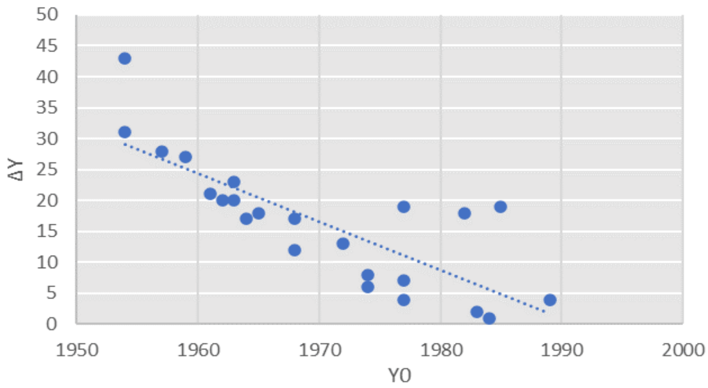


Figure 4-5. ΔY (the number of years between Y0 and TMax) as a function of Y0

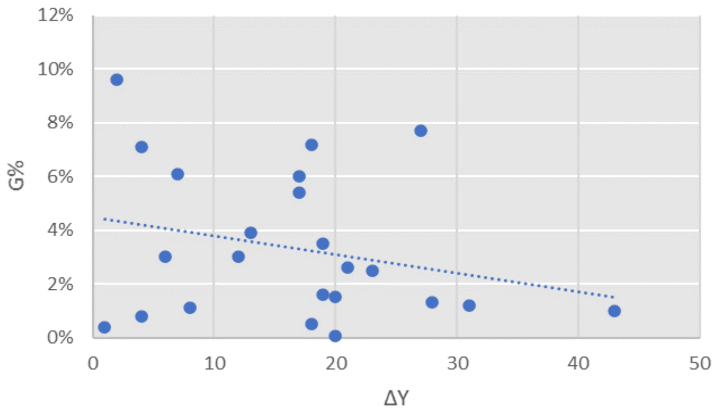


Figure 4-6. G% as a function of ΔY

Figure 4-7 indicates that diffusion time and G% are negatively correlated, which also is confirmed in the regression analysis, see Table 4-3This is expected given that dT and G are inversely proportional (one decreases at the same rate as the other increases), see section 3.3.3.

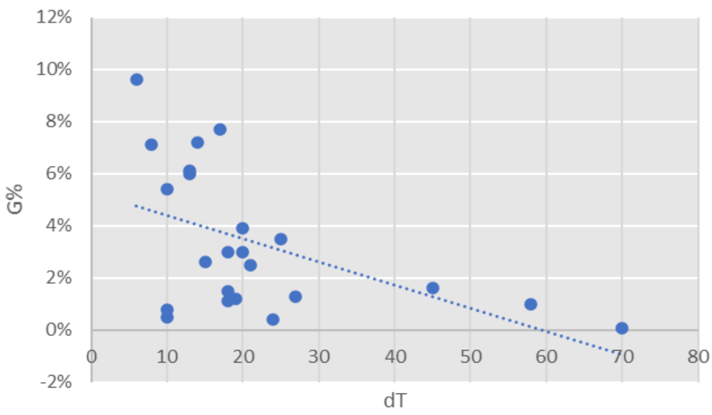


Figure 4-7. G% as a function of dT

In Figure 4-8 L% is plotted against G%. As seen a positive relationship is indicated which implies that countries can end up at high saturation levels while also experience high growth rates which is positive for other low-carbon energy transitions. When testing this relationship in a regression analysis it is only found to be statistically significant when using growth parameters from the logistic function, see Table 4-3. This indicates that not all countries with high saturation levels have experienced fast growth rates.

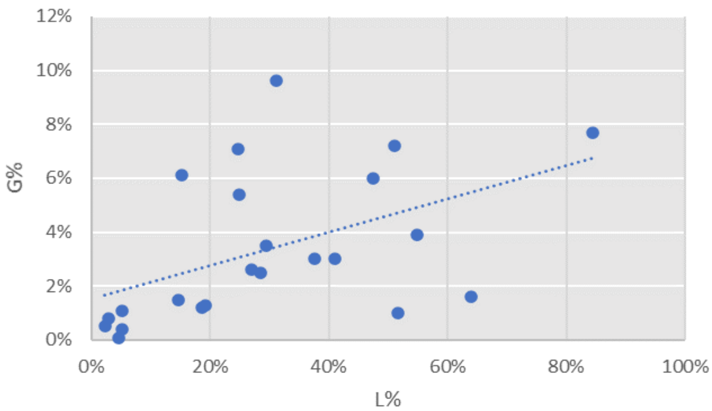


Figure 4-8. G% as a function of L%

4.2.2 Dependence of G and TMax on socio-economic characteristics

In this section, the dependence of G% on factors such as GDP, energy demand growth, etc. is explored both qualitatively and quantitatively.

The empirics have shown that technology diffusion could be driven by a strong economy, meaning that high-income countries might diffuse faster (Brutschin et al., In review; Csereklyei et al., 2016; Griliches, 1957). As nuclear power in many ways is a resource-intensive technology (in terms of upfront cost, institutional capacity, etc.) (Markard, 2020) one could expect that there should be a positive relationship between GDP per capita and G% in the case of nuclear power. However, as seen in Figure 4-9, there are no strong signs of a relationship. If anything, there is a negative relationship meaning that G% is lower in richer countries. The lack of effect from GDP per capita is furthermore supported by regression analysis, see Table 4-3.

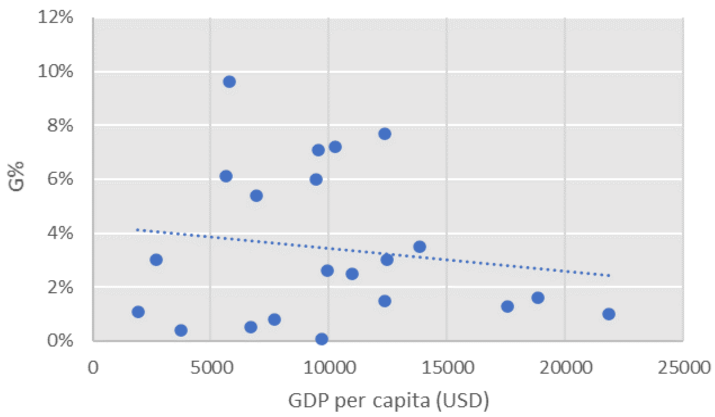


Figure 4-9. G% as a function of GDP per capita

As mentioned, other technology diffusion studies have found that early adopters tend to have higher GDP (Grübler et al., 1999b; Wilson, 2012). This relationship is also found in the case of nuclear power, Table 4-3. This finding allows for further analysis of the differences between the late and early adopters, see section 5.1.

In Figure 4-10 electricity demand growth is plotted against G%. The trendline indicates a slight positive relationship. Omitting the outlier on the X-axis does not change the slope of the trendline substantially. The lack of effect from electricity demand growth is confirmed in the regression analysis, see Table 4-3. These results thereby indicate that nuclear power diffusion has not been driven by increased energy demand.

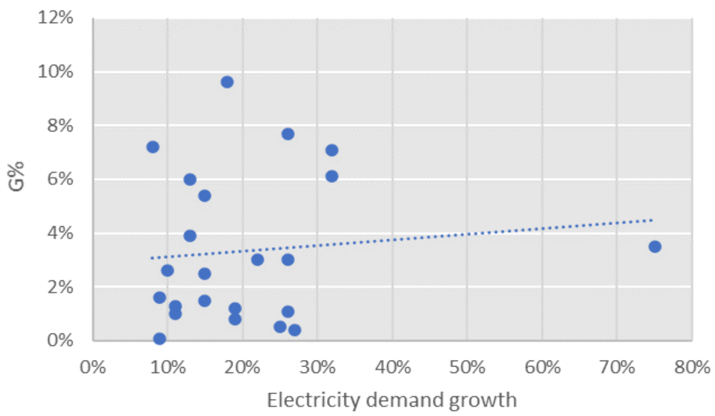


Figure 4-10. G% as a function of electricity demand growth

Figure 4-11 illustrates G% plotted as a function of electricity demand growth. The trendlines and X-axis are log-transformed. The log transformation is done to account for a potential non-linear relationship between electricity supply and G%. One could expect that small changes in electricity demand in smaller countries will have a bigger effect than the same change in a bigger country, all other things being equal. The trendline shows that G% is smaller in countries with bigger electricity supply which, given that G is normalised to the electricity supply, is intuitive as those countries are less dependent on nuclear power specifically. Five out of six countries with the highest G% generated a total of 100 TWh/year or less at TMax, further highlighting that growth appears to be more pronounced in smaller systems. Moreover, this relationship is confirmed by regression analysis, Table 4-3.

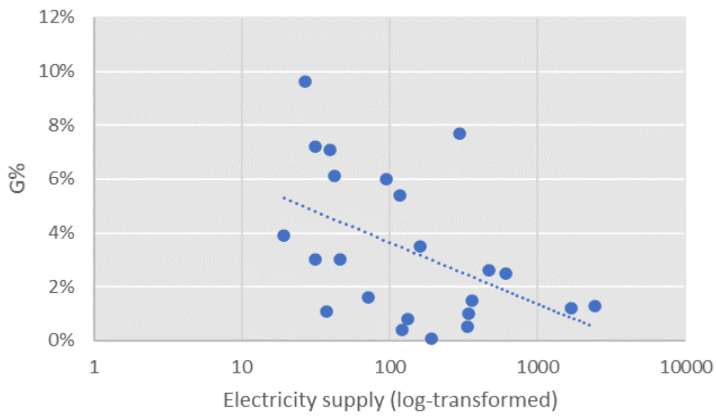


Figure 4-11. G% as a function of electricity supply

Figure 4-12 shows G% as a function of the level of democracy. The slope of the trendline is flat and thereby not indicating a relationship in any direction. Hence, the result suggests that energy transitions can be fostered in a variety of regime types. Given the current democratic recession (Alizada et al., 2021) and the urgency of energy transitions, the lack of relationship could be seen as positive. Note that that the observations are grouped on either end of the X-axis, implying that there could be subgroups within the sample.

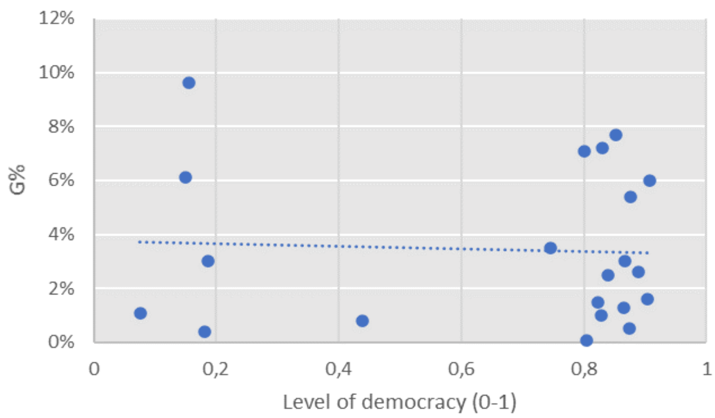


Figure 4-12. G% as a function of the level of democracy

One of the most distinctive features of nuclear power is the perceived risk of serious accidents with extreme potential implications. Accident's effect on the diffusion of nuclear power is, as discussed in the literature review debated. Since nuclear power started to be used, there have been three major nuclear accidents: TMI 1979, Chernobyl 1986, and Fukushima 2011. If the accidents indeed have reduced the diffusion of nuclear power, one could argue that TMax should occur within a few years. The distribution of TMax is presented in Figure 4-13. As seen, a substantial part of the sample experienced TMax in the early 1980s, the years following the TMI accident which supports the hypothesis that accidents decrease diffusion of nuclear power. That being said, several countries did reach TMax before or the same year as TMI and the year before Chernobyl which does not support this theory. Moreover, the distribution of TMax after the initial peaks is relatively even and it is therefore hard to make a general conclusion about how accidents affected nuclear power diffusion. The distribution is also geographically spread but western countries (Western Europe, Canada, and the USA) tend to experience TMax a few years before the rest of the sample.

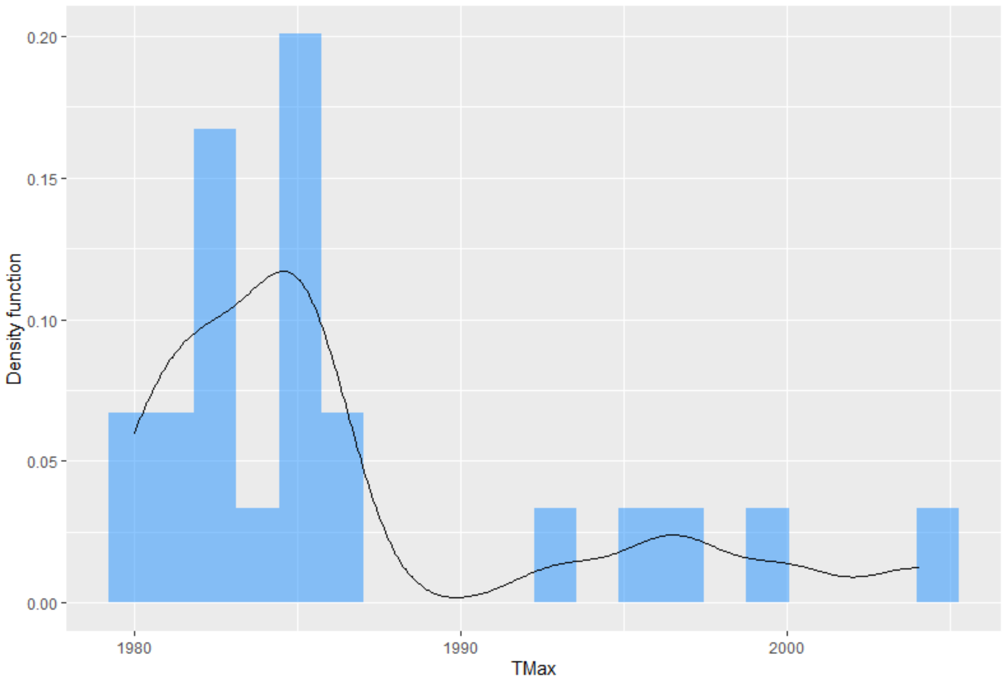


Figure 4-13. Density plot of the distribution of TMax across the sample. The black line is illustrating the Kernel density function. The distribution shows support for the TMI accident reducing nuclear power diffusion.

Another socio-economic characteristic often perceived to have benefited the diffusion of nuclear power is the oil crisis of the 1970s where the idea is that nuclear power was seen as a means of increasing the share of domestically generated electricity. Through returning to Figure 4-13 it is seen that globally many countries reached TMax during the first half of the 1980s. This could be seen as support for the hypothesis that the oil crises pushed the development of nuclear power. However, just as for accidents it is hard to make general conclusions as many countries in the sample reached TMax more than ten years after the oil price started to increase dramatically in 1973.

As discussed, there are indications (although not conclusive) that external shocks in the form of accidents and oil crises have affected the diffusion of nuclear power. Therefore, one could argue that other unexpected external shocks, such as Covid-19, also could have a substantial effect on the diffusion of new energy technologies. Indicating that rapid energy transitions are possible when dramatic changes in the world are occurring.

Table 4-3 Summary of regression analysis addressing variability in G%

Independent variable	Effect (Logistic)	Effect (Gompertz)
Y0 and G%	0.0002	0.0002
dT and G%	**-0.001****	**-0.0004****
GDP per capita and G%	-0.00000	-0.00000
ΔY and Y0	**-0.946*****	**-0.764*****
ΔY and G%	-0.001	-0.001
Y0 and GDP per capita	**-230.017****	**-289.730***
Electricity demand growth and G%	0.025	0.034
Electricity supply and G%	**-0.010****	**-0.010****
Level of democracy and G%	-0.005	-0.011
L% and G%	**0.062****	1.856

Note: that the effect from L% is only statistically significant when using growth parameters from the logistic function.

4.2.3 Regional differences

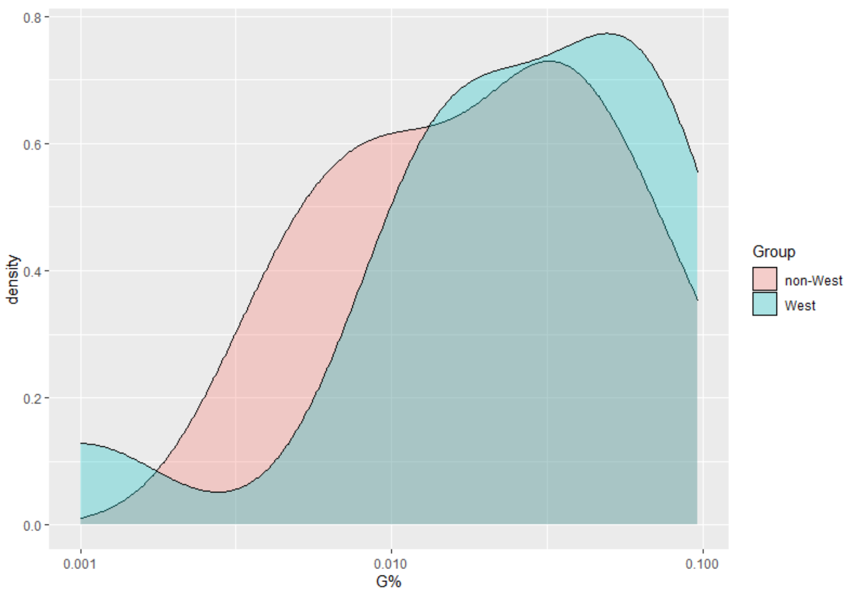


Figure 4-14 Density plot of the distribution of G% in Western and non-Western groups

From Figure 4-14 we can see that the shapes of the distributions of G% are relatively similar in the two groups. However, as seen the distribution in the Western group is more right-skewed, i.e., indicating higher G% in this group. This pattern is furthermore supported by the central tendencies as the median is higher in the Western group, 2.8% compared with the non-Western group, 2.5%, see Appendix E.

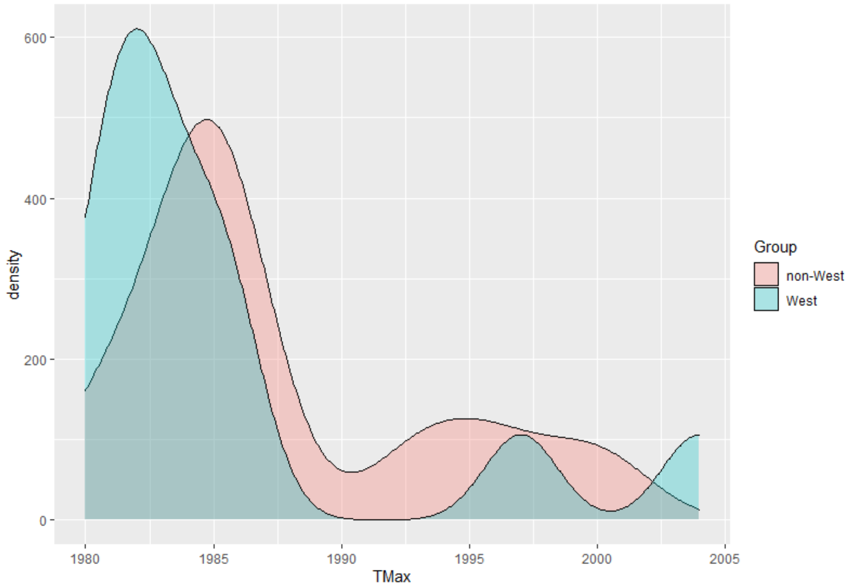


Figure 4-15.Density plot of the distribution of TMax in the Western and non-Western groups

Figure 4-15 shows that the distribution of TMax also is relatively similar in the two groups with the Western group reaching TMax slightly earlier than their non-Western counterpart. The groups respective TMax are 1983 in the Western group and 1985 in the non-Western group, see Appendix E.

All previously explored relationships are also examined with Western and non-Western countries separated. In most cases, the result is similar, see Appendix E. However, two relationships stand out and indicate that there are important differences in what causes variability in G%.

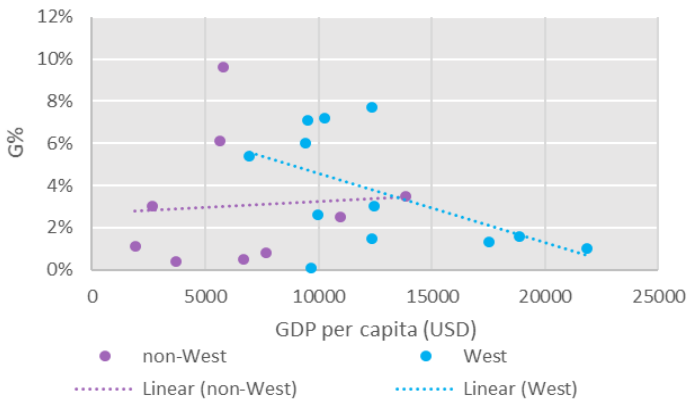


Figure 4-16. G% as a function of GDP per capita in the Western and non-Western groups

Figure 4-16 indicate that there are differences between the Western and non-Western group in the sample. While the trendline for Western countries indicates that GDP per capita is associated with lower G%, the trendline for non-Western countries indicates the opposite relationship. That GDP per capita is important in Western countries but not in non-Western countries is further supported via regression analysis. The regression analysis indicates that GDP per capita has a statistically significant negative, although minor, effect on G% in Western countries but not in non-Western.

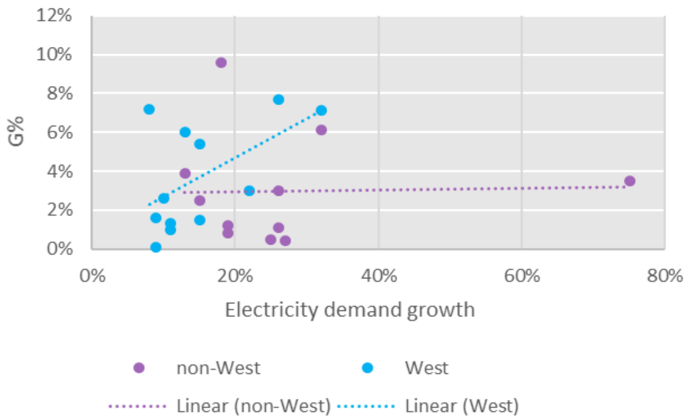


Figure 4-17. G% as a function of electricity demand growth in the Western and non-Western groups

Moreover, in Figure 4-17 it is indicated that electricity demand growth has been associated with higher G% while the trendline for non-Western countries does not indicate any relationship. This relationship is also supported in the regression analysis where the two groups are separated. Electricity demand growth has a statistically significant positive effect on G% in Western countries but not in non-Western countries. That G% does not require increased electricity demand growth in the non-Western group could be seen as positive since implies that lumpy low carbon technologies can be diffused even when the demand for its product is stagnating.

4.3 Saturation level (L) and socio-economic characteristics (RQs 3-4)

Several potential reasons for variance in saturation levels of nuclear power are explored below. The independent variables are derived from theories and hypotheses discussed in the literature review. A summary of all the independent variables along with the mechanism behind the hypothesised relationships are found in Table 3-2. To reiterate the relationships addressing saturation, see Table 4-4.

Table 4-4. Explored relationships addressing variance in saturation levels

Independent variables	**Expected effect**
GDP per capita	+
Y0	-
Electricity demand growth	+
Electricity supply	-
Level of democracy	-

Figure 4-18 shows the distribution of L% across the sample. Depending on the model, the median L% is 26% (logistic) or 29.2% (Gompertz).

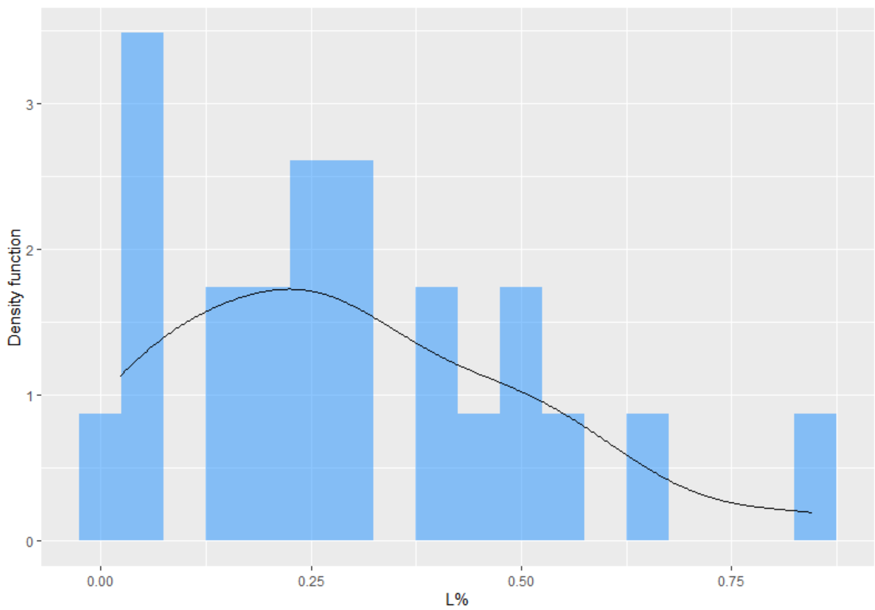


Figure 4-18. Density plot of the distribution of L% across the sample. L is normalised to the electricity supply the year the last empirical observation was made. The Y-axis and black line represent the Kernel density function.

4.3.1 Dependence of L on other growth parameters

In this section, the dependence of L% on other growth parameters such as Y0 and G% is explored.

As discussed in section 2.1 there is empirical evidence that early adopters often tend to reach higher levels of saturation albeit their diffusion cycle is longer than late adopters. Below it is explored whether these theories hold in the case of nuclear power.

Figure 4-19 shows L% plotted against Y0. The relationship is indicated to be negative meaning that countries that connected their first reactor to the grid earlier tend to have higher L%. This relationship is however not confirmed by the regression analysis, see Table 4-5. That early adopters reach higher L% could be problematic for other low-carbon energy transitions as the depth (L%) likely needs to increase to reach climate targets.

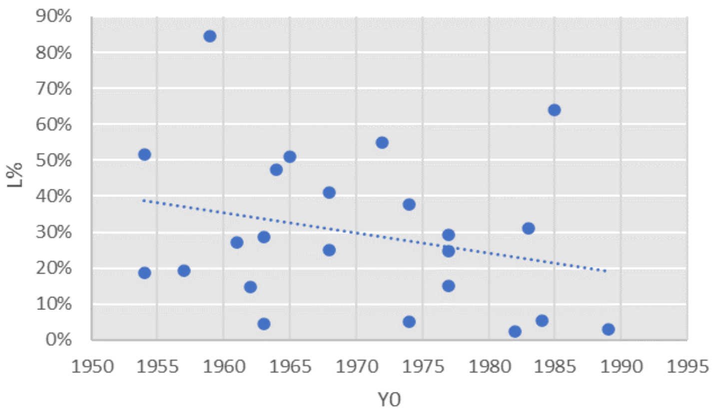


Figure 4-19. L% as a function of Y0

Figure 4-20 shows L% plotted against G%. The figure indicates a positive relationship saying that countries with higher G% tend to experience higher L%. This shows that it is possible to combine rapid and deep diffusion. The relationship is furthermore confirmed to be statistically significant when using growth parameters from the logistic model, although not Gombertz, see Table 4-5. These results indicate that countries can achieve deep and swift energy transitions which is positive.

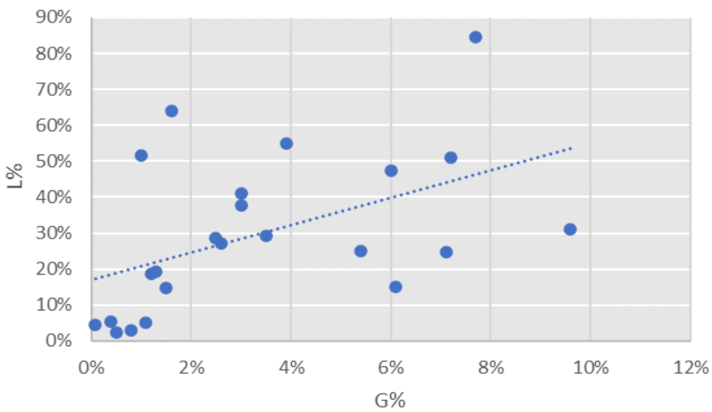


Figure 4-20. L% as a function of G%

4.3.2 Dependence of L on socio-economic characteristics

In this section, the dependence of L% on factors such as GDP per capita and energy demand growth is explored.

Figure 4-21 shows GDP per capita plotted against L%. The trendline indicates that higher GDP per capita associate with higher G%. However, this relationship is not confirmed to be statistically significant in the regression analysis (see Table 4-5). That diffusion does not seem to relate to GDP per capita (G% and GDP per capita were not related either) could be positive since it implies that low-carbon technologies could be diffused in low-income countries and emerging economies.

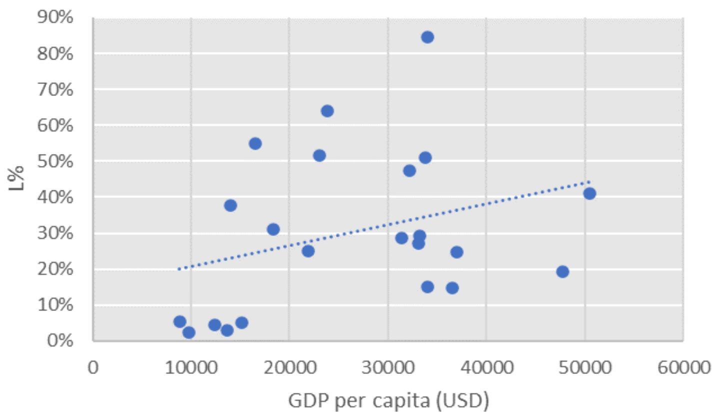


Figure 4-21. L% as a function of GDP per capita

In the literature review, it was found that increasing electricity demand growth was explaining higher rates of adoption of nuclear power. However, in Figure 4-22 it is indicated that electricity demand growth is associated with lower L%. This negative relationship is also supported by regression analysis when using growth parameters from the Gompertz function (see Table 4-5).

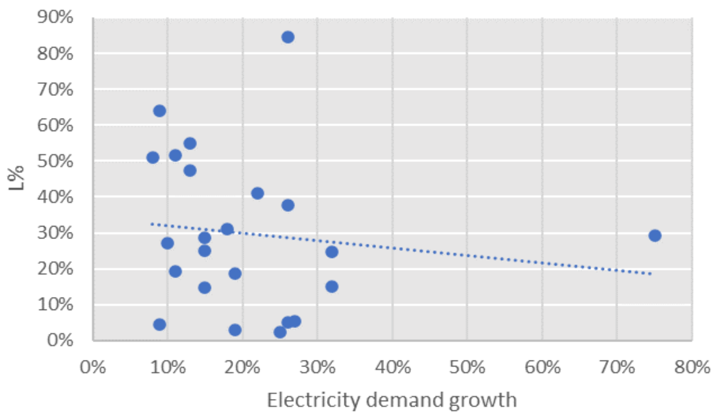


Figure 4-22. Electricity demand growth and L%

In Figure 4-23 it is indicated that, just like for G%, there is a negative relationship with electricity supply. Thereby it seems that as the electricity supply increases, L% is decreasing. Five out of the seven highest levels of L% are found in countries with total electricity supplies below 200 TWh/year. This relationship is however not supported in the regression analysis (see Table 4-5).

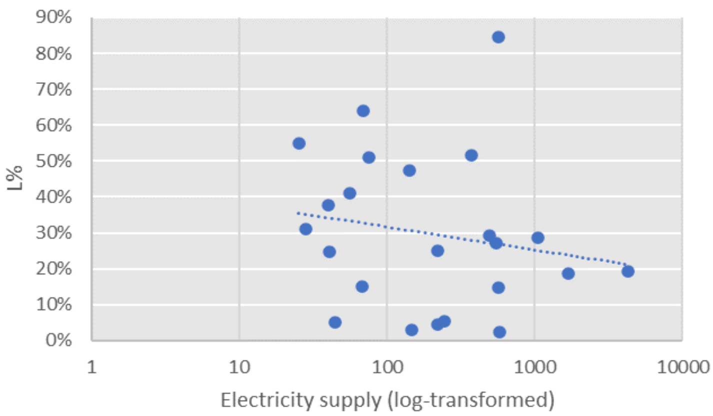


Figure 4-23. L% as a function of electricity supply

In Figure 4-24 it is indicated that more democratic countries reach higher L%, but the relationship is not found to be statistically significant, see Table 4-5. Nevertheless, it is an interesting insight that the qualitative assessment suggests that democracy, potentially has different effects on G% and L%.

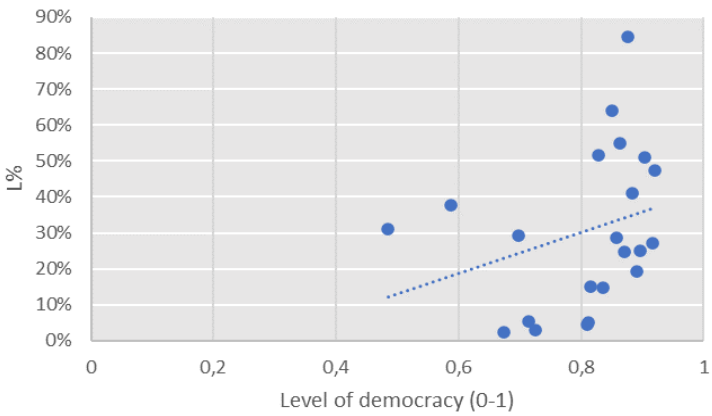


Figure 4-24. L% as a function of level of democracy

In Table 4-5 the regression analyses with L% as the dependent variable are summarised. None of the explored relationships are found to be statistically significant when using growth parameters from both models. However, when using logistic growth parameters, G% has a positive effect which indicates that diffusion can be both fast and deep. Moreover, when using growth parameters from Gompertz's function, electricity demand growth have a negative effect, suggesting that nuclear power has grown when the demand for its product has decreased which is a surprising finding.

Table 4-5. Summary of regression analysis with L% as the dependent variable

Independent variable	**Effect (Logistic)**	**Effect (Gompertz)**
GDP per capita	0.00000	0.00001
Y0	-0.011	-0.005
Electricity demand growth	-0.243	**-0.848***
Electricity supply	-0.001	-0.032
G%	**3.793****	1.856
Level of democracy	0.568	0.734

4.3.3 Regional differences

Figure 4-25 shows how L% is distributed in Western and non-Western countries. The distribution in the Western group is more right-skewed and thereby indicating that L% tends to be higher in this group. The same pattern is found in the central tendencies which show that Western countries have a higher median L% (34%) than non-Western countries (19%), see Appendix E.

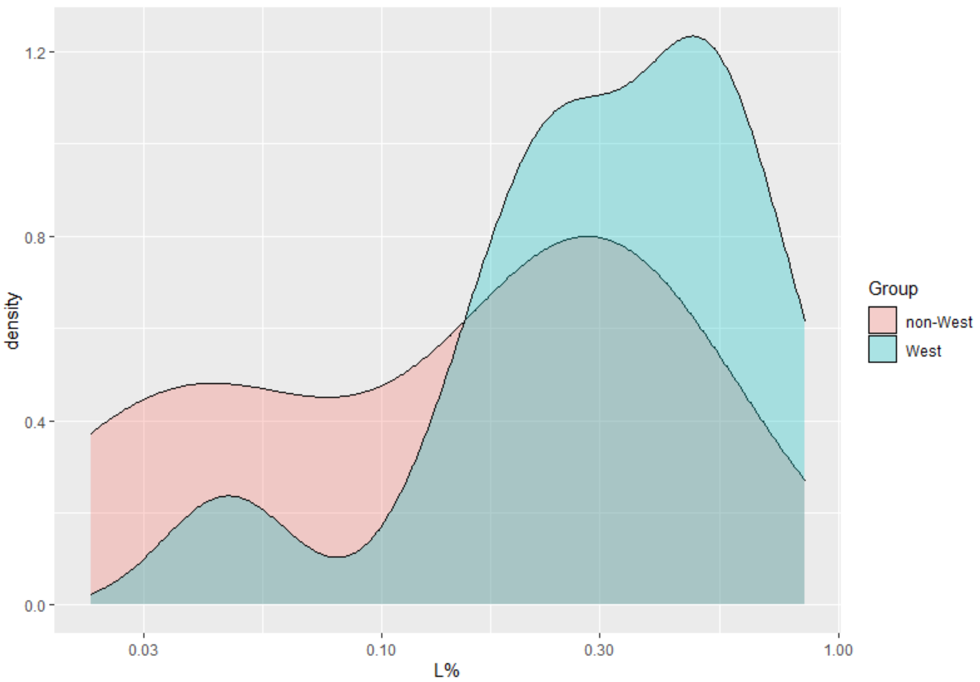


Figure 4-25. Density plot of the distribution of L% in the Western and non-Western groups

All previously explored relationships are also examined with Western and non-Western countries separated. In most cases, the result is similar. However, two relationships stand out and indicate that there are important differences in how Y0 and level of democracy affect L%.

As seen in Figure 4-26 it is indicated that in Western countries earlier Y0 associates with lower L% while the relationship is indicated to be the opposite in the non-Western group. This implies that factors such as technology learning have not benefitted diffusion in non-Western countries. These results could be a problem for reaching climate targets as emissions are expected to increase outside of Europe/North America in the future. Therefore, it is important that the diffusion of low-carbon technologies is deep, and increasingly so, globally. That being said, this relationship is not supported by regression analysis, see Appendix E.

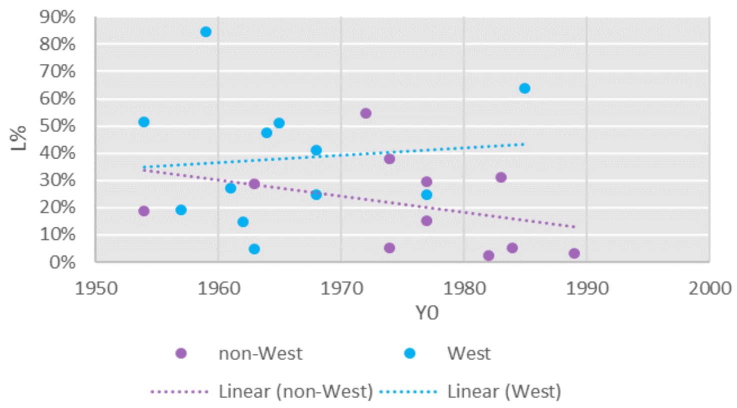


Figure 4-26. L% as a function of Y0 in the Western and non-Western groups

In Figure 4-27 it is furthermore seen that there are indications of higher levels of democracy being related to higher L% in Western countries. This relationship is however not confirmed in regression analysis and the support for democracy affecting nuclear power diffusion is therefore weak. Another finding from the plot is that the non-Western group is notably more dispersed in the level of democracy and thereby on average are less democratic (according to the index used in this thesis). That western countries tend to have higher levels of democracy can also explain why L% was indicated to be positively associated with democracy above. As western countries reach higher L% and higher levels of democracy, it is a logical effect that countries with high L% also tend to have higher democracy levels.

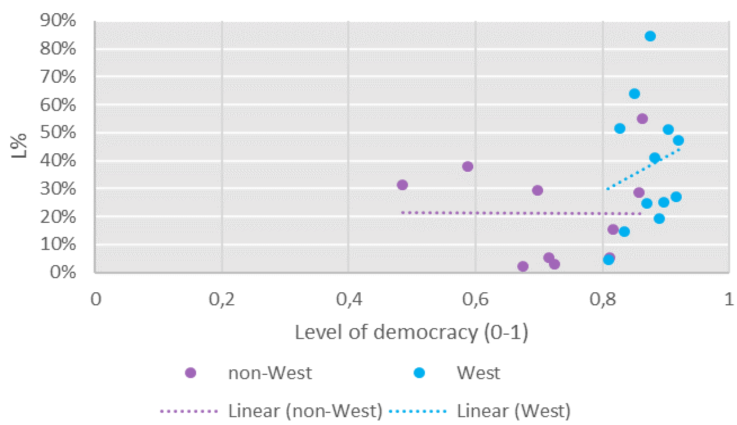


Figure 4-27. L% as a function of level of democracy in the Western and non-Western groups

4.4 Summary of the results

The results from the explored relationships are summarised in Table 4-6

Table 4-6. Explored hypothesis

Hypothesised relationship	**Expected effect**	**Supported/not supported**
GDP per capita and G	+	No
Y0 and G	-	No
Electricity supply and G	-	Yes
Electricity demand growth and G	+	No
dT and G	-	Yes
L and G	+	Partly
Y0 and Δ years	-	Yes
Democracy and G	-	No
Nuclear accidents and G	-	Partly
GDP per capita and L	+	No
Y0 and L	-	No
Electricity demand growth and L	+	No
Electricity supply and L	-	No
Democracy and L	-	No

Note: Yes means that the relationship holds in both the qualitative and quantitative analysis. No means that the relationship did not hold for either qualitative or quantitative or only in the qualitative analysis. Partly indicate that the quantitative analysis was inconclusive, i.e., statistical significance using growth parameters from only one of the models. Note that the effects of nuclear accidents and oil crises are not tested in regression analysis.

4.4.1 The rates of growth and ceiling for nuclear power (RQ1)

Table 4-7 summarises the answer to the first RQ. The global picture is quite heterogenous as some countries are estimated to continue to increase their growth rate for decades while others experience peak growth rates in the late 1970s. Notable is that the acceleration is mainly outside Europe and OECD. When comparing the growth of nuclear power to other, more granular, low-carbon technologies, Figure 4-2, nuclear power is notably less dispersed but in general at a higher level. Furthermore, it is found that nuclear power growth could be described using both a logistic and Gompertz function, meaning that diffusion could be both symmetrical and asymmetrical. Moreover, it was shown that most countries with the highest G% and L% had a total electricity supply at TMax of 100 TWh/year or less for G% and less than 200 TWh/year for L%, indicating that larger system size might constrain the highest growth rates and saturation levels.

Table 4-7. Summarized central tendencies of L%, G%, dT, and TMax for the stable and stalling group

	L%	**G%**	**dT**	**TMax**
Stable group				
Mean	37.8%	1%	55	1990
Median	50.1%	1.1%	58	1985
Stalling group				
Mean	27.5%	3.9%	15	1985
Median	27%	3.5%	15	1985
Both groups				
Mean	27%	3.4%	23	1985
Median	27%	2.8%	18	1985

4.4.2 Growth parameters and socio-economic characteristics (RQ2 & 4)

The results show that there are relatively few variables that aid in explaining variance in G% of nuclear power, see Table 4-6 for a summary. E.g., G% does not seem to be affected by whether a country is an early- or late adopter. Variables with effects being supported in both the quantitative and qualitative analysis are dT and electricity supply which both have a negative statistically significant effect on G%. That G% tends to be larger in countries with lower dT is a logical effect of G and dT being inversely proportional, see 3.3.3.

That electricity supply and G% correlates negatively means that nuclear power diffuses slower in larger systems. Given that emissions are expected to grow in larger systems such as China and India (IEA, 2020), these results could be a potential problem. To reach climate targets it is important that diffusion growth of low-carbon technologies is high in bigger systems as well.

It is also an important finding from this thesis that countries adopting nuclear power later (larger Y0) also tend to have shorter acceleration cycles. Moreover, the qualitative analysis indicated that countries with shorter acceleration cycles have higher G%. Combined, these findings imply that shorter acceleration cycles also might lead to higher G% which would be positive for low-carbon energy transitions. However, this was not confirmed by regression analysis. Therefore, no conclusive results are saying that mechanisms such as technology learning that usually benefits late adopters prevail over their lower GDP in the case of nuclear power.

Moreover, it was found that there are important differences between Western and non-Western countries in terms of G%.

First, both the qualitative and quantitative analysis indicated that GDP per capita is negatively related to G%. Thereby GDP per capita associate with lower levels of G% meaning that lumpy energy transitions can occur under less favourable financial conditions, which is positive for reaching climate targets globally.

Secondly, both the qualitative and quantitative analysis indicated that electricity demand growth was positively associated with G% in Western countries, but not in non-Western countries. That energy transitions in some socio-economic contexts need increasing energy demand could pose a challenge for reaching climate targets. However, since this relationship only was found in Western countries where electricity demand currently is stagnating, it might not be a problem.

In the distribution plots, it is furthermore indicated that Western countries tend to experience higher G%. This is also supported by the central tendencies which also show that the mean and median G% is higher in Western countries.

Lastly, the result does not provide conclusive answers to whether accidents have dampened the diffusion of nuclear power. While several countries experienced their respective TMax in the years following the TMI accident, this pattern was not particularly strong in the years following Chernobyl and Fukushima. On a similar note, the result does not present clear indications that the oil crises of the 1970s pushed nuclear power diffusion. On the one hand, several countries did reach TMax in the first half of the 1980s but on the other hand, many countries reached TMax more than ten years after the initial price surges.

Nevertheless, given that there are indications that accidents and oil crises have made a difference for nuclear power diffusion, one could argue that other large external shocks could push the diffusion of other low-carbon technologies as well. E.g., one could think that ambitious carbon taxes within the EU could have long-reaching and subversive effects on a global level.

4.4.3 RQ 3 & 4

None of the hypothesised relationships for L% are supported in both the qualitative and quantitative analysis, see Table 4-6.

What causes variability in L% is therefore hard to answer. However, when using growth parameters from the logistic model, there is a positive and statistically significant from G% on L% (the same regression, with L% as the independent variable, was also statistically significant). This suggests, although with less robustness, that when diffusion growth rates are high, diffusion is also deep which would be positive.

Similarly, the analysis does not provide conclusive answers to how the time of adopting affects L%. Globally, it appears that whether a country is an early- or late adopter does not affect L%. However, in the qualitative analysis, it was indicated that Y0 had a positive effect on L% (higher saturation for late adopters) in Western countries and a negative effect (lower saturation for late adopters) in non-Western countries. Lower L% for late adopters could be a problem for reaching climate targets. Given that lumpy low-carbon technologies are needed to reach climate targets, more countries likely need to adopt these technologies in the future as current max levels of L% are not sufficient. Therefore, it would be positive if L% was estimated to increase in countries adopting later. That being said, this relationship was not supported by regression analysis which indicates lower robustness.

Lastly, the distribution plots demonstrate that that western countries tend to reach higher L%. This is furthermore supported by the central tendencies that show that the mean and median L% is higher in Western countries which is a potential issue since saturation levels need to be high globally.

4.5 Robustness check

In the research design, it was mentioned that two primary measures are made to increase the reliability and robustness of the results: the use of logistic and Gompertz growth models as well as a comparison of generation and capacity data.

As discussed, when applying the generation data to the growth models, both perform similarly as the goodness of fit (RSS.Rel.) for the models is close to each other. This is an indication that the models themselves are robust.

The next step in the robustness check is to compare the output of the models when they are based on generation data to when they are based on capacity data. When using capacity data, G represents the max growth rate in electrical nuclear capacity from nuclear power plants. G is subsequently normalised to the total electrical capacity at TMax, the same procedure as for the generation data. Data on total electrical capacity is retrieved from IEA, (2021b) which contains relevant data for about half of the sample for the right years (TMax).

When using capacity data, the models provide a mean RSS.Rel. of 1.558 for the logistic model and 1.668 for the Gompertz model. The median RSS.Rel. is 1 for both models. Thus, the models yield similarly good fits. The logistic models are however indicated to be slightly better on average, which was also the case when generation data was used, further indicating the robustness of the models.

Central tendencies of G% based on capacity data are found in Appendix F.

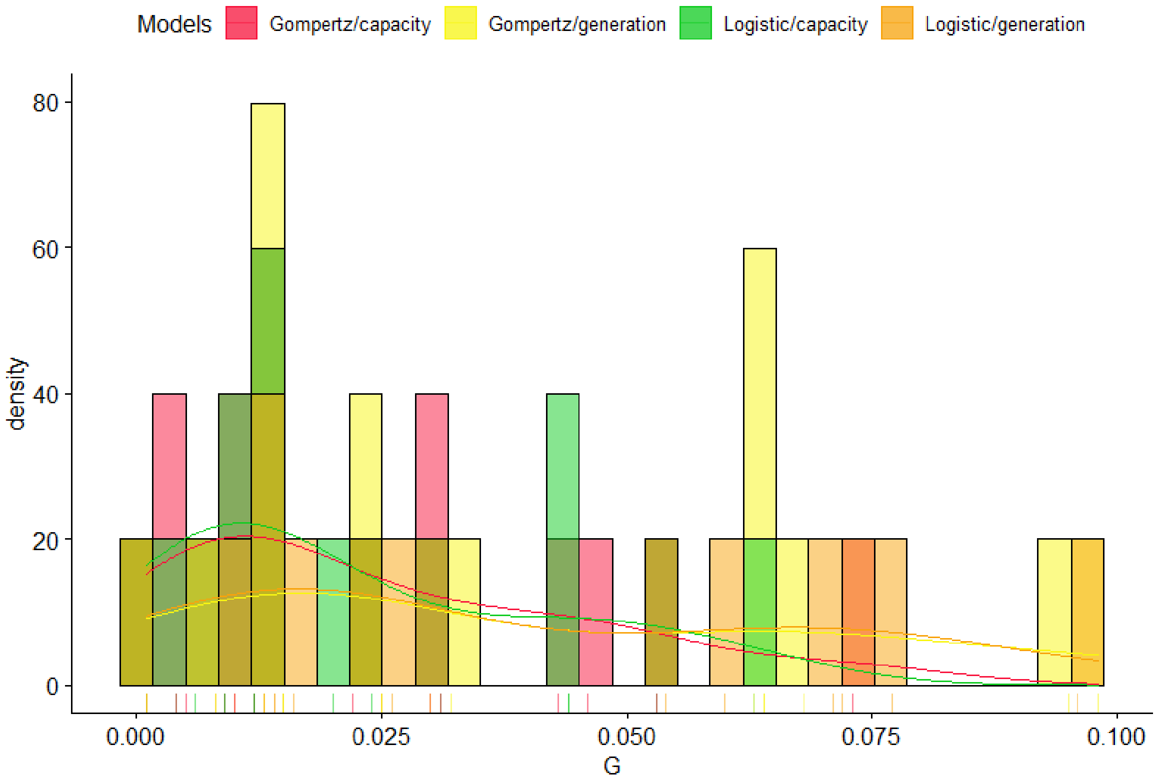


Figure 4-28. Density plot of the distribution of maximum growth rates (G%) of nuclear power. Growth parameters from the Gompertz model based on capacity data (red), the logistic model based on capacity data (yellow), Gompertz model based on generation data (green), the logistic model based on generation data (orange)

In *Figure 4-28*, G% from the logistic and the Gompertz models based on capacity and generation data is found. G% is indicated to be relatively robust as the models that are affiliated to the same group of data, follow each other well. Moreover, when comparing the patterns (the shape of the density lines) for the two groups of models, they are relatively similar. Although the models based on capacity data demonstrate that a larger proportion of the samples is located to the left on the X-axis, i.e., lower G%. All in all, it is indicated that G% based on capacity and generation data yields comparable results. This suggests that the analysis had provided a similar result if capacity data would have been used instead of generation data, which is encouraging.

That the two types of data appear to yield similar results is an interesting finding in itself and also provides an indication of robustness. However, there is no clear line between when results are robust and not robust. Given the limitations discussed in the research design, there are caveats with the study that is important for the interpretation of the result.

5 Discussion

This thesis combines insights from two areas of literature: technology diffusion and political economy of transitions, applied to the case of nuclear power. The thesis builds upon research made by Brutschin et al., (In Press) who used the same theoretical standpoint to explore the formative phase of nuclear power. More specifically this thesis explores the phases of diffusion beyond the initial formative phase, which is less understood, using a new metric to describe the growth of diffusion developed by Cherp et al., (In Press). In relation to previous research, this thesis provides additional insights on variables often described to be important for nuclear power diffusion in the literature. Furthermore, the thesis provides new insights into how diffusion can diverge in a heterogenous world as well as a comparison of growth rates of nuclear, solar, and wind power.

The discussion contains two main parts. First, the results are discussed in relation to what was previously known, one tested relationship at a time. Subsequently, the results are discussed considering the employed methods, the generalisability, and reliability of the results.

5.1 The results in relation to previous research

5.1.1 Growth characteristics of nuclear power (RQ1)

This thesis showed that logistic and Gompertz growth curves in general work well to describe nuclear power diffusion, adding to the list of studies that previously found this to be the case for other technologies (Cherp et al., In Press; Griliches, 1957; Grubler et al., 2016; Grübler, 1996; Marchetti & Nakicenovic, 1979).

This thesis further shows that global diffusion patterns are heterogenous but that most countries in the sample are either experiencing stable or stalling growth, see Table 4-1. Furthermore, countries still experiencing accelerating growth are outside of Europe (except for Romania) and OECD which is in line with Markard et al., (2020) who found this pattern for nuclear power and Cherp et al., (In Press) for wind and solar power. While low-carbon technologies were first introduced in Europe and OECD, the developments in these regions are now stagnating. A possible interpretation from the combined picture of these studies and this thesis is therefore that diffusion of low-carbon technologies in Europe and OECD countries needs to be reinvigorated. Moreover, the accelerated growth, mainly found in Asia (Cherp et al., In Press; Markard et al., 2020) must be maintained.

The median growth rates are 2.6% which is substantially higher than the same metric for wind and solar power (<1%) (Cherp et al., In Press), also see Figure 4-2. Therefore, this thesis suggests that nuclear power can grow faster than granular renewables, contrasting the findings from Wilson et al., (2020) and therefore potentially offset more carbon which contrasts the findings from Sovacool et al., (2020). These findings offer both opportunities and challenges. Opportunities in the development of current nuclear power plants have the potential to offer significant growth of low-carbon technologies. The challenges come with that nuclear power capacity is declining globally and the lead times of building new plants are decades long (Markard et al., 2020). There is therefore a risk that when nuclear power plants are being shut down, it will in practice be impossible to upscale capacity in time to reach climate targets.

However, that the empirics show that nuclear power might offer higher growth rates of low-carbon technologies compared with wind power and solar power does not necessarily mean that nuclear power is the "optimal" or most feasible technology. This thesis does e.g., not compare the cost per TWh of nuclear power and granular renewables. It is possible that technologies such as wind and solar power offer more low-carbon electricity at a lower cost which increases their feasibility of being widely diffused in the future. Furthermore, is that both wind and solar power are younger technologies, and it is plausible that their respective energy efficiency will be improved. The potential for improvements in energy efficiency for nuclear power is more uncertain as the R&D investments for conventional nuclear reactors are declining (Markard et al., 2020) and R&D investments for Small Modular Reactors are moderate (Cooper, 2014). Thus, there are more aspects than the highest observed growth rates that determine what technologies that are most suited to replace fossil fuels.

It was also demonstrated that the highest maximum growth rates were found in smaller systems. Five out of the six highest growth rates were found in countries with <100 TWh/year of total electricity supply. This is consistent with the result found in Cherp et al., (In Press) which also concluded that the biggest growth of solar and wind power took place in smaller systems (<100 TWh/year). This is an interesting finding since it implies that energy transitions often are faster in smaller systems which poses a challenge for bigger systems. Why growth is faster in smaller systems is hard to conclude. Potentially it is due to bigger heterogeneity between regions in larger countries making countrywide transitions harder. Possibly, energy transitions could be accelerated if the management and responsibility of the transition processes were decentralised in bigger systems, such as the USA.

5.1.2 Growth of nuclear power as a function of socio-economic and institutional characteristics (RQ2-4)

The results of the thesis are both supporting and contrasting the previous technology diffusion research. Two variables are found to be statistically significant for explaining variance in G% globally: dT and electricity supply which are both negatively associated with G%. Globally other variables either show weak or no signs of effect. Most notable is the absence of effect from GDP per capita and electricity demand growth on both G% and L%.

However, GDP per capita (negative) and electricity demand growth (positive) have statistically significant effects on G% and in Western countries.

GDP per capita

Several scholars have found that economic development operationalised through GDP per capita is more or less a condition for successful diffusion of both nuclear power (Brutschin et al., In review; Csereklyei et al., 2016; Fuhrmann, 2012; Jewell, 2011) and other technologies (Griliches, 1957). As discussed in the result chapter there are no indications based on the used sample and growth metric that the speed of diffusion of nuclear power is related to GDP development globally.

There are several possible reasons for the lack of effect from GDP. In the literature, it is also described that late adopters tend to experience faster diffusion as they e.g. benefit from technology learning and knowledge spill-overs (Grübler, 1996; Marchetti, 1983). Furthermore, it is also found that the late adopter group tends to be comprised of low-income and emerging economies (Grübler et al., 1999; Wilson, 2012) which was supported through regression analysis in this thesis. It might be that for nuclear power, the net effect of the benefits the late adopters reap, is "zeroed out" by the negative effect of their lack of financial resources.

Another potential reason is that nuclear power is a highly specialised technology that usually requires substantial government investment and political will. This means that it often does not compete on equal terms with other energy technologies. Therefore, it is possible that there are country-specific characteristics or demands, such as a will to become less dependent on imported energy, that make countries diffuse nuclear power.

Nevertheless, it was found that there is a small, but statistically significant, negative effect from GDP per capita on G% in Western countries, the opposite of previous technology diffusion research. Therefore, GDP appears to be constraining nuclear power diffusion, but only in some parts of the world. However, the Western group in general adopted nuclear power before the non-Western group, and therefore one interpretation could be that the potential negative effect of GDP has weakened over time.

Additionally, the results in this thesis showed that the levels of G% on average are higher in Western countries. However, the distribution for the non-Western group is relatively dispersed with some non-Western countries also reaching high G%. This together with GDP not being important in non-Western countries, points to that it is possible to reach high G% without large financial resources. However, when separating the sample into a Western and non-Western group it is found that L%, in general, is higher in the Western group. This builds upon previous findings from Comin & Mestieri, (2018) who find that saturation levels are increasingly diverging between countries. It also indicates that it is not necessarily the case that countries experience high G% and high L% (they were only found to correlate when using growth parameters from the logistic model).

Electricity demand growth

As discussed several studies concludes that electricity demand growth is important for explaining nuclear power diffusion (Brutschin et al., In review; Fuhrmann, 2012; Gourley & Stulberg, 2011; Jewell, 2011). However, the result in this study does not find any suggestions that electricity demand growth on a global level has an important explanatory value for G%. Nevertheless, it is plausible that electricity demand growth is imperative when a country decides to enter nuclear (Brutschin et al., In review), but not in the subsequent phases of diffusion. When separating the sample in a Western and non-Western group it is furthermore found that there is a positive correlation with G% in Western countries. These results are both interesting and useful as it implies that it is possible to reach high diffusion growth rates of lumpy low-carbon technologies even if demand for its product is absent or declining. An absence of correlation could also potentially be due to nuclear power diffusion being driven by the will of becoming energy independent.

When using growth parameters from the Gompertz function there is a positive statistically significant effect from electricity demand growth on L% which thereby supports the transition literature mentioned above.

The time of adoption (Y0)

There was no clear indication that late adopters tend to experience neither lower G% nor lower L%. This is relatively surprising since scholars examining other technologies have found this relationship (Gosens et al., 2017; Grübler, 1996; Wilson, 2012). As mentioned above, it might be that the advantages are levelled by the disadvantages of adopting later in the case of nuclear power. Moreover, there were no clear indications that early adopters experience higher G% either which was one conclusion from Griliches, (1957). Later studies have also pointed to that the relationship between the time of adoption and growth can diverge between technologies. Cherp et al., (In Press) who also utilises the same G metric as in this thesis find support for Griliches, (1957) in the case of solar but not for wind power.

The combined picture of these studies is that it is likely that the significance of the time of adoption varies between technologies which would be an important contribution of this thesis. Furthermore, one can discuss what it is that causes early-adopters of new corn varieties (Griliches, 1957) and solar power (Cherp et al., In Press) having an advantage over late-adopters while the relationship is the opposite for many other technologies (Gosens et al., 2017; Grübler, 1996; Wilson, 2012). Some potential explanations could be that practitioners within certain industries are less inclined to spread their knowledge or that investment cost does not decrease over time (no economy of scale on a global level) which partly has been the case for nuclear power (Markard et al., 2020). However, more research is needed to confirm or reject these speculations.

The time of adoption does not appear to affect either growth rates or saturation levels. Thus, in the case of nuclear power mechanisms such as technology learning might be less important. Nevertheless, it was indicated that Y0 has a negative effect on ΔY (adopting nuclear power early associate with reaching the inflection point with maximum growth rate faster). In essence, it means that late adopters reach the maximum growth rate in a shorter time and subsequently approach their upper asymptote faster (note that reaching the inflection point faster does not mean that G% or L% are higher). This is in line with Comin & Mestieri, (2018) who find that in speed, but not the depth of technology diffusion has increased over time. Cherp et al., (In Press) that analysed wind and solar power also find that late adopters tend to have shorter acceleration cycles but not higher G%. That the acceleration cycles are increasingly shorter while growth rates are not increasing over time, point to a potential challenge if new low-carbon technologies are going to aid the international community to reach climate targets. A short duration of transition is not enough if the growth of generated Wh does not follow the same pattern.

However, the qualitative analysis demonstrated that there are countries that have both short acceleration cycles and higher G%. While this was not confirmed in the regression analysis, it indicates that it is possible to combine swift and deep diffusion cycles.

Democracy

Moreover, the results show no indication that the level of democracy is an important explanatory value for G% or L%. As discussed in section 2, several studies concluded that more democratic countries were less inclined to adopt nuclear power with the most recent example of Neumann et al., (2020). Nevertheless, others have not found any statistically significant effect from regime type, the most recent example being Brutschin et al., (In Press). This thereby indicates that low-carbon energy transitions can be fostered independent of regime type. It is however important to keep in mind that some of the omitted countries such as Iran, Russia, United Arab Emirates, and Belarus potentially could have changed the outcome of this examined relationship, at least for the non-Western group.

Electricity supply

The negative correlation between electricity supply and G% means that growth (in relative terms) is slower in larger countries. This is further highlighted by that the highest levels of G% are found in small systems (<100 TWh/year) similar to the findings of Cherp et al., (In Press). Larger countries are to a greater extent inclined to have heterogeneous socio-economic and geographic characteristics, making nuclear power less attractive in certain regions. E.g., some parts of a large country might have sizable coal supplies, low population density, or high hydropower capacity making nuclear power redundant.

One could furthermore think that due to economy of scales, the cost per Wh is lower in larger systems which, for nuclear power, likely would yield increased competition from cheaper renewables. Therefore, it is possible that the relationship between electricity supply and G% indicates that nuclear power is sensitive to competing energy technologies and that investments are abandoned in favour of technologies with lower up-front costs. A similar point is made by Markard et al., (2020) who argue that competition from granular and cheaper (at least the initial investment) renewables likely is one of the biggest threats to nuclear power diffusion. For technologies to persist they need to stay competitive which is an important insight for other low-carbon energy transitions.

Nevertheless, the electricity supply is not found to explain variance in L%. This means that countries with high growth do not necessarily have high saturation levels and vice versa. Ultimately, that G% and L% are not dependent on the same variables says that there are different mechanisms behind growth and saturation, which is an important finding.

Nuclear accidents and oil crises

One of the more distinguishable features of nuclear power is the perceived risk of accidents. Just as the literature, the result of this thesis does not provide conclusive answers to whether accidents have affected the growth and saturation of nuclear diffusion. Since there have only been three major accidents, establishing inferences is difficult. While there are indications that the TMI accident is associated with several countries reaching their respective TMax, the trend is not as strong for the other accidents. The inconclusive result is reflecting the literature on the subject as several scholars have argued that accidents have stalled nuclear power diffusion (Fuhrmann, 2012; Gourley & Stulberg, 2011) while others have not found accidents to be statistically significant (Brutschin et al., In review; Csereklyei et al., 2016).

The case is similar for the oil crises. Several countries reached TMax within the first half of the 1980s which could indicate that these countries expanded their nuclear capacity due to the oil crisis in the 1970s. These findings show some support to studies such as Csereklyei et al., (2016). However, many countries did not follow this pattern which is in line with Brutschin et al., (In review), who did not find a statistically significant effect from the oil crises on nuclear power diffusion.

5.1.3 Regional differences in maximum growth rates and saturation levels

Lastly, the results demonstrated that western countries experience higher growth rates, achieve them earlier and also end up at higher saturation levels compared with other countries. These results complement other technology diffusion studies as it provides an additional perspective on how diffusion can vary. While economic development and the time of adoption previously have been found to determine growth rates and saturation levels (Gosens et al., 2017; Grubler, 2012; Grubler et al., 2016) the Western non-Western perspective provide an additional perspective. Given that Western countries tend to have higher GDP, these findings also coincide with previously discussed Comin & Mestieri, (2018) that have found that saturation levels are increasingly diverging between countries due to economic development.

That growth rates and saturation levels are diverging is an important finding and emphasises the need to increase efforts to diffuse new low-carbon technologies worldwide.

5.2 Reflecting on the results of this study

5.2.1 Methodology and sensitivity

Several steps have been taken to improve the robustness of the results. The study uses two different growth models, compares generation and capacity data, and triangulates a qualitative and quantitative assessment. Nevertheless, there are several important notes to be made when interpreting the result of this thesis.

The sample used in RQ 2-4 is limited to only 23 countries which means that it is hard to establish robust inferences due to many independent variables. This could be an explanation of why there are some notable differences between the qualitative and the quantitative assessment. One example is GDP per capita and L% where the trendline is relatively steep and indicates a positive relationship (which as discussed would be in line with previous research), but the effect was not statistically significant in the regression analysis.

The size of the sample and population also influence how nuclear power diffusion can be compared to other new low-carbon technologies such as wind and solar power. In the introduction, it was explained that nuclear power is an appropriate case to study, partly due to data representing the whole diffusion cycle being available, which is not the case for many renewables. In the literature review, a paper from Sovacool et al., (2020) is discussed. The authors demonstrate statistically significant results, saying that renewables offset carbon emissions while the same relationship for nuclear power does not have a statistically significant effect. However, as mentioned, these comparisons could be questioned as a lack of statistically significant effects potentially are due to the smaller sample and population of nuclear power (Fell et al., 2021; Perez, 2021).

This is can be further exemplified by Cherp et al., (In Press) that among other variables, found that electricity demand growth is associated with higher growth of wind and solar power. A relationship that was not found to be statistically significant in this thesis. However, that these studies indicate different results, does not conclude that electricity demand is important for renewables but not for nuclear. By using a larger sample and/or more refined statistical analysis, it might be that these variables are important for nuclear power as well.

Moreover, there are always alternative ways to operationalise the variables of interest. In this thesis, a lot of focus has been put on economic development and electricity demand growth as independent variables. Respectively operationalised through GDP per capita and the increase of electricity consumption the five years preceding TMax. Even though these are operationalizations used in other studies it could be argued that other metrics are more suitable to represent the variables of interest. Economic development can be measured the same way as for electricity demand growth (percentage increase over time), and electricity demand growth can be measured as increased electricity consumption during ΔY (the number of years going from grid connection to TMax).

One could also discuss the normalisation of L. In the thesis, L is normalised to the electricity supply, the year when the last empirical observation was made (which is the last year of increased electricity generation). Therefore, in cases where growth is expected to be stagnating after the year of the last observation, the electricity supply could be larger than the saturation level, hence yielding L% >100%, which might skew the results. Thus, there could be other ways to normalise saturation. This is more of an issue for the Gompertz model which tends to have an extended curve after the inflection point whereas the logistic curve is symmetrical.

In this thesis early adopters have been operationalised as the year the first reactors were connected to the grid. While this a valid way to look at adoption, other studies such as Cherp et al., (In Press) have instead used a so-called takeoff year which is defined as when the technology comprises at least 1% of the electricity supply. In this way, only years with a substantial contribution from the studied technology are included. However, for the case of nuclear this issue is not as big compared to when studying more granular technologies. Cherp et al., (In Press) study wind power and solar power which could start at very low levels and requiring a few years until they comprise at least 1% of the electricity supply. In the sample used in this thesis, most countries experienced substantial growth in their electricity generation immediately after they adopted the technology.

There are other aspects of the time of adoption that influence the results. Countries such as Belarus and the United Arab Emirates, which connected their first reactor to the grid after the last empirical observations were made are not included. Even if data were available for these countries, modelling would not be possible due to the short time-series. Nevertheless, it might be the case that in a decade from now when data from these countries are available the trendline will be different.

Another important aspect that is important to remember is that individual countries within the USSR are not included due to data availability. The whole USSR is however included. This also has the unfortunate effect that Russia, one of the cores in the international nuclear power regime (Jewell et al., 2019) is not included in the analysis. Moreover, is that most of the countries omitted due to data availability are non-Western countries which could create an underrepresentation of this group. E.g., China and India are omitted as G cannot be normalised as the rest of the sample, and Iran is omitted due to only having one reactor.

5.2.2 Validity and generalisability of the results

The RQs in this thesis are relevant as the need for wide and rapid transitions is abundant. As this thesis is the first study of nuclear power using the newly developed growth curves modelling and the G metric, the quantitative findings would benefit from further examination. It is e.g., important to see whether found inferences hold when relevant control variables are included.

The results addressing variance in growth and saturation of this thesis are likely more relevant for the diffusion of big and "lumpy" low-carbon technologies that require substantial investments and resources to deploy. Nevertheless, the thesis includes a wide sample and therefore advances our understandings of diffusion in a heterogeneous world, increasing generalisability across countries and socio-economic contexts. That said, more research is needed to fully understand the dynamics of socio-economic factors and their effect on nuclear power diffusion. There are of course more nuances of socio-economic factors than are explored in this thesis.

6 Conclusions

In this section, the purpose and main findings of the thesis are summarised for a non-academic audience. The answers to each research question are provided separately. This is followed by suggestions for further research and recommendations for policymakers and advocacy organisations.

6.1 Summary for a non-academic audience

In order to reach climate targets, there is an increasing need to speed up energy transitions towards low-carbon technologies. Large-scale transitions would likely require the use of lumpy energy technologies such as nuclear power.

The historical study of how technologies have spread across time and space is known as the technology diffusion literature. Lately, scholars within this field have turned their attention to climate change and how we can learn from history to model and project the spread of low-carbon technologies. One of the more recent contributions to this scholarship comes from economics and political science that provide insight into how socio-economic characteristics (e.g., economic development and regime type) can shape how society accepts or rejects new technologies.

This thesis advances the knowledge on the diffusion of low-carbon technologies by bridging these research fields and apply their respective theoretical and conceptual understanding of technology diffusion in the case of nuclear power. Nuclear power is a unique technology that has diffused globally but it is now experiencing decline and therefore offers time-series data from the whole life cycle of the technology. By fitting empirical observations of electricity generation to growth curves, dependent variables representing growth and saturation are estimated and used in qualitative and quantitative analysis. The thesis shows that there are distinct variances in nuclear power growth globally, meaning that there is a great deal of lessons to be learned from the case of nuclear power.

The following research questions are addressed:

RQ1: What are the maximum growth rates and saturation levels of nuclear power and how do they vary across countries?

RQ2: What factors explain variability in the diffusion growth rate of nuclear power?

RQ3: What factors explain the ceiling/saturation of nuclear power use?

RQ4: What happens to the speed and depth of nuclear power diffusion in late adopter markets?

6.1.1 The maximum growth rates and saturation levels (RQ1)

Table 6-1 summarises the key growth metric for the growth types stable and stalling. When combined, the median growth rates, normalised to the total electricity supply the year they were reached, are 2.8%. This is substantially higher than wind and solar power that both had maximum growth rates of less than 1% (Cherp et al., In Press), see Figure 4-2, which indicates that nuclear power can grow faster, and therefore replace more coal than granular renewables. The highest growth rates are ranging between 7% and 10% and are generally found in Europe. Western countries in general have higher growth rates. Moreover, it is found that most of the highest growth rates are found in countries with a total electricity supply of 100 TWh/year or less. It is also found that most of the countries in the sample are experiencing stable or stalling growth and only four of 29 countries have accelerating growth trajectories. The accelerating countries are China, India, Pakistan, and Romania, all outside of OECD.

The median saturation levels normalised to the total electricity supply the year the last observation was made are ranging between 29% and 26% depending on the growth model and are generally found in Europe. Similar to the case with growth rates it is found that most of the highest saturation levels are found in countries with lower total electricity supply, 200 TWh/year or less. Moreover, it is showed that in general, Western countries have higher saturation levels.

Table 6-1. Mean and median values of key growth parameters (from the logistic model) in the stable and stalling group

	L%	G%	dT	TMax
Stable group				
Mean	32%	0.8%	48	1994
Median	34.3%	1%	52	1991
Stalling group				
Mean	27.5%	3.9%	15	1985
Median	26%	3.3%	16	1984
Both groups				
Mean	29%	3.3%	23	1987
Median	26%	2.6%	18	1985

6.1.2 Factors explaining variability in maximum growth rates (RQ2)

It is a generally held position, dating back to the work of Zvi Griliches, (1957), that socio-economic factors such as electricity demand growth and GDP determines the faith of energy technologies. However, the result from this thesis does not find any strong support for these theories for the growth phase in the case of nuclear power. Instead, it is found that an increasing electricity supply has a negative and statistically significant effect on growth rates.

When the total size of the system increases, nuclear power is not able to sustain its growth indicating that energy transitions are faster in smaller systems. The reason for this correlation is hard to establish. However, one could argue that as larger countries, in general, are more geographically heterogeneous, there are more regions with e.g., large supplies of coal where nuclear power is less attractive.

It was also found in regression analysis that countries that adopted nuclear power later reached their maximum growth rate faster. Moreover, the qualitative analysis pointed to that shorter acceleration cycles associated with higher maximum growth. In essence, the results indicate, although not statistically confirmed, that when transitions are fast in terms of time, they could also be rapid in terms of growth of Wh.

Additionally, the thesis shows that there are distinct regional differences in growth patterns as it is indicated that GDP per capita has a negative effect while electricity demand growth has a positive effect on diffusion growth in Western countries (both statistically significant). Since the Western group in general adopted nuclear power before their non-Western counterparts, one could see it as a sign of the effects from GDP and electricity demand have become weaker over time.

Furthermore, the result shows that Western countries in general both experience higher maximum growth rates and achieved those growth rates earlier compared with other countries. This finding, together with Table 6-1, shows that the growth of nuclear power diffusion is not globally homogenous. As growth needs to be high and sustained globally more attention is needed in groups where growth rates are lower.

6.1.3 Factors explaining variability in saturation levels (RQ3)

None of the explored independent variables are found to have a statistically significant effect on saturation levels when using growth parameters from both models.

The qualitative analysis however indicated that the year of connecting the first reactor to the grid, the level of democracy, and electricity demand growth, all affect the two groups differently. Although a statistically significant effect is not found for these variables, it might be due to the small size of the sample, or that effects could be discovered through more sophisticated statistical analysis.

Additionally, it is also found that saturation levels are generally higher in Western countries than in the rest of the world. As for growth, saturation levels must be high globally. Specific consideration should therefore be taken to countries and regions where saturation levels are low.

6.1.4 What happens to growth rates and saturation levels in late adopting markets (RQ4)

Lastly, one of the main findings of this thesis is that the year when the first nuclear reactor was connected to the grid does not seem to affect either growth rates or saturation levels globally. This points to that diffusion of new lumpy low-carbon technologies can be swift and deep in both early and late adopting markets, which is positive since it implies that all countries, all other aspects held equal, can change their energy systems.

6.2 Recommendations for future research

This thesis has been one of the first steps in exploring the later phases (growth and saturation) of the diffusion cycle of nuclear power, using a combination of theories from the technology diffusion and political economy of transitions literature. Previous research has either not controlled for the different phases of diffusion or not examined nuclear power diffusion with global samples, and therefore not accounted for different socio-economic characteristics.

Further research could focus on deepening the analysis by multivariate regressions, including relevant control variables as well as testing different operationalisations of key variables such as electricity demand growth and economic development. Similarly, there is room for qualitative case studies that could examine whether the found inferences in this thesis are causally related.

This thesis suggests that nuclear power has reached higher growth rates than wind and solar power which suggests that nuclear power can replace more fossil-based energy technologies than granular renewables. However as mentioned, there are more aspects that determine the feasibility of diffusion of energy technologies than observed growth rates. Future research could therefore e.g., compare the cost per TWh generated for different low-carbon technologies, to see which technology offers the most low-carbon electricity at the lowest price.

This thesis takes initial steps in trying to understand how socio-economic characteristics in a heterogenous world affect the growth of nuclear power by looking at differences in the subsamples of Western and non-Western countries. While this division of the sample provides interesting insights, there is a lot of heterogeneity within these groups. Therefore, there is a wide array of other national factors whose potential effect on nuclear power diffusion could be explored.

6.3 Policy recommendations

When compared to wind and solar power (Cherp et al., In Press) nuclear power is demonstrated to have substantially higher maximum growth rates. Despite more research is needed, the results indicate that nuclear power is capable to grow faster than granular renewables and thereby potentially offer more low-carbon energy. Given that the capacity of nuclear power is in decline (Markard et al., 2020) policymakers should be aware of the potentials of nuclear power before shutting down reactors. As the lead times for building new reactors often are decades, not maintaining the current fleet of reactors, might make future growth impossible in practice.

In the literature, economic development and energy demand are often referred to as vital for a successful diffusion of nuclear power and other energy technologies. Furthermore, it is often seen that early adoption associate with higher saturation levels. However, the result of this thesis shows that this is not necessarily the case. An important takeaway for policymakers and advocacy organisations is therefore that energy transitions are possible even for latecomers, those with limited resources, and countries experiencing stagnating energy demand.

Lastly, it is important to acknowledge that the results demonstrate that a short duration of transitions, does not necessarily mean that growth rates and saturation levels are high. It is therefore imperative that policymakers and advocacy groups working with energy transitions, aim at keeping transitions fast in terms of time, but also fast in terms of growth rates. Additionally, short transition periods and high growth rates need to be combined with high saturation levels.

Bibliography

Alizada, N., Cole, R., Gastaldi, L., Grahn, S., Hellmeier, S., Kolvani, P., Lachapelle, J., Luhrmann, A., Maerz, S. F., Pillai, S., & Lindberg, S. I. (2021). *Autocratization Turns Viral. Democracy Report 2021*. University of Gothenburg: V-Dem Institute. https://www.v-dem.net/media/filer_public/74/8c/748c68ad-f224-4cd7-87f9-8794add5c60f/dr_2021_updated.pdf

Araújo, K. M. (2017). *Low carbon energy transitions: Turning points in national policy and innovation*. Oxford University Press.

Bazilian, M., & Coddington, K. (2020). *Carbon capture, utilization, and storage under the Paris Agreement*. IEA - Clean Coal Centre. https://www.iea-coal.org/carbon-capture-utilization-and-storage-under-the-paris-agreement/

Bento, N., Wilson, C., & Anadon, L. D. (2018). Time to get ready: Conceptualizing the temporal and spatial dynamics of formative phases for energy technologies. *Energy Policy*, *119*, 282–293. https://doi.org/10.1016/j.enpol.2018.04.015

Blaikie, N. W. H., & Priest, J. (2019). *Designing social research: The logic of anticipation.* (V-husets bibliotek LTH 300.72; Third Edition). Polity Press; Library catalogue (LUBcat). http://ludwig.lub.lu.se/login?url=https://search.ebscohost.com/login.aspx?direct=true&db=cat07147a&AN=lub.5366630&site=eds-live&scope=site

Brutschin, E., Cherp, A., & Jewell, J. (In review). *The diffusion of nucelar power limited by the availability of suitable markets*.

Cao, J., Cohen, A., Hansen, J., Lester, R., Peterson, P., Qvist, S. A., & Xu, H. jie. (2016). Nuclear power: Deployment speed—Response. *Science*, *354*(6316), 1112. https://doi.org/10.1126/science.aal2561

Cao, J., Cohen, A., Hansen, J., Lester, R., Peterson, P., & Xu, H. (2016). China-U.S. cooperation to advance nuclear power. *Science*, *353*(6299), 547. https://doi.org/10.1126/science.aaf7131

Cherp, A., Vinichenko, V., Jewell, J., Brutschin, E., & Sovacool, B. (2018). Integrating techno-economic, socio-technical and political perspectives on national energy transitions: A meta-theoretical framework. *Energy Research & Social Science*, *37*, 175–190. https://doi.org/10.1016/j.erss.2017.09.015

Cherp, A., Vinichenko, V., Jewell, J., Suzuki, M., & Antal, M. (2017). Comparing electricity transitions: A historical analysis of nuclear, wind and solar power in Germany and Japan. *Energy Policy*, *101*, 612–628. ScienceDirect.

Cherp, A., Vinichenko, V., Tosun, J., Gordon, J., & Jewell, J. (In Press). *Historical trajectories of solar and wind growth map a feasability space for 1.5 °C and 2°C pathways*.

Comin, D., & Mestieri, M. (2018). If Technology Has Arrived Everywhere, Why Has Income Diverged? *American Economic Journal: Macroeconomics*, *10*(3), 137–178. JSTOR Journals.

Cooper, M. (2014). Small modular reactors and the future of nuclear power in the United States. *Energy Research & Social Science*, *3*, 161–177. https://doi.org/10.1016/j.erss.2014.07.014

Coppedge, M., Gerring, J., Knutsen, C. H., Lindberg, S. I., Teorell, J., Nazifa Alizada, Altman, D., Bernhard, M., Cornell, A., Fish, S., Gastaldi, L., Gjerløw, H., Glynn, A., Hicken, A., Hindle, G., Ilchenko, N., Krusell, J., Luhrmann, A., Maerz, S. F., … Ziblatt, D. (2020). *Varieties of Democracy*. https://www.v-dem.net/en/data/data/v-dem-dataset-v111/

Cortinhas, C. (2012). *Statistics for Business and Economics.* (1st ed..). Chicester: Wiley Textbooks.

Csereklyei, Z., Thurner, P. W., Bauer, A., & Küchenhoff, H. (2016). The effect of economic growth, oil prices, and the benefits of reactor standardization: Duration of nuclear power plant construction revisited. *Energy Policy*, *91*, 49–59. ScienceDirect.

Dahlberg, S., Sundström, A., Holmberg, S., Rothstein, B., Pachon, N. A., & Cem Mert, D. (2021). *The Quality of Government Basic Dataset, version Jan21* [Database]. Http://Www.Qog.Pol.Gu.Se Doi:10.18157/Qogstdjan21. http://www.qog.pol.gu.se doi:10.18157/qogbasjan21

Davies, S. W., & Diaz-Rainey, I. (2011). The patterns of induced diffusion: Evidence from the international diffusion of wind energy. *Technological Forecasting & Social Change*, *78*(7), 1227–1241. ScienceDirect.

Dekimpe, M. G., Parker, P. M., & Sarvary, M. (1998). Staged estimation of international diffusion models: An application to global cellular telephone adoption. *The Emerging Role of Telecommunication*, *57*(1), 105–132. https://doi.org/10.1016/S0040-1625(97)00085-1

Dixon, R. (1980). Hybrid Corn Revisited. *Econometrica*, *48*(6), 1451–1461. JSTOR Journals. https://doi.org/10.2307/1912817

Fell, H., Gilbert, A., Jenkins, J., & Mildenberger, M. (2021). Reply to "Differences in carbon emissions reduction between countries pursuing renewable electricity versus nuclear power," by Sovacool et al.(2020). *Available at SSRN.*

Fouquet, R., & Pearson, P. (2012). Past and prospective energy transitions: Insights from history. *Energy Policy*, *50*, 1–7. https://doi.org/10.1016/j.enpol.2012.08.014

Fuhrmann, M. (2012). Splitting Atoms: Why Do Countries Build Nuclear Power Plants? *International Interactions*, *38*(1), 29–57. Political Science Complete.

Geels, F. W., Berkhout, F., & van Vuuren, D. P. (2016). Bridging analytical approaches for low-carbon transitions. *Nature Climate Change*, *6*(6), 576–583. Supplemental Index.

Gleditsch. (2002). *Expanded Trade and GDP Data*. http://ksgleditsch.com/exptradegdp.html

Gompertz, B. (1825). On the Nature of the Function Expressive of the Law of Human Mortality, and on a New Mode of Determining the Value of Life Contingencies. *Philosophical Transactions of the Royal Society of London*, *115*, 513–583. JSTOR.

Gosens, J., 1980, Hedenus, F., 1976, & Sandén, B., 1968. (2017). Faster market growth of wind and PV in late adopters due to global experience build-up. *Energy*, *131*, 267–278. SwePub. https://doi.org/10.1016/j.energy.2017.05.046

Gourley, B., & Stulberg, A. N. (2011). Correlates of Nuclear Energy: Back to the Future or Back to Basics? *Conference Papers -- International Studies Association*, 1–29. Political Science Complete.

Griliches, Z. (1957). Hybrid Corn: An Exploration in the Economics of Technological Change. *Econometrica*, *25*(4), 501. JSTOR Journals. https://doi.org/10.2307/1905380

Grubb, M., Drummond, P., & Hughes, N. (2020). *The shape and pace of change in the electricity transition: Sectoral dynamics and indicators of progress*. UCL, Institute for Sustainable

Resources. https://www.wemeanbusinesscoalition.org/wp-content/uploads/2020/10/Shape-and-Pace-of-Change-in-the-Electricity-Transition-1.pdf

Grübler, A. (1996). Time for a Change: On the Patterns of Diffusion of Innovation. *Daedalus*, *125*(3), 19. JSTOR Journals.

Grubler, A. (2012). Energy transitions research: Insights and cautionary tales. *Energy Policy*, *50*, 8–16. ScienceDirect.

Grübler, A., Nakićenović, N., & Victor, D. G. (1999a). Dynamics of energy technologies and global change. *Energy Policy*, *27*(5), 247–280. https://doi.org/10.1016/S0301-4215(98)00067-6

Grübler, A., Nakićenović, N., & Victor, D. G. (1999b). Dynamics of energy technologies and global change. *Energy Policy*, *27*(5), 247–280. https://doi.org/10.1016/S0301-4215(98)00067-6

Grubler, A., Wilson, C., & Nemet, G. (2016). Apples, oranges, and consistent comparisons of the temporal dynamics of energy transitions. *Energy Research & Social Science*, *22*, 18–25. https://doi.org/10.1016/j.erss.2016.08.015

Hägerstrand, Torsten. (1967). *Innovation diffusion as a spatial process*. University of Chicago Press; /z-wcorg/.

Hultman, N. E., Malone, E. L., Runci, P., Carlock, G., & Anderson, K. L. (2012). Factors in low-carbon energy transformations: Comparing nuclear and bioenergy in Brazil, Sweden, and the United States. *Energy Policy*, *40*, 131–146. ScienceDirect.

IEA. (2019). *Global Energy & CO2 Status Report 2019*. https://www.iea.org/reports/global-energy-co2-status-report-2019/emissions

IEA. (2020). *World Energy Outlook 2020*. https://www.iea.org/reports/world-energy-outlook-2020

IEA. (2021a). *'Extended world energy balances', IEA World Energy Statistics and Balances (database)*. https://doi-org.ezproxy.ub.gu.se/10.1787/data-00513-en

IEA. (2021b). *OECD - Net electrical capacity, IEA Electricity Information Statistics (database),*. https://www.oecd-ilibrary.org/content/data/data-00460-en

IEA. (2021c). *'World energy statistics', IEA World Energy Statistics and Balances (database)*. https://doi-org.ludwig.lub.lu.se/10.1787/data-00510-en

IPCC (Ed.). (2015). Technical Summary. In *Climate Change 2014: Mitigation of Climate Change: Working Group III Contribution to the IPCC Fifth Assessment Report* (pp. 33–108). Cambridge University Press; Cambridge Core. https://doi.org/10.1017/CBO9781107415416.006

IPCC. (2018). *IPCC, 2018: Global Warming of 1.5°C. An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change, sustainable development, and efforts to eradicate poverty*. https://www.ipcc.ch/sr15/download/

Iyer, G. C. (1, 2), Hultman, N. E. (1), Clarke, L. E. (2), Edmonds, J. A. (2), McJeon, H. C. (2), Flannery, B. P. (3), & Victor, D. G. (4). (2015). Improved representation of investment decisions in assessments of CO 2 mitigation. *Nature Climate Change*, *5*(5), 436–440. Scopus®. https://doi.org/10.1038/nclimate2553

Jaakkola, H. (1996). Comparison and analysis of diffusion models. In *Diffusion and adoption of information technology* (pp. 65–82). Springer.

Jacobsson, S., & Lauber, V. (2006). The politics and policy of energy system transformation—Explaining the German diffusion of renewable energy technology. *Energy Policy*, *34*(3), 256–276. https://doi.org/10.1016/j.enpol.2004.08.029

Jasper, J. (1992). Gods, Titans and mortals—Patterns of state involvement in nuclear development. *Energy Policy*, *20*(7), 653–653. https://doi.org/10.1016/0301-4215(92)90007-O

Jewell, J. (2011). Ready for nuclear energy?: An assessment of capacities and motivations for launching new national nuclear power programs. *Energy Policy*, *39*(3), 1041–1055. ScienceDirect.

Jewell, J., 1982, & Cherp, A. (2020). On the political feasibility of climate change mitigation pathways: Is it too late to keep warming below 1.5°C? *Analyzing Past and Future Energy Industry Contractions: Towards a Better Understanding of the Flip-Side of Energy Transitions WIREs Climate Change*, *11*(1). SwePub. https://doi.org/10.1002/wcc.621

Jewell, J., & Ates, S. A. (2015). Introducing nuclear power in Turkey: A historic state strategy and future prospects. *Energy Research & Social Science*, *10*, 273–282. ScienceDirect.

Jewell, J., Vetier, M., & Garcia-Cabrera, D. (2019). The international technological nuclear cooperation landscape: A new dataset and network analysis. *Energy Policy*, *128*, 838–852. https://doi.org/10.1016/j.enpol.2018.12.024

Kucharavy, D., & De Guio, R. (2011). Logistic substitution model and technological forecasting. *Procedia Engineering*, *9*, 402–416. ScienceDirect.

Lekvall, P., & Wahlbin, C. (1973). A Study of Some Assumptions Underlying Innovation Diffusion Functions. *The Swedish Journal of Economics*, *75*(4), 362–377. JSTOR Journals. https://doi.org/10.2307/3439146

Lovins, A. B., Palazzi, T., Laemel, R., & Goldfield, E. (2018). Relative deployment rates of renewable and nuclear power: A cautionary tale of two metrics. *Energy Research & Social Science*, *38*, 188–192.

Lund, P. D. (2015). Energy policy planning near grid parity using a price-driven technology penetration model. *Technological Forecasting & Social Change*, *90*(Part B), 389–399. ScienceDirect.

Marchetti, C. (1983). The automobile in a system context: The past 80 years and the next 20 years. *Technological Forecasting and Social Change*, *23*(1), 3–23. https://doi.org/10.1016/0040-1625(83)90068-9

Marchetti, C., & Nakicenovic, N. (1979). *The dynamics of energy systems and the logistic substitution model*.

Markard, J. (2018). The next phase of the energy transition and its implications for research and policy. *Nature Energy*, *3*(8), 628–633. https://doi.org/10.1038/s41560-018-0171-7

Markard, J. (2020). The life cycle of technological innovation systems. *Technological Forecasting and Social Change*, *153*, 119407. https://doi.org/10.1016/j.techfore.2018.07.045

Markard, J., Bento, N., Kittner, N., & Nuñez-Jimenez, A. (2020). Destined for decline? Examining nuclear energy from a technological innovation systems perspective. *Energy Research & Social Science*, *67*. ScienceDirect.

http://ludwig.lub.lu.se/login?url=https://search.ebscohost.com/login.aspx?direct=true&db=edselp&AN=S221462962030089X&site=eds-live&scope=site

Martino, J. P. (2003). A review of selected recent advances in technological forecasting. *Technological Forecasting & Social Change*, *70*(8), 719–733. ScienceDirect.

Menard, S. (2010). *Logistic Regression: From Introductory to Advanced Concepts and Applications*. SAGE Publications, Inc. https://doi.org/10.4135/9781483348964

Napp, T., Bernie, D., Thomas, R., Lowe, J., Hawkes, A., & Gambhir, A. (2017). Exploring the Feasibility of Low-Carbon Scenarios Using Historical Energy Transitions Analysis. *Energies (19961073)*, *10*(1), 116. Academic Search Complete.

Nash, J. C. (2014). *Nonlinear parameter optimization using R tools*. John Wiley & Sons.

Neumann, A., Sorge, L., von Hirschhausen, C., & Wealer, B. (2020). Democratic quality and nuclear power: Reviewing the global determinants for the introduction of nuclear energy in 166 countries. *Energy Research & Social Science*, *63*, 101389. https://doi.org/10.1016/j.erss.2019.101389

Perez, D. (2021). *On Sovacool's et al. Study on the differences in carbon emissions reduction between countries pursuing renewable electricity versus nuclear power*.

RDocumentation.lm. (n.d.). Rdocumentation.Org. Retrieved 15 March 2021, from https://www.rdocumentation.org/packages/stats/versions/3.6.2/topics/lm

RDocumentation.nls. (n.d.). Rdocumentation.Org. Retrieved 15 March 2021, from https://www.rdocumentation.org/packages/stats/versions/3.6.2/topics/nls

RDocumentation.nlsLM. (n.d.). Rdocumentation.Org. Retrieved 15 March 2021, from https://www.rdocumentation.org/packages/minpack.lm/versions/1.2-1/topics/nlsLM

Rogers, E. (2003). *Diffusion of innovations* (p. xxi).

Rosenberg, N. (1994). *Exploring the black box: Technology, economics and history*. Cambridge : Cambridge Univ. Press.

Sadorsky, P. (2009). Renewable energy consumption and income in emerging economies. *Energy Policy*, *37*(10), 4021–4028. ScienceDirect.

Skiti, T. (2020). Institutional entry barriers and spatial technology diffusion: Evidence from the broadband industry. *Strategic Management Journal*, *41*(7), 1336–1361. https://doi.org/10.1002/smj.3146

Sovacool, B. K. (2014). What are we doing here? Analyzing fifteen years of energy scholarship and proposing a social science research agenda. *Energy Research & Social Science*, *1*, 1–29. https://doi.org/10.1016/j.erss.2014.02.003

Sovacool, B. K. (2016). How long will it take? Conceptualizing the temporal dynamics of energy transitions. *Energy Transitions in Europe: Emerging Challenges, Innovative Approaches, and Possible Solutions*, *13*, 202–215. https://doi.org/10.1016/j.erss.2015.12.020

Sovacool, B. K., Schmid, P., Stirling, A., Walter, G., & MacKerron, G. (2020). Differences in carbon emissions reduction between countries pursuing renewable electricity versus nuclear power. *Nature Energy*, *5*(11), 928–935.

Sovacool, B. K., & Valentine, S. V. (2012). *The national politics of nuclear power: Economics, security, and governance*. Routledge.

Tsebelis, G. (1999). Veto players and law production in parliamentary democracies: An empirical analysis. *The American Political Science Review*, *93*(3), 591–608. https://doi.org/10.2307/2585576

Vieira, S., & Hoffmann, R. (1977). Comparison of the Logistic and the Gompertz Growth Functions Considering Additive and Multiplicative Error Terms. *Applied Statistics*, *26*, 143. https://doi.org/10.2307/2347021

Vinichenko, V. (2018). *Mechanisms of energy transitions: National cases and the worldwide uptake of wind and solar power.*

Wilson, C., Grubler, A., Bauer, N., Krey, V., & Riahi, K. (2013). Future capacity growth of energy technologies: Are scenarios consistent with historical evidence? *Climatic Change*, *118*(2), 381–395. Inspec.

Wilson, C, Grubler, A., Bento, N., Healey, S., De Stercke, S., & Zimm, C. (2020). Granular technologies to accelerate decarbonization. *Science (New York, N.Y.)*, *368*(6486), 36–39. MEDLINE. https://doi.org/10.1126/science.aaz8060

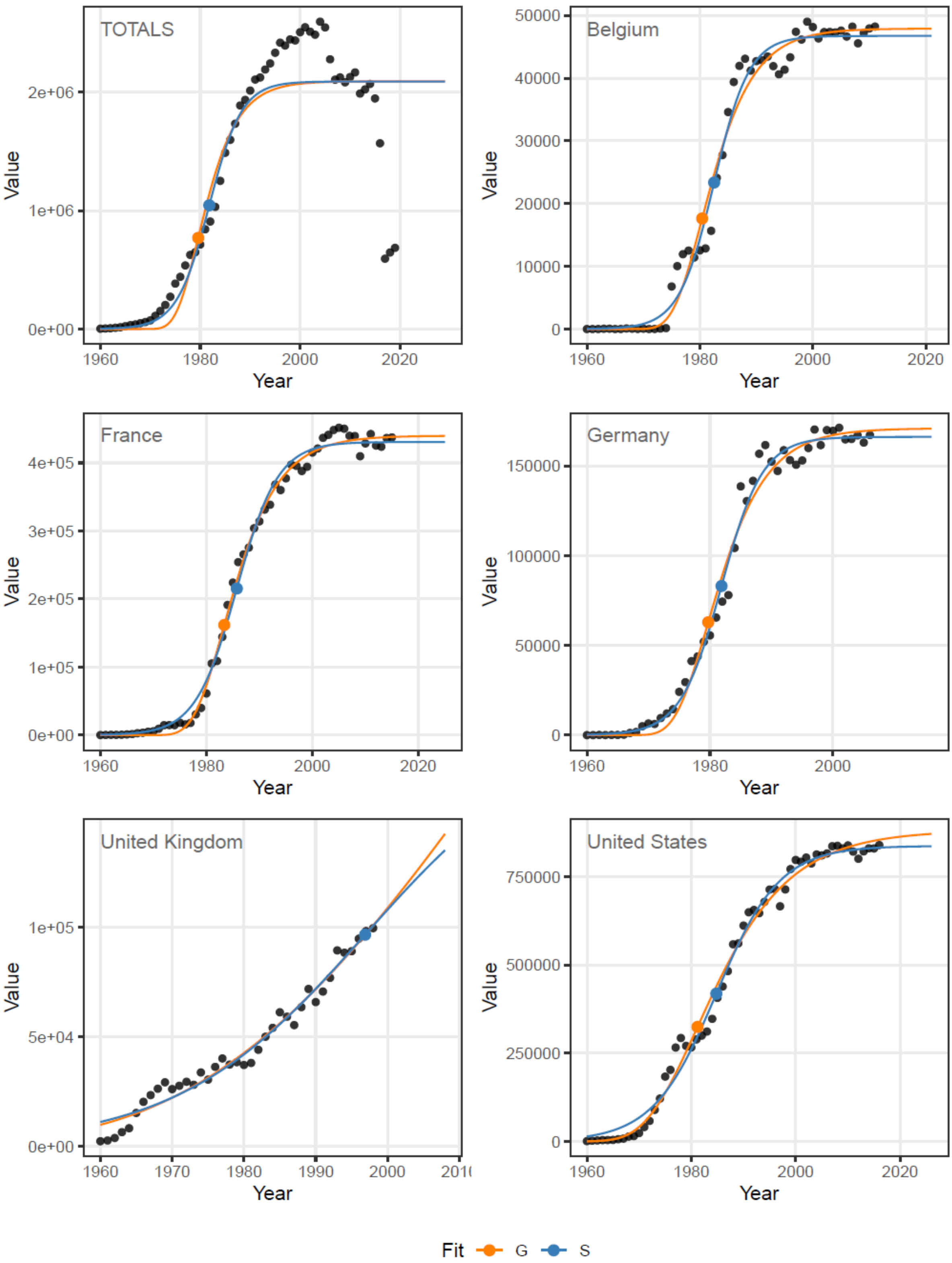
Wilson, Charlie. (2012). Up-scaling, formative phases, and learning in the historical diffusion of energy technologies. *Energy Policy*, *50*, 81–94. ScienceDirect.

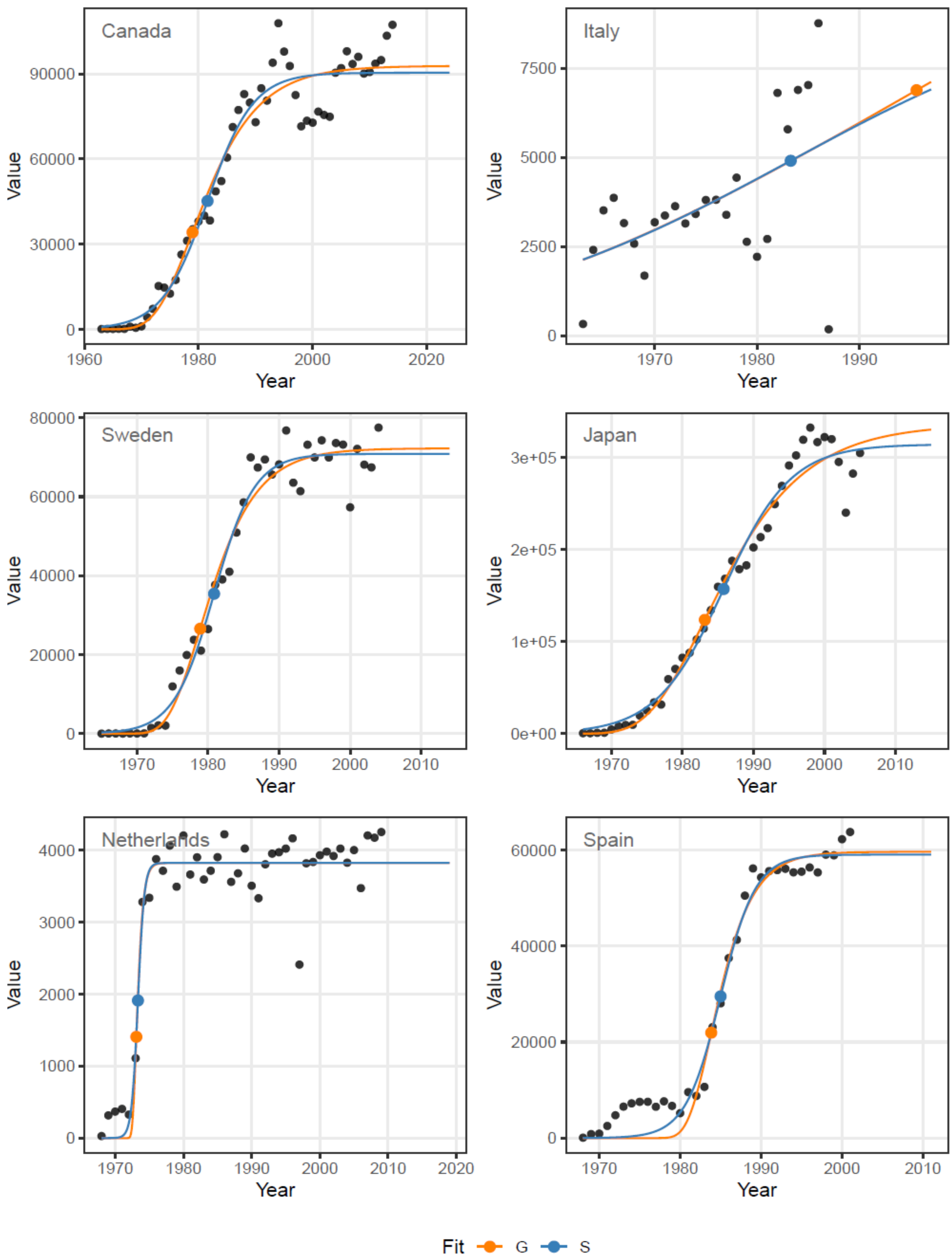
Wilson, Charlie, & Grubler, A. (2011). Lessons from the history of technological change for clean energy scenarios and policies. *Natural Resources Forum*, *35*(3), 165–184. https://doi.org/10.1111/j.1477-8947.2011.01386.x

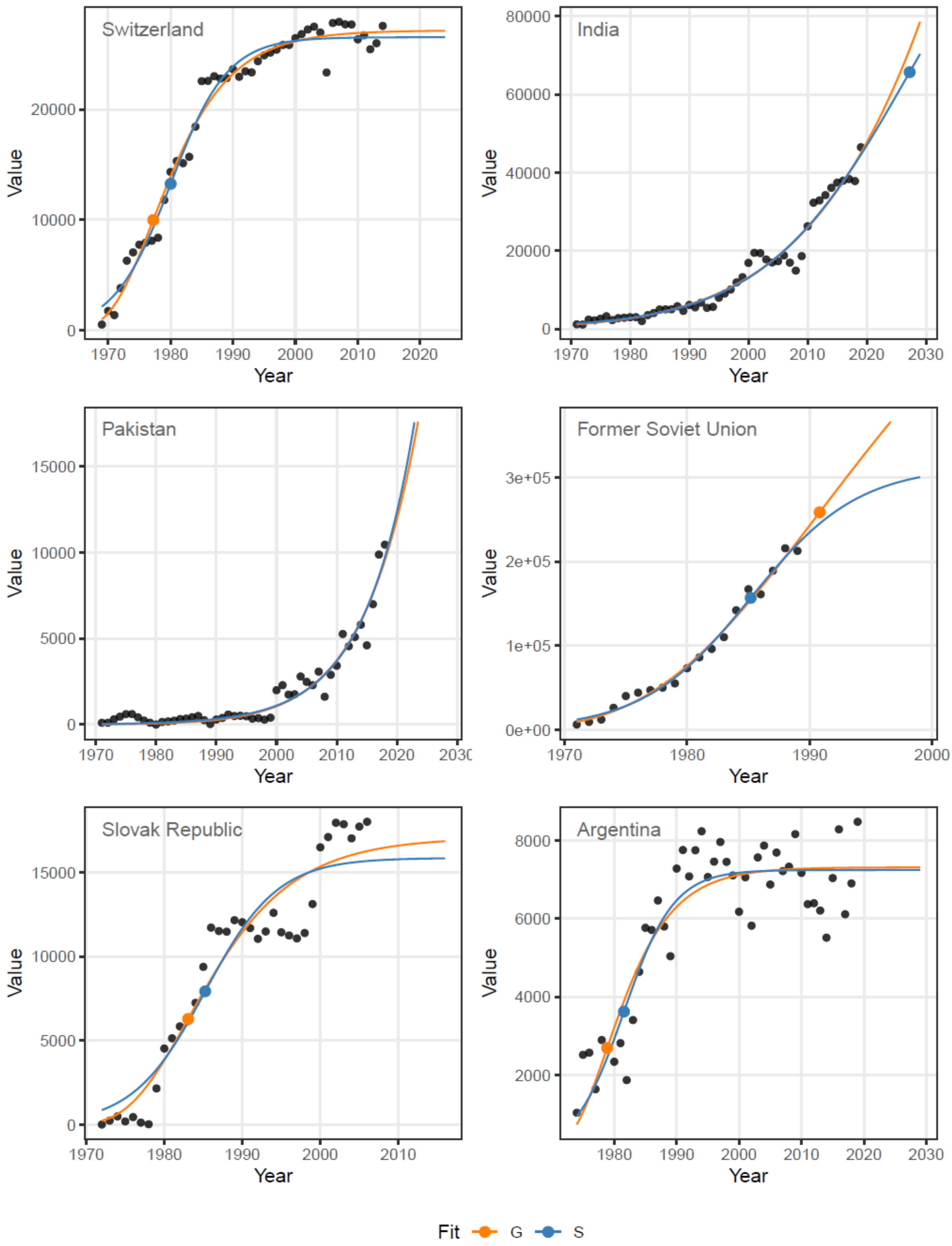
Winsor, C. P. (1932). The Gompertz curve as a growth curve. *Proceedings of the National Academy of Sciences of the United States of America*, *18*(1), 1.

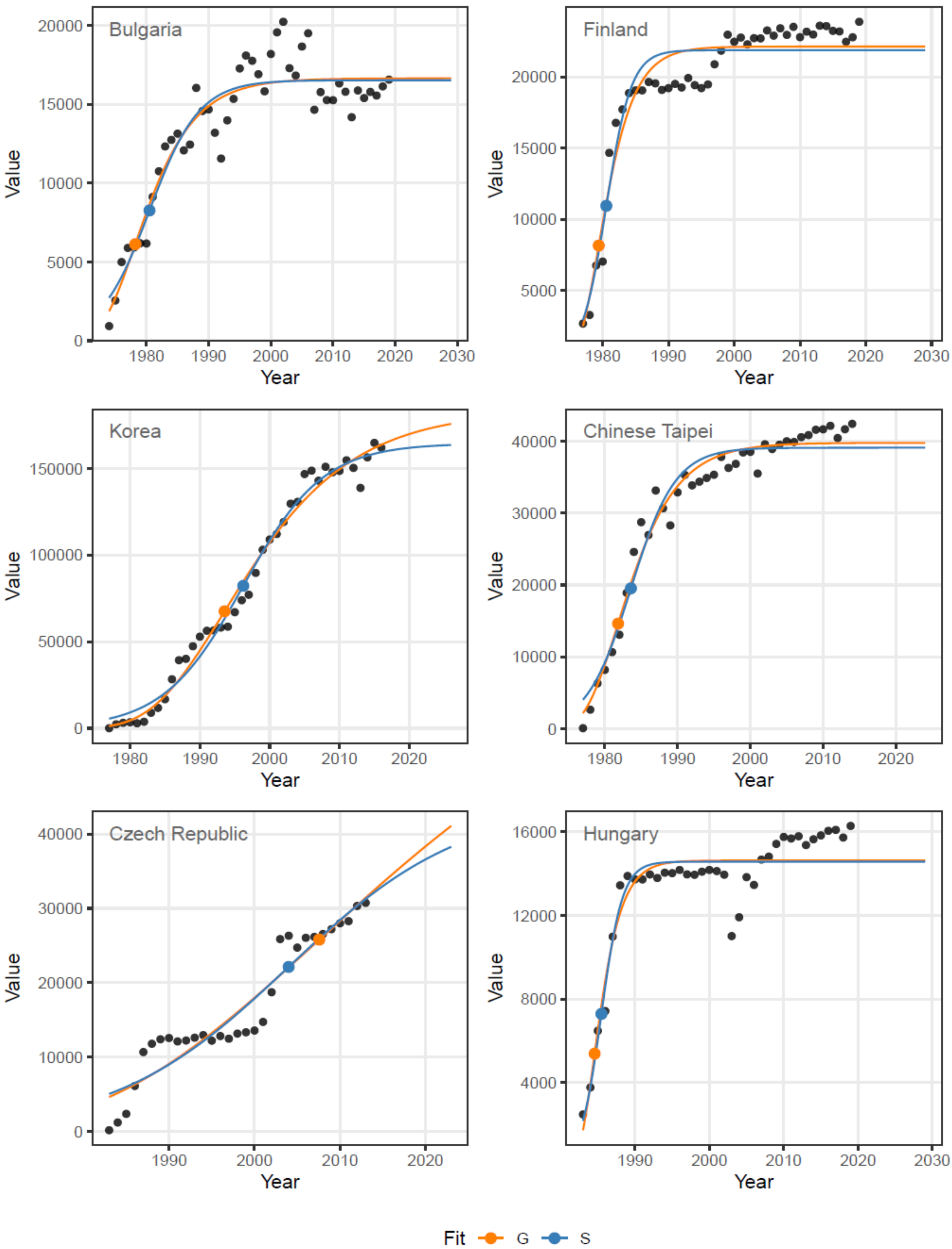
Appendix A

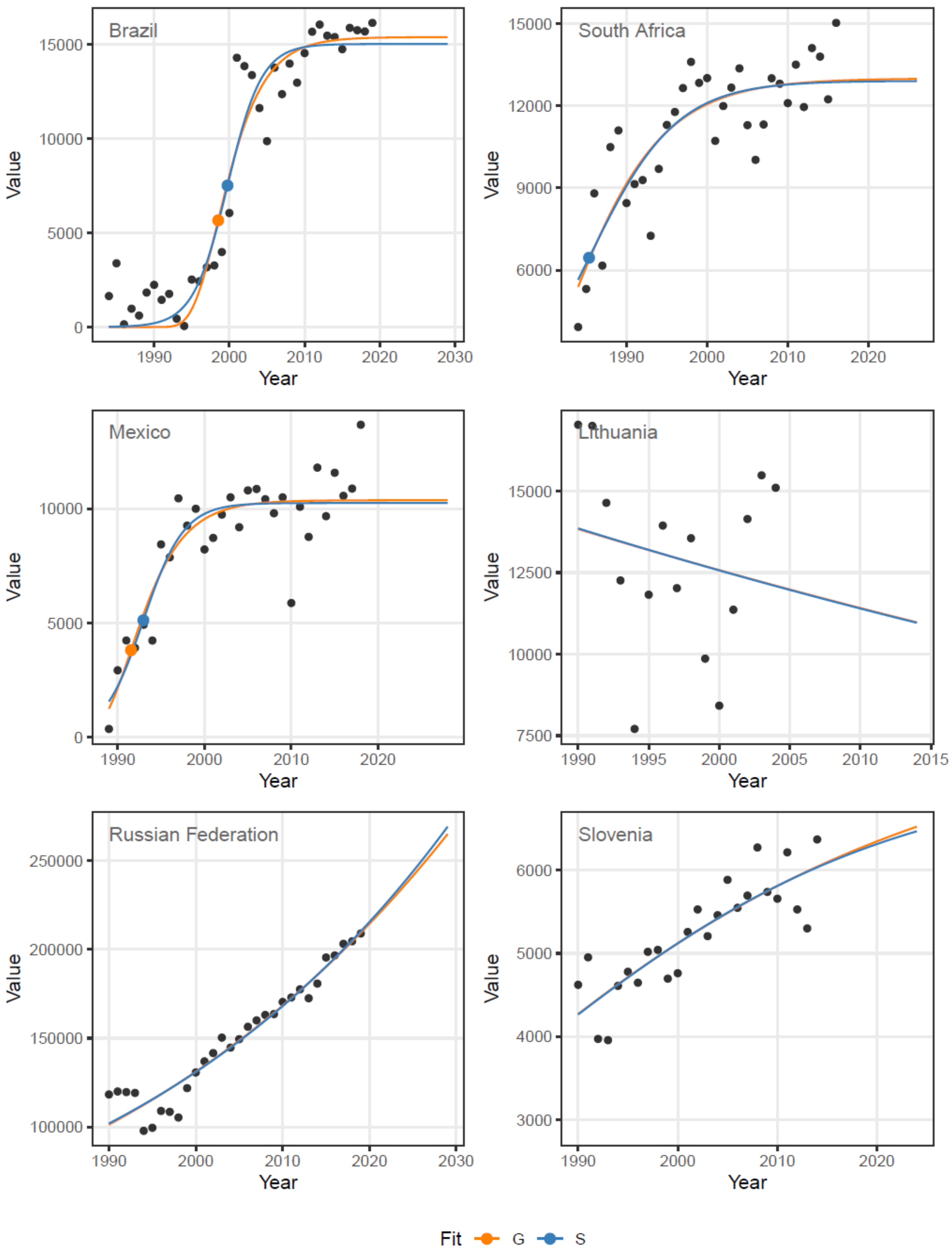
Growth curves for all countries

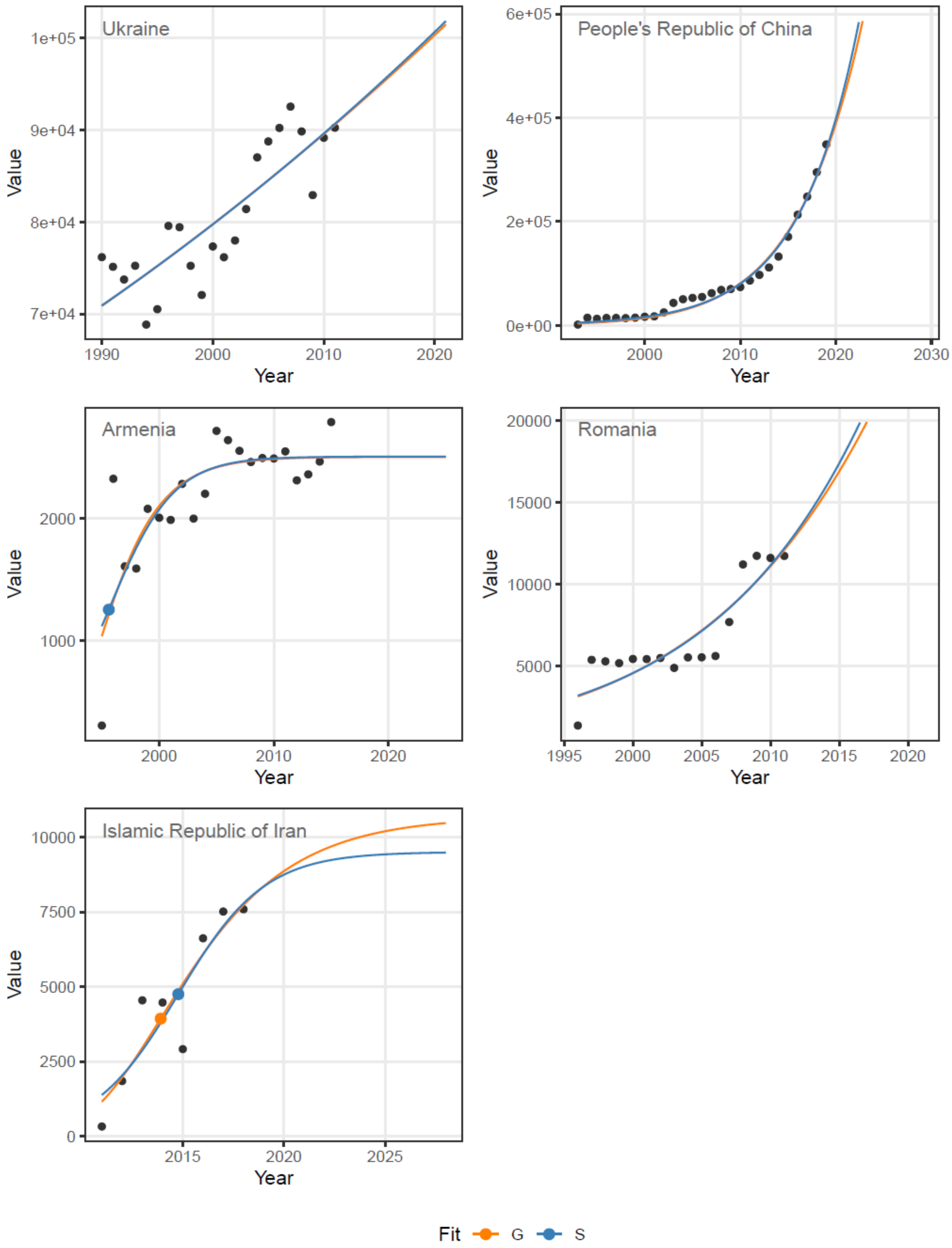



Canada
Value
Year
Italy
Sweden
Japan
Netherlands
Spain
Fit
G
S


Switzerland
India
Pakistan
Former Soviet Union
Slovak Republic
Argentina
Value
Year
Fit G S


Bulgaria
Finland
Korea
Chinese Taipei
Czech Republic
Hungary
Value
Year
Fit
G
S


Brazil
South Africa
Mexico
Lithuania
Russian Federation
Slovenia
Value
Year
Fit
G
S


Ukraine
1e+05
9e+04
8e+04
7e+04
1990
2000
2010
2020
Value
Year
People's Republic of China
6e+05
4e+05
2e+05
0e+00
2000
2010
2020
2030
Value
Year
Armenia
2000
1000
2000
2010
2020
Value
Year
Romania
20000
15000
10000
5000
1995
2000
2005
2010
2015
2020
Value
Year
Islamic Republic of Iran
10000
7500
5000
2500
0
2015
2020
2025
Value
Year
Fit
G
S

Appendix B

Mean and median growth parameters for the three growth types (logistic growth parameters)

Accelerating group							
	Y0	**L**	**TMax**	**dT**	**G%**	**Maturity**	**RSS.Rel**
Mean	1982	6988%	2058	42	-	9%	1
Median	1981	5591%	2059	42	-	0%	1
Stable group							
Mean	1977	32%	1994	48	0.8%	70%	1.021
Median	1971	34%	1991	52	1%	71%	1.005
Stalling group							
Mean	1971	29%	1986	15	3.4%	99.6%	1.08
Median	1970	26%	1985	16	2.8%	100%	1

Appendix C

Western and non-Western subsamples

Western countries	**Non-Western countries**
Belgium	Argentina
Canada	Brazil
Finland	Bulgaria
France	Taiwan
Germany	Hungary
Spain	Japan
Sweden	South Korea
Switzerland	Mexico
United Kingdom	South Africa
United States of America	Former Soviet Union
Czech Republic	
Italy	

Appendix D

Regression tables with G% as the dependent variable

Regression analysis with G% as dependent variable and GDP per capita as the independent variable

	Dependent variable:	
	G% (Gompertz)	GG% (Logistic)
GDP per capita	-0.00000	
	(0.00000)	
GDP per capita		-0.00000
		(0.00000)
Constant	0.049^{***}	0.043^{***}
	(0.011)	(0.014)
Observations	21	21
R^2	0.080	0.024
Adjusted R^2	0.032	-0.028
Residual Std. Error (df = 19)	0.030	0.029
F Statistic (df = 1; 19)	1.657	0.463
Note:		*p<0.1; **p<0.05; ***p<0.01

Regression analysis with ΔY as dependent variable and Y0 as the independent variable

	Dependent variable:	
	ΔY (Gompertz)	ΔY (Logistic)
Y0	**-0.946^{***}**	**-0.764^{***}**
	(0.234)	(0.133)
Constant	$1,879.615^{***}$	$1,520.653^{***}$
	(460.509)	(261.407)
Observations	23	23
R^2	0.438	0.612
Adjusted R^2	0.411	0.593
Residual Std. Error (df = 21)	11.226	6.372
F Statistic (df = 1; 21)	16.365^{***}	33.115^{***}
Note:		*p<0.1; **p<0.05; ***p<0.01

Regression analysis with G% as the dependent variable and electricity demand growth as the independent variable

	Dependent variable:	
	G% (Gompertz)	G% (Logistic)
Electricity demand growth	0.034	
	(0.040)	
Electricity demand growth		0.025
		(0.041)
Constant	0.028**	0.029**
	(0.011)	(0.010)
Observations	23	23
R^2	0.034	0.017
Adjusted R^2	-0.012	-0.030
Residual Std. Error (df = 21)	0.030	0.028
F Statistic (df = 1; 21)	0.738	0.359
Note:		*p<0.1; **p<0.05; ***p<0.01

Regression analysis with G% as the dependent variable and electricity supply as the independent variable. Electricity supply is log-transformed to account for non-linear relationships (a bigger effect in smaller systems).

	Dependent variable:	
	G% (Gompertz)	G% (Logistic)
Electricity supply (log)	**-0.010****	
	(0.004)	
Electricity supply (log)		**-0.010****
		(0.004)
Constant	0.087***	0.082***
	(0.022)	(0.021)
Observations	23	23
R^2	0.210	0.223
Adjusted R^2	0.172	0.186
Residual Std. Error (df = 21)	0.027	0.025
F Statistic (df = 1; 21)	5.576**	6.023**
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 0-1 Regression analysis with G% as the dependent variable and L% as the independent variable.

	Dependent variable:	
	G% (Gompertz)	G% (Logistic)
L%	0.013	
	(0.018)	
L%		**0.062****
		(0.024)
Constant	0.031***	0.015
	(0.009)	(0.009)
Observations	23	23
R^2	0.025	0.235
Adjusted R^2	-0.021	0.198
Residual Std. Error (df = 21)	0.030	0.025
F Statistic (df = 1; 21)	0.538	6.437**
Note:		$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Regression analysis with G% as dependent variable and dT as the independent variable

	Dependent variable:	
	G% (Gompertz)	G% (Logistic)
dT	**-0.0004****	
	(0.0002)	
dT		**-0.001****
		(0.0003)
Constant	0.047***	0.053***
	(0.008)	(0.009)
Observations	23	23
R^2	0.182	0.254
Adjusted R^2	0.143	0.219
Residual Std. Error (df = 21)	0.028	0.024
F Statistic (df = 1; 21)	4.680**	7.164**
Note:		$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Regression analysis with G% as the dependent variable and ΔY as the independent variable.

	Dependent variable:	
	G% (Gompertz)	G% (Logistic)
ΔY	-0.001	
	(0.0004)	
ΔY		-0.001
		(0.001)
Constant	0.046***	0.045***
	(0.009)	(0.011)
Observations	23	23
R^2	0.087	0.062
Adjusted R^2	0.043	0.017
Residual Std. Error (df = 21)	0.029	0.027
F Statistic (df = 1; 21)	1.991	1.386
Note:		*p<0.1; **p<0.05; ***p<0.01

Regression analysis with G% as the dependent variable and level of democracy as the independent variable

	Dependent variable:	
	G% (Gompertz)	G% (Logistic)
Level of democracy	-0.011	
	(0.022)	
Level of democracy		-0.005
		(0.021)
Constant	0.045**	0.038**
	(0.016)	(0.015)
Observations	21	21
R^2	0.014	0.003
Adjusted R^2	-0.038	-0.049
Residual Std. Error (df = 19)	0.031	0.029
F Statistic (df = 1; 19)	0.263	0.061
Note:		*p<0.1; **p<0.05; ***p<0.01

Regression tables with L% as the dependent variable

Regression analysis with L% as the dependent variable and electricity supply (log-transformed) as the independent variable

	Dependent variable:	
	L% (Gompertz)	L% (Logistic)
Electricity supply (log)	-0.001	
	(0.058)	
Electricity supply (log)		-0.032
		(0.035)
Constant	0.380	0.458^{**}
	(0.297)	(0.179)
Observations	23	23
R^2	0.00001	0.039
Adjusted R^2	-0.048	-0.007
Residual Std. Error (df = 21)	0.358	0.217
F Statistic (df = 1; 21)	0.0001	0.849
Note:		*p<0.1; **p<0.05; ***p<0.01

Regression analysis with L% as the independent variable and G% as the dependent variable

	Dependent variable:	
	L% (Gompertz)	L% (Logistic)
G%	1.856	
	(2.530)	
G%		**3.793^{**}**
		(1.495)
Constant	0.310^{**}	0.171^{**}
	(0.117)	(0.064)
Observations	23	23
R^2	0.025	0.235
Adjusted R^2	-0.021	0.198
Residual Std. Error (df = 21)	0.354	0.193
F Statistic (df = 1; 21)	0.538	6.437^{**}
Note:		*p<0.1; **p<0.05; ***p<0.01

Regression analysis with L% as the independent variable and Y0 as the independent variable

	Dependent variable:	
	L% (Gompertz)	L% (Logistic)
Y0	-0.011	-0.005
	(0.007)	(0.004)
Constant	21.482	10.906
	(13.410)	(8.438)
Observations	23	23
R^2	0.106	0.070
Adjusted R^2	0.063	0.026
Residual Std. Error (df = 21)	0.339	0.213
F Statistic (df = 1; 21)	2.477	1.580
Note:		*p<0.1; **p<0.05; ***p<0.01

Regression analysis with L% as the dependent variable and GDP per capita as the independent variable

	Dependent variable:	
	L% (Gompertz)	L% (Logistic)
GDP per capita	0.00000	
	(0.00001)	
GDP per capita		0.00001
		(0.00000)
Constant	0.259	0.150
	(0.191)	(0.113)
Observations	22	22
R^2	0.022	0.100
Adjusted R^2	-0.027	0.055
Residual Std. Error (df = 20)	0.363	0.214
F Statistic (df = 1; 20)	0.440	2.211
Note:		*p<0.1; **p<0.05; ***p<0.01

Regression analysis with L% as the dependent variable and level of democracy as the independent variable

	Dependent variable:	
	L% (Gompertz)	L% (Gompertz)
Level of democracy	0.734	0.568
	(0.688)	(0.415)
Constant	-0.216	-0.154
	(0.559)	(0.337)
Observations	22	22
R^2	0.054	0.086
Adjusted R^2	0.007	0.040
Residual Std. Error (df = 20)	0.357	0.215
F Statistic (df = 1; 20)	1.138	1.873
Note:		*p<0.1; **p<0.05; ***p<0.01

Regression analysis with L% as the dependent variable and Δy as the independent variable

	Dependent variable:	
	L% (Gompertz)	L% (Logistic)
Δ years	**0.016*****	0.004
	(0.004)	(0.003)
Constant	0.113	0.232***
	(0.086)	(0.068)
Observations	23	23
R^2	0.438	0.073
Adjusted R^2	0.411	0.028
Residual Std. Error (df = 21)	0.269	0.213
F Statistic (df = 1; 21)	16.356***	1.644
Note:		*p<0.1; **p<0.05; ***p<0.01

Regression analysis with L% as the dependent variable and electricity demand growth as the independent variable

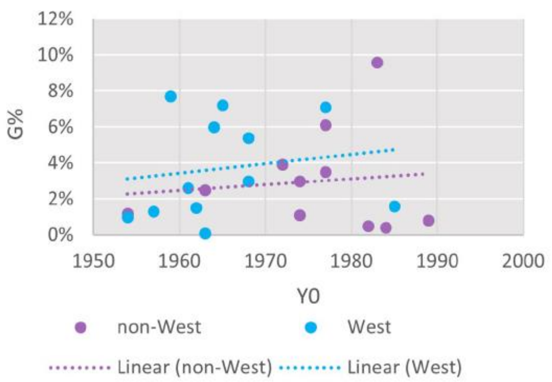
	Dependent variable:	
	L% (Gompertz)	L% (logistic)
Electricity demand growth	**-0.848***	
	(0.435)	
Electricity demand growth		-0.243
		(0.322)
Constant	0.578***	0.347***
	(0.124)	(0.079)
Observations	23	23
R^2	0.153	0.026
Adjusted R^2	0.113	-0.020
Residual Std. Error (df = 21)	0.330	0.218
F Statistic (df = 1; 21)	3.791*	0.569
Note:		*p<0.1; **p<0.05; ***p<0.01

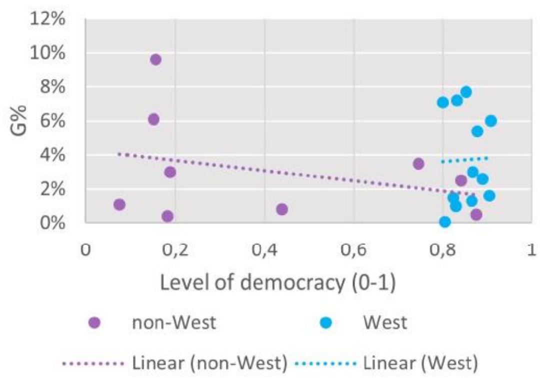
Appendix E

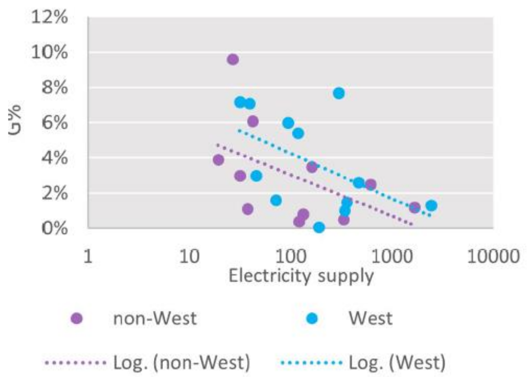
Summarizing table of key growth parameters in the Western and non-Western group, logistic growth parameters

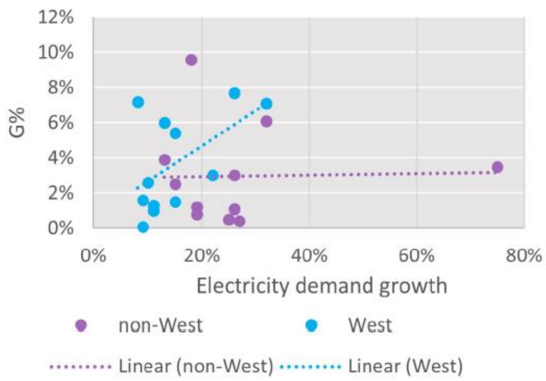
	Yo	L%	G%	dT	TMax
Non-Western group					
Mean	1975	21%	3%	17	1987
Median	1977	19%	2.5%	18	1985
Western group					
Mean	1965	38%	3.4%	26	1986
Median	1964	34%	2.8%	18	1983

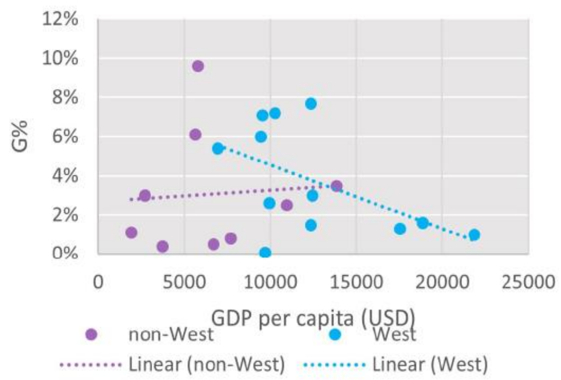
Scatter plots with G% as the dependent variable



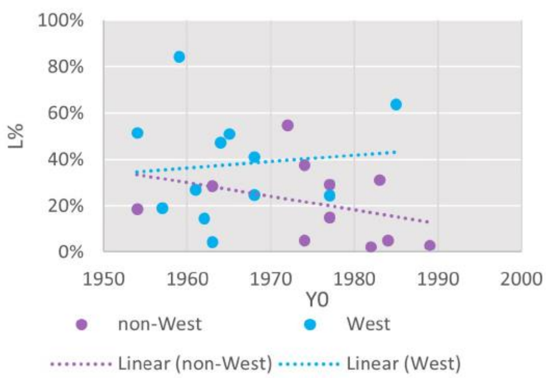


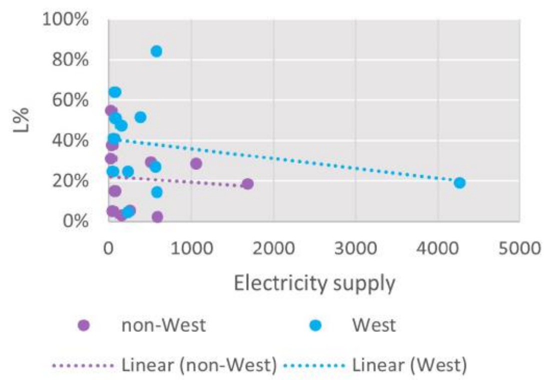


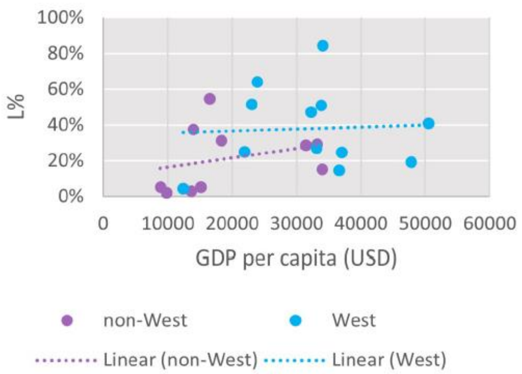


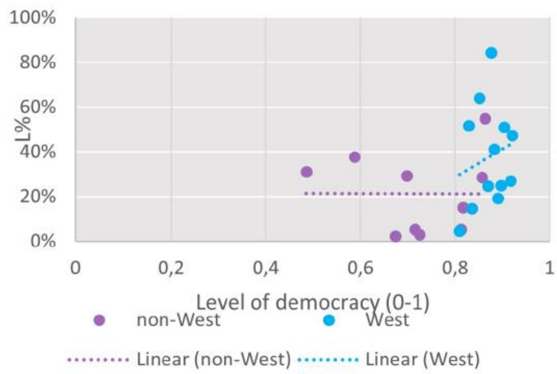


Scatter plots with L% as the dependent variable









Regression tables demonstrating regional differences

Regression analysis with L% as the dependent variable and Y0 as the independent variable in the respective groups.

	Dependent variable:	
	L%	
	(Western group)	(non-Western group)
Y0	0.001	-0.006
	(0.008)	(0.005)
Constant	-2.455	12.140
	(14.791)	(10.539)
Observations	12	11
R^2	0.004	0.125
Adjusted R^2	-0.096	0.027
Residual Std. Error	0.240 (df = 10)	0.167 (df = 9)
F Statistic	0.037 (df = 1; 10)	1.281 (df = 1; 9)
Note:		*p<0.1; **p<0.05; ***p<0.01

Regression analysis with G% as the dependent variable and energy demand growth as the independent variable in the respective groups.

	Dependent variable:	
	G%	
	(Western group)	(non-Western group)
Energy demand growth	**0.191****	0.004
	(0.083)	(0.055)
Constant	0.010	0.028
	(0.014)	(0.017)
Observations	12	11
R^2	0.347	0.001
Adjusted R^2	0.282	-0.110
Residual Std. Error	0.024 (df = 10)	0.030 (df = 9)
F Statistic	5.317** (df = 1; 10)	0.006 (df = 1; 9)
Note:		*p<0.1; **p<0.05; ***p<0.01

Regression analysis with G% as the dependent variable and GDP per capita as the independent variable in the respective groups.

	Dependent variable:	
	G%	
	(Western group)	(non-Western group)
GDP per capita	**-0.00000***	0.00000
	(0.00000)	(0.00000)
Constant	0.078***	0.027
	(0.022)	(0.022)
Observations	12	9
R^2	0.278	0.005
Adjusted R^2	0.206	-0.137
Residual Std. Error	0.025 (df = 10)	0.033 (df = 7)
F Statistic	3.850* (df = 1; 10)	0.036 (df = 1; 7)
Note:		*p<0.1; **p<0.05; ***p<0.01

Appendix F

Mean and median G% using capacity data

	Logistic	**Gompertz**
Mean	2.2%	2.3%
Median	1.2%	1.3%